Intelligent Planning Approaches for Electricity Generation and Distribution

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Intelligent Planning Approaches for Electricity Generation and Distribution

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To operate power generation and distribution industries efficiently and economically, their management must deal with a number of challenging problems. Of them, dynamic economic dispatch (DED) and bidding problems are two important topics. The purpose of a DED problem is to schedule the available generators to satisfy the daily load demands at minimum cost while that of a bidding one is to maximize the individual profit of an energy market by determining the optimal action of each participant.

Over the last few decades, although these problems have been extensively studied, they mainly dealt with the thermal power plants while ignoring the renewable sources and their uncertainties. This thesis considers the mix of different thermal, hydro, solar and wind generators with their uncertainties. For solving these problems, although many solution approaches have been developed, the evolutionary algorithms (EAs) achieve the best results. However, no single EA performs consistently over a wide range of these problems. Also, because of their dimensionality, non-convexity, multi-modality and large number of equality constraints, current EAs are inefficient for solving them. Moreover, most existing methods for solving a bidding problem aim to find a single solution whereas detecting multiple ones is more practical and challenging. In addition, the uncertainties of renewable sources pose a new challenge for the electricity generation and distribution sectors.

In this thesis, a general EA framework based on two EA variants, a self-adaptive differential evolution and real-coded genetic algorithm, is proposed to solve DED and bidding problems. To enhance the convergence rates of the proposed algorithms, a heuristic technique for repairing infeasible individuals while solving a DED problem is developed. For bidding problem, a co-evolutionary approach that detects multiple solutions in a single run is implemented. The effectiveness of the proposed approaches is evaluated on a number of bidding and DED problems considering the uncertainties of renewable generators. Comparisons of the simulation results with each other and those from state-of-the-art algorithms reveal that the proposed methods have merit in terms of solution quality and efficiency.

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Abstract

To operate power generation and distribution industries efficiently and economically, their management must deal with a number of challenging problems. Of them, dynamic economic dispatch (DED) and bidding problems are two important topics. The purpose of a DED problem is to schedule the available generators to satisfy the daily load demands at minimum cost while that of a bidding one is to maximize the individual profit of an energy market by determining the optimal action of each participant.

Over the last few decades, although these problems have been extensively studied, they mainly dealt with the thermal power plants while ignoring the renewable sources and their uncertainties. This thesis considers the mix of different thermal, hydro, solar and wind generators with their uncertainties. For solving these problems, although many solution approaches have been developed, the evolutionary algorithms (EAs) achieve the best results. However, no single EA performs consistently over a wide range of these problems. Also, because of their dimensionality, non-convexity, multi-modality and large number of equality constraints, current EAs are inefficient for solving them. Moreover, most existing methods for solving a bidding problem aim to find a single solution whereas detecting multiple ones is more practical and challenging. In addition, the uncertainties of renewable sources pose a new challenge for the electricity generation and distribution sectors.

In this thesis, several intelligent approaches for efficiently solving various DED and bidding problems are developed. Firstly, a self-adaptive differential evolution (DE) and genetic algorithm (GA) for solving thermal-based DED problems are proposed. To enhance their performances, a heuristic technique for repairing infeasible individuals while solving a DED problem is implemented. Then, to solve an uncertain DED problem, a scenario-based DED model that periodically implements its resources on successive days with uncertain wind speeds and load demands is proposed. A set of scenarios is generated based on realistic data to characterize the random natures of load demands and wind forecasting errors. In order to solve uncertain dispatch problems, the self-adaptive DE and GA, with a new heuristic are used. The heuristic enhances the convergence rate by ensuring feasible load allocations for a given hour based on the uncertain behaviors of the wind speed and load demand. Then, a general EA framework, called GA-DE, which automatically configures the better EA from the two considered during the evolutionary process for solving a wide range of DED problems, is proposed. In it, the GA and self-adaptive DE are performed under on two sub-populations, with the number of individuals in each dynamically varied in every generation based on the algorithms' performances during previous generations. Finally, the bidding problem of an energy market is formulated as a bi-level optimization one in which, in the lower level, the community's social welfare is maximized by solving a dispatch problem while, in the upper level, the profits of individual bidders are maximized. In this problem, instead of using a set of discrete bidding strategies, as is usual, the continuous functions are considered as strategies. To solve it, a co-evolutionary (CE) approach that detects multiple solutions (i.e., multiple Nash equilibria) in a single run is implemented.

The effectiveness of all the proposed approaches are evaluated by solving a number of bidding and DED problems considering the uncertainties of renewable generators and forecasted load demands. The simulation results are compared with each other and those from state-of-the-art algorithms. The major findings of this thesis can be summarized as: (1) the proposed methods obtain much better solutions than the state-of-the-art algorithms, with the heuristic greatly improving their quality; (2) the self-adaptive mechanism in the DE leads to much better solutions and savings in time; (3) a real-coded GA with a non-uniform mutation operator performs much better than ones with other mutation operators while solving a DED problem; (4) the heuristic for uncertain DED problems facilitates the scheduling of renewable generators in a periodic order on successive days; (5) for a wide range of problems, the proposed framework (GA-DE) obtains higher-quality solutions than those from the single EA developed and the state-of-the-art algorithms; (6) for a given stopping criterion, GA-DE performs best followed by DE and GA; (7) for a bidding problem, the proposed CE approach obtains a higher-quality solution than those from traditional methods; (8) the CE approach obtains the desired multiple solutions in a single run; and (9) the computational time of the proposed CE method is 77% less than those of traditional ones.

Keywords

Electricity Generation and Distribution, Energy Market, Economic Dispatch, Dynamic Economic Dispatch, Emission Dispatch, Renewable Energy, Uncertainty, Bidding Problem, Optimization, Evolutionary Algorithm, Genetic Algorithm, Differential Evolution, Heuristic

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Nomenclature

Acronyms	**Description**
Index	
i, h, w, k	Indices of thermal, hydro, wind and solar power plant, respectively
t, d	Indices of scheduling hour and day, respectively
s	Index of scenario of an uncertain system
j	Index of decision variable in an evolutionary algorithm (EA)
p	Index of individual of a population
g	Index of generation number of an EA
Common/Algorithm	
T, N_D	Total operational cycle and day, respectively
P_{D_t}	Electricity demand at t^{th} hour
N_P	Population size for EAs
N_G	Maximum number of generations for EAs
t_{start}	Random starting hour of the heuristic
ε_0, ε_g	Relaxation factor of the equality constraints at the initial and g^{th} generation, respectively
G, H	Dummy variables for the inequality and equality constraints, respectively
N_{gc}	A predefined number of cut-off generation (or cycle)
N_{P1} N_{P2}	Sub-population sizes of GA and DE, respectively
N_{P1}^{min},N_{P1}^{max}	Minimum and maximum sub-population sizes, respectively
$SUR_{1,g}, SUR_{2,g}$	Success rates of GA and DE for g^{th} number of generations, respectively
ASR_1, ASR_2	Average success rates of GA and DE, respectively

Acronyms	**Description**
$\vec{x}$, N_x	Decision variable's vector and number of decision variables, respectively
x^{min}, x^{max}	Lower and upper bound vectors for $\vec{x}$, respectively
$\vec{y}$	Offspring decision vector evaluated from $\vec{x}$
η_c	Predefined parameter of distribution index for simulated binary crossover
θ	Stopping criterion, *i.e.*, best fitness value no longer improved in θ generations
σ, μ	Standard deviation and mean value of a random number, respectively
$\varnothing$	An empty set

Thermal System

N_T	Number of thermal power plants
$P_{T_{i,t}}$	Output power from i^{th} thermal power plant at t^{th} hour
F_{c_i}, F_{E_i}	Fuel cost and gas emission of i^{th} thermal generator, respectively
a_i, b_i, c_i, d_i, e_i	Cost coefficients of i^{th} thermal power plant
α_i, β_i, γ_i, λ_i, η_i	Emission coefficients of i^{th} thermal generators
h_i	Constant used to normalize emission function to cost function
P_{loss}, B	Power transmission loss and its coefficients, respectively
P_i^{min} P_i^{max}	General minimum and maximum output powers of i^{th} unit, respectively
$P_{i,t}^{min}$, $P_{i,t}^{max}$	Minimum and maximum output powers of i^{th} unit at t^{th} hour, respectively
UR_i, DR_i	Upward and downward ramp limits of i^{th} unit, respectively
SRS, SRS_m	Spinning reserves for 1 hour and 10 minutes, respectively
U_T	Operational status of thermal generator, i.e., 0 - unit off, 1 - unit on
T^{on}, T_{min}^{on}	Continuous and minimum on-line times of thermal generator, respectively

Acronyms	**Description**
T^{off}, T_{min}^{off}	Continuous and minimum off-line times of thermal generator, respectively
DR^0, UR^1	Upper and lower ramp limits of thermal generator while unit in process of start-up or shutdown, respectively
$C_{i,t}$	Fuel cost of i^{th} thermal generator at t^{th} time
Hydro System	
N_H	Number of hydro power plants
P_{H_h}, X_{H_h}, V_{H_h}	Power output, water discharge rate and storage volume of h^{th} hydro unit, respectively
$C_{k,h}$,	Hydro power generation coefficients of h^{th} power plant, where k=1,2,..,6
I_h, S_{H_h}	Water inflow rate and spillage water for h^{th} reservoir, respectively
N_{up}, $t_{d_{r,h}}$	Number of upstream plants and water transport delay from r^{th} to h^{th} reservoirs, respectively
$P_{H_h}^{min}$, $P_{H_h}^{max}$	Minimum and maximum output powers of h^{th} hydro power, respectively
$V_{H_h}^{min}$, $V_{H_h}^{max}$	Minimum and maximum water storage volumes of h^{th} hydro reservoir, respectively
X_h^{min}, X_h^{max}	Minimum and maximum water discharge rates of h^{th} hydro reservoir, respectively
$V_{H_h}^{ini}$, $V_{H_h}^{end}$	Initial and final water volumes of h^{th} reservoir, respectively
Solar System	
N_S	Number of solar power plants
F_T	Total operation cost of a solar-thermal DED system
F_{S_k}, F_{P_k}	Operation and penalty costs of k^{th} solar power generation, respectively
$P_{S_{k,t}}$	Available output power of k^{th} solar power plant at t^{th} time period

Acronyms	Description
PU_{cost_k}	Per unit cost of k^{th} solar power plant
$U_{S_{k,t}}$	Binary decision variable that determines whether k^{th} solar unit turns on or off at t^{th} time period
P_{r_k}, T_{ref_k}	Rated power and reference temperature of k^{th} power plant, respectively
Ω	Temperature coefficient
$T_{amb_{k,t}}, Si_{k,t}$	Ambient temperature and incident solar radiation, respectively, for k^{th} solar power plant at t^{th} time period
Wind System	
N_W	Number of wind power plants
$\delta_w, P_{w,t}$	Cost coefficients of w^{th} wind farm and its scheduled output time period t, respectively
F_{w_w}, F_{W_w}, F_{O_w}	Operating, and under- and overestimated costs of w^{th} wind power plants, respectively
F_T	Total operation cost of a wind-thermal system
K_{U_w}, K_{O_w}	Under- and over-estimated penalty cost coefficients of w^{th} wind power plants, respectively
P_{R_w} v_{r_w}	Rated wind power and speed of w^{th} wind farm, respectively
v_{in_w}, v_{out_w}	Cut-in and cut-out wind speeds of w^{th} wind farm, respectively
Γ	Gamma function
μ_t, σ_t	Mean value and standard deviation of wind speeds for t^{th} time period, respectively
k_t, c_t, ϕ, ψ	Constants used to calculate F_{U_W} and F_{O_W}
$C_{w,t}$	Operating cost of w^{th} wind generator at t^{th} time.
Uncertain Wind System	
f	Index of index wind farm
N_S	Numbers of scenarios

Acronyms	**Description**
$P_{T_{i,t,s}}$	i^{th} thermal plant's output at t^{th} time in s^{th} scenario
$P_{G_i}^1$	Power generation from i^{th} plant at T^{th} hour
$P_{S_{t,s}}$	Amount of unexpected electricity shortage
$P_{D_{t,s}}$	Expected electricity demand at t^{th} hour in s^{th} scenario
$P_{D_{t,s}}^r$	Randomly generated load demand in s^{th} scenario at t^{th} time
$P_{w_{t,s}}^r$	Randomly generated wind power in s^{th} scenario at t^{th} time
$P_{i,t,s}^{min}, P_{i,t,s}^{max}$	Possible increase and decrease in i^{th} power plant at t^{th} hour in s^{th} scenario, respectively
$P_{i,s}^{min1}, P_{i,s}^{max1}$	Possible increase and decrease limits of first and last hour in s^{th} scenario, respectively
$S_{j,w,f}$	Slope of segment j for wind farm$-f$
$V_{w,f}, L_D$	Forecast wind speeds and load demands
$V_{ci,w,f}, V_{co,w,f}$	Cut-in and cut-out wind speed, respectively of unit i in wind farm$-f$
$V_{r,w,f}$	Rated wind speed for wind farm$-f$
$V_{j,w,f}$	Breakpoints of segment j for wind farm$-f$
$P_{S_{t,s}}$	Unexpected electricity shortfall at t^{th} hour in s^{th} scenario
λ	Penalty cost coefficient for unexpected electricity shortfall.
F_{C_L}	Penalty cost due to load shedding
F_{c_d}, F_{C_T}, F_T	Daily, weekly and overall operation costs of a DED system, respectively

Bidding Problem

i, j, k, n	Indices of GENCO, consumer, node and player, respectively
K	Total number of transmission grid nodes ($K > 0$)
I	Total number of generators ($I > 0$)
J	Total number of loads (customers) ($J > 0$)
N	Total number of bidders (players) in a market ($N = I + J$)
I_k	Number of generators at node k
J_k	Number of loads at node k

Acronyms	**Description**
P_i	Amount of electricity produced by the $i-$player (*i.e.,* GENCO)
D_j	Amount of electricity demand required by the $j-$player (*i.e.,* consumer)
P_i^{min}, P_i^{max}	Minimum and maximum real power limits of i^{th} generator;
q_j	Real power demand for load $j \in k$ at node k;
δ_1	Voltage angle at reference bus with fixed value of 0
δ_k	Voltage angle (in radians) at node $k, \forall k$ where $k \neq 1$
F_{km}	Real power flow through branch connection from nodes k to m
BR	Set of all distinct branches of k to m, $k < m$
$PNetInject_k$	Net injected real power at each node k
x_{km}	Reactance for branches k
B_{km}	Susceptance $(1/x_{km})$ for branches k to m
F_{km}^U, F_{km}^L	Lower and upper limits of real power flow for branches k to m
a_i, b_i, c_i	Cost coefficients of i^{th} generator
$\acute{b}_i$, $\acute{c}_i$	Quiescent coefficients of marginal cost function for i^{th} generator
d_j, e_j	Coefficients of j^{th} consumers' utility function
$\acute{d}_j, \acute{e}_j$	Quiescent coefficients of j^{th} demand curve
k_{g_i}	Bidding coefficient of i^{th} generator
k_{d_j}	Bidding coefficient of j^{th} consumer
$k_{g_i}^{min}, k_{g_i}^{max}$	Lower and upper limits of i^{th} generator
$k_{d_j}^{min}, k_{d_j}^{max}$	Lower and upper limits of j^{th} consumer
λ_k	Locational marginal price (LMP) at k^{th} node
λ_{P_i}, λ_{d_j}	LMPs of i^{th} generator and j^{th} consumer, respectively

List of Terms

Acronyms	**Description**
ABC	Artificial bee colony
AGC	Automatic gain control
AIS	Artificial immune system
BCDE	Bi-population chaotic DE
BCGA	Binary coded GA
BCO	Bee colony
CBDEX	Center based differential exponential crossover
CE	Proposed co-evolutionary based solution approach
CE-DE	CE based on DE
CE-GA	CE based on GA
CI	Computational intelligence
CMA-ES	Covariance matrix adaptation evolution strategies
CO	Conventional optimization
CQGA	Chaotic quantum GA
CSP	Concentrating solar thermal power
CSW	Community social welfare
CV	Constraints violation
DC-OPF	Direct current (DC)-OPF
DE	Differential evolution
DED	Dynamic ED
DEED	Dynamic economic and emission dispatch
DP	Dynamic programming
EA	Evolutionary algorithm
ED	Economic dispatch
E-DE	Proposed enhanced DE with the inclusion of heuristic
E-GA	Proposed enhanced GA with the inclusion of heuristic
EP	Evolutionary programming
E-PSO	Enhanced PSO

Acronyms	**Description**
ES	Evolutionary strategy
FV	Fitness value
GA	Genetic algorithm
GENCO	Generator company
GSA	Gravitational search algorithm
H-EP	Hybrid EP
HFS	Heuristic with starting from first hour
HRS	Heuristic with a random starting hour
HS	Harmony search
IESCO	Islamabad electric supply company
IGDT	Information gap decision theory
IP	Interior point
IPSO	Improved PSO
IT	Iterative based solution approach
LHS	Latin hypercube sampling
LMP	Locational market price
LP	Linear programming
MC	Marginal cost
MC	Monte Carlo
MCP	Market clearing price
MFV	Mean fitness value
MHEP	Modified EP
MINP	Mixed-integer nonlinear problem
MIQP	Mixed integer quadratic programming
MODE	Multiobjective DE
MOEA	Multiobjective EA
MOGA	Multiobjective GA
MOPSO	Multiobjective PSO
MP	Mathematical programming
MPSO	Modified PSO
MR	Mean rank of a Friedman test

Acronyms	**Description**
NDS	Non-dominated sorting
NE	Nash equilibrium
NERC	North American electricity reliability council
NLP	Nonlinear programming
NNDS	Nash non-dominated sorting
NNDS	Nash non-dominated sorting
nNE	Number of of Nash equilibria
NPGA	Niched Pareto GA
NR	Newton Raphson
NSGA	Non-dominated sorting GA
OPF	Optimal power flow
PDF	Probability density function
PEM	Point estimated method
PSOP	Power system optimization problem
PSO	Particle swarm optimization
QP	Quadratic programming
RCGA	Real-coded GA
RDPSO	Random draft PSO
SBX	Simulated binary crossover
SCQP	Strictly convex quadratic programming
SED	Static ED
SFE	Supply function equilibrium
SI	Swarm intelligence
SPSO	Selective PSO
SQP	Sequential QP
SR	Spinning reserve
SUR	Success rate
TC	Transmission congestion
TL	Transmission line
TRV	Transient ramp violation
TSP	Traveling salesman problem

Acronyms	**Description**
UC	Unit commitment
VPE	Valve point effect
WECC	Western Electricity coordinating council
WPG	Wind power generator

Chapter 1

Introduction

This chapter presents a brief background to the research conducted in this thesis. It describes the importance of solving various power system optimization problems in the electricity generation and distribution sectors, states the research objectives and provides the contributions to scientific knowledge. The organization of this thesis is also provided.

1.1 Background

The electricity industry is the largest industrial sector in the world [1]. It is a vast system for interconnecting many generators, transmission networks and consumers. Its secure and economical operation for transferring electricity to end-consumers with a remarkable degree of reliability is a challenging task. The major concern of an energy market is to guarantee adequate generation to meet variable load demands at different time periods, not only under a system's normal operating conditions but also after it is subjected to a disturbance in any of its interconnected systems. As the operating costs of different generating units vary significantly, it is a challenging problem to schedule the right mix of generation from a number of units to serve variable load demands at minimum cost while satisfying the numerous constraints emanating from different directions. This scheduling problem is known as a dynamic economic dispatch (DED) problem that determines the amount of generation required from each generator to meet hourly load demands for a cycle of T hours (usually 24 hours) [2]. Its objective is to minimize the overall operating cost of the participating generators by optimally allocating the load demands to those generators.

Depending on the generators involved, a DED problem can be thermal, hydro-thermal, wind-thermal or solar-thermal. Thermal-based DED problems are very common as most of the costs of electricity production costs involve the operation of thermal generators. As the use of fossil fuels in electricity generation has been increasing environmental pollution, the growth and development of renewable energy generation systems has been fostered. Therefore, mixed DED problems, such as hydro-thermal, solar-thermal and wind-thermal ones, are now widely used in practice. Although the operating costs and gas emissions of renewable sources are negligible, their uncertain natures present a new challenge for their economical operation in the power generation industry as their availability fluctuates greatly which makes it difficult to determine their exact output power in advance. Therefore, a DED is a challenging optimization problem for scheduling the right mix of generation from a number of renewable and thermal units to serve a daily load demand at minimum cost [3].

Sometimes, the minimization of the production cost is not adequate for an energy market as it requires the economic proficiency is to be maximized. To achieve this, many countries around the world have changed their electricity markets from monopolies to oligopolies to increase competition with the aim of improving their overall economic efficiency by maximizing the individual profits associated with a market. In an oligopoly market, all participants, such as generating companies (GENCOs) and consumers (e.g., distributor sectors and large industries) maximize their profits through a bidding process. In it, they simultaneously submit their bids to an independent system operator (ISO) which determines the market price and power production of each by solving a dispatch problem [4]. To ensure its maximum profit, each bidder optimizes its bidding behavior with respect to those of its competitors and power system constraints. An excessively high bid from a bidder may not be selected by an ISO while a lower one may not be able to cover the bidder's full costs. Therefore, selecting an optimal bid for a bidder is crucial and is known as a bidding problem in an energy market. A common solution of this problem is to determine a Nash equilibrium (NE) that ensures the maximum profits of each participant [5]. A NE is based on the strategies of all bidders in which one cannot increase its payoff by changing its own strategy while the others' strategies remain the same [6].

Both DED and bidding problems have been studied extensively and solved using different optimization techniques. They are represented as constrained nonlinear optimization problems. These problems involve numerous numbers of decision variables, and constraints including linear and nonlinear with equality and inequality types constraints.

The size of the problem increases significantly with the number of power sources. In addition, the cost function of large fossil fuel based generator is nonlinear, non-convex and multimodal characteristics [7]. Therefore, solving these problems are very challenging. However, once they are solved efficiently, significant benefits could be provided to the society; for example, decision for operating the most effective generation units first, then the inferior ones later, that leads to lower fuel usage as well as reduction in greenhouse gas emissions. The economic benefits of solving these problems are also remarkable; for example, a study in the United States' Department of Energy demonstrated that efficient algorithms for solving DED problems could deliver savings ranging from $30 million to more than $900 million [8] and, for bidding problems, increase average revenue by up to 60% over that obtained from conventional marketing systems [9].

During the last few decades, various optimization methods, involving both conventional optimization (CO) and computational intelligence (CI) techniques, have been developed to solve different DED and bidding problems [10]. Fig. 1.1 presents an example of current research regarding dispatch problems which shows that the number of articles published each year has significantly increased between 2005 and 2016 (from data as on 29 August, 2016) according to the database accessed in Scopus (https://www.scopus.com/) with the search field set to 'economic dispatch' in 'Article Title'. As the data is recorded for those already published but not released in the press, the number of articles in 2016 is slightly less than those in 2013 and 2014.

For solving the DED and bidding problems, although CO methods are usually computationally efficient, their main drawback is that some of their mathematical properties, such as convexity, continuity and differentiability, must be satisfied. To do this, researchers and practitioners simplify the actual optimization problems by considering several assumptions, such as the cost function is considered as quadratic, nonlinear power transmission losses are ignored, etc. [3]. On the other hand, CI algorithms are simple in concept, do not require specific mathematical properties to be satisfied, are robust to dynamic changes, can handle evaluating solutions in parallel, have the capability to self-organize and have broader practical applications [11]. During the last decade, many CI algorithms have been widely used to solve different types of DED and bidding

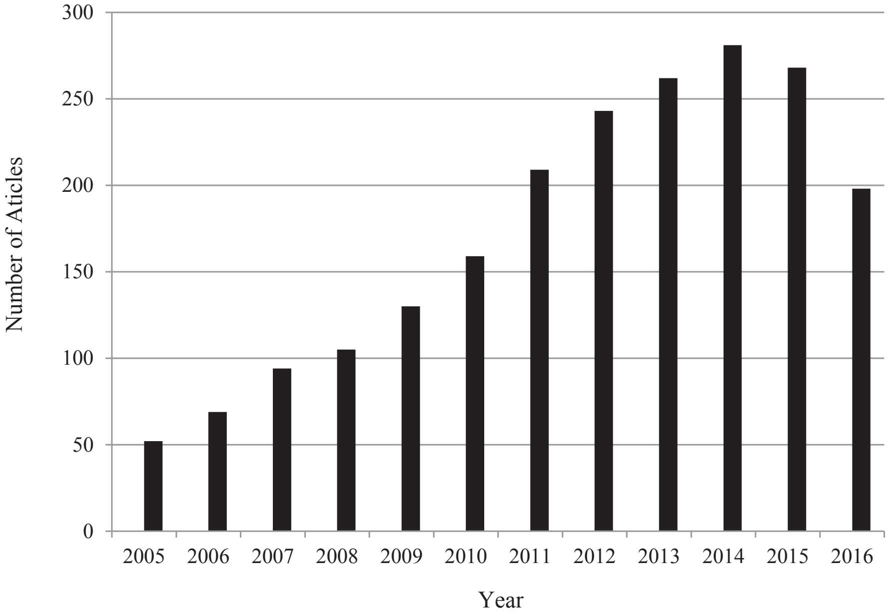

Fig. 1.1: Number of articles related to DED problems published from 2005 to 2016

problems. Despite numerous research studies, there is still a great deal of room for improving the approaches to solving these problems; for example, as most DED problems are solved without considering the uncertainties of renewable sources, their solutions to realistic DED problems are inferior [12]. Also, most existing algorithms find it difficult to meet the large number of equality constraints in these problems which, sometimes, cannot converge to the global optimal and prematurely converge when dealing with a multi-modal objective function [3]. In addition, there is no well-accepted single algorithm that can produce good-quality solutions for a wide range of DED and bidding problems, that is, one algorithm may be very efficient for one but perform poorly for another [3]. Moreover, most current methods for solving a bidding problem aim to find a single solution whereas detecting multiple ones is more practical but challenging [13]. Therefore, designing an efficient approach which could solve a wide range of DED and bidding problems would be an interesting and worthwhile contribution to both the power system and computer science fields.

1.2 Problem Description

The efficient operation of an electricity market is a challenging task with two important optimization problems, DED and bidding ones, greatly influencing its economic proficiency. The objective of a DED problem is to minimize the overall operating cost of the operated units and it is to maximize the economic profits of the market in a bidding problem subject to the load balance, ramp limits and generation capacity constraints.

As previously mentioned, a DED problem can be one of many types depending on the generators considered in its planning; for example, if it is used to schedule thermal generators for a number of periods, it is known as a thermal-based DED problem. Its objective is to minimize the fuel cost of the operated thermal generators while satisfying the hourly load demand, capacity, transmission loss and ramp constraints. The decision variables are the output power to be generated from each thermal generator in each time interval [14].

A hydro-thermal DED problem considers both thermal and hydro generators. It is a constrained optimization problem with the objective to minimize the fuel cost of the thermal generators, by maximizing the use of hydro power, while satisfying several hydraulic and thermal constraints [15]. The constraints are the load balance, water reservoir balance, capacity limits, ramp limits, water discharge rates, and initial and final amounts of water availability. The decision variables are the electricity output generated from the thermal generators and water flow rate from the hydraulic reservoirs.

Both solar-thermal and wind-thermal DED problems are solved under uncertainty due to the stochastic outputs from wind and solar units [16]. The objective is to minimize the fuel cost of the committed thermal generators by fully utilizing the available solar and wind powers in the planning horizon. These renewable sources offer a number of additional constraints such as wind speed for wind sources and solar radiation for solar sources along with traditional technical constraints. The decision variables are the outputs from the thermal, wind and solar generators. These problems are usually represented as mixed-integer non-linear optimization models in which, being continuous for the thermal generators and integers (binary) for the renewable ones, when a renewable unit is scheduled, the available electricity is fully utilized.

To reduce greenhouse gas emissions in electricity generation, sometimes, the DED problem is formulated as a bi-objective dynamic economic and emission dispatch (DEED) one that simultaneously minimizes both the operating costs and gas emissions. However, its computational process is even more complex than that of a single objective DED problem because both objectives are non-linear, multi-modal and non-smooth characteristics [17].

The bidding problem is another difficult problem that is usually formulated as a bi-level optimization problem in which, in the lower level, the community's social welfare (CSW) is maximized by solving a dispatch problem while, in the upper level, the profits of individual bidders are maximized. The decision variables in the lower level are the usual variables of a dispatch problem, that is, the output from the operated generators, while those in the upper level are the bidding parameters of the bidders. If the bidder is a GENCO, the variables are the per unit generating cost of the generators and per unit electricity price for consumers. Each decision entity independently optimizes its own objective but is affected by the actions of others in a hierarchy. Therefore, this bi-level problem is a challenging optimization one because it contains a nested optimization task within the constraints of another optimization problem. Also, it becomes more complex in the presence of non-standard mathematical properties, such as multi-modality, non-convexity and non-differentially. This problem is inherently more difficult to solve than traditional optimization problems, as pointed out in [18].

1.3 Motivation and Objectives

As discussed in the background section, in spite of having numerous successful research works for the DED and bidding problems, there still remain many interesting and challenging issues for exploration. Most of the earlier works dealt with the fossil fuel based power plants ignoring renewable sources. But, in the current scenario, all power system scheduling involves renewable sources, such as solar or wind sources. Besides that, the uncertainty of availability of those sources, sudden demand change, unexpected weather change or even outage of any traditional sources, required a reliable scheduling approach such as a real time based power system scheduling. For solving such DED and bidding problems, although existing CI methods, such as evolutionary algorithms (EAs), perform best, no single algorithm performs consistently over a wide range of these problems. Also, they are inefficient when solving a DED problem due to its large number of equality constraints, and multi-modal and non-convex objective functions. As most current methods solve the bidding problem sequentially (bidders bid one after the other), they may take too long to identify a solution in the presence of many bidders. Also, they detect a single NE from a number of equilibria which is not adequate for a player to make a decision [19]. Motivated by those obvious facts, the overall goal in this thesis is to develop a reliable and dynamic approach based on EAs for solving a wide range of DED and bidding problems that involves both traditional and uncertain renewable sources.

To achieve the primary objective of this study, the following sub-objectives are considered:

- Reformulating the DED and bidding problems by considering real-life constraints such as power loss, day-ahead ramp limits, and uncertainties of the renewable sources and forecasted load demands .
- Analyzing the performances of different EAs for solving different DED, DEED and bidding problems;
- Developing evolutionary computation based algorithms that would be empowered with a new repairing technique for efficiently solving thermal-based DED problems;
- Extending the proposed algorithms to solve renewable-based DED problems with uncertain renewable energy generations and variable load demands;
- Proposing an evolutionary framework based on multiple EAs for solving both deterministic and uncertain DED problems;
- Developing a new co-evolutionary (CE) technique for solving game-based bidding problems;
- Extending the CE method to find multiple solutions (Nash equilibria) to the bidding problems;

- Testing all the proposed methods by solving appropriate test problems for DED, uncertain DED, bi-objective DEED and bidding problems; and
- Comparing the performances of the algorithms with those of each other and state-of-the-art algorithms.

1.4 Contributions to Scientific Knowledge

This thesis develops a number of intelligent algorithms to solve various power system optimization problems and bidding problem in the context of marketing electricity. To accomplish it, several scientific contributions to the literature in the areas of power systems, optimization, and evolutionary computation are made, as discuss below.

- **EAs for thermal-DED problems:** two EAs based on the algorithms: (i) self-adaptive DE and (ii) GA, are developed. In their designs, a new heuristic technique is introduced to guide infeasible solutions towards the feasible space. Moreover, a constraint-handling mechanism, a dynamic relaxation for equality constraints and a diversity mechanism are applied to improve the performances of the algorithms. The effectiveness of the proposed approaches is demonstrated on a number of DED problems for a cycle of 24 hours. Their simulation results are compared with those of each other and state-of-the-art algorithms which reveals that they have merit in terms of the quality and reliability of their solutions.
- **EAs for wind-thermal DED problems:** for the continuous operation of variable wind generators in a periodic order on successive days, the traditional mathematical formulation of an uncertain DED model is reformulated as a scenario-based DED one. To avoid any unwanted electricity shortfall due to a sudden disruption of the wind generators and an increase in load demands over those forecast, a few constraints are incorporated in the model. Two new solution techniques based on a (i) self-adaptive DE and (ii) GA, with a heuristic technique, are developed. They schedule the generators based on the scenarios of wind speeds and load demands over a one-week period those generated using a Gaussian distribution with means and standard deviations found in historical data. In this process, as the

algorithms consider the scenarios of the operating and forthcoming days, the committed generators are scheduled for a day in such a way that they can also satisfy uncertain load demands on subsequent days. The heuristic technique enhances the convergence rate of the algorithms by ensuring feasible load allocations for a given hour under the variable wind speeds and load demands. The proposed methods are tested on two uncertain wind-thermal DED problems, with the simulation results demonstrating their feasibility and effectiveness in terms of solution quality compared with those of other optimization methods in the literature.

- **An evolutionary framework for DED problems:** to solve a wide range of single- and bi-objective DED problems, such as thermal, hydro-thermal, solar-thermal and wind-thermal, considering their uncertainties, a general evolutionary framework which automatically configures the better EA from the two considered (i.e., GA and DE) during the evolutionary process is proposed. The proposed algorithm (GA-DE) begins with a single initial population in which half the individuals are evolved by GA and the rest by DE. In each generation, the success rate (SUR) of each EA is calculated based on its success in generating better offspring than its parents. Then, the number of individuals evolved by each EA is updated for the next generation. This process is continued for a predefined number of generations (N_{gc}), with the better-performing algorithm selected to evolve the entire population for subsequent N_{gc} generations. Then, both the DE and GA are run in parallel in the next cycle and the procedure repeated until an overall stopping criterion is met. Moreover, self-adaptive mutations and crossover mechanisms are used in DE to automatically configure the best control parameters in each generation. The convergence rate of the proposed algorithm is further improved by including a heuristic which ensures feasible load allocations for an entire operational cycle for DED and DEED problems. The results obtained by the proposed approach are compared with those from recently published state-of-the-art algorithms. Also, the effects of different components on their performances are analyzed and demonstrated that the proposed GA-DE method outperforms those of all the other algorithms with which they are compared.

- **Co-evolutionary approaches for bidding problems:** to maximize the profits of participants in an energy market, a bidding problem is represented as a non-cooperative game in which the bidding strategies are considered the continuous functions of the bidders instead of a set of known discrete strategies, as is usual. In this model, both GENCOs and consumers act as independent players that maximize their own profits considering the interactions of their rivals. To solve this complex problem, two CE approaches based on (i) a real-coded GA and (ii) self-adaptive DE are designed. In both, each bidder's strategies are evolved in a sub-population with information exchanged among the sub-populations to find the overall best solutions. As the CE algorithms simultaneously determine the bidding actions using $N-$sub-populations for $N-$players, the computational time is significantly reduced. The performances of these CE approaches for solving several well-known benchmark problems are compared with those of two conventional iterative ones and results from the literature. The effects of different components on their performances are analyzed and it is found that these CE methods outperform all the others with which they are compared.

- **Enhanced co-evolutionary algorithms to determine multiple solutions for the bidding problems:** the CE framework is further extended to determine multiple solutions, i.e., multiple NEs in a single run for the competitive energy market. To achieve this, N sub-populations for N competitive players are considered. Each sub-population contains each player's actions which are updated by either a self-adaptive DE or GA operator during the optimization process. The payoff for the individuals of a player (sub-population) is evaluated considering the best actions of the other players determined using a new ranking technique called Nash non-dominated sorting (NNDS) driven from a well-known non-dominated sorting algorithm [20]. Two propositions that are proven validate that the best solutions obtained from the NNDS are the NEs. The performances of the proposed CE algorithms for solving four standard test functions and three well-known real-world energy markets are compared with those of two conventional ones.

1.5 Organization of Thesis

This dissertation has seven chapters and is organized as follows.

- Chapter 1: Introduction
- Chapter 2: Background Study and Literature Review
- Chapter 3: EAs for Thermal-DED Problems
- Chapter 4: EAs for Renewable Energy based DED Problems
- Chapter 5: Evolutionary Framework for DED Problems
- Chapter 6: EAs for Bidding Problems in Energy Market
- Chapter 7: Conclusions and Future Research

Chapter 1 presents an introduction to this thesis which includes its background, problem description, motivations and research objectives, scientific contributions to the literature and organization.

Chapter 2 provides a comprehensive review of the literature on the topics considered in this thesis. Firstly, it describes different power system optimization problems, including DED and bidding ones, and then presents various solution approaches for them.

Chapter 3 discusses the importance of solving a thermal-based DED problem in electricity generation, describes the problem and its mathematical formulation, and presents an overview of existing solution approaches. Then, after stating the motivation for developing new algorithms, it presents two new algorithms, a self-adaptive DE and GA, with a new heuristic technique. Finally, details of the experimental study and outcomes are provided.

In Chapter 4, the importance of solving renewable-based wind-thermal DED problems and the difficulties of their continuous operation due to the uncertainties of the wind generator's output are discussed. Then, the problem description and its mathematical formulation, and an overview of existing solution approaches are provided. Subsequently, the proposed algorithms for determining a periodic scheduling of wind and thermal generators on successive days are presented. Finally, details of the experimental study and its outcomes are highlighted.

Chapter 5 presents the importance of solving different types of DED and DEED problems, such as thermal, hydro-thermal, wind-thermal and solar-thermal, and their uncertainties in power system operations. Then, the descriptions and mathematical formulations of these problems are provided. Subsequently, an overview of existing solution approaches, the motivation for developing a new algorithm to solve a wide range of DED and DEED problems, the proposed evolutionary framework, and experimental results and outcomes are presented.

In Chapter 6, the significance of a bidding problem in an energy market is discussed. Then, a bidding problem, its mathematical formulation and an overview of existing solution approaches with their drawbacks are provided. Subsequently, two CE solution approaches for this problem, one based on a GA and the other DE, and their experimental results, parametric analyses and outcomes are presented.

Finally, Chapter 7 discusses the conclusions drawn from the research conducted for this thesis, provides a summary of its findings, presents several of its technical contributions to the literature and recommends some possible directions for future research.

Chapter 2

Background Study and Literature Review

This chapter provides an overview of the fundamentals of the topics considered in this thesis. It firstly describes various power system optimization problems, including dispatch and bidding ones, and then conventional optimization (CO) and computational intelligence (CI) techniques for solving them.

2.1 Energy Market

The energy market is one of the largest industrial systems created by humans. It consists of three major sectors: (i) generation; (ii) transmission; and (iii) distribution. In the generation sector, generator companies (GENCOs) produce an optimal level of electricity from each generator to meet the daily load demands while minimizing the total operating cost. The second sector refers to the responsibility to carry that electricity from its place of origin to those of consumption using transmission lines (TLs). Finally, distributors distribute the electricity to end-users safely, securely and economically [21].

In recent years, energy markets around the world have become a vertical marketing system in which generation, transmission and distribution companies work together in a unified manner [22]. One of the primary objectives of all three sectors is to reduce operational costs and increase overall profits. To achieve this, an energy market's operator often solves different power system optimization problems (PSOPs), with more effective solutions obtaining greater profits. Of various PSOPs, economic dispatch (ED) and bidding problems are significant and challenging for an energy market [3]. The former is used in the generation sector to determine the economic scheduling of different power plants to minimize their total production cost while satisfying their numbers of technical and environmental constraints [23]. The bidding problem is relatively new and used in a deregulated energy market in which the participants, such as GENCOs and consumers, compete and determine their best bidding actions for maximizing their own profits compared with those of others. However, proper competition among participants is a challenging task, usually formulated as a 'bidding problem' which aims to optimize the profit of each bidder in an energy market by satisfying its technical and social constraints [24].

In the following sections, different ED and bidding problems of an energy market and their challenges are discussed.

2.2 ED Problems

As electrical power generation is a complicated process, there has been significant interest within the research community in managing it efficiently to ensure affordable and reliable electricity services to end-consumers at a minimum cost. In practice, there are many types of electric power generators, such as thermal, gas turbine, diesel engine, hydro, tidal, solar and wind. Their per unit generation costs differ significantly, for example, the operating cost of a hydro plant is low compared with that of a thermal one as water is regarded as a renewable resource. Also, as generators are not at the same distance from the load center, their wheeling costs vary. As the demand for electricity is much greater than the amount a plant with a low operating cost can produce, it is necessary to also run some other costly and inferior options, such as thermal plants, from a distance. Since generators are interconnected in a national grid and their total generation capacities under normal operating conditions are greater than actual load demands with losses, it is necessary to mix them correctly so that there is an overall minimum cost. To achieve this, the two optimization problems of unit commitment (UC) and ED are performed by a power system operator. A UC problem, which precedes an ED one, determines a generators' on/off status for certain time periods while an ED one establishes the actual generations from each unit operated in each interval which minimizes the production cost as it assumes that the regulated units are predetermined by the solution to the UC problem [25]. The simple formulations of both problems are the same except that the decision variables of a UC one are discrete (‘1’ and ‘0’ for on and off, respectively) and continuous for an ED one [26]. A simple representation of an ED problem is as follows.

$$\text{Minimize: } F_{C_i} = \sum_{i=1}^{N} C_i \tag{2.1}$$

$$\text{Subject to: } \sum_{i=1}^{N} P_i = P_D + P_{loss} \tag{2.2}$$

$$P_{loss} = \sum_{i=1}^{N}\sum_{j=1}^{N} P_i B_{ij} P_j + \sum_{i=1}^{N} B_{0i} P_i + B_{00} \tag{2.3}$$

$$P_i^{min} \leq P_i \leq P_i^{max}\, i \in N \tag{2.4}$$

where N is the number of operating generators, P_D the load demand, P_{loss} the wheeling transmission loss, and B and B_0 its coefficients, P_i the optimal generation of the i^{th} generator, with its minimum and maximum generation limits of P_i^{min} and P_i^{max}, respectively, and C_i the cost function of the i^{th} generator that is primarily represented as the quadratic function:

$$C_i = a_i + b_i P_i + c_i P_i^2\, i \in N \tag{2.5}$$

where a_i, b_i and c_i are the cost coefficients of the i^{th} generator, and their units dollars (\$) per hour (h), \$ per megawatt hour (MWh) and \$ per MW^2h, respectively.

This simple formulation assumes that the cost function is quadratic while ignoring the valve point effect (VPE) and prohibited operating zones of a thermal generator with a multiple fuel option [23]. However, due to this assumption, the solutions obtained from an approximated formulation may result in a monetary loss of up to millions of dollars per year [27]. In real life, a large steam generator has a multi-fuel option, with some ripple appearing in the cost function while the steam is admitted through a valve, which is known as the VPE [28]. As a result, the cost function of the optimization problem develops non-smooth, non-convex and multi-modal characteristics, as shown in Fig. 2.1

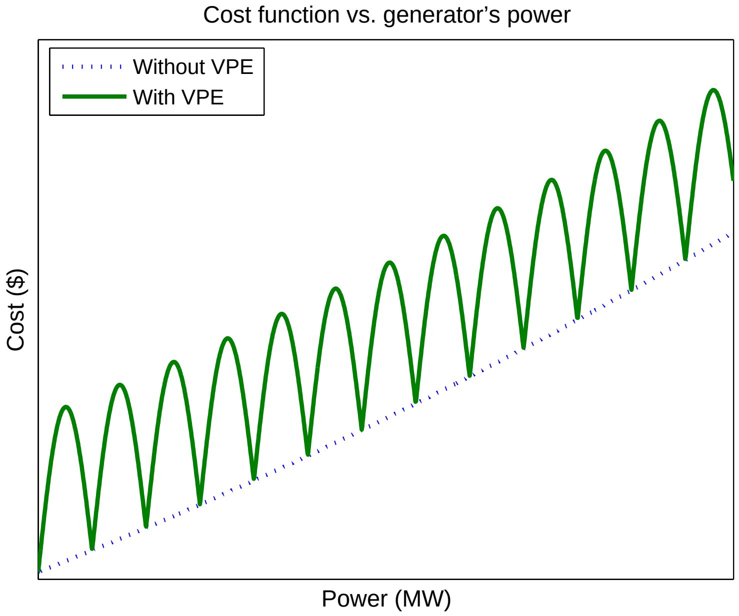

Fig. 2.1: Cost function with and without VPE

[29, 30]. The non-convex cost function is obtained by accumulating a rectified sine wave to the conventional quadratic function of Eqn. (2.1) as [30]:

$$C_i = a_i + b_i P_i + c_i P_i^2 + \left| d_i \sin\left\{ e_i \left(P_i^{\min} - P_i \right) \right\} \right| \quad i \in N \tag{2.6}$$

where $d_i(\$/h)$ and $e_i(rad/MW)$ are the valve point coefficients of the i^{th} thermal unit.

2.3 Dynamic ED

Previously, the dispatch problem was formulated as a static ED (SED) one assuming that the system was scheduled to serve a particular load level for an hour [2, 31]. Although such scheduling may be beneficial for a particular hour, it may not work for the next one (or the next few) depending on demand because the generation from a unit may not change significantly from one operating hour to the next due to ramp limits. The ramp is defined as the rate of change in the output from a plant over time and is usually expressed in MW/h [3]; for example, in Fig. 2.2, if a unit generates P MW in the t^{th} hour, and its upward and downward ramp limits are UR and DR, respectively, in the next $(t+1)^{th}$ hour, it can produce maximum and minimum of $(P+UR)$ and $(P-DR)$

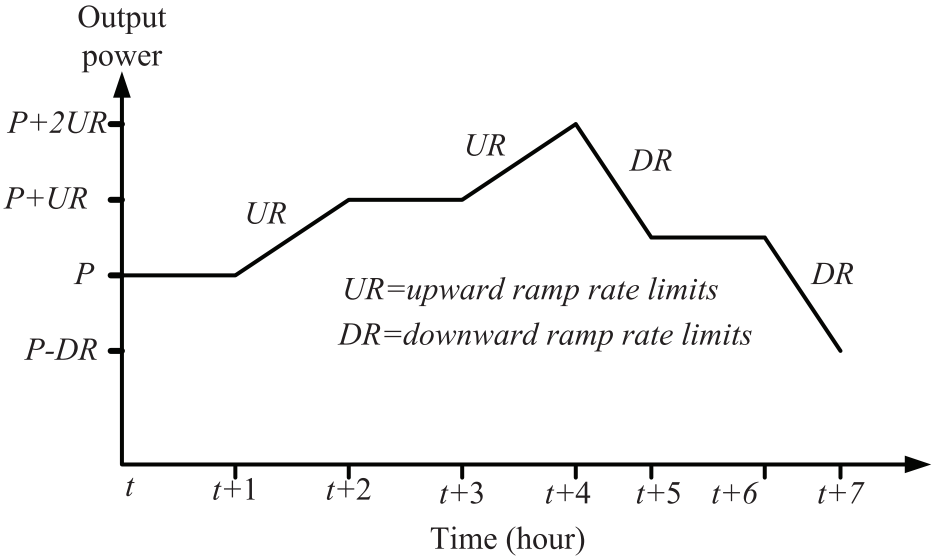

Fig. 2.2: Ramp limits

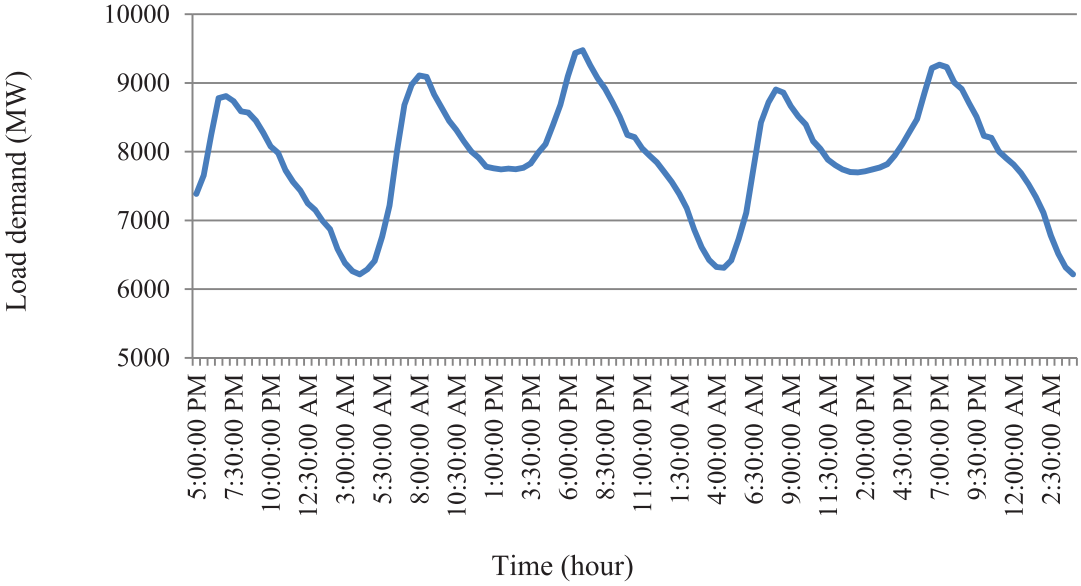

Fig. 2.3: Typical electricity demand in NSW, Australia, on 4 September 2016 [32]

MW, respectively. Therefore, for large variations in demand, such as are shown in Fig. 2.3 [32], a conventional ED may not work as the demand instantaneously changes up to thousands of MW.

To overcome this problem, the dynamic ED (DED) problem, which schedules generators for an operational cycle in a time horizon divided into multiple periods while taking into account the intrinsic links between two hours of the ramp limit of a thermal generator, was introduced [14]. Its objective is to minimize the total production cost of the generators operating over the time period considered by satisfying the generation capacity and ramp limits as well as the customer loads forecast over a multi-period time span. Although this problem is usually formulated for the dynamic scheduling of a load cycle of 24 hours with a time interval of 1 hour, it can be used for any $T-$ hour [3]. A simple representation of a $T-$hour DED problem is as follows.

$$\text{Minimize } F_d = \sum_{t=1}^{T}\sum_{i=1}^{N} C_{i,t} \tag{2.7}$$

$$C_{i,t} = a_i + b_i P_{i,t} + c_i P_{i,t}^2 + \left| d_i \sin\left\{ e_i \left(P_i^{\min} - P_{i,t} \right) \right\} \right| \; i \in N,\, t \in T \tag{2.8}$$

$$\text{Subject to: } \sum_{i=1}^{N} P_{i,t} = P_D^t + P_{loss}^t \; t = 1, 2, \ldots, T \tag{2.9}$$

$$P_{loss}^t = \sum_{i=1}^{N}\sum_{j=1}^{N} P_{i,t} B_{ij} P_{j,t} + \sum_{i=1}^{N} B_{0i} P_{i,t} + B_{00} \; t = 1, 2, \ldots, T \tag{2.10}$$

$$P_i^{min} \leq P_{i,t} \leq P_i^{max} \; i \in N \; t = 1, 2, \ldots, T \tag{2.11}$$

$$DR_i \leq P_{i,t} - P_{i,t-1} \leq UR_i \; i \in N,\, t = 1, 2, \ldots, T \tag{2.12}$$

where $P_{i,t}$ represents the i^{th} generator's electricity production at the t^{th} hour, and UR_i and DR_i its upward and downward ramp limits, respectively.

Although a DED is a more realistic problem than an ED one, its computational process is more complicated because of its large number of decision variables and chain of equality constraints that means the chronological balance of electricity generation and demand, as shown in Eqn. (2.9). Also, a real-life power system encounters some unexpected events, such as unit faults and changes in demand. To counter this, a spinning reserve (SR), usually the largest unit's capacity, is maintained in scheduling to increase system reliability (as explained in section 2.5) and, subsequently, derives a solution from its optimal point because a cheaper unit cannot run at its full capacity [28]. Therefore, as finding an optimal scheduling for a DED is not an easy task, it remains a challenge in the fields of computer and electrical engineering.

2.4 DED with Emission Limitations

Over the last few decades, the rapid increase in the use of fossil fuels has led to a consequent worldwide reduction in this resource while fossil fuel-based thermal power plants release several contaminants, such as nitrogen oxides (NO_x), sulfur oxides (SO_x) and carbon dioxide (CO_2), into the atmosphere. As, due to public awareness regarding protecting the environment and the Clean Air Act Amendments of 1990 [17], power industries are now required to reduce their pollution levels during electricity production, they have taken several steps, such as (i) installing pollution-cleaning equipment, (ii) using low-emission fuels, (iii) switching to alternative renewable sources, such as hydro, wind and solar, and (iv) formulating a DED problem as a bi-objective one to simultaneously minimize both the fuel costs and gas emissions [33]. The first two approaches are expensive, and the third and fourth are discussed in the following sub-sections.

2.4.1 Hydro-thermal DED

With the rapid development of societies and technologies, the demand for electricity has been increasing daily. However as, to produce a large amount of electricity from conventional thermal generators, while the use of fossil fuels has been significantly reduced but emissions into the environment have increased, an alternative to thermal power plants has become highly desirable. A hydro plant is a power source that, essentially, does not incur running costs and its environmental pollution is negligible. In a common one, river water is stored in a reservoir using a dam and then released to a spinning turbine which results in a generator becoming active and generating electricity. However, as demand for electricity is much greater than the amounts hydro plants can produce alone, it is necessary to run some other costly and inferior options, such as thermal plants. Therefore, mixed hydro-thermal systems have been widely studied in the literature and practice. As previously mentioned, the operating cost of a hydro plant is comparatively low as water is regarded as a renewable resource whereas that of a thermal one is high. Therefore, a challenging decision problem is to schedule all the plants under consideration to minimize the total cost while satisfying the demand, generation capacity and technical constraints. This issue is known as a hydro-thermal ED problem for single-hour scheduling and a hydro-thermal DED for T-hour scheduling [17].

Despite the numerous advantages of using a hydro-thermal system, it is one of the most difficult optimization problems in terms of the economical operation of a power system. This is mainly because it involves a number of difficult hydro constraints that must be met on a real-time basis; for example, the amount of electricity produced from a hydro plant depends on the water inflow rate and amount of water reserved, i.e., the water reservoir. At the same time, the water available in each time cycle of a dispatching time horizon depends on that used in the previous cycle. Therefore, it is necessary to develop a dynamic relationship among operational decisions over the entire time horizon. Using minimal water in each cycle, the objective of a hydro plant is to release an optimal amount of water from each reservoir for maximum hydro generation so that the total fuel cost of a hydro-thermal DED system over a dispatching period can be minimized. This problem is formulated as a large-scale, non-linear, non-convex and dynamic optimization one, with the significance of the economical operation of a hydro-thermal system well recognized as being that an optimal dispatch must reduce not only costs but also environmental pollution [17].

2.4.2 Wind-thermal DED

As previously mentioned, the widespread use of fossil fuels in electricity generation has increased environmental pollution. Therefore, alternatives to thermal sources have emerged with the introduction of renewable energy, with wind one source now being used more widely, particularly in Australia, the United States of America (USA) and Europe [34]. In fact, some European countries such as Denmark have an ambitious goal to shortly produce 50% of their total electricity from wind power generators (WPGs) [12]. The USA and Australia also have plans to use as much green energy as possible, with their research related to WPGs accelerating significantly [12]. The operating principle of a wind generator is simple. It uses a turbine installed 100 feet or more above the ground which has two or more of its blades connected to the rotor of a generator which spins, as the blades rotate according to the wind speed, and generates electricity.

Although wind energy is a promising alternative for electricity generation because of its significant environmental and social benefits and no major running costs, as its availability fluctuates greatly, it is difficult to accurately determine it in advance. Therefore, to schedule the right mix of generation from a number of wind and thermal units to serve a daily load demand at minimum cost is a challenging, uncertain optimization problem known as a wind-thermal DED problem [35].

2.4.3 Solar-thermal DED

Based on recent ongoing improvements regarding replacing fossil fuel-based thermal sources with emerging renewable ones, solar energy is now widely used because of its lower production cost and environmentally friendly characteristics [36]. As solar energy cannot be used directly, electricity can be obtained from it in two main ways, through solar photovoltaic (PV) generation and concentrating solar thermal power (CSP) whereby thermal energy uses sunlight to generate electricity [37]. However, the primary problem associated with incorporating solar energy in an ED model is the uncertainty of solar radiation levels during an entire day.

For long-term operation, uncertainty is a serious issue in a solar-thermal DED problem. Based on the North American Electricity Reliability Council (NERC), the electricity output from a PV-based solar power plant changes on a $\pm 70\%$ daily basis. However, it is manageable for short-term scheduling as its hourly forecasting errors are much lower than its daily forecasting ones [38]. Therefore, for a solar-thermal power system, it is more appropriate to adopt dynamic scheduling for a T-hour planning horizon with a one-hour interval. The DED model can achieve an hourly optimal schedule for a particular time horizon taking into account intrinsic links between systems at different times, such as the ramp rate of a thermal generator.

A solar-thermal DED problem is generally represented as a mixed-integer non-linear problem (MINP), where the solar unit is a binary variable and the thermal unit a continuous one [39], with the binary variable representing the status of the solar unit's turning on (= 1) and off (= 0). As a result, a solar energy unit would be fully used in a DED model as it's cheaper than a conventional thermal one [39]. The binary variable of a solar source represents the status of the solar unit as turning on (= 1) or off (= 0). As a result, the solar energy would be fully utilized in a DED model as it's a cheaper unit comparing to a conventional thermal one [39]. Therefore, solving a solar-thermal DED problem is a challenging optimization problem that requires an efficient algorithm [39].

2.4.4 Bi-objective DED

Formulating a dispatch problem as a bi-objective optimization one with the aims of simultaneously minimizing both the fuel cost and gas emissions is another approach for reducing greenhouse gas emissions in the environment [40]. This is called a dynamic economic and emission dispatch (DEED) problem, where the two conflicting objectives, fuel cost and gas emissions, are simultaneously minimized by satisfying a number of equality and inequality constraints. A simple representation of a bi-objective DEED is as follows [41].

$$\text{Minimize (fuel cost): } F_d = \sum_{t=1}^{T}\sum_{i=1}^{N} C_{i,t} \tag{2.13}$$

$$\text{Minimize (gas emissions): } F_E = \sum_{t=1}^{T}\sum_{i=1}^{N} E_{i,t} = \sum_{t=1}^{T}\sum_{i=1}^{N} \left(\alpha_i + \beta_i P_{i,t} + \gamma_i P_{i,t}^2 + \eta_i e^{\lambda_i P_{i,t}}\right) \tag{2.14}$$

subject to Eqns. (2.9) to (2.12), where $\alpha_i(ton/h)$, $\beta_i(ton/MWh)$, $\gamma_i(ton/MW^2h)$, $\eta_i(ton/h)$ and $\lambda_i(1/MW)$ are the emission coefficients for the i^{th} thermal unit and F_E the total emission effect of the thermal units for a single day of operation with one-hour intervals. As the fuel cost function, the characteristic of the gas emission function, is quadratic, multi-modal and non-convex [42]. The presence of multiple non-linear objectives, dynamic ramp limits and non-linear equality constraints in a DEED problem make it more complicated than a single-objective dispatch one [42]. Therefore, determining the optimal use of fossil fuels in power generation which has a minimum impact on the environment is still a challenging research topic [43].

2.5 DED with Uncertainty

As high amounts of uncertain renewable sources are currently used in DED and DEED models, it is necessary to comprehensively consider their uncertainty factors, such as sudden and unexpected changes in load demand and intermittent generations from solar and wind generators. A common method for addressing them has been to maintain the reserve requirements as, according to the Western Electricity Coordinating Council (WECC) [44], a standard electricity market must maintain certain reserves. The sample distribution of a conventional source presented in Fig. 2.4 shows that the generator is dispatched to maintain sufficient reserve requirements for automatic gain control (AGC) and contingency reserves. AGC is used to adjust production based on small changes in electricity demand due to customer needs; for example, one person turning on his or her household appliances while another is turning them off. Contingency reserves, which are used to maintain the balance in a system when there is a forced outage of a generator and/or any forecasting errors, can be SR or non-SR. In SR, online generators are automatically synchronized to the reserve requirements according to their capacities and ramp limits; for example, a generator dispatching 200 MW with lower and upper limits of 100 and 500 MW, respectively, and a ramp of 50 MW can generate $200 + 50 = 250$ MW if balancing is required. On the other hand, non-SR is the total reserve capacity for generators not currently operating but ready for emergency requirements.

However, as maintaining a reserve is a challenging task in terms of both cost and quantity, researchers have begun to incorporate uncertainty in DED and DEED models to address the uncertainties of wind and intermittent solar generations. In the literature, several approaches have been developed to address the impact of random parameters of the dispatch models, one of which is a stochastic one, with its main goal to minimize the reserve cost for uncertainty along with the production cost, and is formulated as an uncertain wind-thermal DED problem as [45]:

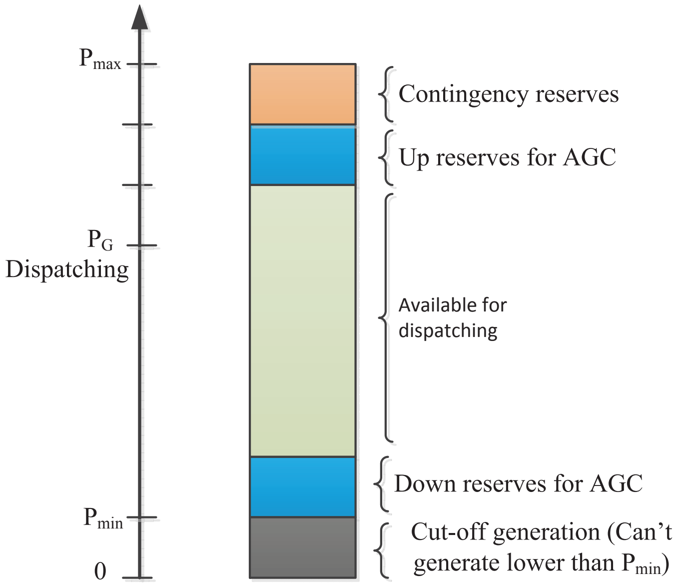

Fig. 2.4: Allocation of capacity of generation unit [44]

$$\text{Min: } F_d = \underbrace{\sum_t \sum_i C_{i,t}(P_{i,t})}_{\text{fuel cost for thermal units}} + \underbrace{\sum_t \sum_w C_{w,t}(\hat{W}_{w,t})}_{\text{operating cost for wind gen.}} +$$
$$\underbrace{\sum_t \sum_w C^t_{p,w}(W^t_{ac,w} - \hat{W}_{w,t})}_{\text{penalty cost for underestimation}} + \underbrace{\sum_t \sum_w C^t_{r,w}(W^t_{ac,w} - \hat{W}_{w,t})}_{\text{penalty cost for reserves}} \tag{2.15}$$

$$P_i^{min} \leq P_{i,t} \leq P_i^{max}\, t \in T \tag{2.16}$$

$$0 \leq \hat{W}_{w,t} \leq W^t_{R,w}\, t \in T \tag{2.17}$$

$$\sum_i P_{i,t} + \sum_w \hat{W}_{w,t} = \hat{P}_{D,t}\, t = 1, 2, \ldots, T \tag{2.18}$$

where $\hat{W}_{w,t}$ and $C_{w,t}$ are the random variables of the uncertain output of the w^{th} wind source in the t^{th} hour and its cost, respectively, $C^t_{p,w}$ and $C^t_{r,w}$ the penalty and reserve costs, respectively, $W^t_{w,ac}$ the actual available power from the w^{th} wind source and $\hat{P}_{D,t}$ another random variable for the variable power demand at the t^{th} hour. $\hat{W}_{w,t}$ and $\hat{P}_{D,t}$ are determined using the Weibull and Gaussian probability density functions (PDFs) from the stochastic wind speeds and natural electricity consumptions, respectively. The objective function in Eqn (2.15) involves the production costs of thermal and wind generations as well as the penalty ones. The first penalty cost for the under-estimation of wind generation, the 3^{rd} factor in Eqn. (2.15) indicates that, if the wind generation available is greater than the actual amount dispatched, as the surplus energy could be wasted, it is necessary to compensate the wind producer for any economic loss incurred. Meanwhile, when a system operator under-estimates the amount of wind energy it could actually produce, as additional reserves are required to overcome the scarcity of power, this results in a higher operational cost. Therefore, the penalty cost of reserve requirements is added to the objective function as the 4^{th} term in Eqn. (2.15).

However, this uncertain DED problem is a very challenging optimization one due to increasing penetrations of these uncertain renewable sources which have high degrees of volatility and deviation in dispatch problems. Consequently, it faces uncertainty in the net demand and needs to retain a predetermined high amount of reserve generation to ensure feasibility which may yield a sub-optimal solution.

2.6 Deregulated Energy Market

In a traditional electricity market, a DED problem is used to minimize the production cost by maintaining an adequate level of supply. However, as this system does not facilitate any competition among both suppliers and consumers, its overall profit is not adequate. In order to increase economic proficiency and reduce production costs, the energy markets in several countries, such as Chile (1978), the United Kingdom (1990), the USA (1999), Norway (1991), Colombia (1993), Argentina (1992), Australia (1993), New Zealand (1994), Finland (1997), Brazil (1997), Spain (1998), Sweden (1996) and Germany (1999), have become more decentralized and deregulated [46]. Note that the year in brackets indicates when the electricity market in that country became deregulated. In this environment, markets are no longer monopolistic but are becoming open to competition among both suppliers and consumers [47, 48]. Implementing this new

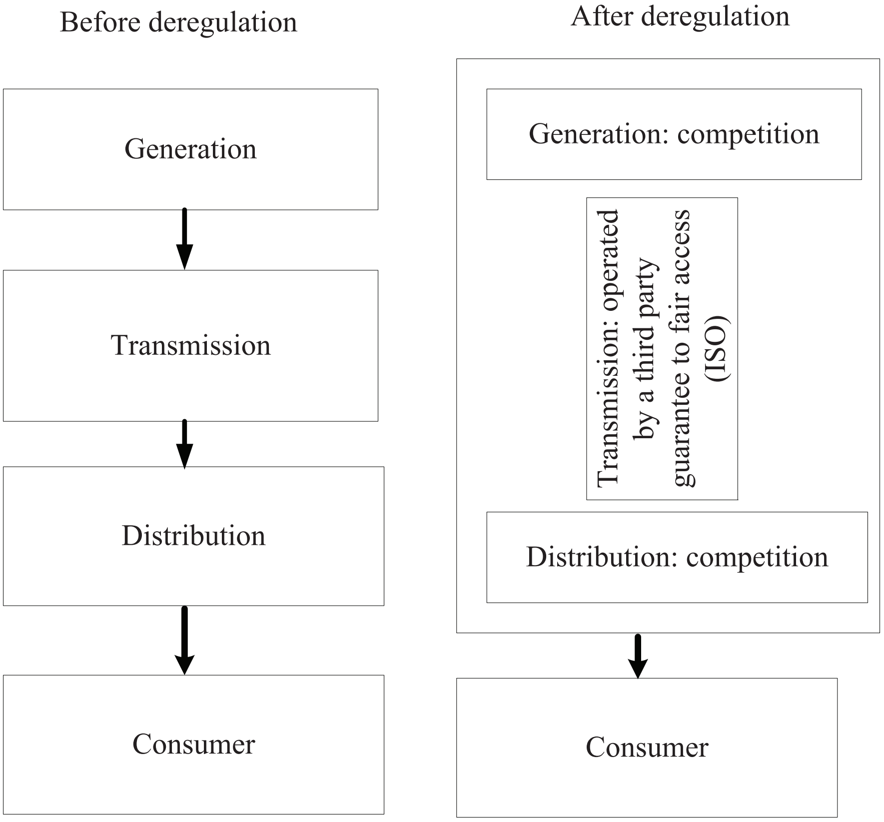

Fig. 2.5: Electricity markets before and after deregulation

strategy, the overall profits of these markets have increased significantly, by approximately 20% in the USA [49], and it has also been proven that, subsequently, electricity prices have fallen and customer services improved [49].

The differences between current (or future in some countries) and past electricity markets are illustrated in Fig. 2.5 in which it is clear that a conventional market was a monopoly with no commitment among generators and consumers. On the other hand, a deregulated market introduces competition everywhere, with generators, distributors (retailers) and independent system operators (ISOs) working in a unified system [50]. In it, suppliers, i.e., GENCOs and consumers (e.g., large industries, retailers, distributor companies, residential loads, etc.) are required to submit their bids to a third party known as an ISO that determines the market clearing price (MCP) and the amount of electricity required of each winning bidder by solving a DED problem considering the power-flow constraints through TLs. Note that, when a dispatch problem is solved considering the transmission congestion (TC) constraints, the problem is known as an

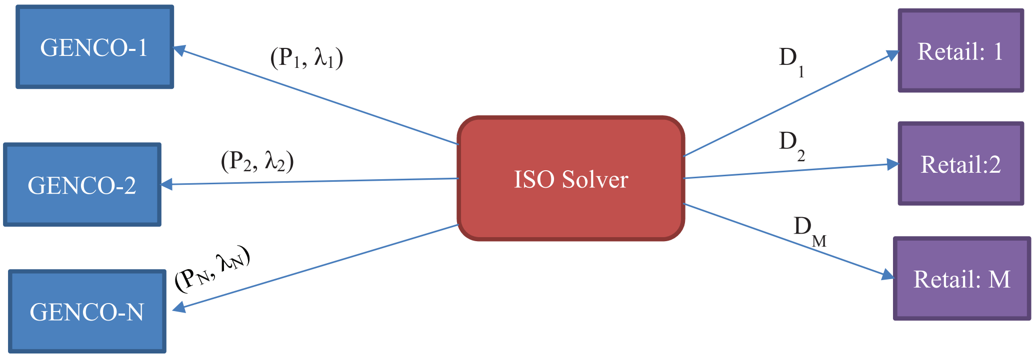

Fig. 2.6: Bidding process

optimal power flow (OPF) one, where the aim is to determine an optimal operating point of a power system by maximizing its community social welfare (CSW) subject to its network and physical constraints [51]. The CSW is defined as the difference between the profits obtained by providing electricity to consumers and the expenses of purchasing it from GENCOs.

However, in order to maximize the profit of a bidder, it is necessary to determine its optimal bid in advance as bids are generally submitted a day before the actual delivery of electricity. This is a challenging optimization problem known as a bidding problem of an energy market[52], as described below.

2.6.1 Bidding Problem

In a bidding problem, each participant in an energy market submits its own bid to the ISO which then runs an OPF problem to determine the status of each bidder, with the winning one informed of its MCP and allocated quantity of electricity. Fig. 2.6 shows the competition in a typical market in which each participant submits its own bid, with its profit calculated based on its actual cost and revenue as:

$$\pi_i = \lambda_i P_i - (a_i + b_i P_i + c_i P_i^2)\,\forall i \in N \tag{2.19}$$

where π_i and λ_i are the profit and MCP, respectively, of the $i^{th} \in N$ bidder. Note that, when TCs are ignored, the MCPs of all bidders are the same but, if they are considered, the MCPs vary significantly from location (or node) to location which is called the

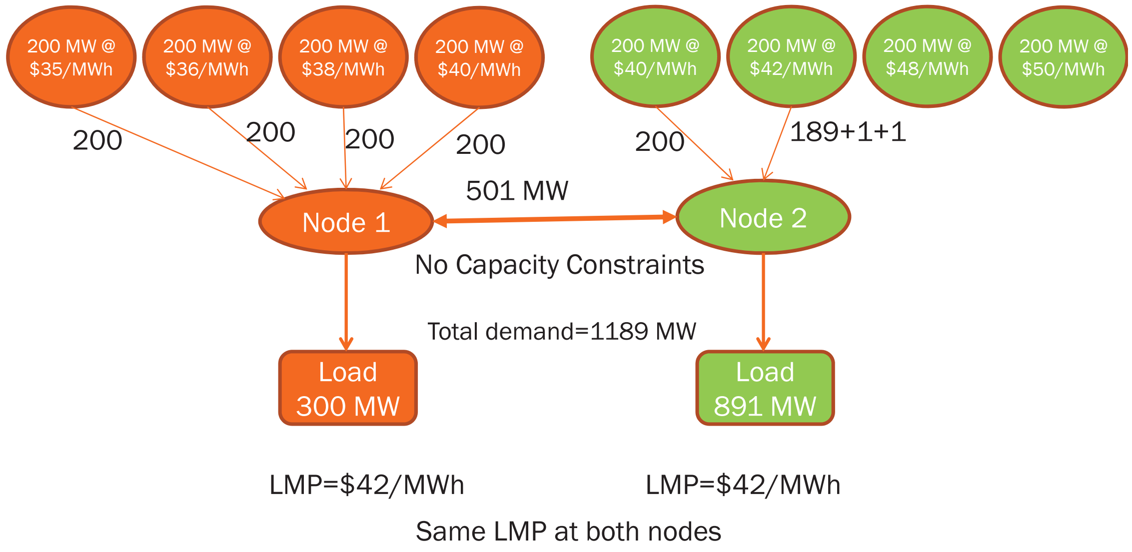

Fig. 2.7: Example of LMP calculations without considering TC

locational market price (LMP) [53]. The LMP is calculated at each node in the system based on the last MW dispatched plus 1 MW at each node selected to provide power; for example, LMP calculations with and without considering the TC, are shown in Figs. 2.7 and 2.8, respectively. In both cases, the system has two nodes, both of which have four GENCOs each with a capacity of 200 MW, and the per unit generation costs of the units are different, as shown in Fig. 2.7. If the total load demand of the system is 1189 MW, in Fig. 2.7 in which the TC is ignored, the optimal dispatches are 200, 200, 200, 200, 200, 189, 0 and 0 MW from the cheapest to most expensive units. Since there is no TC on the TL, the additional 1 MW of both nodes can be obtained from the 2^{nd} unit of node 2 and then the total line flow through the TL is 501 MW and the LMPs of both nodes the same, i.e., \$42/MWh. On the other hand, in Fig. 2.8, in which the maximum capacity limit of the TL is set to 300 MW, the optimal dispatches of the GENCOs are changed to 200, 200, 199, 0, 200, 200, 190 and 0 MW, and as the additional 1 MW of each node comes directly from its own node because the line flow is already congested of 300 MW, the LMPs of nodes 1 and 2 are different, i.e., \$38 and \$48 /MWh, respectively. Therefore, it is clear that TC has a significant impact on both the market price and profit of each individual bidder.

Moreover, as the profit of a bidder depends on both its own submitted bid and those of its rivals, it plays a game by optimizing its own bidding behavior based on those of its competitors as well as power system constraints. An excessively high bid

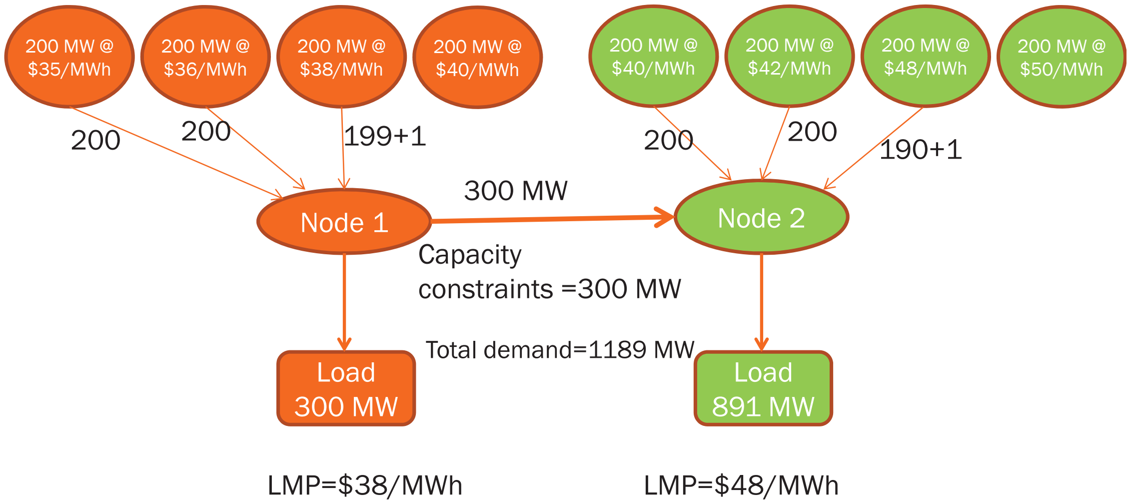

Fig. 2.8: Example of LMP calculations considering TC

by a player may not be selected by the ISO while a lower one may not cover its own costs. Therefore, selecting appropriate bids to maximize the profits of all bidders is a challenging optimization problem.

2.7 Overview of Solution Approaches

In this section, an overview of approaches for solving the different types of ED and bidding problems, which can be broadly categorized as CO and CI techniques, is presented.

2.7.1 Conventional Optimization Techniques

In this sub-section, a few CO methods based on different mathematical programming (MP) techniques, such as linear programming (LP), dynamic programming (DP), quadratic programming (QP), and gradient based as well as Newton and interior point (IP) methods are discussed.

LP is a simple method widely used to solve an optimization problem that is minimized by treating its objective function and constraints in a linear form with non-negative variables. The simplex method is widely used for solving a LP problem. It is very reliable, fast and accurate for a linearized model of any engineering problem [54].

The DP-based method is popular for solving both the linear and quadratic functions of an optimization problem. In it, the problem is divided into a large number of simple sub-problems with possible solutions to each evaluated. A single solution, which must be selected in each sequential sub-problem, may affect its succeeding one. Once all the sub-problems are solved, a solution that combines the best ones of all the sub-problems is obtained. However, a major drawback of this approach is that it can only be used for some specific types of problems [55].

QP is a special form of non-linear programming (NLP) in which the objective function is quadratic and the constraints in a linear form. It has better accuracy than an LP-based method for solving an optimization problem, particularly one with a quadratic objective function. Solving some real-world problems as a series of quadratic problems is known as sequential QP (SQP) [54]. A simple SQP solves a problem sequentially considering that the constraints in each sequence in the sub-problem are linear. However, if the problem is unconstrained, it solves it using the Newton gradient-based method.

An IP method is widely used to solve both linear and non-linear optimization problems. In each iteration, it generates one or more search directions in the interior while keeping the position of the current solution in the center of the interior and finding a better direction for the next move, with the solution iteratively moved to the optimal direction. Once the optimal step size of an iteration is chosen, an optimal solution is achieved in a few iterations. It is known as an interior method because it improves the search directions in the interior of the feasible space. For constrained problems, it considers some slack variables to transform the inequality constraints into non-negativities which are further replaced with a logarithmic barrier to the objective function. The advantage of this approach is that it restricts the starting point to within the interior of the inequalities and the barrier stops a variable reaching a boundary. For equality constraints, a penalty function using a Lagrange multiplier is incorporated with the objective function and, subsequently, the barrier problem is solved using Newton's method [56].

2.7.2 Computational Intelligence Techniques - An Overview

Over the last few decades, meta-heuristic-based optimization techniques, such as genetic algorithm (GA) [57], differential evolution (DE) [58], particle swarm optimization (PSO) [59], evolutionary programming (EP) [60], evolutionary strategy (ES) [3], artificial bee colony (ABC) [61], artificial immune system (AIS) [62] and bat-inspired algorithms, have been widely used to solve different types of PSOPs. Their main steps are similar while their chromosome representations and ways of generating new individuals from old ones vary as they encode individuals in different ways, e.g., with binary, integer, real and string values. In order to generate a new individual from existing ones, common operators, such as recombination (crossover), mutation and selection, are used. The new individuals, which are called offspring, only survive to the next generation if their fitness values (FVs) are better than those of their parents. These steps are repeated until a stopping criterion is met [11].

In the following sub-section, some meta-heuristic-based optimization techniques are discussed.

A Genetic Algorithm

The GA is a population-based algorithm which use different operators, including crossover, mutation and elitism-preserving techniques [57]. Crossover is the process of exchanging chromosome material to create new offspring. Elitism encourages the convergence properties to achieve global optimal results while a mutation operator guarantees no early convergence of a solution. GA has been successfully applied to many difficult real-world problems, has the capability to handle both continuous and discrete variables. It is well suited to parallel computing and can deal with the optimization of incredibly complex fitness landscapes [11]. Its primary operators are described below.

A.1 Genetic Representation

Depending on the nature of the problem, its genetic representations can be binary, permutations and real-valued in which the chromosomes are represented as either 0 or

1, a sequence up to a certain number and real values, respectively. Although a binary representation works well, its computational cost is high while permutation ones are usually used in order problems, such as the traveling salesman problem (TSP) or task ordering one, and a real-valued one in the continuous domain, such as DED problems [11].

A.2 Crossover

To generate new offspring from parents, a crossover operator, which exchanges genetic materials among the chromosomes, is performed. Over the decades, depending on a problem's characteristics, a number of crossover operators, such as single-point, multi-point, uniform, blend, intermediate, simulated binary, uni-modal distribution, simplex, parent-centric and triangular crossovers, have been introduced [11], each of which has its own pros and cons when applied to solving evolutionary problems. Of them, the simulated binary crossover (SBX) is widely used for many test problems [63]and, as it generates child solutions by avoiding arbitrary closeness to the parents, the diversity of the solutions is inherently preserved. Also, it does not require any additional mating restriction scheme for achieving better performance and is very popular for a problem with an unknown solution boundary and a multi-modal one which may have multiple optima [11]. To generate new offspring from parents, firstly, a pair of parents, (x^1 and x^2) is selected from the population, then two offspring (y^1 and y^2) generated as:

$$y_j^1 = 0.5[(1+\beta_{qj})x_j^1 + (1-\beta_{qj})x_j^2],\ \forall j = 1,2,...,N_x \tag{2.20}$$

$$y_j^2 = 0.5[(1-\beta_{qj})x_j^1 + (1+\beta_{qj})x_j^2]\ j = 1,2,...,N_x \tag{2.21}$$

where β_{qj} is calculated as:

$$\beta_{qj} = \begin{cases} (2u_j)^{1/\eta_c+1} & \text{if } u_j \leq 0.5 \\ \left(\frac{1}{2(1-u_j)}\right)^{1/\eta_c+1} & \text{if } u_j > 0.5 \end{cases} \tag{2.22}$$

where u_i is a uniform random number in the range [0, 1] and η_c a user-defined parameter called the SBX distribution index.

A.3 Mutation

To avoid a problem becoming trapping in local optima, a mutation operator is applied to maintain genetic diversity from one generation to the next. There are many mutation schemes, such as polynomial, uniform, non-uniform, power and boundary [63]. Of them, a non-uniform mutation is widely used for a continuous constrained optimization problem (COP) [11]. In it, the step size of the mutation operator is decreased with increasing numbers of generations so that it conducts a uniform search in the initial stage of evolution and little searching in later stages [11], with a child mutated as:

$$y_{j,g}' = x_{j,g} + \delta_{j,g} \tag{2.23}$$

$$\delta_{j,g} = \begin{cases} \left(x_j^{max} - x_{j,g}\right)\left(1 - u_g^{\left(1-\frac{g}{N_G}\right)^{b_q}}\right) & \text{if } u \leq 0.5 \\ \left(x_j^{min} - x_{j,g}\right)\left(1 - u_g^{\left(1-\frac{g}{N_G}\right)^{b_q}}\right) & \text{if } u > 0.5 \end{cases} \tag{2.24}$$

where $u_g \in [0, 1]$ is a random number, and g and N_G the current generation number and maximum number of generations, respectively. The speed of the step length can be controlled by choosing different 'b_q' values [11].

A.4 Selection

A selection operator selects the best individual from a parent and its child based on their FVs. Of the different ones available, the feasibility-based selection [64] technique, in which (i) feasible individuals are always preferred over infeasible ones, (ii) of two feasible individuals, the better-fitted one is chosen and (iii) of two infeasible individuals, the one with a lower constraints violation is selected, is very popular for COPs. Also, in a GA, the best individuals in a generation are kept unchanged in the next one, which is called elitism that helps to increase the convergence rate. However, if there are many elite solutions, the diversity decreases.

B Differential Evolution

DE is another variant of an evolutionary algorithm (EA) introduced by Storn and Price [58]. Its solutions are presented in vector form and, to construct a new vector from existing ones, mutation, crossover and selection operators are used. It is consistent and reliable for solving many real-life non-linear COPs, such as those of communication, power and chemical systems, and pattern reconciliation [65]. Its structure and main operators are described below.

B.1 Mutation

Unlike a GA, DE uses a mutation operator before crossover. In a simple mutation, three candidates are randomly selected and a mutant vector generated by multiplying an amplification factor (F) as [11]:

$$\vec{y}_{p,,j} = \vec{x}_{r_1,j} + F \times (\vec{x}_{r_3,j} - \vec{x}_{r_3,j}) \; j = 1, 2, \ldots, N_x \tag{2.25}$$

where $r_k \in [1, N_x], k = 1, 2, 3$ are three random integer numbers such that $p \neq r_1 \neq r_2 \neq r_3$, N_x the number of decision variables and $F > 0$ a control parameter of the mutation operator. The variant shown in Eqn. (2.25) is called 'DE/rand/1' [11] while many other variants are presented in the literature [11].

B.2 Crossover

Two simple crossover operators usually used in DE are exponential and binomial. In the former, firstly, two integer values (l and L) within the decision space are randomly chosen so that $l \leq L \in [1, N_x]$ act as starting and ending points, respectively, to exchange elements between the target and donor vectors. Once l and L are decided, a trial vector is generated as:

$$v_{p,j} = \begin{cases} y_{p,j} & \text{for } j = l \, : \, L \\ x_{p,j} & \text{otherwise} \end{cases} \tag{2.26}$$

In the very simple binomial crossover, if a random number is less than the crossover rate (Cr), the particular value of the target vector is replaced by its parent as:

$$v_{p,j} = \begin{cases} y_{p,j} & \text{if } rand \leq Cr \text{ or } j = jrand \\ x_{p,j} & \text{otherwise} \end{cases} \tag{2.27}$$

where $rand \in [0, 1]$ and $jrand \in [1, 2, \ldots, N_x]$ are randomly chosen to ensure that at least one value is obtained from the offspring [11].

B.3 Selection

Like a GA, DE also uses a selection operator to choose a vector from the donor and trial ones for later exploration based on the best FVs.

C Particle Swarm Optimization

PSO is also a population-based algorithm introduced by Kennedy and Eberhart [66] based on the social behavior of flocks of birds and schools of fish. In it, the initial individuals called particles are randomly assigned and move around the $N-$dimensional search space based on the values of their FVs. Unlike a GA, it has no mutation or crossover operators but uses a velocity vector to update the current position of each particle in the swarm (e.g., the population), with this position updated based on the particle's own experiences (i.e., local best) and those of its neighbors (i.e., global best) in previous generations. The general outline of a basic PSO is:

1. an initial particle is randomly assigned and distributed in the design space;

2. similarly, random initial velocities of all the particles are generated;

3. for each particle, its fitness function is evaluated and, subsequently, the local (x^*) and global (x^{**}) best particles based on the FVs of the current and all particles, respectively, are determined; and

4. in the following generations, the particles are updated as:

$$x_{g+1} = x_g + v_{k+1} \tag{2.28}$$

where the velocity vector (v) is calculated as:

$$v_{g+1} = w \times v_g + c_1 r_1 \left(x_g^* - x_g \right) + c_2 r_2 \left(x_g^{**} - x_g \right) \tag{2.29}$$

where c_1 and c_2 are the positive constants, r_1 and r_2 two random numbers between 0 and 1, and w the inertia weight (also called the acceleration factor) for controlling the exploration properties of the algorithm, with the lower and higher values facilitating local and global behaviors, respectively.

D Evolutionary Programming

EP is also a global optimization technique that starts with a random population. Then, a new population is obtained from the old one using a mutation operator which perturbs each component of every individual in the population with a random number. The process of generating a new individual from an existing one in a classical EP is [11]:

$$\vec{x}_k^{g+1} = \vec{x} + \vec{\eta}_k^{g+1} \times N_j\left(0,1\right) \tag{2.30}$$

$$\eta_k^{g+1} = \eta_k^{g+1} \times e^{\left(\tau \times N(0,1) + \tau' \times N_j(0,1) \right)} \tag{2.31}$$

where $N(0,1)$ is a Gaussian random number with a zero mean and variance of 1, and the subscript j in $N_j(0,1)$ indicates that the random number is newly generated for each value of j [11]. The learning rates (τ and τ') are set to be equal to $\frac{\varphi^*}{\sqrt{2}\sqrt{D}}$ and $\frac{\varphi^*}{\sqrt{2D}}$, respectively, where φ^* is the expected rate of convergence.

2.8 Solving ED and Bidding Problems: A Review

In this section, the abovementioned methods for solving different types of conventional thermal-based and renewable energy-based ED problems, such as hydro-, wind- and solar-thermal ones, and then bidding problems in deregulated electricity markets, are discussed.

2.8.1 Conventional Thermal-based ED Problems

These problems have been solved using both CO and CI methods, as described below.

A Conventional Optimization Methods

Due to the excellent advancements in MP-based methods, the previous efforts for solving traditional ED problems shown in Eqns. (2.1) to (2.4) have been employed based on different ones, such as simplex [67], lambda iteration [68] and the IP [69]. Although they are very fast to obtain a solution, they are only applicable for solving static ED problems in which a single-period demand is considered.

To solve a DED problem, several researchers used an iterative technique in which a $T-$ hour DED problem was decoupled into a $T-$ number of SED sub-problems, each of which had a single-hour load demand [70]. Initially, the generation capacity limits of each sub-problem were estimated based on its actual capacity and ramp limits. Then, each sub-problem was solved using the lambda iterative method to iteratively update its generation capacity limits. Wood [71] conducted similar work but also considered SR and P_{loss} constraints. However, both methods obtained only sub-optimal solutions [3].

As ramp limits are one of the challenging constraints in a DED problem, if they are neglected, this problem can be represented as a set of SED ones which can be solved independently. Several researchers [72, 73] used this technique to split a DED problem into a number of SED sub-problems and then used a gradient projection method with a conjugate search [72] and LP-based method [73] to solve each sub-problem. Both methods used an additional penalty function with the primary objective of minimizing the cost to tackle ramp violations because solutions with lower ramp violations were preferred over others in this cost minimization problem. In [74], a Lagrange multiplier for the equality constraints and a penalty function for ramp violations were used to solve a DED problem which was reformulated as a dual optimization one with an iterative approach used to update the Lagrange dual variables [3]. Although the solution was superior to others, it took a long computational time to obtain a feasible one. Han et al. [75] analyzed each constraint of a DED problem and concluded that the reason for the long time required to obtain a single feasible solution was the chain of equality constraints with ramp limits. Later, by ignoring the ramp limits, they developed two approaches for solving a DED problem in which the first was used to obtain a feasible solution from an infeasible one and the second to improve the quality of feasible solutions but neglecting the ramp constraints was a large flaw. Also, most of the above methods considered linear equality constraints without taking account of the non-linear P_{loss} term in the power balance constraints.

Recently, the power system industry has been emphasizing security in its operations whereby the electricity flow through a TL is strictly maintained. Then, the standard DED problem is formulated considering the additional P_{loss} constraints of a TL and subsequently solved using different conventional methods, such as constrained relaxation[76], IP [77], gradient projection [78], and re-dispatch [67]. In the constrained relaxation techniques in [76], a dual revised simplex algorithm with a decomposition technique was used to solve a DED problem in which the coupling constraints (ramp limits) were taken into account while, in the gradient projection method in [78], the coupling constraints were relaxed and the $\mathrm{T}-$ hour DED problem decomposed into $\mathrm{T}-$ numbers of sub-problems solved using a priority list technique or simply one to T-hours consecutively. Lagrange multipliers were used for the equality and inequality constraints and a penalty function for the coupling ones. Then, the Lagrange variables were updated using a gradient-based method, with a solution considered optimal when the variables were no longer updated. An IP method was also applied to solve this variant of a DED problem considering the P_{loss} constraints [77] and was found to be much faster than a simple LP method. Later, several classes of IP methods, such as quadratic IP [69], homogeneous IP [79] and linear IP [77] were used to solve different DED problems. However, as most treated constrained DED problems as unconstrained ones, whereby the constraints were aggregated with the objective function using a penalty function technique, maintaining their feasibility was a serious issue. A modified Han-Powell algorithm with a sparseness technique for the construction and updating of the Hessian matrix of the Lagrange function was used to solve a DED problem [80]. In [67], a similar method with a re-dispatch technique based on QP was used to solve another DED problem which was decoupled into a number of SED sub-problems by relaxing the coupling constraints (ramp ones). However, as these sub-problems were solved separately, the overall computational time for a DED problem was too high.

Also, the abovementioned MP-based techniques dealt mainly with convex cost functions without considering the VPE [81] and, as a cost function with the VPE is non-smooth, non-convex and has multi-modal characteristics [29, 31], they were unable to generate good-quality solutions [82]. To solve this non-convex DED problem, although a few authors used QP, SQP and IP methods [82–84], their final results depended on the initial given solutions. In fact, in most cases, they converged to a local solution even after adopting a number of assumptions.

Recently, a few researchers [14] developed a mixed-integer quadratic programming (MIQP) approach for solving non-convex DED problems considering the VPE of the cost function. In their model's formulation, they obtained an approximation by linearizing the piece-wise convex cost function, whereby the excessive number of linear segments in a large generator introduced many integer variables and additional constraints. Therefore, the quality of solutions from this method was not guaranteed.

B Use of Computational Intelligence Methods

Conventional MP-based optimization methods need to approximate the actual DED problem by assuming that the cost function is smooth. Meta-heuristic-based optimization techniques, such as EAs and swarm intelligence (SI) methods, do not require certain mathematical properties of the objective function to be satisfied and have been successfully applied to solving many complex real-life COPs. During the last decade, several of them, such as a GA, DE, PSO and EP, have been effectively used to solve various single-objective DED problems [3], as discussed below.

B.1 Genetic Algorithm

Due to the flexible features of GA, many researchers have been attracted to using them to solve different types of generator scheduling problems. Initially, GAs were used to determine the on/off status of generators in UC problems; for example, Arroyo and Conejo [25] developed a modified GA for that purpose and used a hybrid parallel model to avoid premature convergence and improve computational efficiency. Compared with two conventional methods, it was proven that this GA was the best algorithm for UC problems but it was only validated for a small-scale one. A binary-coded GA (BCGA) with a constraint-handling technique for satisfying the equality constraints, and the inequality constraints represented as a penalty function added to the objective function, was applied in [85] to solve large-scale UC problems. Although this method was successfully performed for up to 10 units with a 24-hour time span, its computational time was high. To reduce this time, Damousis et al. [86] proposed an integer-coded GA to decrease the string size of the BCGA. In it, instead of using a penalty function to handle the inequality constraints, some constraints were directly managed in the chromosome representation and, subsequently, the efficiency of the algorithm was greatly improved despite the ramp constraints being ignored.

To solve a DED problem considering the ramp constraints, some specialized search operators of GA were used in [87] to help improve the efficiency of the algorithm with its mutation probability dynamically updated depending on its performance. However, this was applicable for only the specific problems tested. Another practical UC problem with P_{loss} in which two constraint-handling mechanisms were used to repair infeasible individuals to feasible ones, was solved in [88]. However, both approaches obtained sub-optimal solutions for a practical 12-unit system and their computational times were long due to their low rates of convergence. To improve the convergence rate, a deterministic GA, in which a deterministic annual crossover and selection procedure were applied, was proposed in [89]. Its performance was improved by exchanging information between individuals through an annual crossover and repairing mechanism. It was superior to the traditional GA and obtained a sub-optimal or near-optimal solution very quickly. To obtain global optima, an improved GA with an intelligent mutation operator and scaling function for the selection operator was used to solve generator scheduling problems

Units	**1**	**2**	**3**	**4**	**5**	**.**	**.**	**.**	**T**
1	0	0	1	1	0	.	.	.	1
2	1	0	0	1	1	.	.	.	0
.	.	.	.	.	.	.			
.	.	.	.	.	.		.		
.	.	.	.	.	.			.	
N	0	1	0	0	1				0

Fig. 2.9: Solution to UC problem using binary coding [90]

[90], with the constraints handled effectively using a repair technique. This approach obtained high-quality solutions with lower computational times than those of others in the literature. However, it was tested on only small-scale problems with 10 and 20 units in a 24 hour time horizon.

In each of the abovementioned methods, a chromosome was represented as a vector of binary variables, where ‘1’ and ‘0’ meant that a unit was on and off, respectively, with a sample chromosome representation in a UC problem for T-hour scheduling presented in Fig. 2.9 which shows that this problem determines only the on/off status of a generator not its actual output.

As previously mentioned, the actual generation from committed units is determined using an ED problem in which the decision variables regarding the output from a generator can be discrete or continuous. A number of approaches based on GAs for solving such problems have been developed; for example, Walters [31], Chen et al. [91] and Sheble et al. [92] employed three different variants of a GA to solve thermal-based ED problems with the aim of finding better solutions than other optimization algorithms. Of them, Chen et al. [91] developed a new encoding technique for representing a chromosome which contained only the normalized system’s incremental cost, λ (the slope of the objective function), rather than the actual cost of power generation. The main advantage of using λ was that, as it was independent of the number of active units, its number of decision variables was significantly less than those required in other techniques. In that GA, a chromosome’s λ was represented using binary variables, with the precision of a solution dependent on the number of bits. When more bits were considered, the quality of a solution increased but the efficiency decreased. Chen et al. [91] considered

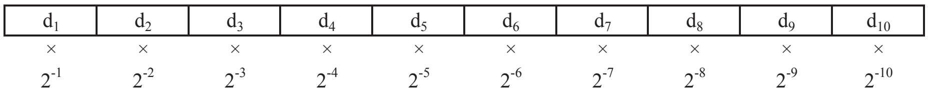

Fig. 2.10: Encoding scheme of λ [91]

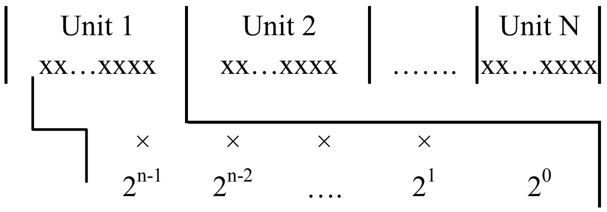

Fig. 2.11: $n-$bit concatenated encoding scheme [93]

the 10-bit encoding presented in Fig. 2.10 in which the value of λ was determined by decoding an encoded chromosome, as:

$$\lambda = \sum_{k=1}^{10} \left(d_k \times 2^{-k} \right) \; d_k \in [0, 1] \tag{2.32}$$

where d represents the binary bits as either 1 or 0. This approach made the proposed GA attractive for large systems for which other methodologies had failed to achieve an economic scheduling. However, determining λ is not an easy task for a modern power system in which the objective function is non-differentiable (see Eqn. (2.6)) [47]. Ongsakul et al. [93] proposed a parallel micro GA based on merit-order loading solutions for solving a large-scale ED problem to reduce computational time. The decision variables were encoded using binary strings with their sizes dependent on the number of units (N) each of which had n bits, as presented in Fig. 2.11.

To determine the decimal values of each chromosome, the function used was:

$$P_i = P_i^{min} + \frac{B_i \times \left[P_i^{max} - P_i^{min} \right]}{2^n - 1}, \; i = 1, 2, \ldots, N \tag{2.33}$$

where B_i is the decimal integer value of the binary string of the i^{th} generating unit. As, in this method, the chromosomes were represented in binary format, with the actual generation determined using a decoding approach, the computational time was long for a large system.

A few authors, such as Zhao et al. [94] and Lee et al. [95], proposed real-coded quantum-inspired GAs in which quantum bits (α and β, where $\alpha^2 + \beta^2 = 1$) were used to encode chromosomes. In it, the quantum bits, α and β, such that, $\alpha^2 + \beta^2 = 1$ were used to represent the chromosome. Firstly, the probabilistic variable (H) was defined as $H_g = \left\{ Q_1^g, Q_2^g, \dots Q_{N_P}^g \right\}$, where N_P is the size of the population and $Q_l^g = \{q_1^g, q_2^g, \dots, q_N^g\}$, $l = 1, 2, \dots, N_P$, $q_i^g \; i \in N$ the binary coding of the generation volume of the i^{th} generator as:

$$q_i^g = \left[\begin{array}{c|c|cc|} \alpha_1^g & \alpha_2^g & \cdots & \alpha_m^g \\ \beta_1^g & \beta_2^g & \cdots & \beta_m^g \end{array} \right], i = 1, 2, \dots, N \tag{2.34}$$

where m is the length of the quantum chromosome. To evaluate the fitness function, the chromosome was again decoded by some state observations. This approach was faster than previous binary-based GAs because the quantum chromosome carried information about multiple states which helped to generate better offspring. However, a continuous GA is inherently faster than a binary or quantum one because, in it, the chromosomes do not have to be decoded prior to evaluation of the cost function. Elsayed [96] proposed a new GA with a multi-parent crossover (GA-MPC) and diversity operator for solving a wide range of engineering problems, including SED and DED ones. The chromosomes were represented as the actual real values of the power output of each generator as:

$$\vec{x_p} = [P_1, P_2, \dots, P_N], p = 1, 2, \dots, N_P \tag{2.35}$$

To solve mixed-integer DED problems, some discrete decision variables were represented as continuous ones by being rounded. Although their algorithm obtained better results than state-of-the-art methods for solving small-scale thermal-based DED problems, it was not guaranteed to perform consistently for a large system because it took a long time to satisfy the equality constraints.

B.2 Differential Evolution

As DE performs consistently for solving continuous COPs, it has been widely used to solve different types of ED problems [97]. Unlike many GAs, it does not require encoding and decoding schemes to represent solutions as it deals directly with the continuous values of the decision variables, as shown in Eqn. (2.35). However, its performance is greatly influenced by its control parameters, such as F and Cr. Many research studies have been conducted to determine the best set of F and Cr for solving a problem; for example, Balamurugan and Subramanian [98] used an adaptive DE algorithm to solve a DED problem in which the decision variables were represented as continuous ones of the actual power generation and F dynamically updated during the evolutionary process as:

$$F_{g+1} = \begin{cases} F_l + rand_1 \times F_u & \text{if } rand_2 < \tau \\ F_g & \text{otherwise} \end{cases} \tag{2.36}$$

where $rand_k \in [0,1]$, $k = 1, 2$ were the random values, g the current generation number, τ the probability for adjusting the F, and F_l and F_u the lower and upper values of F set to 0.1 and 0.9, respectively. However, setting the value of τ was not an easy task for a wide range of DED problems and this approach was tested on only small-scale problems (up to 10 units).

To improve the exploitation capability of a DE algorithm in the search space and enhance its convergence property, Lu et al.[99] and Chen et al. [100] developed an improved one based on a chaotic search operator for solving DED problems. Its convergence rate was further improved by introducing a heuristic crossover technique and gene swap operator. A chaotic sequence-based tent function [101] was applied to obtain the dynamic parameter settings of F and Cr as:

$$F_{g+1} = \begin{cases} 2F_g & \text{if } 0 < F_g < 0.5 \\ 2\left(1 - F_g\right) & \text{if } 0.5 < F_g < 1 \end{cases} \tag{2.37}$$

$$Cr_{g+1} = \begin{cases} 2Cr_g & \text{if } 0 < Cr_g < 0.5 \\ 2\left(1 - Cr_g\right) & \text{if } 0.5 < Cr_g < 1 \end{cases} \tag{2.38}$$

under the initial conditions $(F_0, Cr_0) \in \{0, 1\}$ and $(F_0, Cr_0) \notin \{1/4, 1/2, 2/3, 3/4\}$. Although their results were superior to those of other algorithms, their approach was expensive in terms of computational time.

Leandro et al. [102] developed a chaotic DE for solving ED problems in which a chaotic sequence was used to update its parameters, with F updated based on two logistic maps as:

$$\text{Approach 1: } F_{g+1} = \mu \times F_{g-1} \times (1 - rand_1) \tag{2.39}$$

$$\text{Approach 2: } F_{g+1} = \left[(f_{2f} - f_{2i}) \frac{g}{N_G} + f_{2i} \right] \times [\mu \times F_{g-1} \times (1 - rand_1)] \tag{2.40}$$

where $rand_1 \in [0, 1]$, $\mu = 4$ and N_G the maximum number of generations. For the incremental use of F, the settings of f_{2i}, and f_{2f} were were 1.5 and 0.5, respectively and, for the decremental approach, 0.5 and 1.5, respectively. This method outperformed state-of-the-art algorithms for solving various DED problems with up to 40-unit thermal systems. However, as these problems considered a single-period demand (i.e., SED), they did not have as many decision variables as a common DED one and their computational times were of great concern.

Another modified DE was tested by solving a practical Taiwan power company's 15-unit SED problem [103] in which F was updated based on the 1/5 success rule of ES, such as:

$$F_{g+1} = \begin{cases} c_d \times F_g & \text{if } p_S^g < 1/5 \\ c_j \times F_g & \text{if } p_S^g > 1/5 \\ F_g & \text{if } p_S^g = 1/5 \end{cases} \tag{2.41}$$

where p_g^g represents the frequency of a successful mutation occurring in terms of obtaining fitted individuals. Initially, F was set to 1.2, $c_d = 0.82$ and $c_j = 1/0.82$, with c_d and c_j adjusted after a certain number of generations, following a $10b$ rule where b was a constant value. Although the proposed algorithm was successful for solving the problem, it was difficult to expect that it would perform as well for large-scale DED ones and it also introduced new parameters.

Since a DED problem involves a number of equality and inequality constraints, Yuan et al. [104] adopted a DE algorithm with a feasibility-based selection comparison technique [64] and heuristic search rule for effectively handling its constraints. Compared with traditional penalty function approaches, it obtained better-quality results. However, as it used fixed control parameters, it might be inferior to other algorithms for solving different classes of DED problems.

As no single DE algorithm performs consistently well for a wide range of optimization problems, Elsayed et al. [105] developed a DE algorithmic framework for solving a wide range of real-life problems, including ED ones, in which multiple search operators were used under multiple sub-populations, the sizes of which were adaptively updated in each generation based on the success of the evolution during previous generations. In it, they used four different variants of mutation strategies, 'rand/3', 'best/3', 'rand-to-current/2' and 'rand-to–best and current/2'. Although the proposed framework was found to be superior to state-of-the-art algorithms for solving static ED problems, there was no guarantee that it would perform well for large-scale DED ones.

B.3 Particle Swarm Optimization

Over the last two decades, PSO techniques have been used to solve many real-world optimization problems due to their simple structures and reliable performances, with most focusing on improving their performances using different empirical analyses of their parameters. However, the best set of parameters for one problem may not work for another.

To solve DED problems using PSO, many researchers attempted to determine the best set of parameters; for example, in [106], a PSO approach with time-varying acceleration coefficients was designed to solve non-convex DED problems in which the acceleration factor dynamically decreased over generations to improve performance and avoid premature convergence. It was validated by solving five test systems and outperformed traditional PSO algorithms. However, its convergence rate was reduced in later stages of the search process due to its lower values of the acceleration coefficients. To improve the speed of convergence, a selective PSO (SPSO) method, in which a refined search operator was used to eliminate the particles with poor FVs and emphasize those with promising ones, was designed [107]. It was tested on simple DED problems but ignored the VPE of the cost function. Considering the VPE, the authors in [108] and [42] proposed modified PSO (MPSO) and random draft PSO (RDPSO) techniques, respectively, both of which used a dynamic penalty function to handle the equality constraints as:

$$\text{Min: } F = \sum_{i=1}^{N} C_i + K_g \left| \sum_{i=1}^{N} P_i - P_D - P_{loss} \right| \tag{2.42}$$

where K_g is the penalty coefficient which increases over generations from a predefined value. Although this approach outperformed others, selecting the values of K_g in each generation is a difficult task. Moreover, satisfying the chain of equality constraints for a DED problem using this penalty function technique is very time-consuming.

Park et al. [108] dynamically reduced the search space over generations to accelerate the convergence of a PSO. Sun et al. [42] modified the movements of particles based on a trajectory analysis which indicated that the performance of the algorithm could be improved when a particle converged to local optima. When compared with some state-of-the-art algorithms, the results from both these algorithms were superior although they were tested on only small-scale SED problems.

An adaptive PSO algorithm for solving large-scale DED problems, in which the control parameters were dynamically updated at every stage in the search process, was designed [109] while Yuan et al. [110] developed an improved PSO (IPSO) one for solving the same problems. Both used a heuristic for a priority-based scheduling that efficiently handled the equality (power balance) constraints, where the cheaper generators delivered first and the more expensive ones later. The algorithms were tested on DED problems with up to 30 units and produced better results than state-of-the-art algorithms. However, since allocations of the load demand were started from the first hour when the demand was usually low (i.e., off-peak hours, see Fig. 2.3), the cheaper generators might not have operated at their full capacities in peak hours due to ramp constraints [3], while, conversely, the expensive ones were fully used to meet peak demands. Consequently, the overall production cost for a problem might have been high, that is, the algorithm could have produced a biased solution in which the FVs (costs) were inferior.

B.4 Evolutionary Programming

An EP method is very suitable for effectively solving the non-smooth, non-continuous and non-differentiable objective functions of an optimization problem, such as an ED one [111]; for example, a classical EP technique was used in [111] to solve a few ED problems considering their non-smooth and non-differentiable objective functions, with its results better than those from state-of-the-art algorithms. Hong-Tze et al. [112] and Venkatesh et al. [113] also used classical EP approaches to solve non-convex ED problems and their results compared with those from other algorithms, including a GA, indicated that they were superior but required longer computational times [3].

A fast EP method based on a Cauchy mutation was employed to solve an ED problem in [114], in which new individuals were generated from existing ones as:

$$\vec{x}_k^{g+1} = \vec{x} + \vec{\eta}_k^{g+1} \times H_j \tag{2.43}$$

where H_j is a Cauchy random variable. Compared with a classical EP, fast EP provided a near-global solution quickly because a Cauchy mutation has the capability to jump towards global optima by escaping many local minima. Although this jump is beneficial when solutions are far from the global optima, it is difficult to determine a global point during the search process.

B.5 Hybrid Techniques

Several hybrid methods, which combined two or more approaches have been widely used to efficiently solve non-smooth DED problems; for example, Aziz et al. [115] used a classical EP, Victoire et al. [30] a modified EP (MHEP) and Attaviriyanupap et al. [82] a hybrid EP (H-EP) combined with a CO method such as SQP. In all these approaches, EP techniques were used for the global search, and SQP for fine tuning the EP solutions.

Although these algorithms obtained relatively higher-quality solutions than state-of-the-art algorithms, their computational times were very long.

An improved DE with a gradient-based local search, in which the algorithm improved by introducing a new crossover operator called the center-based differential exponential crossover (CBDEX), was proposed in [116]. In it, a few best individuals were stored in an archive population that participated with another population to generate a new individual while the control parameter was set in a probabilistic way. This algorithm was superior to state-of-the-art ones for solving the CEC-2011 test problems that included an ED one. However, as it used a local search technique to improve the convergence rate, it might be computationally expensive for solving large-scale DED problems.

To solve large-scale DED problems, some other hybrid methods, such as the bee colony optimization (BCO) and SQP (BCO-SQP) [117], EP-SQP [82], and PSO-SQP [83], have also been applied. In such approaches, the equality constraints in Eqn. (2.2) were usually satisfied using the penalty function technique shown in Eqn. (2.42). However, since there were too many equality constraints in a DED problem (*e.g.,* T for a $T-$ hour one) that were mutually coupled (*i.e.,* $t-$hour's constraint depends on that of a $(t-1)-$hour), although a feasible solution was obtained in the long run, it may have become infeasible after evolving crossover and mutation, for example, in a GA. As a result, the convergence rate was indigent and returned to a local solution.

B.6 Multi-method Techniques

Multi-method EAs integrate two or more optimization techniques in order to combine their strengths and overcome each other's weaknesses to solve optimization problems. This idea has been used for solving many optimization problems; for example, both Spears [118] and Eiben et al. [119] developed adaptive GA frameworks with multiple crossover operators for solving unconstrained problems. They divided a population into a number of sub-populations, each of which used a particular crossover operator, with their sizes updated according to the success of their crossovers. Elsayed et al. [120] proposed a multi-operator evolutionary framework using GA and DE for solving constrained and unconstrained optimization problems, with the experimental results demonstrating its superiority to state-of-the-art methods. Elsayed et al. [121] also developed a general framework for combining several EAs (e.g., GA, DE, ES, EP) each of which used multiple operators with an individual sub-population, the size of which was adaptively updated. This framework was applied to solve two sets of constrained problems and it was determined that it outperformed single operator-based single-algorithm approaches. Similar works are found in ref. Skolicki [122] and Skolicki et. al. [122] in which populations were divided into sub-populations, each of which used a different EA but shared information between the two algorithms differently.

However, to the best knowledge, adopting such approaches to solve highly complex, constrained and real-world electrical power generator-scheduling problems, such as DED ones, has not yet been explored.

2.8.2 Solving Renewable-based DED Problems

In this section, a review of different methods for solving renewable-based DED problems, such as hydro-, wind- and solar-thermal ones, is presented.

A Hydro-thermal DED

In a hydro-thermal system, the aim is to schedule the mixed-power plants under consideration to minimize the total cost while satisfying the demand, generation capacity and many hydro constraints such as water storage and discharge. This problem is much more challenging than a conventional thermal-based DED one because the hydraulic constraints change over time [7].

Over the last few decades, several optimization methods have been successfully applied for solving different types of hydro-thermal DED problems, with conventional ones, such as Lagrange multipliers [123], DP [124], dual programming [125], mixed IP [126] and primal-dual IP [127], used for smaller-scale SED problems with single-hour load allocations.

To solve large-dimensional hydro-thermal DED problems, several population-based algorithms have been successfully applied; for example, Gil et al. [128] developed a GA for solving a 24-hour DED problem considering binary representations of the decision variables. Although their results showed that this approach obtained better solutions than conventional ones, it was validated on only small-scale problems. To address large-scale hydro-thermal DED problems, an enhanced GA with a priority-list heuristic for handling the equality constraints, where the allocation of production was performed on a priority basis which meant that the cheaper ones were dispatched first and the inferior ones later, was developed [129]. This method was validated by solving a simple hydro-thermal DED problem considering the convex cost function but ignoring the VPE. A non-smooth, non-convex hydro-thermal DED problem with the VPE was solved using both a real-coded GA (RCGA) and BCGA [130], with the results obtained demonstrating that the RCGA outperformed the BCGA but, as these algorithms were not compared with other state-of-the-art ones, it was not clear if they would perform better.

In [131], although a conventional DE outperformed other state-of-the-art algorithms for solving hydro-thermal DED problems, its computational time was long. To tackle this drawback, in [132], a dynamic reduction in the population size of DE and, in [15], a parallel DE were developed, both of which analyzed the DE's parameters and determined that their selection had a significant influence on their performances. To randomly control those parameters, a DE for solving a hydro-thermal DED problem was proposed in [133]. However, as the control parameters were randomly updated in each generation, there was room to improve the solution quality by updating them more logically.

Also, several researchers tested various versions of PSO algorithms for solving hydro-thermal DED problems; for example, Yu et al. [134] applied different variants and found that the local versions outperformed other algorithms as the diversity of the population in a local one was maintained throughout the search process. Jadoun et al. [135] developed an enhanced PSO (E-PSO) in which the control parameters were dynamically updated using the exponential functions for better exploration. Their method obtained better results than a conventional PSO for two hydro-thermal DED problems but its computational time was longer than those of conventional and other state-of-the-art methods.

Moreover, several meta-heuristic-based approaches for solving different hydro-thermal DED problems, such as GA, DE, PSO and EP, have been successfully applied, with most of them trying during the process to find their best set of control parameters for better performances. However, there is still a great deal of potential to obtain better-quality solutions by improving an algorithm's performance. Also, the problem itself can be improved by considering the uncertainty factors of hydro sources.

B Wind-thermal DED

As previously discussed, wind energy is a promising renewable source currently used extensively in power systems to meet many electricity demands. However, as it is only imprecisely predicted for the long term, a method for solving an uncertain wind-thermal DED problem is one of the challenging issues in the operation of a power system. Recently, several researchers developed different approaches for solving non-smooth, multimodal and non-convex wind-thermal DED problems, with most using different metaheuristics for their stochastic characteristics, for example, Jadhav et al. [136] applied a modified ABC algorithm to solve a wind-thermal DED problem. In it, the best individual always participated in generating offspring which resulted in a greatly improved convergence rate and, although it was trapped in a local minimum as the diversity of the population was not properly maintained, this algorithm performed better than state-of-the-art ones. To maintain diversity, Peng et al. [137] introduced a bi-population chaotic DE (BCDE) algorithm for solving a wind–thermal DED problem and a chaotic quantum GA (CQGA) was developed in [95]. Both methods used a chaotic mutation based on chaotic sequences which helped to increase diversity among the population. A hybrid PSO with a gravitational search algorithm (GSA), in which PSO was used to explore the decision space and GSA to fine tune the solutions, was developed in [35]. Although this method had a fast convergence speed for obtaining a local solution, its total computational time was too long. Moreover, in the above methods, wind power was considered deterministic based on forecasted scenarios with the uncertainty of wind speeds ignored.

Considering uncertainty, researchers formulated stochastic DED models which incorporated a random variable for the wind speed. Then, several solution approaches, such as a neural network [138], fuzzy optimization [139], and Weibull distribution approach [140–143], were used to solve stochastic wind-thermal DED problems. In the fuzzy method, the wind speed was considered a fuzzy variable and the fuzzy set theory used to represent a DED problem. Two parameters of the Weibull distribution, scale and shape, were determined from historical data and then converted into a probability DED model [144]. A few authors, such as Mondal et al. [145] and Peng et al. [137] used penalty function approaches to determine the impacts of inaccurate estimations of the wind's energy caused by its uncertain nature; for example, a probabilistic analysis of cases in which the expected values of wind power generation were over- and under-estimated [146]. As the penalty function sometimes has a great impact on a system's operation, it's difficult to choose an appropriate one for a certain system.

To overcome the drawbacks of penalty functions, researchers recently used scenario-based probabilistic DED models in which the scenarios represented the stochastic behaviors of variable load demands, intermittent generations from wind power and failures of generators [147, 148]. However, in these methods, Monte Carlo (MC) sampling was often used to generate scenarios of wind speeds which was a very expensive approach because of its heavy computational burden [149]. Therefore, Markov chains [150] with a roulette wheel mechanism [34, 139] were used to generate appropriate predictive values of the wind speeds and load demands over a 24-hour time period. In this approach, many scenarios were initially generated using a Markov transition matrix determined from large amounts of historical data. Each scenario involved data of hourly wind speeds and load demands which had one-to-one relationships with the time intervals. Moreover, each scenario had a certain normalized probability, with those with lower probabilities deleted based on a simultaneous backward scenario reduction technique [150] because a large number of scenarios would increase the computational burden.

Later, a probabilistic DED model, in which each scenario was solved using various optimization methods, such as MILP [151], the branch and bound algorithm [152] and the 2m-point estimated method (PEM) [139], was formulated. Although conventional algorithms were chosen due to their fast searching features, the VPEs of their cost functions increased the difficulties of solving a wind-thermal DED problem with non-smooth, non-linear and non-convex characteristics [34, 153]. For this kind of complex problem, solution approaches based on MP may fail to reach the global optimum, a shortcoming which motivated the development of alternative methods, such as EA and SI techniques [34].

Therefore, several meta-heuristic methods, such as DE [137], GA [154, 155], and PSO [34], were successfully applied to solve wind-thermal DED problems based on a single period of load demand. However, work on implementing them to solve a multi-period, high-dimensional complex uncertain wind-thermal DED problem is still limited, with the major obstacle that a problem may lose diversity [150].

C Solar-thermal DED

As the penetration of solar power in power systems has significantly increased, its interactions with conventional thermal units need to be investigated. For the better coordination of solar-thermal power, a DED problem with an efficient solution method is required to determine the optimal dispatch scheme that can reliably and effectively integrate solar energy [38]. Recently, a few solar-thermal DED models and their solution approaches, most of which used different meta-heuristic algorithms, were developed; for example, an RCGA in [36] and harmony search (HS) in [33] were applied to solve non-smooth solar-thermal DED problems considering the VPE of the cost function for a thermal generator. However, both these algorithms suffered from premature convergence and became trapped in local minima. Jeddi et al. [33] proposed a new mutation operator based on the roulette wheel mechanism for HS, with its performance investigated by solving some solar-thermal DED problems. Although the results indicated that this operator could improve the quality of solutions, the method was tested on only small-scale problems.

Other EAs, such as GA, DE and EP, were also used to solve different solar-thermal DED problems [3], with most using penalty function techniques to handle constraints. Although these approaches were easy to implement, as maintaining feasible solutions throughout the whole evolutionary process was very difficult, to obtain optimal solutions, high computational costs were incurred. On the other hand, a few of them [3] used a feasibility-based selection technique, as previously discussed, to select individuals from the parents and offspring. Although it was widely used for COPs, satisfying several equality and dynamic ramp constraints in a solar-thermal DED problem is still a challenging task. Moreover, the abovementioned methods did not consider the uncertainty of solar irradiation which was a big assumption for this problem.

ElDesouky [16] formulated a stochastic solar-thermal DED problem in which the uncertainty of solar irradiation was determined based on the Weibull PDF that was solved using a conventional PSO with a Newton-Raphson (NR) method used to meet/satisfy the non-linear equality constraints. Although this PSO-NR method obtained a feasible solution quickly, it took a long computational time to reach a high-quality one. Khan et al. [39] proposed another variation of an uncertain solar-thermal DED problem in which the uncertainty of solar irradiation was considered an objective function and aggregated to the cost function. Then, they applied a binary PSO to a practical test problem taken from the Islamabad Electric Supply Company (IESCO). However, the performance of this algorithm was not clear as it was not compared with those of any other state-of-the-art algorithms.

2.8.3 Bi-objective DEED Problems

So far discussed, DED problems with and without uncertainties have been solved by minimizing the fuel cost both with and without considering emission reductions as a constraint. However, as minimizing gas emissions into the environment is now vital, these problems can be solved as bi-objective DEED ones.

Over the last few years, different methods for solving bi-objective DEED problems, such as thermal, wind-thermal, solar-thermal and hydro-thermal, have been developed. Several researchers reformulated a bi-objective DEED problem into a single-objective optimization one, with the objective set as a linear combination of two objectives [43]. In the literature, this type of objective is also known as a composite one [43]. To solve a composite problem, different EAs, such as GA [43], DE [99], PSO [156] and binary PSO (for a solar-thermal problem) [39] were used to produce a single solution. However, when solving a bi-objective DEED model as a composite objective, as it was difficult to generate a Pareto frontier with a uniform distribution of solutions [157], it was necessary to solve the models many times to produce a set of trade-off solutions. Moreover, for a linear combination of two objectives, it was very difficult to select an appropriate penalty factor for normalizing the scales of those objectives.

Recently, a few researchers began using different multi-objective EAs (MOEAs), which are capable of obtaining a set of Pareto optimal solutions instead of a single one in composite problems, to solve bi-objective DEED problems. In contrast to obtaining a single optimal solution to a composite objective problem, the solutions to multi-objective problems are presented as a set of alternative solutions that forms a Pareto frontier. These are known as Pareto-optimal solutions, where no one can be considered better than the others, and it is usual practice to produce them for multi-objective optimization problems [20].

During the last decade, various EAs, such as the multi-objective GA (MOGA), niched Pareto GA (NPGA), non-dominated sorting GA (NSGA), NSGA-II, multi-objective DE (MODE) and multi-objective PSO (MOPSO) have been studied. The basic idea of Pareto-based EAs was to find a set of solutions in a population that were not dominated by the rest of the population, assign them the highest rank and eliminate them from further contention.

Of various multi-objective EAs, a NSGA-II [20] has been widely used to solve constrained multi-objective problems; for example, Purkayastha et al. [158] applied one with an adaptive crowding distance mechanism to improve diversity when solving a bi-objective DEED problem. Although this proposed method was tested on a 40-unit test problem, the results were not compared with any others, even those of the traditional NSGA-II. Also, when the modified crowding distance was applied, the solutions with lower crowding distances were rejected as survivors for the next generations and, although diversity was improved, the convergence rate decreased. To tackle this drawback, an NPGA with a clustering technique, in which the tournament size for the crossover was adaptively set, was developed in [159, 160]. The algorithm started with a large population and the clustering technique was used to determine the manageable non-dominated solutions from the population members. This method was tested on a 6-unit static problem, with the results indicating that it obtained a wider set of Pareto solutions than other state-of-the-art algorithms. Later, the same authors developed the MOPSO to solve the same problem [161] using the abovementioned clustering technique to update the set of non-dominated solutions. A comparison of the NPGA and MOPSO methods showed that the latter performed better in terms of the quality of the non-dominated solutions obtained. However, both were tested on only a small-scale problem with a single-hour load demand. Basu [162] developed a MODE for solving a 24-hour DEED problem in which a non-dominated sorting technique [20] was used as a selection operator in a DE algorithm. It was the best of several other MOEAs but, since its parameters were arbitrarily set, it might not work well for other DEED problems.

However, multi-objective mixed DEED problems, such as hydro-, wind- and solar-thermal ones, have not been fully studied in the literature. Recently, a few attempts were made to solve mixed bi-objective DEED problems using MOEAs, such as a NSGA-II and MODE for hydro-thermal [17, 163], and MOPSO for wind/solar-thermal [16, 164]. Although these methods had the capability to generate the entire trade-off solutions in a single run, to handle a large number of equality constraints, they required extensive computational time and some also simplified the DEED formulations by ignoring ramp constraints.

2.8.4 Bidding Problems

As previously mentioned, the bidding problem is another important optimization one in an energy market. An extensive review of different solution techniques related to this problem in the literature is presented in this section.

During the last decade, the numerous techniques designed to solve bidding problems with the aim of determining the optimal bids of each participant in a deregulated energy market can be broadly categorized as two types, non-game- and game-based [165]. In a non-game-based method, this problem is solved for a particular player while ignoring other players' bidding behaviors [47]. In this process, a GENCO or consumer first forecasts the MCP and rivals' bids, and then solves a profit maximization problem using an appropriate algorithm, such as a dynamic, fuzzy linear or stochastic DP one [22]. However, estimating the MCP and rivals' bids is very difficult and, even after doing so, the actual profits may vary significantly from predictions as it is assumed that the LMP is independent of players' submitted bids [166].

On the contrary, in a game-based method, a player optimizes its choices, called bidding strategies, by investigating the interactions of its rivals. In it, a GENCO or retailer is represented as a player, economic benefits constitute payoffs and players' options are treated as strategies. Then, a game is formed by several players, each of which ultimately chooses one strategy from a set of known ones that has a payoff assigned to it based on the profit function each wishes to maximize [24]. The profit of a player depends on its own and its rivals' actions that rely on the respective players' interests but are not specified [13]. Once all players have chosen their actions by maximizing their individual profits with respect to the actions of others, the optimal bidding strategies of all the players in a deregulated electricity market are obtained [167, 168].

Game-based bidding problems are broadly categorized as two types based on the players' characteristics, (i) cooperative and (ii) non-cooperative [169]. In the former, the participants coordinate their strategies to maximize their profits while, in the latter, a player maximizes its profit regardless of those of its rivals, with no commitment to coordinating their strategies [170]. However, the non-cooperative model is more appealing due to its realistic characterizations of the strategic variables which reflect real-life bidding rules in an electricity market [47, 171].

In a non-cooperative bidding problem, each player has a set of bidding strategies, one of which is submitted to obtain the maximum profit and is known as its payoff. A player obtains a maximum payoff when its best strategy is selected with respect to the strategies of its rivals. Once all the players find their best strategies, an outcome called the Nash equilibrium (NE) is reached. An NE is a stable state in a game in which a player cannot improve its profit unilaterally if the actions of its rivals remain unchanged [13].

The most popular method for determining an equilibrium of a non-cooperative game is the concept of finding an NE [172]. If s, is a strategic profile of S, the best strategic profile (s^*) is an NE when no player has anything to gain by changing only its own actions or strategy. Let π_i be a profit value of player $i \in N$ and a set of the best strategies of its rivals s^*_{-i}; then s^* is an NE, when no strategy of a player is profitable except s^*, that is if, for all players $i \in \{1, \ldots, N\}$ and all the strategies $s_{i_j} \in S_i$ (s_{i_j} is the j^{th} strategy of player-i) satisfy the inequality constraint, as [172]:

		B	
		0	1
A	0	(1,1)	(-1,2)
	1	(2,-1)	**(0,0)**

Single NE

		B	
		0	1
A	0	**(8,7)**	(4,6)
	1	(6,5)	**(7,8)**

Multiple NEs

Fig. 2.12: Single vs multiple NEs

$$\pi_i(s_{i_j}, s^*_{-i}) \leq \pi_i(s^*),\ i \in N,\ j = 1, 2, \ldots, NS_i \tag{2.44}$$

where NS_i is the number of strategies of player $i \in N$.

Determining the NEs in a competitive electricity market is a challenging optimization problem which is even more difficult when more than one NE are determined. Based on the number of NEs, a game can be called a pure or mixed strategy if it has a single or multiple NEs, respectively. For a mixed strategic game, at least one player has an alternative action available to obtain the same profit [173]]; for example, in the two-player prisoners' dilemma game [174] with two different payoff matrices illustrated in Fig. 2.12, where the rows of matrices correspond to the profits of the possible actions for player A and the columns those for player B. It can be seen that the left matrix has only one equilibrium point of $(0, 0)$ while the right has two different ones of $(8, 7)$ and $(7, 8)$. In a pure strategy, each player has a specific action to play to obtain its maximum profit while a mixed strategy is an assignment of the probability of the equilibria. Several methods based on different conventional and meta-heuristic approaches for determining a single or multiple NEs have been developed, as discussed below.

A Computing Nash Equilibria

Computing either a single or multiple NEs for solving an $N-$ player game is difficult and an NP-hard problem [175]. It becomes even more challenging if the characteristics of the game are continuous instead of traditional discrete ones. In a discrete game, each player has a set of discrete strategies, with the size of a payoff matrix dependent on the permutations of all possible discrete strategies while, in a continuous one, a player has a mathematical function with the variables defined within a range and the size of the payoff matrix becoming infinite. Most methods in the literature aimed to find an NE for a discrete game; for example, the bi-matrix approach developed by Lemke and Howson [176] for finding one equilibrium for a two-player discrete game which was later generalized to solve $N-$ player games [177].

Then, many researchers inspired by the Lemke-Howson algorithm developed several modified bi-matrix games; for example, Shapely [178] presented a geometrical representation of the Lemke-Howson algorithm for a non-degenerate case while Eaves [179] developed a modified bi-matrix game for a degenerate one. The difference between degenerate and non-degenerate games is that, in the latter, there must be a few solutions with the same profits for some players while, in the former, the constraint is not necessary [19]. Anne Balthasar [180] developed a modified bi-matrix game which was shown to be better than the actual Lemke and Howson bi-matrix one. In [181–183], the authors proposed three different algorithms, a Newton, iterative approximation and decomposition, respectively, to determine an NE in an $N-$ person discrete game. Although their methods successfully identified NEs for up to 12 players, their computational times were long.

An alternative approach for efficiently finding an NE for a discrete game was formulated as a non-linear optimization problem in [184] in which it was proven that an optimal solution with a zero FV of the model was exactly the same as the NE of a given game and was called a zero-sum game. However, the method in [184] obtained a local solution for a non-convex game. Later, some EAs, such as GA [185] and DE [186], were developed to determine the global NE of zero-sum and non-convex games. Furthermore, N $-$ player games were efficiently solved using a hybrid technique which combined both bi-matrix and zero-sum game techniques [187] in which a hierarchy technique was used whereby zero-sum games were applied at the beginning and general bi-matrix ones at the end. Although this method was useful for determining an NE for even a large game, it was only applicable for discrete ones.

On the other hand, most real-world problems are in the form of a continuous game, such as the game-based model of a bidding problem [188] which can be formulated into four equilibrium models, the (i) Bertrand, (ii) Cournot, (iii) Stackelberg and (iv) supply function equilibrium (SFE) [167, 168]. In the Bertrand game, the market price is considered a bidding variable in which it is assumed that all the players have a constant unit cost, with capacity constraints ignored when competing on the price offered to consumers. In both the Cournot and Stackelberg models, the amount of power to be produced by each player is considered a strategic variable, with the difference between these approaches being that the former allows the strategic variables of all players to be simultaneously improved while, in the latter, the leader improves its strategic variable first and then the followers sequentially change theirs. As a consequence, because all players in the Stackelberg model do not choose their quantities simultaneously, the largest one acts as the leader and can manipulate the market. In the SFE model, a linear function is used for each bidder's strategic variable, where the coefficients of the supply function are simultaneously improved to reach the maximum profit [189]. Of all these models, the non-cooperative SFE one is the most popular among researchers and practitioners [47, 171]. An SFE model has been applied to the English and Welsh wholesale electricity spot markets to analyze their competitive strategic bidding practices [168]. In the following section, different solution methods for a SFE model are discussed.

B Solving SFE model

Recently, solving a non-cooperative SFE model of a bidding problem has attracted a great of attention, and it has been formulated as a bi-level optimization problem in which each player maximizes its profit in the upper level while the ISO's CSW is maximized in the lower level by solving a non-linear OPF optimization problem [4, 169]. However, as this bi-level problem contains a nested optimization task within the constraints of another optimization problem [169] and becomes more complicated in the presence of its difficult mathematical properties, such as multi-modality, non-convexity and non-differentiability [169], conventional methods for solving it are inefficient. Subsequently, different EAs, such as GA [24, 190–192], EP [188] and a bat-inspired algorithm [41, 47], for solving these problems are now generating interest in the research community; for example, Azadeh et al. [24] applied a GA to determine the optimal bidding strategies of GENCOs in both cooperative and non-cooperative electricity markets. In [192], another GA was used to solve a scenario-based bi-level strategic game in which a player optimized its bidding strategy by predicting the possible bidding scenarios of its rivals determined from historical data. However, as there were risk factors associated with assuming opponents' bids when a player optimized its own, an information-gap decision theory (IGDT) was used to formulate a risk-based optimal bidding strategy optimization model, with a modified PSO (MPSO) used to solve it [53].

In the abovementioned methods, game-based bidding strategies were used with the bids represented as discrete quantities, such as high, medium and low. The payoff matrices were determined by computing all possible combinations of the strategies and, subsequently, an equilibrium state of the bidding game corresponding to the optimal bidding strategies was obtained. Moreover, in many of these methods, consumers were considered non-strategic and the number of players reduced to the number of GENCOs while customers could buy only predefined amounts of electricity from the market.

Conversely, a strategic customer is one that can participate in the bidding process, thereby increasing the number of players in that game. Considering a strategic consumer in a game, the SFE model was solved using four different types of bidding parameters, *intercept*, *slope*, *slope-and-intercept*, and *slope intercept*, with the slope and intercept one of the bidding curve a strategic variable in order to achieve a definite equilibrium [189, 193]. To obtain the NE for a competitive energy market, iterative (IT) solution approaches based on a GA [5] and bat-inspired algorithm [47]], in which the bidding strategy of a player was iteratively updated while the other players retained their bidding strategies as their best ones, were used. Once all the players updated their best bidding strategies in a hierarchy, the NE was found. However, as the bidding strategy of each player was updated sequentially in each iteration, approaching the NE was very time-consuming even for a small problem and required a long computational time for a large one.

The co-evolutionary (CE) algorithm that uses an individual sub-population for each player is an alternative approach for simultaneously determining the optimal bidding strategies of all players and results in a significant reduction in the computational time required compared with those of iterative methods. In the literature, the following CE approaches for solving different competitive energy markets have been successfully applied.

C CE-based Solution Methods for SFE model

Over the last two decades, a few CE-based approaches for solving the SFE model of the bidding problem have been applied [1, 6, 194]; for example, a CE one based on a GA was developed to determine the multi-period optimal bidding strategy for an oligopoly electricity market [195]. In it, there were different sub-populations, each of which used a reinforcement learning algorithm to increase a player's profit from one trading period to the next based on experience from past trading hours. Chen et al. [165] developed a CE approach based on a GA for solving the real-world electricity market in which two different SFE models, the affine and piece-wise affine cost functions, were solved and analyzed, with the solution rapidly converging to the affine one. In order to obtain an NE, another CE-based solution approach was tested in two different competitive electricity markets, spot and settlement, with the simulation results indicating its effectiveness for finding optimal strategies in both markets [196].

In most of the abovementioned approaches, an EA was used on the upper level to determine the optimal bidding strategy of a bi-level problem, with simple LP or Lagrange multipliers used to solve the lower level to determine the dispatch quantity and LMP of each player. Since the lower-level problem contained a non-convex and non-linear objective function, conventional techniques failed to identify optimal solutions and, consequently, the upper-level solution might have been a local one [197]. Considering TC in the model, the optimization space became discrete which meant that the problem had multiple NEs [24]. Although most of the abovementioned approaches were successfully used to find a single NE of a continuous or discrete game, they were not applicable for solving games which may have had multiple equilibria. They could not guarantee to converge to the optimal solution when there wasn't an NE or provide a local solution in the presence of multiple NEs [198]. However, multiple solutions to mixed strategic games can be different in terms of profit, stability and commitment, with a single equilibrium maybe not capable of providing adequate information for a player to make a decision.

To obtain all the equilibria of a mixed strategic game is a very challenging problem often formulated as a non-convex and non-smooth optimization one [13], with different CI methods used to solve it [19], most of which required multiple runs to obtain multiple equilibria. Also, it was not guaranteed that an algorithm could converge to a previously detected NE. To obtain multiple equilibria in a single run, three CI methods, covariance matrix adaptation evolution strategies (CMA-ES), PSO and DE, employing a multi-start and deflection technique were developed in [13]. Their algorithms obtained more than one local minimum of the objective function of the optimization problem which were multiple NEs of the game. However, as they were developed for only discrete games, extending them to solve continuous ones, such as energy market equilibrium problems, is not straightforward and, to the best of our knowledge, determining multiple NEs of an energy market game has not yet been explored.

2.9 Chapter Summary and Research Directions

In this chapter, an introduction to different ED and bidding problems and their importance in the energy market was presented. Numerous techniques for solving these problems, including CO and CI methods, were briefly discussed.

Based on the literature review, it was found that EAs are very popular for solving both ED and bidding problems due to their stochastic searching feature, with an adaptive EA outperforming a simple one. However, they suffered from their inability to handle a large number of equality and inequality constraints, manage the uncertainties and improve the convergences of DED problems, and determine multiple NEs of a bidding problem in a relatively low computational time. These research gaps are considered in the following chapters, with a self-adaptive EA and efficient heuristic technique for handling large numbers of constraints when solving many DED problems proposed.

Chapter 3

EAs for Thermal-DED Problems

This chapter discusses the importance of solving the dynamic economic dispatch (DED) problem, describes the problem, presents its mathematical formulations, provides an overview of existing solution approaches and presents the algorithms developed and the motivation. The design of two algorithms: a self-adaptive differential evolution (DE) and genetic algorithm (GA) with a new heuristic technique are discussed in detail. Finally, the experimental study and outcomes are provided.

3.1 Introduction

As discussed in Chapter-2, the main objective of a power system's operation is to supply electrical energy to consumers at a minimum production cost which depends directly on the fuel cost of electricity generation. Therefore, power industries are now focusing on generating electricity at the lowest possible fuel cost.

In practice, a power system has several power plants which vary significantly in terms of their operating costs and generation capabilities. A system operator needs to appropriately schedule the available generators in the most profitable way. To do this, an economic dispatch (ED) problem that schedules them to meet the load demand for an hour at the minimum production cost by satisfying operational and environmental constraints is often used. Although the solution to an ED problem may be beneficial for an hour, it may not work for the next or following few hours, depending on demand, because the generation from units may not change significantly over these operating

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The following article has been published based on this Chapter:
[1]. M. F. Zaman, S. M. Elsayed, T. Ray and R. A. Sarker, "Evolutionary Algorithms for Dynamic Economic Dispatch Problems," in ***IEEE Transactions on Power Systems***, vol. 31, no. 2, pp. 1486-1495, March 2016.

hours due to ramp limits. A ramp limit is defined as the rate of change in a unit's production between two consecutive hours.

The DED model can achieve hourly optimal scheduling for a certain time horizon (usually 24 hours) taking into account the intrinsic links among components of the system at different times, such as the ramp rate of a thermal generator. The DED problem is one of the significant real-world important optimization problems that ensures reliable and economical operation in power system. However, its computational process is more complex than that of a conventional ED because of its large number of decision variables and chain of equality constraints. Moreover, in many real-life situations, the scheduling of generators has to be updated with changes in the data and availability of new information. For a DED problem, updated scheduling is obtained using a rolling horizon approach in which the generators are rescheduled when the demand and operational data are changed for a period within the planning horizon [199]. Therefore, solving a real-time DED problem is very challenging and an important research topic in terms of power system operation.

A DED problem can be categorized as thermal, wind-thermal, hydro-thermal and solar-thermal based on the types of generators involved. In this Chapter, the thermal-based DED problems are considered (the others are discussed in following Chapters) as most of the production costs in a power system are related to thermal generators.

Solving thermal-based DED problems has a long history. However, as most current solution approaches are inefficient for solving a real-time one because of its dimensionality, non-convexity and multi-modality, in this Chapter, an efficient solution method is developed.

3.2 Description of Thermal-DED System

In this section, a thermal-based DED problem is described.

The DED problem is a non-convex, non-smooth, constrained optimization one, with its objective to minimize the operating cost by scheduling the available generators to meet load demands over a cycle of T hours. Although, traditionally, the cost function

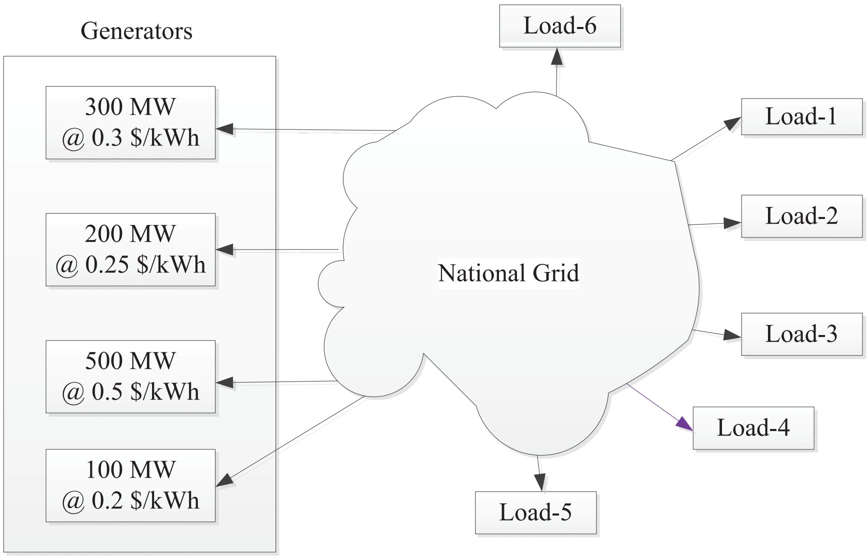

Fig. 3.1: Typical power system

is considered quadratic, in real life, large steam generators have a multi-fuel option and some ripple appears on the cost function while steam is admitted through a valve which is known as the valve-point effect (VPE) [28]. Subsequently, the cost function becomes non-smooth, non-convex and multi-modal characteristics, as shown in Fig. 2.1.

As the equality constraints mitigate the load demands over the specified time horizon, if a DED system performs for T hours, there are T equality constraints while the inequality constraints involve the overall generation capacity as well as the ramp limits. Also, a real-life power system encounters some unexpected events, such as unit faults and demand changes. To counter this, a spinning reserve (SR), usually the largest unit's capacity for scheduling, is considered an inequality constraint to increase the system's reliability.

The decision variables of this problem are the electricity output from each generator. Since the DED problem schedules the generators for T hours, the number of decision variables is $T \times N_T$, where N_T is the number of thermal units.

The typical power system network shown in Fig. 3.1 depicts four thermal generators, each with a specific capacity limit and different per unit cost, and six loads. The objective of the DED problem is to schedule these generators to serve the loads over a time horizon of T hours at the minimum cost while satisfying the ramp, capacity and SR constraints. The mathematical formulation of this DED problem is discussed in the following section.

3.3 Mathematical Formulation

In this section, the mathematical model of a thermal based DED system is presented. It is assumed that a given number of generators will be considered by a unit commitment (UC) problem and that these generators will be operated for certain time periods (T).

3.3.1 Objective Function

In a DED problem, the objective function is to minimize the sum of all fuel costs for the thermal power plants under consideration which can be expressed as:

$$\text{Minimize } F_C\left(P_{T_{i,t}}\right) = \sum_{t=1}^{T}\sum_{i=1}^{N_T} C_{i,t} \tag{3.1}$$

where N_T is the number of thermal power plants, T the operational cycle and $C_{i,t}$ the fuel cost of the i^{th} thermal generator at t^{th} time. The characteristic curve of C is usually expressed by a quadratic function. However, the sudden opening of the intake valve of a steam turbine may cause a VPE which can be reflected by integrating a rectifying sinusoidal wave in the main function. The fuel cost function, including the VPE of each thermal unit, can be expressed as [14]:

$$C_{i,t}\left(P_{T_{i,t}}\right) = a_i + b_i P_{T_{i,t}} + c_i P_{T_{i,t}}^2 + \left| d_i \sin\left\{ e_i \left(P_{T_{i,t}}^{\min} - P_{T_{i,t}} \right) \right\} \right| \ \nabla i, t \in T \tag{3.2}$$

where a_i, b_i, c_i, d_i and e_i are the cost coefficients of the i^{th} thermal generator, and $P_{i,t}$ the electricity output of i^{th} generator at t^{th} time interval which is also the decision variable for the thermal-based DED problem.

3.3.2 Constraints

In this research, a number of constraints, both equality and inequality types, some of which are nonlinear and some dynamic in nature are considered, as discussed below.

A Power Balance Constraints

Since electricity cannot be stored economically, its generation must meet demand on a real-time basis which means that the total generation planned must be equal to the demand in a given load period as:

$$\sum_{i=1}^{N_T} P_{T_{i,t}} = P_{D_t} + P_{loss_t} \; t \in T \tag{3.3}$$

$$P_{loss_t} = \sum_{i=1}^{N_t} \sum_{j=1}^{N_T} P_{T_{i,t}} B_{i,j} P_{T_{j,t}} \; t \in T \tag{3.4}$$

where $P_{D,t}$ the electricity demand at t^{th} hour, and P_{loss} and B the power loss and its coefficients, respectively.

B Generator Capacity Constraints

Each generator has a capacity bound as:

$$P_i^{\min} \leq P_{T_{i,t}} \leq P_i^{\max} \; i \in N_T, \, t \in T \tag{3.5}$$

where P_i^{min} and P_i^{max} are the minimum and maximum thermal power limits, respectively.

C Generating Unit Ramp-rate Constraints

Although many studies of DED have simplified their models by assuming that a unit's generation output can be adjusted instantaneously, this does not reflect the actual operating conditions of generating units. The ramp rate is described as a unit's power-response capability in terms of accommodating power changes in a specified time interval. The operating ranges of all on-line units are restricted by their ramp-rate limits as expressed by:

$$P_{T_{i,t}} - P_{T_{i,t-1}} \leq UR_i \;\; i \in N_T \, t \in T \tag{3.6}$$

$$P_{T_{i,t-1}} - P_{T_{i,t}} \leq DR_i \;\; i \in N_T \, t \in T \tag{3.7}$$

where UR_i and DR_i are the upward and downward ramp limits of i^{th} thermal generator, respectively.

D Spinning Reserve Requirements

In real life, a power system network suffers a number of unexpected events, such as load changes and failure of a certain large operating unit. In order to increase its reliability and avoid errors, three safety factors included in this model are:

$$\sum_{i=1}^{N_T} P_{T_i}^{\max} - (P_{D_t} + P_{loss_t} + SR_t) \geq 0 \; t \in T \tag{3.8}$$

$$\sum_{i=1}^{N_T} \min\left(P_i^{\max} - P_{T_{i,t}}, UR_i\right) - SR_t \geq 0 \; t \in T \tag{3.9}$$

$$\sum_{i=1}^{N_T} \min\left(P_i^{\max} - P_{T_{i,t}}, UR_i/6\right) - SR_t^m \geq 0 \; t \in T \tag{3.10}$$

where SR_t and SR_t^m are the hourly and 10-minitues spinning reserve (SR) requirements, respectively. Constraints in Eqns. (3.7) and (3.9) are frequently applied in DED problems to satisfy the one-hour SR requirements, and constraint on Eqn. (3.10) used to satisfy the SR requirements for the operated generators in each time within 10 minutes which is related to the ramp-up rate constraint of that unit $\left(\frac{UR_i}{6}\right)$.

3.4 Solution Approaches

As discussed in Chapter-2, all the approaches for solving DED problems in the literature can be categorized as: i) conventional optimization methods; and ii) meta-heuristic-based optimization techniques [14]. Although the former are computationally efficient, they deal mainly with convex cost functions [81] and, as the cost function with the VPE is non-smooth and non-convex, they are incapable of generating good-quality solutions.

On the other hand, as meta-heuristic-based optimization techniques do not require certain mathematical properties of the objective function to be satisfied and have been successfully applied to many complex practical optimization problems, they have become more popular than conventional ones [200].

3.4.1 Motivation

As previously mentioned, meta-heuristic algorithms are widely used to solve thermal-based DED problems. In many of these methods, the equality constraints are typically handled using a penalty function technique and the problem solved as an unconstrained one. Although this may obtain good objective values, it does not ensure feasibility [201] and selection of the penalty factor is very challenging. Conversely, some researchers used a feasibility-based selection operator [20] with a meta-heuristic algorithm to solve DED problems, with an individual with a lower constraint violation (CV) preferred. As a DED problem has many equality constraints, those that are mutually coupled affect the capability of an algorithm to reach a feasible solution. Even after obtaining a feasible individual in many generations, it is challenging to maintain its feasibility after applying search operators with a meta-heuristic algorithm, such as a GA, because

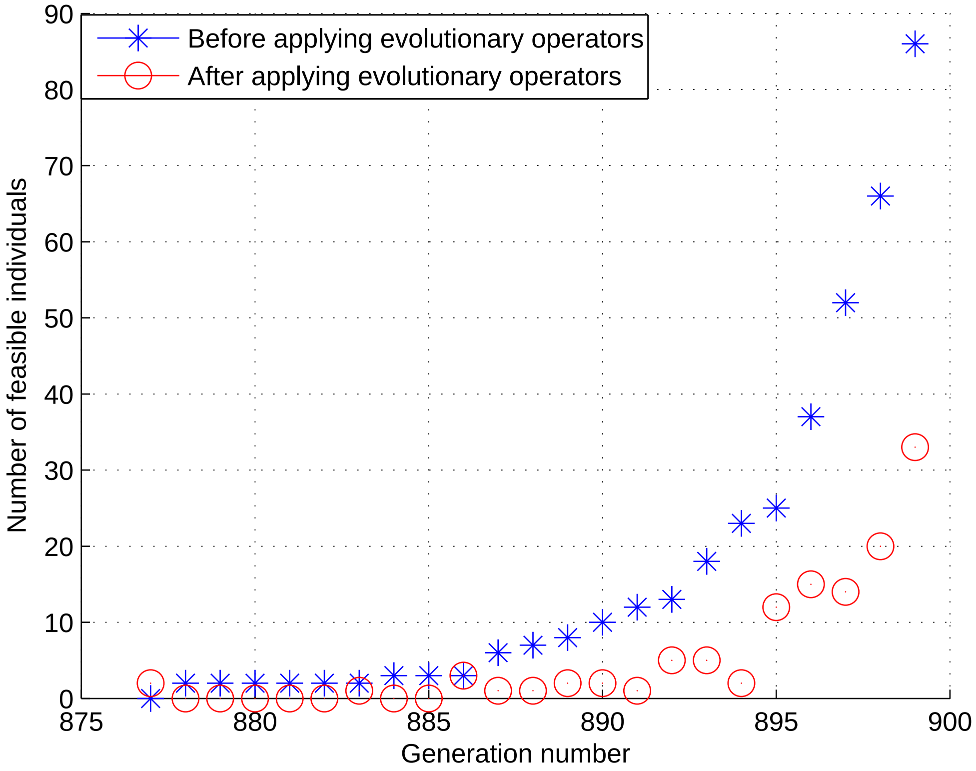

Fig. 3.2: A sample set of solutions for a 5-unit DED problem

sometimes, a feasible individual may then move away from the feasible area to an infeasible space. To demonstrate this, an experiment is performed using the simulated binary crossover (SBX) and non-uniform mutation (NUM) operators of GA, with the probability of crossover, distribution index and probability of mutation set to 0.9, 3 and 0.1, respectively. After solving a 5-unit DED problem, the numbers of feasible individuals (out of 100) before and after applying these search operators are presented in Fig. 3.2. It is clear that the first feasible solution is obtained after 877 generations while approximately 50% of the individuals become worse (according to their CVs) when both crossover and mutation operators are applied.

Also, it was found that EAs might suffer from premature convergence and become trapped in local solutions [3], with their performances highly dependent on their control parameters, population diversity and constraint-handling mechanism. Therefore, in this Chapter, special care is taken in the designs of an efficient GA and DE algorithm for solving complex DED problems, as discussed in the following section.

3.5 Proposed Algorithm

In this section, two proposed algorithms incorporating a new heuristic technique are presented. The first is called the enhanced GA (E-GA) and the second the enhanced DE (E-DE). Both begin with an initial population in which N_P individuals are randomly generated using Latin Hyper-cube (LHS) sampling [202]to ensure that they are evenly distributed over the optimization area. Then, in subsequent generations, new individuals are generated using the search operators of either the GA or DE. To avoid difficulties in selecting the best set of control parameters for the DE, a self-adaptive approach is employed while, to increase diversity among the individuals in the GA, a non-uniform mutation operator is used. To evaluate the individuals, firstly, their CVs are calculated using Eqn. (3.32), with an infeasible individual repaired using the proposed heuristic described in section 3.5.4. Then, the fitness values (FVs) and CVs of the individuals are determined, based on which the individuals are ranked using the selection operator presented in section 3.5.5. In order to improve the performances of both the E-GA and E-DE, a diversity mechanism and $\varepsilon-$constrained method [203] are used to skip from premature convergence.

The steps of both E-GA and E-DE are provided below:

- Step 1: Generate an initial population based on Eqn. (3.11).
- Step 2: Satisfy system constraints (Eqns. (3.1) to (3.10)) using the heuristic described in section 3.5.4.
- Step 3: Evaluate the fitness values using the formula in Eqn.(3.1).
- Step 4: Create child populations using the crossover and mutation operators described in section 3.5.2 and 3.5.3 for GA and DE, respectively.
- Step 5: Select the best individuals from both the parent and child populations using the selection process described in section 3.5.5.
- Step 6: Modify the infeasible individuals (if any) to satisfy the constraints using the proposed heuristic 3.5.4.

- Step 7: If required, apply the diversity mechanism stated in section (3.5.6).
- Step 8: If a stopping criterion is met, stop; otherwise, go to step 3.

The description of each step is discussed in the following subsections.

3.5.1 Representation and Initial Population

The chromosome or representation of decision variables for both GA and DE can be expressed as follows:

$$x_p = [P_{T_{1,1}}, P_{T_{2,1}}, \ldots, P_{T_{N_T,1}}, P_{T_{1,2}}, P_{T_{2,2}}, \ldots P_{T_{N_T,2}}, \ldots, \ldots, P_{T_{N_T,T}}] \tag{3.11}$$

where x_p is the decision variable for the P^{th} individual at $p \in N_p$ with N_P population size. The number of decision variables for a DED problem is $N_x = T \times N_T$.

In general, an evolutionary algorithm (EA) starts with a randomly generated population. As the DED problem has a bounded feasible region with many equality constraints, the individuals in the initial population are generated as per the following equation:

$$x_{i,j} = x_i^{min} + (x_i^{max} - x_i^{min}) LHS(1, N_x) \tag{3.12}$$
$$i \in N_x \text{ and } j = 1, ..., N_P$$

where x^{min} and x^{max} are the upper and lower bounds of each variable x that can be found from each generator's limits. $LHS(1, N_x)$ represents N_x random individuals are generated using LHS rules. As the initial values of x are highly significant, to achieve better-quality solutions in later stages of the evolutionary process, random x are generated using LHS which ensures that each probability distribution is evenly sampled within the area of optimization [202].

3.5.2 GA search operators

Of various GA search operators, SBX and NUM are used as they showed better performance in comparison with other operators [63].

A Simulated Binary Crossover

In SBX, child populations are generated from two parents those determined using a tournament selection. Tournament selection is a process to select an individual from N_P individuals. In it, depending on the tournament size, several random individuals among N_P individuals are chosen, and the winner (the one with best fitness value) of each tournament is selected for crossover. When a larger tournament size is chosen, it means the weak individuals have a smaller chance to be selected which results to the algorithm has to converge quickly but possibility prematurely. If the larger tournament size is chosen, the algorithm has a great diversity, but the convergence rate to be slow. Therefore, it is chosen depending on the problem nature. For example, the DED problem involves several non-trivial equality and inequality constraints, for solving this problem, a great diversity among the individuals is required. Therefore, the tournament size is chosen as two. The process of generating offspring from their parents is described in Eqns. (2.20) and (2.21).

Once the two winner individuals, x_j^1, x_j^2, $j = 1, 2, ..., N_x$ are selected, the two children y_j^1, y_j^2, $j = 1, 2, \ldots, N_x$ are generated as:

$$y_j^1 = \frac{1}{2}\left[(1+\beta_{qj})\,x_j^1 + (1-\beta_{qj})\,x_j^2\right], \; j = 1, 2, ..., N_x \tag{3.13}$$

$$y_j^2 = \frac{1}{2}\left[(1-\beta_{qj})\,x_j^1 + (1+\beta_{qj})\,x_j^2\right] \; j = 1, 2, ..., N_x \tag{3.14}$$

where β_{qj} is calculated as:

$$\beta_{qj} = \begin{cases} (2u_j)^{1/\eta_c+1} & \text{if } u_j \leq 0.5 \\ \left(\frac{1}{2(1-u_j)}\right)^{1/\eta_c+1} & \text{if } u_j > 0.5 \end{cases} \tag{3.15}$$

where η_c is a distribution index of SBX and u_i a random number between 0 to 1.

B Non-uniform Mutation

The NUM is chosen that decreases the step size and increases the probability that the amount of mutation will decrease as the number of generation increases. This prevents the population from stagnating in the early stages of evolution and then allows the GA to fine-tune the solution in later stages. In it, a child is mutated as:

$$y_{\acute{j},g} = x_{j,g} + \delta_{j,g} \tag{3.16}$$

$$\delta_{j,g} = \begin{cases} \left(x_j^{max} - x_{j,g}\right)\left(1 - u_g^{\left(1-\frac{g}{N_G}\right)^{b_q}}\right) & \text{if } u \leq 0.5 \\ \left(x_j^{min} - x_{j,g}\right)\left(1 - u_g^{\left(1-\frac{g}{N_G}\right)^{b_q}}\right) & \text{if } u > 0.5 \end{cases} \tag{3.17}$$

where g and N_G are the current generation number and maximum number of generations, respectively, and b_q the speed of the step length to control the mutation percentage. In this research, the value of b_q is set to 5 as per ref. [121].

3.5.3 DE Search Operators

As discussed, DE is another variation of EAs, and also a powerful algorithm for real parameter optimization, with its performance highly depends on the control operators of the search operators [120]. Also, it is proven that no single mutation operator can perform well for a wide range of test problems. Therefore, in this research, two mutation operators are considered, such as 'DE_{rand}' and 'DE_{best}'. The first one facilitates the population diversity while the second one improves the convergence rate [204]. Regarding crossover operator, it has been found that binomial is better than exponential crossover while, in the selection operator, an offspring is selected if it is better than its parent.

A new offspring is generated from its parents as follows.

$$\vec{y_p} = \begin{cases} \vec{x}_{r_1} + F_p(\vec{x}_{r_2} - \vec{x}_{r_3}) & \text{if } rand_1 \leq Cr_p \text{ and } rand_2 \leq prob_1 \\ \vec{x}_p + F_p\left((\vec{x}_{r_1} - \vec{x}_{r_2}) + (\vec{x}_{best} - \vec{x}_p)\right) & \text{if } rand_1 \leq Cr_p \text{ and } rand_2 > prob_1 \\ \vec{x_p} & \text{otherwise} \end{cases} \quad (3.18)$$

where $\forall p = 1, 2, ..., N_P$, $\{r_1, r_2, r_3\} \in [1, N_P]$, $p \neq r_1 \neq r_2 \neq r_3$, and F_p and Cr_p are the amplification factor and crossover rate for mutation and crossover operators, respectively for the p^{th} individual, $prob_1$ a predefined probability (here, it is set to a value of 0.5) of choosing the mutation operators (either DE_{rand} or DE_{best}) for generating new individuals from the current one. The values of F_p and Cr_p are very important for algorithm's performance and calculated in every generation self-adaptively as described in the next section.

A Updating F and Cr

As mentioned, a DE's performance depends on its control parameters but selecting them is a combinatorial optimization problem. Therefore, a self-adaptive mechanism is deployed in this research [205].

Initially, for each individual in the population, two sets of control parameters, $\dot{F} \in N(0.5, 0.1)$ and $\dot{Cr} \in N(0.5, 0.1)$ are generated using normal distributions with mean and standard deviation values of 0.5 and 0.1, respectively. Then, to generate new offspring as per Eqn. (3.18), F_p and Cr_p are calculated as follows:

$$F_p = \begin{cases} \dot{F}_{r_1} + rand_1(\dot{F}_{r_2} - \dot{F}_{r_3}) & \text{if } (rand_2 < \tau_1) \\ rand_3 & \text{otherwise} \end{cases}, \; p \in N_P \quad (3.19)$$

$$Cr_p = \begin{cases} \dot{Cr}_{r_1} + rand_4(\dot{Cr}_{r_2} - \dot{Cr}_{r_3}) & \text{if } (rand_5 < \tau_1) \\ rand_6 & \text{otherwise} \end{cases}, \; p \in N_P \quad (3.20)$$

where $\forall rand_k \in [0, 1]$, $k = 1, 2, ..., 6$, and $\tau_1 = 0.5$, as per [205]. Once the values of F_p and Cr_p are calculated using the above two Eqns. (3.19) and (3.20), the values should be between 0.1 to 1. However, if they are less than 0.1 or larger than 1, fixed to 0.1 and 1, respectively.

Based on the selection criteria (discussed in next section), if an offspring is better than its parent, the parent's F_p and Cr_p replaced by its offspring's F_p and Cr_p, and vice verse. This process is repeated until all N_P individuals are selected, which means at the end of the current generation, the better-performing F and Cr are survived to the next generation.

3.5.4 Heuristic for DED constraints

It has already been mentioned that DED is a nonlinear constrained optimization problem involving a number of equality and inequality constraints. The solutions generated by EAs may not satisfy all constraints, especially equality (demand balance) and dynamic (ramp limits) ones. Even if a feasible solution is obtained in one generation, it may become infeasible after crossover and mutation in another generation. This situation becomes even worse when many equality constraints are involved. A great deal of research has been undertaken into dealing with equality constraints, including penalty function integration [206], slack generation consideration [28] and local search consideration [201]. However, these approaches are not adequate for handling a chain of equality constraints, as is the case in DED problems. A few researchers have used SQP to deal with equality constraints and increase the convergence rate [201] but, although this approach returns a feasible solution after a long run, it loses significant diversity.

In this thesis, a new heuristic is proposed to transform the infeasible individuals into feasible ones. In the process, the 24 hours load cycle is divided into 24-hourly subproblems, and allocate production to meet the load demand in each hour starting from different random hours. Although the allocation can be started from the first hour of the operational cycle, as done in [206], the allocation can be infeasible at a later stage due to ramp constraint and any significant changes in demand (i.e., peak demand period). Note that the generation limit in any hour depends on the generation of the immediate past hour. The heuristic consists of the following steps.

Step 1: Arrange the decision variables (x) into a matrix form as:

$$P = \begin{bmatrix} P_{T_{1,1}} & P_{T_{2,1}} & \cdots & P_{T_{N_T,1}} \\ P_{T_{1,2}} & P_{T_{2,2}} & \cdots & P_{T_{N_T,2}} \\ \vdots & \vdots & \ddots & \vdots \\ P_{T_{1,T}} & P_{T_{2,T}} & \cdots & P_{T_{N_T,T}} \end{bmatrix} \tag{3.21}$$

Step 2: Randomly select an hour $t \in T$ and its generation $P_t \in P$. Start the forward process.

Step 3: Set, $P_{i,t}^{max} = P_i^{max}$ and $P_{i,t}^{min} = P_i^{min}$.

Step 3.1: Check $P_{i,t}^{min} \leq P_{i,t} \leq P_{i,t}^{max} \quad \forall i$ and, if a unit is infeasible, fix it using Eqn. (3.26).

Step 3.2: Check feasibility at the t^{th} hour as follows.

$$\left| \sum_{i=1}^{N_T} P_{i,t} - (P_{D_t} + P_{loss_t}) \right| \leq \varepsilon \tag{3.22}$$

Here, ε a tolerance limit which has a large value at the early stages of evolutionary process and is reduced to $1e-06$ (an acceptable limit as of [14]) over the generations [203] such as:

$$\varepsilon_g = \begin{cases} \varepsilon_0 (1 - \frac{g}{N_{G_c}}) & \text{if } 0 < g < N_{G_c} \\ 1e-6 & \text{otherwise} \end{cases} \tag{3.23}$$

$$\text{where, } \varepsilon_0 = \sigma * CV \tag{3.24}$$

where ε_0 is a constant that determines the initial preserving CV, and g and $N_{G_c}(0 < N_{G_c} < N_G)$ the current and cut-off generations, respectively. The cut-off generation indicates that there are no infeasible solutions after that generations.

If the solution is feasible, go to step 3.4, otherwise, go to the next step.

Step 3.3: Obtain a random permutation of N_T and generate a random sequence of the operating units as $R_s = \{r_1, r_2, ...r_{N_T}\}$ to satisfy the equality constraints. Now, choose the first generator ($r = r_1$) as the slack generator to balance the residual load, as decided by the rest of the generator's known output, as:

$$P_{r,t} = (P_{D_t} + P_{loss_t}) - \sum_{\substack{i=1 \\ i \neq r}}^{N_T} P_{i,t} \tag{3.25}$$

$$P_{r,t} = \begin{cases} P_{r,t}^{min} & \text{if } P_{r,t} < P_{r,t}^{min} \\ P_{r,t}^{max} & \text{if } P_{r,t} > P_{r,t}^{max} \end{cases} \quad r \in i \ \forall i = 1, 2, ..., N_T \tag{3.26}$$

Check feasibility using Eqns. (3.22), (3.26) and the look-ahead demand constraint which determines the $(t+1)^{th}$ hour generation range that must satisfy the $(t+1)^{th}$ hour load demand and can be mathematically formulated as:

$$\sum_{i=1}^{N_T} P_{i,t+1}^{min} \leq (P_{D_{t+1}} + P_{loss_{t+1}}) \leq \sum_{i=1}^{N_T} P_{i,t+1}^{max} \tag{3.27}$$

where $i \in N_T$, $t \in T$ and

$$P_{i,t+1}^{max} = \min\left[P_i^{max}, (P_{i,t}^t + UR_i)\right] \tag{3.28}$$

$$P_{i,t+1}^{min} = \max\left[P_i^{min}, (P_{i,t}^t - DR_i)\right] \tag{3.29}$$

If the solution of $P_{i,t}\, i = 1, 2, \ldots, N_T$ is still infeasible, recalculate Eqn. (3.25) considering the next random slack generator ($r = r_2$) from the R_s vector. This process is repeated until a feasible solution which satisfies Eqns. (3.22), (3.26) and (3.27) is found. Then, the new operating range at the hour is updated using Eqns. (3.28) and (3.29), and set to $t = t + 1$.

Step 3.4: Repeat steps 3.1 to 3.3 and obtain a feasible solution at the t^{th} hour. As this process is repeated until $t = T$, the P matrix is updated from the t to T hours and the rest of the hours determined using the backward process which is applied to obtain feasible solutions at the $(t-1)^{th}$ to 1^{st} hour as follows.

Step 4: Set $t = t - 1$ and update the capacity range of $P_{i,t} \forall i$ using Eqns. (3.30) and (3.31), as:

$$P_{i,t-1}^{max} = \min\left[P_i^{max}, (P_{i,t}^t + UR_i)\right] \tag{3.30}$$

$$P_{i,t-1}^{min} = \max\left[P_i^{min}, (P_{i,t}^t - DR_i)\right] \tag{3.31}$$

Step 4.1: Calculate the feasible solution at the t^{th} hour using the process described in steps 3.1 to 3.3 and then repeat steps 4 and 4.1 until $t = 1$.

Step 5: Reconstruct from the calculated matrix ($\vec{x}$) using Eqn. (3.11).

Step 6: Return a feasible $\vec{x}$ to the algorithm.

As this proposed heuristic does not place any priority on a unit or particular hour, it will help to maintain the diversity of solutions expected in EAs. Although it is highly likely that an infeasible solution is transformed into a feasible one (*i.e.*, CV=0) after applying the heuristic, some may still infeasible. However, their CVs are indeed improved.

3.5.5 Selection Process

Once the offspring are generated using either GA or DE search operators from their parents, the infeasible one are repaired using the heuristic and subsequently the FVs and CVs of the individuals are evaluated using the Eqns. (3.1) and (3.32), respectively.

$$CV_i = \sum_{k=1}^{K} \max\left(0, G_k\left(\overrightarrow{x_i}\right)\right) + \sum_{e=1}^{E} \max\left(0, H_e\left(\overrightarrow{x_i}\right) - \varepsilon_g\right) \ \forall i \in N_P \tag{3.32}$$

where $\overrightarrow{x_i}$ represents the i^{th} individual of a sub-population, G and H the inequality and equality constraints, respectively, K and E the numbers of inequality and equality constraints for a DED problem, respectively, and ε_g the relaxation factor of the equality constraints in the g^{th} generation which is dynamically updated using Eqn. (3.23). An individual is called infeasible when the value of $CV < 0$, otherwise, it is called feasible.

For selecting an individual from a parent and its child, a greedy selection scheme is followed that uses one of the three scenarios:

1. between two feasible candidates, the fittest (according to FVs) is selected;
2. a feasible point is always better than an infeasible one; and
3. between two infeasible solutions, the one with a smaller CV is chosen.

This can be mathematically expressed in Eqn. (3.33) as [20]:

$$\vec{x}_{g+1} = \begin{cases} \vec{y}_{g+1} & \text{if } FV(\vec{y}_{g+1}) \leq FV(\vec{x}_g) \text{ and } CV(\vec{y}_{g+1}) \leq CV(\vec{x}_g) \\ \vec{x}_g & \text{if } FV(\vec{y}_{g+1}) \leq FV(\vec{x}_g) \text{ and } CV(\vec{y}_{g+1}) \geq CV(\vec{x}_g) \\ \vec{x}_g & \text{if } FV(\vec{y}_{g+1}) \geq FV(\vec{x}_g) \text{ and } CV(\vec{y}_{g+1}) \geq CV(\vec{x}_g) \\ \vec{y}_{g+1} & \text{if } FV(\vec{y}_{g+1}) \geq FV(\vec{x}_g) \text{ and } CV(\vec{y}_{g+1}) < CV(\vec{x}_g) \end{cases} \tag{3.33}$$

This process is repeated until all the individuals are selected which lead to survive better generations at the end of the current generation for evolving in the next generation. Moreover, during the selection process, the selected individuals' F and Cr are also considered for next generation evaluation. As a result, at the end of the current generation, the only better-performing individuals and their corresponding F and Cr are placed for the next generation evaluation.

3.5.6 Diversity Mechanism

In fact, any EA can become stuck in local solutions, especially those for DED problems. To tackle this, if the average fitness function of the current population does not improve for a predefined number of generations, some individuals are randomly replaced as:

$$\textbf{if } |\min(f_g - f_{g-\kappa})| < \zeta \tag{3.34}$$

$$y_{i,j}^{\prime} = \begin{cases} y_{i,j}^{min} + (y_{i,j}^{max} - y_{i,j}^{min})rand & \text{if } rand \leq \phi \\ y_{i,j} & \text{otherwise} \end{cases}$$

$$\forall i = 1, 2, ..., N_x, \forall j = N_P/2, N_P/2+1, ...N_P$$

$$\textbf{EndIf}$$

where f_g and f_{g-k} are the best fitness values at g^{th} and $(g-\kappa)^{th}$ generations, respectively, κ and ζ the tolerance factors tolerates a k^{th}(assume 100) number of generations by changing the fitness value within ζ (assume 0.001), and ϕ a constant (set it to 20%) to represent the number of individuals to be randomly replaced.

3.6 Experimental Study

For our experimental study, a number of problems from the literature are considered that involve up to 150 thermal units for a 24-hour planning horizon with a one-hour long time period. Based on the availability of data (shown in Appendix A.1), these problems can be solved both with and without consideration of power-loss constraints. The problems are solved briefly described below.

Case *1*: a 5-unit problem without P_{loss} [206];

Case *2*: a 5-unit problem with P_{loss} [206];

Case *3*: a 10-unit system without P_{loss} [14];

Case *4*: a 10-unit system with P_{loss} [14];

Case *5*: a 30-unit system generated by combining three 10-unit systems of Case 3 without P_{loss} [14];

Case *6*: a 100-unit system generated by combining ten 10-unit systems without P_{loss} [14]; and

Case *7*: a 150-unit thermal system without P_{loss} [28].

For a fairer comparison, the same SRs as in [14] is selected, whereby the one-hour SR is set to 5% of the load and the 10-minute one to $2/6 \times 5\%$ of the load. The relaxation factor of the equality constraints (ε) is set to $1e-6$ and the cut-off generation (N_{G_c}) to 200. The GA parameters, the probability of crossover, distribution index (η) and probability of mutation are set to 0.9, 3 and 0.1, respectively. The population sizes are set to 100 for the $5-$, $10-$ and $30-$unit, and 200 for the $100-$ and $150-$unit problems, and the maximum number of generations to 4000 for all cases. Thirty independent runs are performed for each test case and the solutions recorded and compared with the results from the-state-of-the-art algorithms.

The algorithms are implemented on a desktop personal computer with a 3.4 GHZ Intel Core i7 processor with 16 GB of RAM using the MATLAB (R2012b) environment. The algorithm runs until the number of generations is higher than 4000 (criterion 1) or the best and average fitness values are no longer improved in 100 generations (criterion 2).

3.6.1 DED with TL

As power TL cannot be avoided in a power distribution system, it is important to consider it when scheduling generating units. In this research, due to data unavailability, the TL is considered for only two cases (1 and 3). Their results are compared with those from E-GA and E-DE as well as state-of-the-art algorithms. The solutions obtained for the 5-unit and 10-unit problems with SR constraints using the proposed algorithms (E-DE and E-GA) are presented in Tables 3.1 and 3.2, respectively, along with the results from the state-of-the-art algorithms. It can be seen that the proposed algorithms can obtain much better results than the state-of-the-art algorithms. Additionally, E-DE is found to be better than E-GA.

Table 3.1: Summary of solutions for 5-unit system with loss

Method	Production cost ($)			STD
	Minimum	Average	Maximum	
SA [207]	47356	NR	NR	NR
APSO [208]	44678	NR	NR	NR
GA [200]	44862	44922	45894	NR
PSO [200]	44253	45657	46403	NR
ABC [200]	44046	44065	44219	NR
AIS [62]	44385	44759	45554	NR
H-PSO [206]	43223	43732	44252	274.95
E-GA	42528.9	42580.6	42638.4	30.16
E-DE	**42528.7**	**42571.2**	**42664.5**	**36.9**

Table 3.2: Summary of solutions for 10-unit system with loss

Method	Production cost ($)			STD
	Minimum	Average	Maximum	
EP [82]	1054685	1057323	NR	NR
EP-SQP [82]	1052668	1053771	NR	NR
MHEP-SQP [83]	1050054	1052349	NR	NR
DGPSO [83]	1049167	1051725	NR	NR
IPSO [209]	1046275	1048154	NR	NR
AIS [62]	1045715	1047050	1048431	NR
ECE [210]	1043989	1044963	1046805	NR
ABC [200]	1043381	1044963	1046805	NR
TVACIPSO [211]	1041066	1042118	1043625	NR
EBSO [212]	1038915	1039188	1039272	NR
CSAPSO [213]	1038251	1039543	NR	NR
SAMFA [214]	1037698	1037938	1039199	NR
MTLA [215]	1037489	1037712	1038090	NR
MIQP [14]	1038376	NR	NR	NR
E-GA	1036460	1037020	1037430	251.83
E-DE	**1036280**	**1036310**	**1036380**	**51.31**

3.6.2 DED without TL

The 5-, 10-, 30-, 100- and 150-unit DED test problems without TLs are solved and the results obtained from the proposed approaches along with those from some others in the literature, are presented in Tables 3.3 to 3.7 in which it is clear that our algorithms outperform all the others.

The computational costs of different approaches to different problems are presented in Table 3.8 in which it can be seen that E-DE is better than E-GA for all problems because it provides better quality solutions and requires less computational time. Note

Table 3.3: Summary of solutions for 5-unit system without loss

Method	Production cost ($)			STD
	Minimum	Average	Maximum	
E-GA	42524.4	42565.9	42630.8	26.77
E-DE	**42523.6**	**42524.8**	**42621.6**	**28.87**

Table 3.4: Summary of solutions for 10-unit system without loss

Method	Production cost ($)			STD
	Minimum	Average	Maximum	
EP [82]	1048638	NR	NR	NR
SQP [82]	1051163	NR	NR	NR
EP-SQP [82]	1031746	1035748	NR	NR
MHEP-SQP [83]	1028924	1031179	NR	NR
AIS [62]	1021980	1023156	1024973	NR
GA [200]	1033481	1038014	1042606	NR
ABC [200]	1021576	1022686	1024316	NR
DE [99]	1036756	1040586	1452558	3225.8
CDE [99]	1019123	1020870	1023115	1310.7
MDE [104]	1031612	1033630	NR	NR
CSDE [216]	1023432	1026475	1027634	NR
Hybrid DE [104]	1031077	NR	NR	NR
HS [217]	1046726	NR	NR	NR
HHS [217]	1019091	NR	NR	NR
CE [210]	1022702	1024024	NR	NR
ECE [210]	1022272	1023335	NR	NR
PSO [200]	1027679	1031716	1034340	NR
IPSO [209]	1023807	1026863	NR	NR
ICPSO [218]	1019072	1020027	NR	NR
PSO-SQP [219]	1027334	1028546	NR	NR
ICA [220]	1018468	1019291	1021796	NR
H- PSO [206]	1018159	1019850	1021813	826.94
MIQP [14]	1016601	NR	NR	NR
E-GA	1016360	1016710	1016880	221.11
E-DE	**1016160**	**1016260**	**1016420**	**69.93**

that, for the 150-unit DED problem, the number of chromosomes is 3600 which means it has a huge search space. Therefore, both GA and DE take a large computational time. It is worth to mention here that the algorithms reach the stopping criteria of the maximum number of generations before converging to a solution (local or global). It is observed that their fitness values can be further improved with very slow convergence rate which will consume a significant computational time with a very little improvement.

Table 3.5: Summary of solutions for 30-unit system without loss

Method	Production cost ($)			STD
	Minimum	Average	Maximum	
EP [83]	3164531	3200171	NR	NR
EP-SQP [83]	3159024	3169093	NR	NR
MHEP-SQP [83]	3151445	3157438	NR	NR
DE [99]	3162997	3173102	NR	NR
CDE [99]	3083930	3090542	NR	NR
CE [210]	3086110	3088870	NR	NR
ECE [210]	3084649	3087847	NR	NR
IPSO [209]	3090570	3096900	NR	NR
ICPSO [218]	3064497	3071588	NR	NR
H-PSO [206]	3062144	3067277	NR	2177.6
MIQP [14]	3049359	NR	NR	NR
E-GA	3049110	3049550	3051150	879.62
E-DE	**3046110**	**3046640**	**3046970**	**227.87**

Table 3.6: Summary of solutions for 100-unit system without loss

Method	Production cost ($)			STD
	Minimum	Average	Maximum	
GA [214]	10908741	11584628	11987675	NR
PSO [214]	10366076	10766385	11310279	NR
FA [214]	10197269	10419457	11216243	NR
SAFA [214]	10183819	10286043	10388958	NR
SAMFA [214]	10170104	10171876	10179061	NR
MIQP [214]	10170508	NR	NR	NR
E-GA	10170343	10174764	10180669	3978.57
E-DE	**10158600**	**10165800**	**10168300**	**3362.58**

Table 3.7: Summary of solutions for 150-unit system without loss

Method	Production cost ($)			STD
	Minimum	Average	Maximum	
BA [28]	15287005	15291497	15296855	NR
SALBA [28]	15256663	15258781	15260355	NR
E-GA	15260000	15266300	15267100	2529.31
E-DE	**15247900**	**15259800**	**15260100**	**1117.66**

Table 3.8: Summary of computational cost for different problems

Problem size	E-GA		E-DE	
	Maximum generation	CPU time (min)	Maximum generation	CPU time (min)
5 units	665	4.7	635	2.8
10 units	1984	12.8	2652	11.7
30 units	1327	39.2	3126	83.2
100 units	2736	118.23	2354	112.43
150 units	4000	187.21	4000	157.03

Table 3.9: Average fitness values obtained by GA and DE with and without heuristic

Algorithm	Type of heuristic	$N_P \times N_G$	Fitness values
GA	None	100 × 4000	Infeasible
	HFS	100 × 4000	1018190
	HRS	100 × 4000	**1016360**
DE	None	100 × 4000	1076540
	HFS	100 × 4000	1017370
	HRS	100 × 4000	**1016160**

3.7 Analysis of Different Components

In this section, the effect of different components of the algorithms such as heuristic, mutation, self-adaptation, and selection process for our algorithms are extensively analyzed. To do, a 10-unit problem of (case-3) as a representative case is considered.

3.7.1 Effect of Heuristic

The proposed heuristic transforms the infeasible solutions into good quality feasible solutions. To demonstrate the effect of the proposed heuristic, the average of best objective function values over 30 independent runs of each variant are recorded in Table 3.9. From this Table, it can be seen that GA without the heuristic does not find a single feasible solution, even after $4k$ generations, and although DE is able to find a few feasible solutions, the quality is poor. When the heuristic is applied starting from the first hour (HFS), both algorithms are able to obtain feasible solutions, and the solutions are better than the same for without heuristic if any feasible solution is obtained. However, with the proposed heuristic that is with a random starting hour (HRS), the solutions are better than those obtained with HFS.

3.7.2 Effect of Mutation

In this subsection, the performance of non-uniform, chaotic and polynomial mutation operators with GA are analyzed by solving a sample 10-unit test problem (case -3). A sample of 4000 generations with same parameters is set for all variants and the convergence plots for the best fitness values of each variant are shown in Fig. 3.3. Although

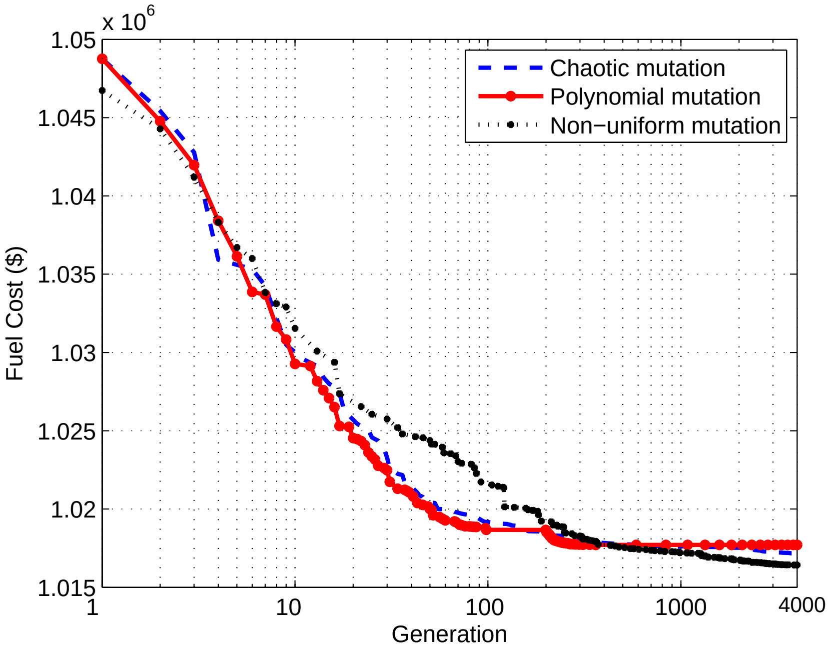

Fig. 3.3: Effect of non-uniform mutation in GA for a solving DED problem (case-3)

the non-uniform mutation variant has a slow convergence rate in early generations, it can obtain better results at the end of the evolutionary process, i.e., GA with a non-uniform mutation operator obtains an objective function value of \$1016360 while, with polynomial and chaotic mutation operators obtain \$1017710 and \$1017170, respectively. In conclusion, non-uniform mutation is dominant over the other two mutation operators for solving DED problems.

3.7.3 Effect of Self-adaptation

To demonstrate that the self-adaptation strategy used in this research provides better results than that with fixed-parameters, a DE algorithm with two different mutation and crossover rates are considered, and its results compared with those obtained from the algorithm with the self-adaptive mechanism. In the adaptive process, initially, two sets of control parameters, $\dot{F} \in N(0.5, 0.1)$ and $\dot{Cr} \in N(0.5, 0.1)$ are generated using normal distributions with mean and standard deviation values of 0.5 and 0.1, respectively. Then, in subsequent generation, they are calculated as per Eqn. (3.18). After solving the sample test problem (case-3) using three different scenarios, the average values, of best objective solutions, obtained from 30 runs for each variant are shown in Table 3.10

Table 3.10: Comparison of average fitness values for different types of mutation and crossover rates for a solving DED problem (case-3)

Type of F and Cr	Parameter values	Objective value
Fixed	$F = 0.9, Cr = 0.1$	1016380
	$F = 0.5, Cr = 0.5$	1016570
Adaptive	$\dot{F}_z = 0.5 \sim 0.95,$ $\dot{C}r_z = 0.5 \sim 0.95$	**1016160**

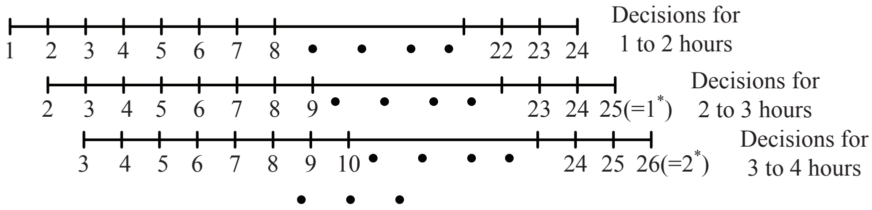

Fig. 3.4: Concept of rolling horizon with 1 hour time periods and $T = 24$

in which it is clear that using the self-adaptive method to calculate DE parameters is beneficial in terms of the objective values obtained.

3.7.4 Scheduling with Rolling Horizon

In this section, the use of the proposed algorithms for the scheduling of the DED problem based on a rolling horizon basis [199] is presented. The scheduling based on a rolling horizon is defined as the schedule is revised due to any changes take place in any input at any point in time. In the process, at the beginning, the schedule is generated for 24 hours that is for 1 to 24 hours with an intention that only the production plan for period one will be implemented. At the end of period 1, the schedule is generated for 2 to 25, considering any changes/updates in data or input that may experience in period 1. At the end of period 2, the schedule is generated for 2 to 26, and so on. Such a scheduling process will provide a better operational plan, shown in Fig. 3.4.

To demonstrate the application of rolling horizon process, a 5-unit test problem is considered, and subsequently generated random demands with 5% standard deviation from the forecasted demand. The demand data is shown in Fig. 3.5. The generating units are considered as committed for all runs. Based on the new data, the second and subsequent runs are performed by our proposed methodology. The simulation has run thirty times and the best fitness values are reported on Table-3.11. From the results, it is seen that the E-DE has provided better results comparing to other algorithms for each

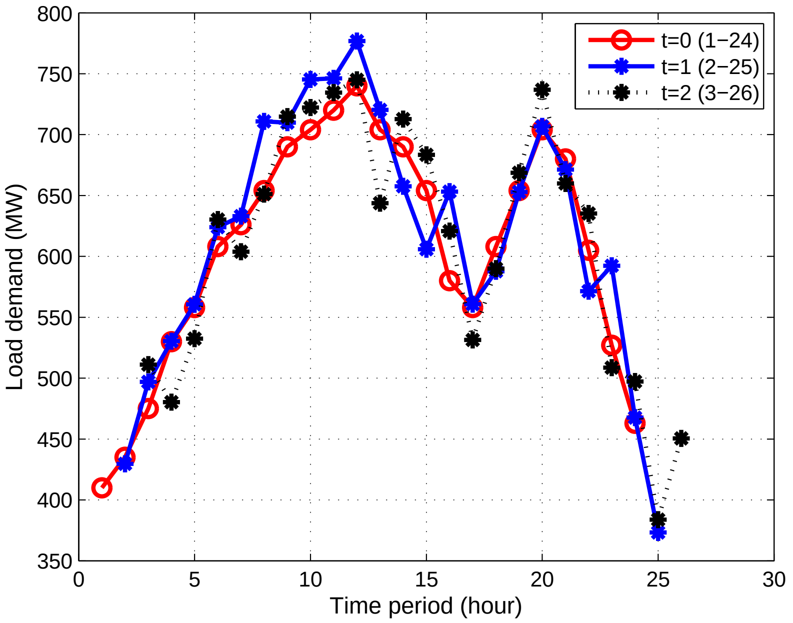

Fig. 3.5: Load demands for different scenarios

Table 3.11: 5-unit test results obtained from the rolling horizon framework

Run (hour)	Schedule period (hour)	Fuel cost ($)			
		GA	DE	E-GA	E-DE
at $t = 0$	1-24	55800.70	46691.60	42539.40	**41943.10**
at $t = 1$	2-25	51281.00	46817.30	43835.10	**43289.10**
at $t = 2$	3-26	50165.60	46565.90	43775.50	**43169.20**

run. From this experience, it can say that DED model can be dynamically implemented in practice using rolling horizon framework as the procedure always uses most recent information, while the data are updated at every single period. Hence, the proposed approach in conjunction with rolling horizon framework will enhance the practice of DED problem solving.

3.8 Chapter Summary

In this chapter, a self-adaptive E-DE and E-GA were demonstrated those exhibited superior performances in solving DED problems. In this approach, a random sequential technique was used to consider periodic simpler sub-problems to satisfy the equality constraints and dynamic ramp constraints. A dynamic relaxation factor for the equality constraints was set to preserve a few marginally infeasible solutions to enhance the convergence rate. A parametric analysis explicitly showed the effect of different components used in this Chapter. Applications of both the E-GA and E-DE algorithms in a number of test problems taken from recent literature, revealed their better performances. Moreover, based on the rolling scheduling horizon framework, it was seen that the solution procedure could be implemented dynamically on consecutive hours in following days, with the E-DE provided better results comparing to other algorithms.

Although the proposed algorithms were applied to solve a number of thermal-based DED test problems, uncertain renewable sources-based ones are yet to be explored, with the rolling horizon framework possibly not working immediately. In the next chapter, the uncertain wind-thermal DED model is solved using a new solution technique that can be periodically implemented on successive days.

Chapter 4

EAs for Renewable Energy based DED Problems

Firstly, this chapter discusses the importance of solving renewable-based wind-thermal dynamic economic dispatch (DED) problems and the difficulties of the continuous operation of wind generators due to their uncertainties. Then, it presents a description of the problem and its mathematical formulation, an overview of existing solution approaches and the algorithms proposed for its solution. Finally, the experimental study and its outcomes are provided.

4.1 Introduction

As discussed in Chapter 3, solving fossil fuels-based thermal-DED problems is an important research topic in the power system domain. However, during the last few decades, the use of fossil fuels in the power industry has significantly increased, resulting in increases in emissions of greenhouse gases into the environment. To reduce these emissions, renewable sources, such as wind power, are increasingly being used for electricity generation for which a wind-thermal DED problem is used to schedule the wind and thermal generators to serve a forecasted daily load demand at a minimum cost while satisfying technical and environmental constraints.

Despite the numerous advantages of wind power generators (WPGs), their uncertain nature presents a new challenge for their economical operation in the power generation

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The following articles have been published based on this Chapter:

[1]. M. F. Zaman, S. M. Elsayed, T. Ray and R. A. Sarker, Evolutionary algorithms for power generation planning with uncertain renewable energy, ***Energy***, vol. 112, 1 October 2016, Pages 408-419.

[2]. M. F. Zaman, S. M. Elsayed, T. Ray and R. A. Sarker, A double action genetic algorithm for scheduling the wind-thermal generators, **Artificial Life and Computational Intelligence. Lecture Notes in Computer Science**, vol 9592. Springer, Cham. 2016. pp. 258-269.

industry because, as the wind's speed changes randomly, it is difficult to determine their actual outputs for day-ahead scheduling [95].

Also, as discussed in Chapter 3, the solutions to a DED problem are generated and repeatedly implemented over a one-day horizon by dividing the day into multiple periods based on a rolling horizon approach. This assumption of periodicity is based on the fact that the resources (generators) are fixed and demand periodic due to cyclic consumption and seasonal changes [201]. However, the resources of a wind-thermal DED problem fluctuate depending on the weather conditions. Therefore, for a periodic implementation of wind and thermal generators for an uncertain DED system, there is the possibility of an unwanted electricity shortfall occurring between the last hour of one day and the first of the following one which is known as a transient ramp violation (TRV) [201].

Consequently, the continuous operation of an uncertain wind-thermal DED problem is still of great concern and attempts to solve it have led many researchers to propose different approaches. Of them, a scenario-based probabilistic DED model is very popular for handling the uncertainty of resources in which the scenarios represent the stochastic behaviors of wind speeds and forecasted load demands [34]. However, existing methods are only valid for a single-day static scheduling and not feasible for real-time continuous operation. Therefore, in this chapter, an efficient solution approach for real-time wind-thermal DED problems with uncertainties is developed.

4.2 Description of Wind-thermal DED System

This section describes an uncertain wind-thermal DED system. As a thermal DED problem, an uncertain wind-thermal DED one is a constrained, non-convex, non-smooth optimization problem used to schedule the available thermal and wind generators for a time period of T hours. The objective is to minimize the fuel costs of the thermal generators and, as the wind generators are regarded as renewable, their operational costs are ignored.

The uncertain behaviors of wind speeds and variable load demands are incorporated in the DED model in which the mathematical formulation is re-formulated as a scenario-based DED one. The scenarios are generated using the Gaussian distribution with their means and standard deviations obtained from historical data. Each is considered an individual DED problem in which the decision variables are the electricity output from the committed thermal units which ensure that the available WPGs are fully utilized.

The equality constraints are the power balance and the inequality ones the capacities, ramp limits and spinning reserves (SRs) of the thermal generators. Also, the transient ramp constraints are considered to avoid an unwanted electricity shortfall between the last hour of one day and the first hour of the next for the continuous operation of the available generators. However, if an electricity shortfall occurs in a certain case, the penalty cost is added to the objective function. Therefore, the objective function of the uncertain wind-thermal DED system is considered the summation of the fuel costs of the thermal generators and penalty costs of an unexpected electricity shortfall for scheduling the generators over a time horizon of seven days with one-hour time intervals. Details of the mathematical model of this scenario-based wind-thermal DED problem are presented in the following section.

4.3 Problem Formulation

In this section, a mathematical model of the DED problem for periodic implementation of its resources on successive days, where the objective is to minimize the overall operating cost while satisfying a number of equality and inequality constraints, is discussed below.

4.3.1 Objective Function

The main objective of a DED problem is to minimize the sum of all fuel costs for the thermal power plants under consideration. The fuel cost function with valve-point effects (VPE) is non-smooth, non-convex and multi-modal can be expressed as [14]:

$$C_{i,t,s} = a_i + b_i P_{T_{i,t,s}} + c_i P_{T_{i,t,s}}^2 + \left| d_i \sin\left\{ e_i (P_i^{min} - P_{T_{i,t,s}}) \right\} \right| \quad \forall i, t, s \tag{4.1}$$

where $P_{T_{i,t,s}}$ and $C_{i,t,s}$ are the i^{th} thermal power output and its operating cost at t^{th} hour for s^{th} scenario, respectively, and N_s the number of scenario considered. The fuel cost for a number of given time periods of a day (or a scenario) is:

$$F_{C_d} = \sum_{t=1}^{T} \sum_{i=1}^{N_T} C_{i,t,s} \quad s \in N_S \tag{4.2}$$

where F_{c_d} is the daily operating cost and the total fuel cost for a number of given days is:

$$F_{C_T} = \textstyle\sum_{d=1}^{N_D} F_{C_d} \tag{4.3}$$

However, the overall cost for N_D days is associated with the total fuel cost in Eqn. (4.3) and penalty cost in Eqn. (4.5) for load shedding. Load shedding occurs mainly when demands are too high and wind power too low compared with predictions. Also, it arises when the demands of two consecutive hours including the last hour of a day and the first hour of next day vary significantly as the ramp does not allow the generator's output to be changed rapidly, which is mathematically expressed as:

$$P_{S_{t,s}} = \begin{cases} P_{D_{t,s}} - \sum_{i=1}^{N_T} \min(P_{T_{i,t-1,s}} + UR_i, P_i^{max}) \\ \qquad \text{if } P_{D_{t,s}} > \sum_{i=1}^{N_T} \min(P_{T_{i,t-1,s}} + UR_i, P_i^{max}), \\ \sum_{i=1}^{N_T} \max(P_{T_{i,t-1,s}} - DR_i, P_i^{min}) - P_{D_{t,s}} \\ \qquad \text{if } P_{D_{t,s}} < \sum_{i=1}^{N_T} \max(P_{T_{i,t-1,s}} - DR_i, P_i^{min}), \\ 0, \ \text{otherwise} \end{cases} \tag{4.4}$$

where $P_{S_{t,s}}$ is the amount of unexpected electricity shortage, where the first term in Eqn. (4.4) represents the power shortage of an hour arises if the demand is too high than previous hour demand, while the second term represents the over-generation of an hour causes demand is too low than the previous hour demand. The over or under-generations are compensated using additional equipment (e.g. quick start-up diesel generators) and/or planning the generators an intelligent way so that the $P_{S_{t,s}}$ is become zero. However, if the demand is still higher than the available generation capacity, then the residual demand is considered to be a load shedding, which leads to a large penalty cost to the consumer, are:

$$F_{C_L} = \gamma \sum_{s \in d}^{N_D} \sum_{t=2}^{T} P_{S_{t,s}} \tag{4.5}$$

where F_{C_L} is the penalty cost due to unexpected load shedding and γ its coefficients. Then, the overall cost or the objective function for the DED model is:

$$F_T = F_{C_T} + F_{C_L} \tag{4.6}$$

The Eqn. (4.6) is the objective function of the scenario-based wind-thermal DED model, considering the N_D-day operational cycle.

4.3.2 Constraints

As traditional DED model, the constraints of the uncertain DED system are discussed below.

A Power Balance Constraints

It is assumed that the generation must meet demand on a real-time basis which means that the total generation planned must be equal to the demand in a given load period as:

$$\sum_{i=1}^{N_T} P_{T_{i,t,s}} = P_{D_{t,s}} + P_{loss_{t,s}} \quad \forall t \quad s \in N_S \tag{4.7}$$

where $P_{D_{t,s}}$ and $P_{loss_{t,s}}$ are the power demand and transmission loss at t^{th} hour for the s^{th} scenario, respectively in which $P_{loss_{t,s}}$calculated as:

$$P_{loss_{t,s}} = \sum_{i=1}^{N_T} \sum_{j=1}^{N_T} P_{T_{i,t,s}} B_{ij} P_{T_{j,t,s}} \quad \forall t \quad s \in N_S \tag{4.8}$$

B Generator Capacity Constraints

Each generator has a capacity bound of:

$$P_i^{min} \leq P_{T_{i,t,s}} \leq P_i^{max} \quad \forall i, t \quad s \in N_S \tag{4.9}$$

C Generating Unit Ramp-Rate Constraints

Many studies of DED have simplified their models by assuming that the unit generation output can be adjusted instantaneously. However, it does not reflect the actual operating conditions of generating units. The ramp rate is described as the power response capability of a unit in terms of accommodating power changes with a specified time interval. The operating ranges of all on-line units are restricted by their ramp-rate limits as:

$$P_{T_{i,t,s}}^{t} - P_{T_{i,t-1,s}} \leq UR_i \quad \forall i, t \quad s \in N_S \tag{4.10}$$

$$P_{T_{i,t-1,s}} - P_{T_{i.t,s}} \leq DR_i \quad \forall i, t \quad s \in N_S \tag{4.11}$$

D Spinning Reserve Requirements

In real life, a power system network suffers a number of unexpected events, such as certain load changes and failure of a large operating unit. In order to increase its reliability and avoid errors, three safety factors included in the model are:

$$\sum_{i=1}^{N_T} P_i^{max} - \left(P_{D_{t,s}} + P_{loss_{t,s}} + SR_t\right) \geq 0 \quad t \in T \quad s \in N_S \tag{4.12}$$

$$\sum_{i=1}^{N_T} \min\left(P_i^{max} - P_{T_{i,t,s}}, UR_i\right) - SR_t \geq 0 \quad t \in T \quad s \in N_S \tag{4.13}$$

$$\sum_{i=1}^{N_T} \min\left(P_i^{max} - P_{T_{i,t,s}}, UR_i/6\right) - SR_t^m \geq 0 \quad t \in T \quad s \in N_S \tag{4.14}$$

The constraints in Eqns. (4.12) and (4.13) are used to satisfy the one-hour reserve requirements and Eqn. (4.14) describes the 10-minutes reserve requirements for any temporary outages of a generator, in which the ramp in Eqn. (4.14) is arithmetically considered as $UR/6$ [221].

E Transient Ramp Constraints

Although it is a general practice of a conventional DED problem to consider the ramp limits between two consecutive hours over the 24 hours time period for a day (or a scenario) shown in Eqns.(4.10) and (4.11), an unexpected electricity shortfall may be appeared when the generators of a uncertain wind-thermal DED problem are scheduled based on the forecasted daily load pattern assuming that the same scheduling (with or without a deviation) will be repeated in a cyclic order. Because, there is a possibility to arise TRV between the last hour of a day and the first hour of next day due to uncertain characteristics of wind speed. This violation is even worse, when the output of wind energy reduces and load demand increases. To overcome this issue, an additional constraint is employed in a wind-thermal DED problem to represent the transient ramp limits between the first and last hour generation of a scenario which is using for a day or another possible scenario that to be used on next day, respectively, as [201]:

$$-DR_i \leq P_{T_{i,1,p}} - P_{T_{i,T,q}} \leq UR_i, \quad \forall p, q = 1, 2, ...N_S \quad i \in N_T \tag{4.15}$$

where p and q represent the relation with the transient ramp limits among scenarios.

4.4 Solution Approach

As discussed in Chapter 2, the uncertain wind-thermal DED problem has been solved using a number of solution approaches in which some researchers applied different mathematical optimization-based methods due to their fast searching features [149]. However, the VPEs of their cost functions heightened the difficulties of solving this problem which has non-smooth, non-linear and non-convex characteristics [34]. On the other hand, several meta-heuristic methods, such as evolutionary algorithms (EAs), have been effectively used because they are flexible, efficient and have a stochastic searching feature.

4.4.1 Motivation

As previously mentioned, meta-heuristic methods for solving the wind-thermal DED problem have had a successful history. However, existing approaches experience difficulty handling the uncertainties of wind speeds and load demands and this problem is even more difficult when the generators are operated in a periodic order on subsequent days. As shown in Chapter 3 (sub-section 3.7.4), the generators in a real-time DED problem are scheduled based on a rolling horizon approach for 1 to 24 hours, assuming that the daily load curve (Fig. 2.3) will be repeated in a cyclic order considering minor deviations in electricity consumption. In such a case, once the scheduling for one day is completed, it could be used on the following day. However, a technical deficiency may arise when the optimal solution to a DED problem for a dispatch interval from 1 to 24 hours is directly implemented even after assuming that the resources are unchanged.

An example of such a case is illustrated in Fig. 4.1, where it is assumed that a unit has generation limits from 10 to 400MW and a ramp rate of 50MW for a sub-optimal case in which it generates 20MW in the 1^{st} hour, 350MW in the 23^{rd} and 300MW in the 24^{th}. If the same load pattern and resources are repeated on the following day, that unit's economic generation in the 1^{st} hour is 20MW, as on the previous day. However, this unit can generate between 250 and 350 MW in the 1^{st} hour which may not be economical. Therefore, the solution to this problem cannot be implemented for the following 24 hours by merely repeating the rolling horizon approach because the transient ramp constraints may be violated when the generating units are moved from the $24^{th} -$ hour of one day to the 1^{st} of the next.

TRVs become even worse when uncertain wind sources are integrated into the DED problem because of the assumption that these resources are no longer unchanged but

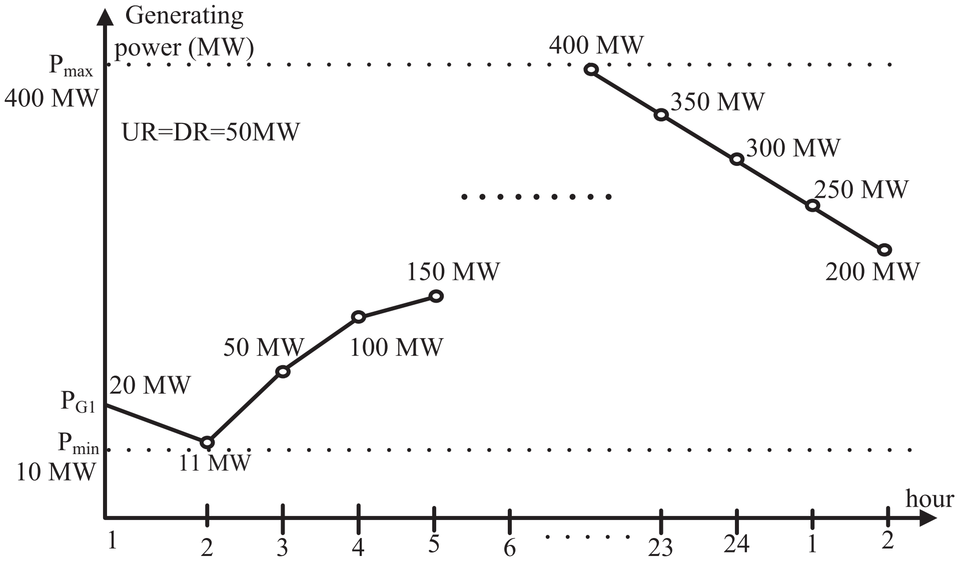

Fig. 4.1: Potential technical deficiency of using present approach

fluctuating depending on the weather conditions. As a result, for a periodic implementation of wind-thermal generators, there is the possibility of an unwanted electricity shortfall occurring between the last hour of one day and the first of the next. To overcome this, several steps can be taken, such as: (i) committing additional generating units for the following day's scheduling; (ii) maintaining additional reserves; (iii) facilitating an energy storage approach; or (iv) designing an effective method for scheduling. The first three steps increase the operating cost as additional equipment needs to be added to the system while the fourth is an intelligent solution approach in which the generators are scheduled in such a way that no modifications are required to satisfy the subsequent days' load demands.

Therefore, in this chapter, two effective solution approaches for solving the uncertain wind-thermal DED problem are presented below.

4.5 Proposed Algorithm

This section describes the proposed solution approach for uncertain wind-thermal DED problems.

As previously mentioned, when wind and thermal generators are scheduled periodically, there is the possibility of an electricity shortfall occurring between the last hour of one day and the first of the next due to the uncertain characteristics of wind speeds and load demands. To deal with this, the uncertain wind-thermal DED model is solved for N_s practical scenarios over a one-week period in order to characterize these uncertainties. It is assumed that the forecasted scenarios will be used in an operating day and any of the N_s scenarios used on subsequent days. Each individual scenario is considered a deterministic DED problem solved using the proposed enhanced genetic algorithm (E-GA) and self-adaptive DE (E-DE) algorithm, both of which use a heuristic to maintain feasibility for the entire operational periods. They schedule the committed generators for a scenario in such a way that the generators can be implemented periodically over a one-day period without violating any ramp limits between any scenarios. The general framework of the proposed algorithms is shown below and their components described in detail in the following sub-sections.

Step 1: generate N_s scenarios using the process described in sub-section 4.5.1.

Step 2: solve the forecasted scenario (called the basic scenario *i.e.*, $s = 1$) that will be used for an operating day's scheduling as follows:

Step 2.1: generate an initial population based on Eqn. (4.18) in sub-section A;

Step 2.2: repair infeasible individuals to feasible directions using the heuristic described in sub-section 4.5.3;

Step 2.3: evaluate the fitness value (FV) and constraint violations (CVs) of each individual using Eqns. (4.6) and (3.32), respectively;

Step 2.4: create child populations using the crossover and mutation operators described in sub-sections 3.5.2 and 3.5.3 for GA and DE, respectively;

Step 2.5: repeat steps 2.2 and 2.3 for child populations;

Step 2.6: select the best individuals from both the parent and child populations using the process described in sub-section A; and

Step 2.7: if a stopping criterion is met, stop and determine the best solution for the basic scenario, otherwise, go to step 2.4.

Step 3: set, $s = s + 1$. Based on the solution in the last hour of the operating day's (basic scenario) scheduling, set $P^1_{G_i} = P^T_{T_{i,s=1}} \forall i$ and calculate the new lower and upper limits of first hour's generation for the s^{th} scenario, such as $P^{min1}_{i,s}$ and $P^{max1}_{i,s}$ using Eqns. (4.24) and (4.25), respectively.

Step 4: based on the new values of $P^{min1}_{i,s}$ and $P^{max1}_{i,s}$, solve the s^{th} predicted scenario using steps 2.1 to 2.7.

Step 5: repeat steps 3 and 4 until $s = N_s$.

Step 6: consider seven random scenarios, including the basic one, for a one-week operation and calculate the overall cost using Eqn. (4.6).

4.5.1 Process for Generating Scenarios

As, in the wind-thermal DED problem, the resources and load demands are uncertain, the periodic implementation of its resources is very difficult unless the exact wind speeds and load demands can be determined. However, accurate predictions of them are not possible due to their random behaviors. Therefore, in order to make dispatch decisions, in this DED model, their uncertain characteristics are considered in which load and wind power forecasting errors are treated as random variables and different scenarios generated using probability distributions [34].

As the wind speed and load demand can be assumed to be normally distributed [222], the scenarios over the time horizon are generated based on the assumptions that their mean values (μ) are the forecast wind speeds and load demands, and their standard deviations (σ) depend on their forecasting errors. These errors are calculated based on the fluctuation ranges of these two parameters in a time series covering the entire range of real-life circumstances. The N_S number of scenarios for the wind speeds and load demands are generated as follows.

Step 1: set $s = 1$,

Step 2: set $t = 0$,

Step 3: determine the ranges of wind speeds and load demands with their standard deviations (forecasting errors) from historical data over the seven days period, which can be found in ref. [223, 224],

Step 4: generate random N_S samples of both the wind speeds ($V_{w,f}$) and load demands (P_D^r) using the truncated Gaussian distribution [225].

Step 5: determine the normalized probability of each random sample instant.

Step 6: calculate the expected wind power $\left(P^r_{wt,s}\right)$ from the random wind speed using the piecewise linear approximation modeled in Eqn. (4.16), as described in [226]:

$$P^r_{W_{w,t,s}} = P^{max}_{w,f}\begin{cases} S_{1,w,f}(V^s_{w,f} - V_{ci,w,f}), & \text{if } V_{ci,w,f} \leq V^s_{w,f} \leq V_{1,w,f}, \\ S_{1,w,f}(V_{1,w,f} - V_{ci,w,f}) + S_{2,w,f}(V^s_{w,f} - V_{1,w,f}), & \\ & \text{if } V_{1,w,f} \leq V^s_{w,f} \leq V_{2,w,f}, \\ S_{1,w,f}(V_{1,w,f} - V_{ci,w,f}) + S_{2,w,f}(V_{2,w,f} - V_{1,w,f}) + & \\ S_{3,w,f}(V^s_{w,f} - V_{2,w,f}), & \text{if } V_{2,w,f} \leq V^s_{w,f} \leq V_{r,w,f}, \\ 1, & \text{if } V_{r,w,f} \leq V^s_{w,f} \leq V_{co,w,f}, \\ 0, & \text{otherwise} \end{cases} \tag{4.16}$$

Step 7: since the available wind power will be fully utilized at each period, the actual load demands to be dispatched by the thermal units are:

$$P_{D_{t,s}} = P^r_{D_{t,s}} - \sum_{w=1}^{N_W} P^r_{wt,s} \quad \forall t, \quad s \in N_S \tag{4.17}$$

Step 8: if $t < T$, set $t = t + 1$ and return to step 3,

Step 9: if $s < N_s$, set $s = s + 1$ and return to step 2,

Once the possible scenarios of the load demand and wind speeds are generated for the seven days scheduling, the optimization methods are applied to allocate the available generators to satisfy all possible demands.

4.5.2 Optimization Methodologies for the DED Problems

In this research, for solving complex uncertain wind-thermal DED problems, GA and DE are considered because of their long and successful history [3]. The evolutionary approaches for both GA and DE in solving uncertain wind-thermal DED system are briefly described in the following subsections.

A Chromosome and Initial Generation

The chromosome or representation of the decision variables for both DE and GA is expressed as:

$$x_j = [P^1_{T_{1,s}}, P^1_{T_{2,s}}, ..., P^1_{T_{N_T,s}}, P^2_{T_{1,s}}, P^2_{T_{2,s}}, ..., P^2_{T_{N_T,s}}, ..., P^T_{T_{1,s}}, P^T_{T_{2,s}}, ..., P^T_{T_{N_T,s}}] \qquad (4.18)$$

$$s \in N_S, \;\; j \in N_P$$

where $P^t_{T_{i,s}}$is the power output of i^{th} generator at t^{th} time period of s^{th} scenario, and the number of decision variables for a DED problem ($s \in N_s$) is $N_x = T \times N_T$. The initial generations of both EAs are generated randomly, and expressed as:

$$x^j_i = x^{min}_i + (x^{max}_i - x^{min}_i)lhs(N_x) \qquad (4.19)$$

$$i \in N_x \quad and \quad j = 1, ..., N_P$$

where x^{min} and x^{max} are the lower and upper bounds of each variable, respectively, that can be found from each power plant's limits, and the $lhs(N_x)$ represents the $N_x$random samples generated as usual LHS rule.

B GA and DE Operators

As last Chapter, the SBX crossover and NUM mutation operators are used in GA while a self-adaptive control parameters used in DE, those described in sections 3.5.2 and 3.5.3, respectively.

4.5.3 Proposed Heuristic

As previously mentioned, the wind-thermal DED is a nonlinear optimization problem involving a number of equality and inequality constraints. The solutions from EAs (either GA or DE) do not satisfy all these constraints, especially the equality (demand balance) and dynamic (ramp limits) ones. Although a feasible solution may be obtained after a long run, it is difficult to maintain feasibility after applying the evolutionary operators. To overcome this deficiency, in the previous Chapter, a heuristic is developed for deterministic DED problems which transforms an infeasible individual into a feasible one by repairing the load allocation among the committed generators. In this process, the daily load cycle is divided into 24-hour sub-problems and the operating generators allocated to meet the load demand in each hour starting from different random hours.

In this Chapter, the heuristic is modified for the uncertain DED problem which satisfies the equality, ramp and transient ramp constraints for any given hour. To repair an infeasible individual for a given hour in a scenario, the heuristic uses a look-ahead approach in which the possible load demand and wind speed in subsequent hours for that and other scenarios are considered. As a result, as it has prior knowledge of possible deviations in load demands and wind speeds in the upcoming hours, the generators are scheduled for a certain hour in such a way that they are able to meet the load demands in following hours without modification. The detailed procedure for obtaining a feasible individual for a given hour from an infeasible one can be found in previous Chapter of section 3.5.4, where the capacity limits of each generator at each time interval for each scenario are updated in a different way, as described below.

For solving the forecasted (basic *i.e.*, $s = 1$) scenario, the total ramp-ahead first and last hour generations capacity limits are updated as follow.

$$\sum_{i=1}^{N_T} P_{i,s=1}^{min1} \leq \min\Big(P_{D,t=1}^{s=1}, P_{D,t=1}^{s=2}, ..., P_{D,t=1}^{s=N_S}, P_{D,t=T}^{s=1}, P_{D,t=T}^{s=2}, ..., P_{D,t=T}^{s=N_S}\Big) \tag{4.20}$$

$$\sum_{i=1}^{N_T} P_{i,s=1}^{max1} \geq \max\Big(P_{D,t=1}^{s=1}, P_{D,t=1}^{s=2}, ..., P_{D,t=1}^{s=NS}, P_{D,t=T}^{s=1}, P_{D,t=T}^{s=2}, ..., P_{D,t=T}^{s=N_S}\Big) \tag{4.21}$$

Equations (4.20) and (4.21) help keeping the first- and last-hour electricity generations of basic scenario within the limits so that the power generations in other predicted scenarios can meet the load demands at those two hours.

The capacity limits of each generator at each time interval (excluding first and last hour) for each scenario (including basic one) are updated as follows:

$$P_{i,t,s}^{min} = \max\left(P_i^{min}, P_{i,s}^{min1} - (T-t)DR_i, P_{i,s}^{min1} - (t-1)DR_i\right) \forall i \ s \in N_S \tag{4.22}$$

$$P_{i,t,s}^{max} = \min\left(P_i^{max}, P_{i,s}^{max1} - (T-t)UR_i, P_{i,s}^{max1} + (t-1)UR_i\right) \forall i \ s \in N_S \tag{4.23}$$

The all parameters of Eqns. (4.22) and (4.23) are predetermined, while the $P_{i,s}^{min1}$ and $P_{i,s}^{max1}$ are calculated as follow.

For the basic ($s = 1$) scenario, set, $P_{i,s}^{min1} = P_i^{min}$ and $P_{i,s}^{max1} = P_i^{max} \forall i$ at starting hour ($P_{T_{i,s}}^{t_{start}}$) to provide full flexibility, while the capacity limits at rest of the hours are calculated using Eqns. (4.24) and (4.25), where $P_{G_i}^1 = P_{T_{i,s}}^{t_{start}} \forall i$ is considered. On the other hand, set, $P_{G_i}^1 = P_{T_{i,s=1}}^T \forall i$ at entire operational periods for the predicted scenarios, and calculate $P_{i,s}^{min1}$ and $P_{i,s}^{max1}$ as follows:.

$$P_{i,s}^{min1} = \max\Big(P_i^{min}, (P_{G_i}^1 - \frac{DR_i}{2})\Big) \, i \in N_T, \ s \in N_s, \tag{4.24}$$

$$P_{i,s}^{max1} = \min\Big(P_i^{max}, (P_{G_i}^1 + \frac{UR_i}{2})\Big)\, i \in N_T,\ s \in N_s, \tag{4.25}$$

The values of $P_{i,s}^{min1}$ and $P_{i,s}^{max1}$ in Eqns. (4.24) and (4.25) are considered as half of the ramp limits so that the ramp constraints between two scenarios are always satisfied even in worst condition.

A Selection

In order to determine the best set of individuals from the both parents and offspring, a selection process is used based on their FVs and CVs those calculated using the Eqns. (4.6), and (3.32), respectively. Based on these values, a greedy selection scheme described in section 3.5.5 is used so that a feasible solution is always considered better than an infeasible one.

4.6 Experimental Study

For the experimental study, two test problems from the literature are taken that involve both thermal and wind power plants and solved for a one-week planning horizon, considering the uncertainty effects of wind speeds and load demands. The uncertain wind energy and variable load demand are included in both problems, with scenario-based characterizations of the uncertainties associated with the load demand and wind speed considered. As, in this Chapter, the main focus is on demonstrating the solution approaches for overcoming the TRV to implement the committed generators in a periodic order on successive days, a smaller population sizes of 20 and 50 for the 5- and 10-unit systems, respectively, is considered to reduce the computational burden, with $N_G = 100$ set for both systems.

As previously mentioned, the control parameters of DE are set adaptively, the GA parameters, the probability of crossover, distribution index and probability of mutation are set to 0.9, 3 and 0.1, respectively. Thirty independent runs are performed for each test case of each scenario and the solutions recorded and compared with each other along with the results from state-of-the-art algorithms.

Table 4.1: Wind speed data for 5 and 10 unit systems

Period	1	2	3	4	5	6	7	8	9	10	11	12
$V_{w,f}^1(m/s)$	13.25	13.9	12.8	12	12.5	14	11.75	12.75	12.8	12.2	15	13.25
$V_{w,f}^2(m/s)$	11.75	12	12.25	12.3	12.5	14	15	14.5	13	13.75	13.5	13.5
Period	13	14	15	16	17	18	19	20	21	22	23	24
$V_{w,f}^1(m/s)$	14.25	14.1	14.2	11.75	13.75	12.75	11.5	11.9	14.5	16	12.65	13
$V_{w,f}^2(m/s)$	12.8	12.25	11.25	11.5	11	11.25	11.2	11	11.3	11.8	11.8	12.25

Each algorithm runs until the number of generations is greater than the predefined maximum number (criterion 1) or the best fitness value is no longer improved in 50 generations (criterion 2) or the average fitness value is no longer improved in 20 generations (criterion 3).

4.6.1 Test Problems

In this section, the considered test problems are described. Firstly, two deterministic 5- and 10-unit DED systems without P_{loss} shown in Appendix A.1.1 and A.1.2, respectively are considered then modified by incorporating the variable wind speeds and fluctuating load demands. To do, the first thermal unit of the 5-unit system is replaced by a wind farm, which has 75×1-MW WPG. Similarly, the 10-unit system is modified by replacing thermal unit 9 by 40 × 2 MW and 10 by 55 × 1 MW WPGs [34]. Wind speed forecasts are depicted in Table-4.1, where $V_{w,f}^1$ and $V_{w,f}^2$ are used for the modified 5- and 10-unit DED system, respectively. The forecasted load demands for both problems are shown in Tables A.2 and A.5, respectively in Appendix A.1.

According to ref. [34], the parameters for wind power generation are calculated as: $V_{ci,w,f} = 4m/s$, $V_{r,w,f} = 14m/s$, $V_{co,w,f} = 25m/s$, $V_{1,w,f} = 7m/s$, $V_{2,w,f} = 12m/s$, $S_{1,w,f} = 0.2/(V_{1,w,f} - V_{ci,w,f})$, $S_{2,w,f} = (0.96 - 0.2)/(V_{2,w,f} - V_{1,w,f})$, $S_{3,w,f} = (1 - 0.96)/(V_{r,w,f} - V_{2,w,f})$. For the sake of simplicity, the same parameters are considered for both wind generators. Based on realistic Australian wind speed [224] and load demand [223] data, the variations in demands and wind powers on the subsequent seven days after the initial operating day are considered as ±5% and ±100%, respectively.

Table 4.2: Characteristics of an additional diesel generator

P_{min} (MW)	P_{max} (MW)	a (\$/h)	b (\$/MWh)	c (\$/$(MW)^2h$)	UR (MW/h)	DR (MW/h)	T_{min}^{on} (h)	T_{min}^{off} (h)
10	20	137.4	17.6	0.005	15	15	1	1

As in the reality some spare units always there to meet unexpected electricity shortfall due to rapid demand changes or generation outage, here an additional quick start-up diesel generating unit is also included in the model to remedy the TRV in (4.15), that reported in Table-4.2 [21]. Note that, this unit is expensive comparing to other committed units, and only operated when the existing units are unable to meet the load demand, otherwise remains off-status. For example, if the wind speed suddenly falls to zero and, conversely, the load demand significantly increases, the operating units may not be able to meet that demand. In this extreme case, either the additional generator will help to meet demands, or there must be load shedding to provide a high compensation to the consumer. Based on the specifications of an Australian utility company [227, 228], the penalty cost for load shedding is set to \$2000/MW in this research.

4.6.2 Simulation Results

In this section, the experimental results for solving the above uncertain wind-thermal DED systems is explained. Firstly, based on the scenario-generation process described in section 4.5.1, 100 practical scenarios are generated and recorded. Then, starting with the forecasted or basic scenario, all these scenarios are solved separately using both the proposed and traditional approaches with two considered EAs, DE and GA. In addition, for a fair comparison with GA and DE, an adaptive DE (JADE) [229] called JADE is also implemented for solving both problems.

From the analysis of last Chapter, it is clear that the EAs without the heuristic are inferior to those with the proposed heuristic. Of the approaches using a heuristic, the traditional means the heuristic is proposed for a scheduling in 24 hours time horizon for s specific scenario of the resources described in 3.5.4, while the proposed one for the scheduling of continuous time-horizon that described in section 4.5.3. In other words, the traditional ones neglect the transient ramp constraints (4.15) and subsequently solve

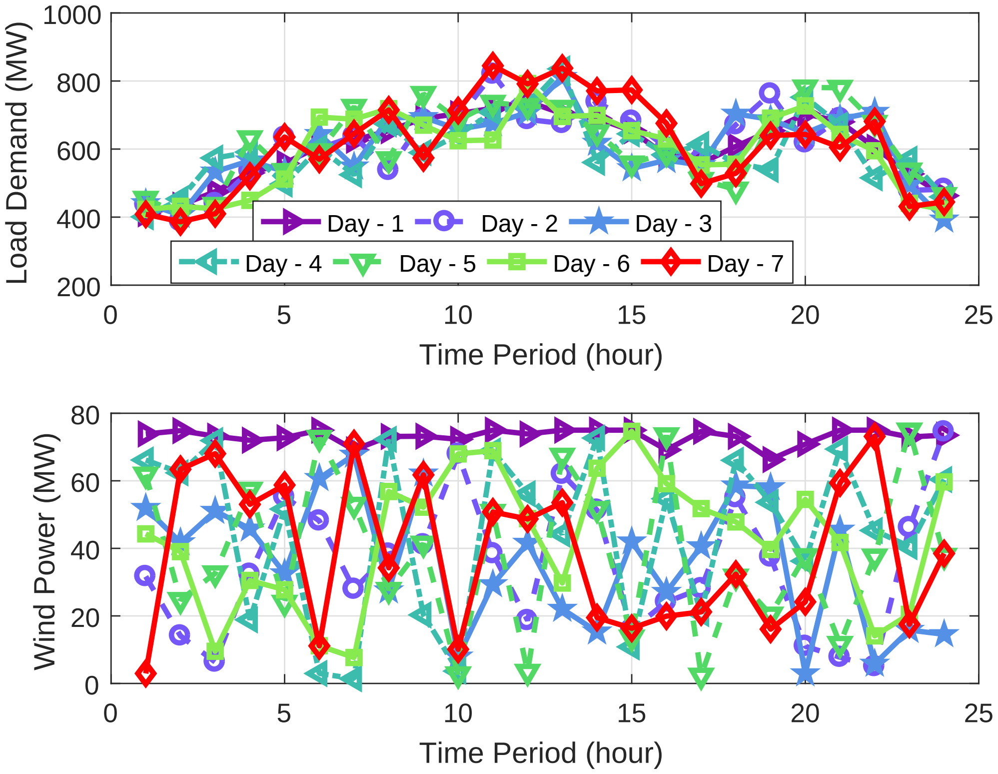

Fig. 4.2: Load demands and wind speeds for 5-unit system over seven days

each scenario as a deterministic DED without considering the other possible scenarios' information while the proposed ones consider these constraints and solve each individual scenario using the information of wind speeds and load demands for the following scenarios. Therefore, when the algorithms use the heuristic for 24 hours, called simple GA, DE, and JADE, while they use the proposed scenario based heuristic, called enhanced GA (E-GA), DE (E-DE), and JADE (E-JADE), respectively.

Once the 100 scenarios are solved using the both approaches, seven random scenarios including basic one are selected for seven days of operation, with their load demands and wind powers of the 5-unit system illustrated in Fig. 4.2. From this figure, it is seen that the load demand and wind power are widely varied within a range of 300 MW to 820 MW, and 0 to 75 MW, respectively, where these ranges for seven days were determined based on the Australian real-life data [223, 224].

Tables 4.3 and 4.4 present the results obtained from seven days' scheduling for 5- and 10-unit uncertain DED system, respectively, in which the results involve the daily

Table 4.3: Seven days scheduling out of 100 random scenarios for 5-unit system

Daily cost ($)= $F_{C_d} + F_{C_L}$						
	Traditional approach			Proposed approach		
Days	JADE	DE	GA	E-JADE	E-DE	E-GA
day-1	36783	36700	36900	38506	39700	38600
day-2	120443	95300	112100	42652	43000	43000
day-3	86045	170800	180800	42000	41800	41100
day-4	41297	72000	50140	41799	41300	40900
day-5	136125	129800	151500	42609	44200	43100
day-6	76829	93300	39800	40643	40700	40100
day-7	144060	45300	79400	43854	44900	44100
F_T($)	641582	643200	650640	292062	295600	**290900**
TRV	71.43%	57.13%	71.43%	**0.00%**	**0.00%**	**0.00%**
Time	14.8 sec	11.1 sec	13.0 sec	15.9 sec	**11.2 sec**	13.3 sec

Table 4.4: Seven days scheduling out of 100 random scenarios for 10-unit system

Daily cost ($)= $F_{C_d} + F_{C_L}$						
	Traditional approach			Proposed approach		
Days	JADE	DE	GA	E-JADE	E-DE	E-GA
day-1	854066	837000	840000	876333	883000	878000
day-2	884929	898000	944800	895136	894000	889000
day-3	900027	887000	959300	876681	881000	875000
day-4	1011005	946200	954700	904432	909000	897000
day-5	925531	1033000	984200	906403	930000	923000
day-6	890889	913000	909900	911237	862000	856000
day-7	937762	1007000	901700	922532	860000	863000
F_T($)	6404209	6521200	6494600	6292754	6219000	**6181000**
TRV	57.14%	79.24%	72.17%	**0.00%**	**0.00%**	**0.00%**
Time	45.2 sec	44.0 sec	55.05 sec	45.8 sec	**44.2 sec**	55.48 sec

fuel cost of the thermal generators which are the aggregation of daily fuel cost and penalty cost for unexpected electricity shortfall due to TRVs, percentages of TRVs, and run time per scenario. From these tables, it is seen that the TRV of a best economical scheduling of a day found in traditional approaches are very high for both problems, which indicate that the ramp limits between the last hour of that day and first hour of following day are violated, and consequently a shortfall of electricity is appeared at the early hours of following day which incurred a high penalty cost to the consumer. On the other hand, the proposed approaches (E-JADE, E-DE and E-GA) solve the problems based on operating day's data in addition to seven subsequent days' data, and consequently found zero TRV which means all solutions are feasible with zero load shedding at a minimum overall cost. As a result, the total daily operation cost (F_T)

Table 4.5: Sample weekly transient hour solutions for 5-unit system obtained from GA and E-GA

Day	Hour	GA				E-GA			
		P1	P2	P3	P4	P1	P2	P3	P4
1	1	20.00	30.00	89.16	225.53	47.48	30.00	124.91	162.30
	24	20.00	55.61	129.09	**222.89**	77.28	50.00	127.34	162.96
2	1	46.13	75.08	116.19	**90.16**	67.30	33.32	87.65	136.39
	24	36.82	**107.02**	111.54	135.28	72.65	47.05	130.88	140.04
3	1	20.00	**30.00**	138.73	145.92	47.28	30.00	118.09	139.28
	24	**20.00**	30.00	165.49	183.71	75.35	30.00	130.88	162.96
4	1	**99.66**	30.00	151.21	139.77	77.28	50.00	130.40	162.96
	24	**75.26**	46.43	162.16	135.85	77.28	50.00	129.46	162.96
5	1	**20.00**	30.00	142.94	143.18	62.28	30.00	105.88	137.96
	24	41.55	30.00	124.91	**193.04**	77.28	30.00	125.31	156.92
6	1	27.09	30.00	122.91	**139.77**	59.77	30.00	90.24	139.76
	24	57.49	30.00	82.70	139.78	59.32	30.00	80.88	139.76
7	1	84.82	30.00	106.98	184.04	77.28	48.22	125.86	154.48
	24	70.99	30.00	107.50	148.28	67.81	30.00	118.91	138.89

in the proposed approaches are found much lower than those of traditional ones. Also, comparing between proposed methods (E-DE and E-GA) and a state-of-art (E-JADE), E-GA performs superior for both problems. In terms of computational cost, both traditional and proposed approaches take almost similar time with E-DE is found minimum in the proposed approaches.

4.6.3 Discussion

In this section, a numerical explanation is presented that provides insights into the reasons for obtaining better results from the proposed approaches than traditional ones. Firstly, the first- and last-hour solutions of the 5-unit system using GA and E-GA are illustrated in Table 4.5, with those in bold representing infeasible generations in terms of their TRVs. It is seen that the proposed approach (E-GA) provides seven-day solutions without any CV while the traditional one (GA) encounters five infeasible solutions for the seven selected scenarios of 7-day generation scheduling; for example, the ramp violation between days 1 and 2 is 82.73 MW because the maximum allowable ramp limit for unit-4 is 50 MW. To compensate this unwanted violation (i.e., electricity shortfall), a high amount of penalty cost is incurred by the producers.

Table 4.6: Summary of 100 scenarios for periodic implementation wind-thermal DED

	5-unit problem				10-unit problem			
	F_{C_T} (\$)	F_{C_L}(\$)	F_T(\$)	TRV	F_{C_T} (\$)	F_{C_L}(\$)	F_T(\$)	TRV
JADE	4.25E+06	6.23E+08	6.28E+08	74.44%	8.88E+07	9.56E+08	1.04E+09	83.34%
DE	4.30E+06	5.43E+08	5.47E+08	69.60%	8.87E+07	9.07E+08	9.96E+08	79.24%
GA	4.25E+06	5.30E+08	5.34E+08	71.08%	8.73E+07	6.36E+08	7.23E+08	72.17%
E-JADE	4.28E+06	0.00	4.27E+06	**0%**	8.82E+07	0.00	8.80E+07	**0%**
E-DE	4.27E+06	0.00	4.27E+06	**0%**	8.80E+07	0.00	8.80E+07	**0%**
E-GA	4.22E+06	0.00	**4.22E+06**	**0%**	8.75E+07	0.00	**8.75E+07**	**0%**

Table 4.6, lists the total fuel costs (F_{C_T}) for 100 predicted scenarios with their percentages of TRV and ramp compensation costs (F_{C_L}). The F_{C_L} is the cumulative TRV cost in which each TRV is calculated based on the ramp violation between the first hour of a scenario and the last hour of that or another scenario. According to the results from traditional approaches, when a scenario is solved based on an operating day's data without invoking the predicted scenarios for the subsequent days' data, more than 70% of solutions for those scenarios violate ramp limits between the last hour of one scenario and the first hour of another. To compensate these ramp violations, as a high compensation cost is incurred, the overall cost (F_T) of a traditional approach becomes higher as the F_{C_L}increases with an increasing TRV, with the maximum F_{C_L} found in JADE. On the contrary, as previously mentioned, the proposed approaches (E-JADE, E-DE and E-GA) solve a scenario (e.g., a forecast one) by considering other possible predicted scenarios of both that day and seven subsequent days. The solutions obtained from E-JADE, E-DE and E-GA maintain the ramp limits over the seven-day period and produce a minimum overall cost solution for a DED problem. Table-4.6 also reveals the superiority of the proposed approaches over the traditional ones for both problems using both algorithms. Moreover, the proposed E-GA is found to be best among six algorithms for solving the both the uncertain DED problems.

4.7 Chapter Summary

Two solution approaches based on GA and DE with a new heuristic for solving both deterministic and uncertain DED problems involving unpredictability in wind speed and load demand were presented in this Chapter. The mathematical model of a DED problem was reformulated, considering the possible scenario of those two uncertain variables over the seven days operational period. In addition, a constraint is considered for periodic implementation of the committed generators on successive days under the uncertain behavior of wind speed and load demand. The heuristic technique was used to transform an infeasible solution into a feasible one which satisfies periodic demand, capacity and ramp limits constraints over the seven days horizon. The proposed methods, along with a state-of-the-art algorithm, with considering two different heuristics were applied on two uncertain DED benchmarks consisting of 5- and 10-unit wind-thermal hybrid power plants, with the uncertainty was represented 100 realistic scenarios generated based on the Australian wind speed and electricity demand data. For solving the uncertain DED, the solutions obtained from the proposed and traditional approaches were compared which revealed that the proposed methods provided scheduling with zero loads shedding at a minimum operating cost. Also, comparing the performances of the six algorithms implemented, the proposed E-DE and E-GA were superior for solving uncertain DED problems, and E-GA relatively performed well for both problems.

Based on the evidence in this chapter and Chapter 3, it is evident that an EA with the proposed heuristic outperformed state-of-the-art algorithms. However, neither E-GA nor E-DE performed consistently well for both thermal and wind-thermal DED problems, i.e., E-DE was better for the former and E-GA for the latter. To solve a wide range of DED problems, such as thermal, wind-thermal, solar-thermal and hydro-thermal, in the next chapter, an evolutionary framework is designed.

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Chapter 5

Evolutionary Framework for DED Problems

This chapter discusses the importance of solving different types of dynamic economic dispatch (DED) problems, such as thermal, hydro-thermal, wind-thermal and solar-thermal, and their uncertainties in power system operations. Then, descriptions and mathematical formulations of these problems, and an overview of existing solution approaches are provided. After stating the motivation for developing a new algorithm for solving this wide range of DED problems, a general evolutionary framework is designed. Finally, the experimental results and outcomes are presented.

5.1 Introduction

As discussed in the previous chapters, the aim of a DED problem is to minimize the production costs of generators operating in a time horizon while satisfying technical and physical constraints. However, due to the significant use of fossil fuels in power generation, vast amounts of atmospheric pollutants are continuously released into the environment. As recent energy act emphasized the need to reduce greenhouse gas emissions when generating electricity, it is necessary to consider emission reductions in a

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The following papers have been published from this chapter:

[1]. M. F. Zaman, S. M. Elsayed, T. Ray and R. A. Sarker, Configuring two-algorithm-based evolutionary approach for solving dynamic economic dispatch problems, ***Engineering Applications of Artificial Intelligence***, vol. 53, August 2016, Pages 105-125.

[2]. M. F. Zaman, R. A. Sarker, and T. Ray, Solving an economic and environmental dispatch problem using evolutionary algorithm, ***IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)***, 2014, pp. 1367-1371.

[3]. M. F. Zaman, S. M. Elsayed, T. Ray and R. A. Sarker, An evolutionary framework for the bi-objectives dynamic economic and environmental dispatch problems, ***Intelligent and Evolutionary Systems. Proceedings in Adaptation, Learning and Optimization***, vol 8. Springer, Cham, 2017. pp. 495-508.

problem of scheduling generators. Therefore, power industries are now focusing on limiting greenhouse gas emissions while minimizing costs by introducing alternatives to thermal sources, such as solar, wind and hydro ones, for generating electricity.

The operating cost of renewable energy is very low and its gas emissions not a big issue while, in contrast, both those of thermal plants are quite high. As the energy demand is much greater than that which a renewable generator can produce, it is necessary to also run some other costly and inferior options, such as thermal plants. Therefore, a mixed DED system is used to schedule both thermal and renewable sources to serve daily load demands but, despite the advantages for the environment and economy of renewable energy, handling its uncertainty is difficult.

As discussed in Chapter 2, sometimes the generators are scheduled with the aim of minimizing both the gas emission and fuel cost. In this case, a DED problem is formulated as a bi-objective, dynamic economic and emission dispatch (DEED) one that considers non-commensurable and contradictory objectives. However, as it involves multiple non-linear and conflicting objective functions, solving it and obtaining trade-off solutions is very challenging [7].

Over the last few decades, although several EAs have been successfully applied for solving both DED and DEED problems, no single algorithm has performed consistently over a wide range of these problems. One EA may perform well in an early stage of the optimization process but less well in later generations and vice versa. Therefore, in this chapter, a general evolutionary framework for solving many of these problems is presented.

5.2 Problem Description

In this section, different types of DED and DEED problems, thermal, hydro-thermal, wind-thermal and solar-thermal systems, are described.

As mentioned in Chapter 3, the objective of a thermal-based DED problem is to minimize the fuel costs of all the committed thermal generators while satisfying their capacities, ramp limits, spinning reserves (SRs) and load demand constraints. It involves a multi-modal, non-convex and non-smooth cost function as the valve point effect (VPE) of thermal generators is considered. As its decision variables are the electricity output from the thermal generators over a time horizon of T hours, there are $T \times N_T$ of them, where N_T is the number of thermal units.

The hydro-thermal DED is a large-scale non-linear complex optimization problem. Its objective is to determine the optimal power generation of both hydro and thermal units to minimize the fuel costs of the thermal ones while satisfying the various constraints of both systems. The constraints of thermal generators have already been described while those of a hydraulic system are the reservoir's capacity, water flow rate and water balance between the inflow and outflow, and time delay and capacities of its hydro generators. The objective function is considered the usual non-convex and multi-modal fuel cost function of the thermal generators, with the costs of the hydro generators ignored. The load demands for the thermal generators are re-calculated after subtracting the generations of available hydro power, which depend on the water flow rates of the reservoir and their time delays, from the forecasted load demands. The decision variables are the electricity output from the thermal generators and the water flow rate of the reservoir in the hydraulic system. If a hydro-thermal system has N_T and N_H thermal and hydro generators, respectively, that perform for a time period of T hours, the number of decision variables is $T \times (N_T + N_H)$.

The wind-thermal DED problem is a nonlinear constrained optimization problem. After incorporating the uncertain characteristics of wind speeds into the DED model, the objective function becomes the summation of four components. The first is the usual fuel cost of the thermal generators and the next three the costs of the uncertain wind generators, that is, the expected, and over-estimated and under-estimated unbalance conditions. The expected cost is that which the wind power producer has to pay when the system has no wind turbine. The over-estimated one refers to when the available wind energy is less than the scheduled output for a time interval and is incurred because an additional charge is imposed on the system to balance the load demand and generation, with the shortage compensated by the reserve power. The under-estimated cost means that the available wind energy is greater than the scheduled output in a time interval. In this case, the extra generations are either dispatched elsewhere or wasted, thus incurring a penalty cost for regaining the system's stability by meeting the load balance constraints. The constraints of a wind-thermal DED are the power balance, capacity limits of both its thermal and wind generators and ramp limits of the thermal ones. Its decision variables are the electricity output from both the thermal and wind generators with $T \times (N_T + N_W)$ variables, where N_W is the number of wind turbines.

The solar-thermal DED problem is also formulated as a single-objective minimization one in which the objective is to minimize the operating costs of both the thermal and solar photovoltaic (PV) units. The constraints are the power balance, capacity limits of both the thermal and solar units and ramp limits of the thermal ones. Also, an equality constraint of the maximum solar share is used to ensure system stability under uncertain solar generation conditions, with the electricity usage not exceeding the reserve capacity. The decision variables of this system are considered the output from both thermal and solar PV generators while their types are different, being continuous for the former and integers for the latter because, when a solar unit is scheduled, the available solar energy is fully utilized. The number of decision variables in a wind-thermal DED problem is $T \times (N_T + N_S)$, where N_S is the number of solar units.

As previously mentioned, a DEED problem is a bi-objective constrained, non-convex and non-smooth minimization one in which the objective is to simultaneously minimize both the operating costs of the committed generators and gas emissions from the thermal ones. The constraints and decision variables in this problem are considered to be the same as those in the single-objective DED one. Details of the mathematical formulations of both the DED and DEED problems for thermal, hydro-thermal, wind-thermal and solar-thermal systems are discussed in the following section.

5.3 Mathematical Formulations

In this section, the single objective DED problems for thermal, hydro-thermal, wind-thermal and solar-thermal systems, and based on the availability of the data, the bi-objective DEED problems for hydro-thermal and solar-thermal are presented. For all the problems, it is assumed that their given numbers of generators are predetermined using UC problems [230] and that these generators will be operated for the time periods of $T-$hour. Also, to compare the simulation results with the state-of-the-arts, the uncertainty factors of the renewable sources (e.g. wind, solar, etc.) are tackled using the conventional penalty function approach that accumulated with respective objective function. Each of the models is described below.

5.3.1 Thermal System

In a single objective thermal based DED problem, the objective is to minimize the sum of all fuel costs for the thermal power plants under consideration (N_T) during the operational cycle, T while satisfying a number of equality and inequality constraints, such as power balance with P_{loss}, capacity, ramp limits and SR constraints. The objective function and the constraints are described in section 3.3 of chapter-3 in which the fuel cost function including the VPE shown in Eqn. (3.1) and the constraints shown in Eqns. (3.3) to (3.10).

5.3.2 Wind-Thermal System

In the wind-thermal DED system, the main aim is to determine the optimal power generation of the thermal and wind generators by minimizing the overall operating cost while satisfying the number of constraints, as described below.

A Objective Function

The objective function of a wind-thermal DED system comprises the fuel and environmental costs of thermal generators and the operating cost of wind turbines. In addition, the penalty costs, such as the over- and under-estimated ones of wind energy due to the stochastic nature of wind speeds are considered. According to a cost analysis of conventional and wind turbine generators, the objective function of the DED model in T time intervals can be expressed as [137]:

$$\text{Minimize } F_T = \sum_{t=1}^{T} \left(\sum_{i=1}^{N_T} \left(F_{C_i}(P_{T_{i,t}}) + F_{E_i}(P_{T_{i,t}}) \right) \right) + \tag{5.1}$$
$$\sum_{t=1}^{T} \left(\sum_{w=1}^{N_W} \left(F_{Ww}(P_{W_{w,t}}) + F_{U_w}(P_{W_{w,t}}) + F_{O_w}(P_{W_{w,t}}) \right) \right)$$

where $P_{T_{i,t}}$ and $P_{W_{w,t}}$are the output of i^{th} and w^{th} thermal and wind generator, respectively, F_{W_w}, F_{U_w} and $F_{O_w}$the operating, under- and over-estimated penalty cost, respectively, the fuel cost (F_C) of thermal generators can be found in (3.1) and the cost for gas (F_E) emissions expressed as:

$$F_E(P_{T_{i,t}}) = 10^{-2} \left(\alpha_i + \beta_i P_{T_{i,t}} + \gamma_i P^2_{T_{i,t}} \right) + \eta_i e^{\lambda_i P_{T_{i,t}}},\ i \in N_T\, t \in T \tag{5.2}$$

where α_i, β_i, γ_i, η_i and λ_i are the emission coefficients of the i^{th} thermal generator, respectively. The operating cost of wind generators is assumed to be linear as:

$$F_{Ww}(P_{W_{w,t}}) = \delta_w P_{W_{w,t}},\ w \in N_W\, t \in T \tag{5.3}$$

where δ_w is the per unit cost of w^{th} wind generator, and the output power of the w^{th} wind generators at the t^{th} time interval can be expressed as [141]:

$$P_{W_{w,t}} = \begin{cases} 0 & \text{if } v_{out_w} < v_{w,t} < v_{in_w} \\ P_{R_w} \frac{v_{w,t} - v_{in_w}}{v_{r_w} - v_{in_w}} & \text{if } v_{in_w} < v_{w,t} < v_{r_w} \\ P_{R_w} & \text{if } v_{r_w} < v_{w,t} < v_{out_w} \end{cases} \tag{5.4}$$

where v_{out_w}, v_{in_w}, v_{r_w} and $v_{w,t}$ are the cut-out, cut-in, rated and t^{th}-hour wind speed of w^{th} wind farm, respectively, and P_{R_w} rated wind power from the w^{th} wind generator. As wind energy is efficient and economical, it is obvious to consider penalty costs in cases of the expected wind energy being under- and over-estimated which are linearly related to the difference between the available and actual wind power used and expressed as:

$$F_{U_w}(P_{W_{w,t}}) = k_{U_w} \int_{P_{W_{w,t}}}^{P_{R_w}} (w - P_{W_{w,t}})\, f_{P_{W_{w,t}}}(w) dw\ \ \forall w, t \tag{5.5}$$

$$F_{Ow}(P_{W_{w,t}}) = k_{O_w} \int_0^{P_{R_w}} (P_{W_{w,t}} - w)\, f_{P_{W_{w,t}}}(w)dw,\ \forall w, t \tag{5.6}$$

Although it is obvious that it is not possible to know the actual wind speed in advance, prior research has demonstrated that it follows the Weibull distribution function. Using historical wind speed values, the PDF of each wind power plant at each time interval, *i.e.*, $f_{P_{W_{w,t}}}$ can be calculated as:

$$f_{P_{W_{w,t}}}(W) = \frac{K_t l v_{in}}{c_t} \phi^{K_t - 1} e^{-\phi^{K_t}},\ 0 < W_t < W_R \tag{5.7}$$

where the constants k_t,c_t and ϕ are calculated as:

$$K_t = (\sigma_t/\mu_t)^{-1.086}, \tag{5.8}$$

$$c_t = \frac{\mu_t}{\Gamma(1 + K_t^{-1})} \tag{5.9}$$

$$\phi = \frac{(1 + (W/W_R)l)v}{c_t} \tag{5.10}$$

$$\text{where } l = \frac{v_r - v_{in}}{v_{in}} \tag{5.11}$$

where μ_t and σ_t are the mean and standard deviations of the wind speed at t^{th} hour, respectively.

B Constraints

Similar to the other DED models, the wind-thermal DED problem involves the power demand, capacity and ramp constraints described in the following subsections.

B.1 Power Balance Constraints

The total power output of thermal and wind power plants must be the same as the load demand at each time interval as:

$$\sum_{i=1}^{N_T} P_{T_{i,t}} + \sum_{w=1}^{N_W} P_{W_{w,t}} = P_{D_t} + P_{loss_t} \tag{5.12}$$

where N_W is the number of wind power plants.

B.2 Capacity Constraints

Each thermal and wind generator has lower and upper capacity limits as:

$$P_{T_i}^{\min} \leq P_{T_{i,t}} \leq P_{T_i}^{\max} \ i \in N_T,\, t \in T \tag{5.13}$$

$$0 \leq P_{W_{w,t}} \leq P_{R_w} \ w \in N_W,\, t \in T \tag{5.14}$$

B.3 Minimum on/off Time Constraints

Each thermal unit has minimum on and off times as:

$$\begin{aligned} \left[T_{t-1,i}^{on} - T_{\min_i}^{on}\right]\left[U_{T_{t-1,i}} - U_{T_{t,i}}\right] \geq 0 \\ \left[T_{t-1,i}^{off} - T_{\min_i}^{off}\right]\left[U_{T_{t,i}} - U_{T_{t,i-1}}\right] \geq 0 \end{aligned} \tag{5.15}$$

where $T_{min_i}^{on}$ and $T_{max_i}^{off}$ are the minimum on and off time of i^{th} unit, respectively, $T_{t-1,i}^{on}$ and $T_{t-1,i}^{off}$ are the continuous on and off time of i^{th} unit at t^{th} time interval, respectively, and $U_{t-1,i}$ the operational status of those thermal unit, i.e., 0 - unit off, 1 - unit on.

B.4 Ramp Constraints

As the output of a thermal unit cannot change rapidly, to avoid an unwanted electricity shortfall during two consecutive hours, the ramp constraints are considered as:

$$-DR_i \leq (P_{t,i} - P_{t-1,i}) \leq UR_i, \text{ if } P_{t-1,i} > P_i^{\min} \tag{5.16}$$

$$-DR_i^0 \leq |P_{t,i} - P_{t-1,i}| \leq UR_i^1, \text{ if } 0 < P_{t-1,i} < P_i^{\min} \tag{5.17}$$

where UR^1 and DR^0 are the initial ramp up and down respectively. The first traditional ramp constraint in Eqn. (5.16) represents the normal ramp constraint between the two hours and the second in Eqn. (5.17) the ramp limits while the generating unit is in the process of startup or shutdown.

5.3.3 Hydro-Thermal System

In this section, both DED and DEED of a hydrothermal system are presented.

A Objective Function

The aim of a hydrothermal problem is to determine the optimal level of power generation of each thermal and hydro power plant by minimizing the fuel cost of all thermal generators in single objective DED, and minimizing simultaneously both fuel costs and gas emissions of all thermal units in bi-objective DEED, as shown below.

A.1 Single-Objective Function

The objective function of a single-objective hydro-thermal DED system is to minimize the fuel cost of thermal power plants with the overall cost during the operational period (T) expressed as [17]:

$$\text{Min: } F_C = \sum_{t=1}^{T} \sum_{i=1}^{N_T} \left(a_i + b_i P_{T_{i,t}} + c_i P_{T_{i,t}}^2 + \left| d_i \sin \left\{ e_i \left(P_{T_{i,t}}^{\min} - P_{T_{i,t}} \right) \right\} \right| \right) \forall i, t \tag{5.18}$$

In a hydrothermal system, firstly, the output from a hydro system is determined based on the the optimal determination of water reservoir rate (X_H) then the output of a hydro generator (P_H) calculated using Eqns. (5.22) and 5.23. Finally, the rest of the electricity is determined from the thermal generators. Therefore, the decision variables of the hydro-thermal DED system are considered as the output power of each thermal unit and water discharge rate of each hydro reservoir at each time interval, *i.e.,* $P_{T_{i,t}}$ and $X_{H_{h,t}}$, respectively.

A.2 Bi-Objective Functions

In a bi-objective DEED problem, the objectives are to minimize both fuel costs and gas emissions simultaneously, as:

$$\text{Min: } F_C = \sum_{t=1}^{T} \sum_{i=1}^{N_T} \left(a_i + b_i P_{T_{i,t}} + c_i P_{T_{i,t}}^2 + \left| d_i \sin \left\{ e_i \left(P_{T_{i,t}}^{\min} - P_{T_{i,t}} \right) \right\} \right| \right) \forall i, t \tag{5.19}$$

$$\text{Min: } F_E = \sum_{t=1}^{T} \sum_{i=1}^{N_T} \left(10^{-2} \left(\alpha_i + \beta_i P_{T_{i,t}} + \gamma_i P_{T_{i,t}}^2 \right) + \eta_i e^{\lambda_i P_{T_{i,t}}} \right) \forall i, t \tag{5.20}$$

The first objective of Eqns. (5.19) and (5.20) are the fuel costs and the gas emission of the thermal power plants under consideration during an operational cycle T.

B Constraints

The combined hydro-thermal problem for both DED and DEED includes a number of constraints, such as the water reservoir balance, water discharge rates and initial and final water availability, as well as the other technical constraints of a thermal generator, which are briefly discussed in the following subsections.

B.1 Power Balance Constraints

The summation of the power outputs of the thermal ($P_{T_{i,t}}$) and hydro ($P_{H_{h,t}}$) generators must be equal to the load demand ($\mathrm{P_{D_t}}$) for a certain time interval as:

$$\sum_{i=1}^{N_T} P_{T_{i,t}} + \sum_{h=1}^{N_H} P_{H_{h,t}} = P_{D_t} \ t \in T \tag{5.21}$$

where the power output of the h^{th} hydro plant at the t^{th} time interval can be expressed as:

$$\begin{aligned} P_{H_{h,t}} = C_{1,h} V_{H_{h,t}}^2 + C_{2,h} X_{H_{h,t}}^2 + C_{3,h} V_{H_{h,t}} X_{H_{h,t}} + C_{4,h} V_{H_{h,t}} + \\ C_{5,h} X_{H_{h,t}} + C_{6,i} X_{H_{h,t}} \ h \in N_H \,, \ t \in T \end{aligned} \tag{5.22}$$

where $C_{k,h}\, h = 1, 2, \ldots, 6$ are the generation coefficients of h^{th} hydro generator, $V_{h,t}$ the water storage volume for the h^{th} reservoir at the t^{th} time interval that can be expressed as:

$$\begin{aligned} V_{H_{h,t+1}} = V_{H_{h,t}} - X_{H_{h,t}} + I_{H_{h,t}} - S_{H_{h,t}} \\ + \sum_{r=1}^{N_{up}} \left(X_{H_{r,\left(t-t_{d_{r,h}}\right)}} + S_{H_{r,\left(t-t_{d_{r,h}}\right)}} \right) \ h \in N_H \,, \ t \in T \end{aligned} \tag{5.23}$$

where $I_{H_{h,t}}$ and $S_{H_{h,t}}$ are the water inflow and spillage water reservoir for the h^{th} hydro generator at t^{th} time interval, respectively, and N_{up} and $t_{d_{r,h}}$ the number of upstream plants and water transport delay from r^{th} to h^{th} reservoirs, respectively. It is noted that the P_{loss} and water spillage are assumed to be zero for comparison with ref. [17] while the N_{up} and $t_{d_{r,h}}$ are calculated from the structure of the hydro reservoir shown in Appendix A.2 of Fig. A.1.

B.2 Capacity Constraints

The generation capacity constraints of the hydro and thermal power plants are, respectively:

$$P_{H_h}^{\min} \leq P_{H_{h,t}} \leq P_{H_h}^{\max} \; h \in N_H,\, t \in T \tag{5.24}$$

$$P_{T_i}^{\min} \leq P_{T_{i,t}} \leq P_{T_i}^{\max} \; i \in N_T,\, t \in T \tag{5.25}$$

where $P_{H_h}^{min}$ and $P_{H_h}^{max}$ are the minimum and maximum hydro power plant, respectively.

B.3 Water Storage and Discharge Constraints

The capacity limits of the water storage and water discharge rates of each reservoir are, respectively:

$$V_{H_h}^{\min} \leq V_{H_{h,t}} \leq V_{H_h}^{\max} \; h \in N_H,\, t \in T \tag{5.26}$$

$$X_{H_h}^{\min} \leq X_{H_{h,t}} \leq X_{H_h}^{\max} \; h \in N_H,\, t \in T \tag{5.27}$$

where $V_{H_h}^{min}$ and $V_{H_h}^{max}$ are the minimum and maximum value of V_{H_h}, respectively, and $X_{H_h}^{min}$ and $X_{H_h}^{max}$ the minimum and maximum X_{H_h}, respectively. In the hydraulic system, the initial and final reservoir storage volumes must meet the requirements of all the reservoirs as:

$$\left|V_{H_{h,t}}\right|^{t=0} = V_{H_h}^{ini},\, \left|V_{H_{h,t}}\right|^{t=T} = V_{H_h}^{end} \; h \in N_H \tag{5.28}$$

where $V_{H_h}^{ini}$ and $V_{H_h}^{end}$ are the initial final water volumes of h^{th} reservoir, respectively. However, as these two constraints are not easy to satisfy using a conventional approach, an iterative method is employed for dealing with them efficiently, details of which shown below[17].

B.4 Dealing with Reserve Constraints

Let, $[P_{T_{1,t}}, P_{T_{2,t}}, \dots, P_{T_{i,t}}, X_{1,t}, X_{2,t}, \dots, X_{h,t}]$ be an initial solution array for an operational time period, $t \in T$. The output power of the thermal units (P_T), and the water discharge rate (X_H) must satisfy their range as in Eqns. (5.27) and (5.25). Then, the water reservoir storage volume capacity (V_H) can be determined using Eqn. (5.23), which also satisfy its limit in Eqn. (5.28), in addition to its initial and final storage volume capacity in Eqn. (5.28). Since, spillage water is assumed to be zero, thus, the water reserves balance constraints of Eqn. (5.23) can be rewritten as follow [17]:

$$V_{H_{h,0}} = V_{H_{h,T}} - \sum_{t=1}^{T} X_{H_{h,t}} - \sum_{t=1}^{T} \sum_{r=1}^{N_{up}} X_{H_{r,\left(t-t_{d_{r,h}}\right)}} - \sum_{t=1}^{T} I_{H_{h,t}} \quad \text{where } h \in N_H \tag{5.29}$$

Now, it is assumed that any random dependent time interval (n_d) can be used to satisfy the initial and final water storage constraints, the water discharge rate at that time interval can be calculated from the Eqn. (5.29) as:

$$X_{H_{h,n_d}} = V_{H_{h,0}} - V_{H_{h,T}} + \sum_{t=1}^{T} I_{H_{h,t}} + \sum_{t=1}^{T} \sum_{r=1}^{N_{up}} X_{H_{r,\left(t-t_{d_{r,h}}\right)}} - \sum_{\substack{t=1 \\ t \neq n_d}} X_{H_{h,t}} \quad \text{where } h \in N_H \tag{5.30}$$

This dependent water discharge rate should also satisfy the constraint in Eqn. (5.27). Once the feasible water discharge rate is determined, compute the hydro power using Eqn. (5.22).

5.3.4 Solar-Thermal System

As solar-thermal problems formulate both single objective DED and bi-objective DEED ones, which involves thermal and solar photovoltaic (PV) generators. Based on the nature of the decision variables, the solar-thermal DED problem is essentially considered a MINP in which the solar unit represented as a binary variable and the thermal unit as a continuous one. The objective function and constraints of the DED and DEED systems are described in the following subsection [39].

A Objective Function

In the solar-thermal the primary objective of a DED is to minimize the overall cost of these generators by allocating the load demand among the committed ones. Moreover, in DEED, the secondary objective of minimizing the gas emission of the considered thermal generators is considered, those described below.

A.1 Dynamic Economic Dispatch

The objective function of the solar-thermal DED consists of both the fuel and gas emission costs of the thermal generators and the operating cost of the solar unit as:

$$\text{Min: } F_T = \sum_{t=1}^{T} \left(\sum_{i=1}^{N_T} \left(C_{i,t}\left(P_{T_{i,t}}\right) + E_{i,t}\left(P_{T_{i,t}}\right)\right) + \sum_{k=1}^{N_S} \left(F_{S_k}\left(U_{S_{k,t}}\right) + F_{P_k}\left(U_{S_{k,t}}\right)\right)\right) \tag{5.31}$$

$$\text{where } C_{i,t}\left(P_{T_{i,t}}\right) = a_i + b_i P_{T_{i,t}} + c_i P_{T_{i,t}}^2 + \left| d_i \sin\left\{ e_i \left(P_{T_{i,t}}^{\min} - P_{T_{i,t}} \right) \right\} \right| \tag{5.32}$$

$$E_{i,t}\left(P_{T_{i,t}}\right) = h_i \left(\alpha_i + \beta_i P_{T_{i,t}} + \gamma_i P_{T_{i,t}}^2 + \eta_i e^{\lambda_i P_{T_{i,t}}} \right) \;\; i \in N_T \; t \in T \tag{5.33}$$

$$\text{where } h_i = \frac{C_{i,t}\left(P_i^{\max}\right)}{E_{i,t}\left(P_i^{\max}\right)} \tag{5.34}$$

where N_S is the number of solar power plants, $U_{S_{k,t}}$ the binary decision variable that determines whether k^{th} solar unit turns on or off at t^{th} time period, and h_i a normalized factor is multiplied to the gas emission function of Eqn. (5.33) to align the degree of the cost function in Eqn. (5.32). Taking into account the actual solar generation, the operating cost of the k^{th} solar unit at the t^{th} time is:

$$F_{S_k}(U_{S_{k,t}}) = PU_{\cos t_k} P_{S_{k,t}} U_{S_{k,t}}, \;\; U_{S_{k,t}} \in \{0,1\} \;\; k \in N_S \;\; t \in T \tag{5.35}$$

where PU_{cost_k} is the per unit cost of the k^{th} solar unit and and $P_{S_{k,t}}$ the available solar power from s^{th} solar unit at t^{th} time interval which generated as:

$$P_{S_{k,t}} = P_{r_k} \left\{ 1 + \Omega \left(T_{amb_{k,t}} - T_{ref_k} \right) \right\} \frac{Si_{k,t}}{1000} \tag{5.36}$$

where P_{r_k}, Ω, $Si_{k,t}$, T_{amb} and T_{ref} are the rated power, temperature coefficients, ambient and reference temperature, respectively, found from historical data. In order to achieve the maximum benefit of solar availability, another objective function that minimizes the difference between the total available solar power and actual solar share is expressed as:

$$F_P(U_{S_{k,t}}) = \sum_{t=}^{T} K_k \left(\sum_{k=1}^{N_S} P_{S_{k,t}} - \sum_{k=1}^{N_S} P_{S_{k,t}} U_{S_{k,t}} \right) \tag{5.37}$$

where K_k is a large value used to control the importance of the difference term relative to the other terms.

A.2 Dynamic Economic and Emission Dispatch

The fuel costs and gas emissions of a solar-thermal DEED problem are presented, respectively:

$$\text{Min: } F_C = \sum_{t=1}^{T} \left(\sum_{i=1}^{N_T} \left(C_{i,t}(P_{T_{i,t}}) \right) + \sum_{k=1}^{N_S} \left(F_{S_k}(U_{S_{k,t}}) \right) \right) \tag{5.38}$$

$$\text{Min: } F_E = \sum_{t=1}^{T} \sum_{i=1}^{N_T} h_i \left(E_{i,t}(P_{T_{i,t}}) \right) \tag{5.39}$$

The values of F_{c_i}, F_{S_k} and F_{e_i} are found from Eqns. (5.32), (5.33) and (5.35), respectively.

B Constraints

For both DED and DEED, the solar-thermal system has the following equality and inequality constraints.

$$\sum_{i=1}^{N_T} P_{T_{i,t}} + \sum_{k=1}^{N_S} P_{S_{k,t}} U_{S_{k,t}} = P_{D_t} + P_{loss_t} \; t \in T \tag{5.40}$$

$$P_{T_i}^{\min} \leq P_{T_{i,t}} \leq P_{T_i}^{\max} \; i \in N_T,\, t \in T \tag{5.41}$$

$$-DR_i \leq P_{T_{i,t}} - P_{T_{i,t-1}} \leq UR_i \;\; i \in N_T \, t \in T \tag{5.42}$$

$$\sum_{t=1}^{T} \sum_{k=1}^{N_S} P_{S_{k,t}} U_{S_{k,t}} \leq 0.3 P_{D_t} \tag{5.43}$$

Eqn. (5.40) defines the power balance constraints, and Eqns. (5.41) and (5.42) the capacity and ramp constraints of the thermal generators, respectively, The constraint in Eqn. (5.43) is used to limit the solar share at any time based on a 30% upper limit to avoid any uncertainty in terms of solar irradiance, as it is uncertain and depends on nature, the total contribution of solar generation must not be greater than the reserve capacity of a DED system [39].

5.4 Solution Approach

As discussed in Chapter 2, different variants of evolutionary algorithms (EAs) have been commonly used to solve different types of DED and DEED problems with non-convex cost functions because they have simple structures and do not need to satisfy any certain mathematical properties of the objective function. Of various EAs, genetic algorithms (GAs) have performed well for mixed-integer DED problems, such as solar-thermal and wind-thermal, as has differential evolution (DE) for those in the continuous domain, such as thermal and hydro-thermal ones, with GAs demonstrating a superior

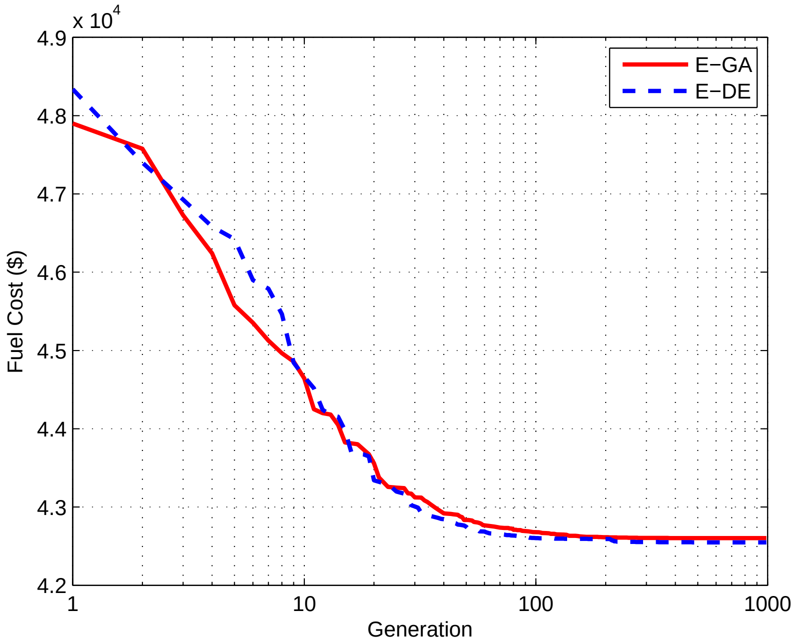

Fig. 5.1: Sample convergence plots of E-GA and E-DE for solving 5-unit thermal-based DED problem

convergence property but long computational times and DE obtaining a sub-optimal solution in a very short time [3].

5.4.1 Motivation

As previously mentioned, although EAs have gained popularity for solving both DED and DEED problems, no single algorithm has been shown to be superior to another over a wide range of these problems. Also, it is found in Chapters 3 and 4 that, although the self-adaptive DE and GA with a heuristic (i.e., E-DE and E-GA, respectively) outperform some state-of-the-art algorithms, neither performs consistently for both thermal and wind-thermal DED problems, e.g., E-DE is better for thermal-based DED ones and E-GA for a wind-thermal DED system. It is also determined that one EA might perform well during one stage of the search process and poorly in others; for example, the convergence plots of a 5-unit thermal-based DED problem shown in Fig. 5.1 illustrate that the E-GA performs well in an early stage of the evolutionary process and E-DE in later ones.

On the other hand, as discussed in Chapter 2, different multi-method-based algorithms which configure two or more EAs are widely used to efficiently solve various complex optimization problems. However, to the best of our knowledge, adopting such methods to solve highly complex, constrained and real-world electrical generators' scheduling problems, such as DED and DEED ones, has not yet been explored.

Therefore, in this chapter, a general evolutionary framework which adaptively places more emphasis on the most suitable EA (GA or DE) during the evolutionary process to solve different types of DED and DEED problems, including thermal, hydro-thermal, solar-thermal and wind-thermal ones, is developed and discussed in the following section.

5.5 Proposed GA-DE Algorithm

In this section, a general framework that configures two EAs (GA and DE) with a heuristic for solving a wide range of DED and DEED problems is discussed. In its design, an initial population of size N_P is generated and then randomly divided into two sub-populations of equal size, N_{P1} and N_{P2}, for GA and DE, respectively. In subsequent generations, new individuals in GA and DE are generated from random individuals from either subpopulation (N_{P1} and N_{P2}) rather than only their own which results in information being exchanged between the two algorithms in each generation. To evaluate the fitness function, firstly, the constraint violation (CV) of each individual of each algorithm is calculated using Eqn. (3.32) and, if zero, indicates that the individual is feasible, and then the fitness value (FV) is calculated, with the number of fitness evaluations increased by one. Otherwise, if a CV is greater than zero, i.e., the individual is infeasible, it is repaired by the proposed heuristic (Algorithm 5.2) and then its FV and CV calculated. As this CV is calculated first, the number of fitness evaluations is not increased but, after the FV of the final repaired solution is calculated, it is increased by one. Once the FVs and CVs of both the parents and children are evaluated, a selection operator is applied to rank each individual, with the best N_P individuals selected for the next generation. Subsequently, each sub-population is updated by the new individuals generated, with the best selected, as described in sub-section 5.5.4. Based on the number of individuals selected from the children, the success rate (SUR) of each algorithm is calculated, e.g., if 30% of the new individuals of GA survive to the next generation, the SUR of GA is 30%. Then, the sub-population sizes (N_{P1} and N_{P2}) for the subsequent generation are updated according to their normalized SURs, and their lower (N_{P1}^{min}) and upper (N_{P1}^{max}) bounds as:

$$N_{P1} = \max\left[N_{P1}^{\min}, \min\left\{N_P \frac{SUR_{1,g}}{SUR_{1,g} + SUR_{1,g}}, N_{P_1}^{\max}\right\}\right] \tag{5.44}$$
$$SUR_{1,g} \cup SUR_{2,g} \neq 0,\; g \in N_G$$

$$N_{P2} = N_P - N_{P1} \tag{5.45}$$

This means that the better-performing algorithm contributes to producing offspring for the next generation. As an algorithm may perform well in an early stage of the evolutionary process but poorly in a later one or vice versa, in this design, the lower and higher bounds are set based on the sub-population sizes. However, if both $SUR_{1,g}$ and $SUR_{2,g}$ are zero, the values of N_{P1} and N_{P2} remain the same as in the immediate previous generation. This process is continued until a predefined number of generations (N_{gc}) is performed. Then, the best algorithm is determined based on its average SUR during the last N_{gc} generations and used to evolve the entire population (one sub-population size is set equal to N_P and the other to zero) for the next N_{gc} generations. Once N_{gc} generations are completed, the latest individuals are again equally and randomly allocated to both algorithms in the two sub-populations (N_{P1} and N_{P2}) and the same process continued until a stopping criterion is reached.

It is worth mentioning that, although the proposed GA-DE algorithm shares some similarities with those in [121, 122, 231], as its initial population is divided into sub-populations, each of which uses a different EA, it has the following differences:

1. it dynamically updates the sub-population sizes and allows the better-performing algorithm to evolve all individuals in a cycle;

2. each algorithm obtains some information from the other and generates N_{P1} or N_{P2} offspring from all the parents (not only its own) of N_P individuals; and
3. a heuristic is employed to obtain a feasible solution from an infeasible one which can improve the convergence rate.

The proposed GA-DE algorithm and its pseudo-code are presented in algorithm 5.1 while each of its components is described in more detail in the following sub-sections.

5.5.1 Initial Population

The chromosomes or representations of the decision variables for both GA and DE are expressed as:

$$\vec{x}_p = \begin{cases} \left[P_{T_{i,t}}\right]_{1:N_x} & N_x = T \times N_T, \text{for thermal system} \\ \left[P_{T_{i,t}}, P_{W_{w,t}}\right]_{\mathrm{1:N_x}} & N_x = T \times (N_T + N_W) \text{ for wind-thermalsystem} \\ \left[P_{T_{i,t}}, X_{h,t}\right]_{1:N_x} & N_x = T \times (N_T + N_H)\,, \text{ for hydrothermal system} \\ \left[P_{T_{i,t}}, U_{S_{k,t}}\right]_{\mathrm{1:N_x}} & N_x = T \times (N_T + N_S)\,, \text{ for solar-thermal system} \end{cases} \tag{5.46}$$

where i= $1, 2, .,N_T, h$= $1, 2, .,N_H$, k= $1, 2, .,N_S$, w= $1, 2, ., W$, t= $1, 2, ..,T$, $U_{S_{k,t}} \in [0, 1]$, $p \in N_P$, with N_P the population size, and N_x the number of decision variables as, $T \times N_T$, $T \times (N_T + N_W)$, $T \times (N_T + N_H)$ and $T \times (N_T + N_S)$ for the thermal, wind-thermal, hydrothermal, and solar-thermal systems, respectively.

Each individual $(\overrightarrow{x})$ of GA-DE is generated by:

$$\vec{x}_p = \vec{x}^{\min} + \left(\vec{x}^{\max} - \vec{x}^{\min}\right) \ \mathrm{LHS}(N_x),\ p \in N_P \tag{5.47}$$

where $\vec{x}^{min}$ and $\vec{x}^{max}$ are the lower and upper bound vectors, and $\overrightarrow{x_p}$ the p^{th} individual in the N_P population, with LHS (N_x) random individuals generated using LHS rules.

Algorithm 5.1 GA-DE algorithm

```
Require: $N_G$, $N_P, N_{P1}^{min}$ and $N_{P1}^{max}$
 1: Set, $count_1 = count_2 = 0$
 2: Randomly generate an initial population of size $N_P$ as in section (5.5.1)
 3: Evaluate the individuals after repairing the infeasible ones using heuristic described in section
    5.5.3
 4: Randomly distribute $N_P$ individuals over two subpopulations with sizes of $N_{P1}$ and $N_{P2}$,
    such that $N_{P1} = N_{P2}$
 5: for $g = 1 : N_G$ do
 6:     $count_1 = count_1 + 1$
 7:     if $count_1 \leq N_{gc}$ then
 8:         procedure Perform GA(1 to $N_{P1}$)
 9:             Generate $N_P1$ number of offspring from the entire $N_P$ parents using the GA operators
                described in section 3.5.2
10:             for $i = 1 : N_{P1}$ do
11:                 Calculate CV of the $i^{th}$ individual using (3.32)
12:                 if If $i^{th}$ individual is infeasible then
13:                     Repair $i^{th}$ individual using the heuristic described in section 5.5.3
14:                     Calculate the FVs and new CVs
15:                 else
16:                     Calculate the FV of the $i^{th}$ individual, and set, $CV = 0$
17:                 end if
18:             end for
19:             Determine the best $N_{P1}$ individuals from the parents and offspring based on the selection
                approach described in section 5.5.4
20:             Calculate $SR_{1,g}$ based on numbers of offspring of surviving to the next generation
21:         end procedure
22:         procedure Perform DE(1 to $N_{P2}$)
23:             for $i = 1 : N_{P2}$ do
24:                 Generate a child from all the parents ($N_P$) using the DE operators described in section
                    3.5.3
25:                 Evaluate the FV and CV of the $i^{th}$ individual by repeating the steps 11 to 11
26:                 If the problem is a single objective DED, accept or reject the new individual based on
                    the Eqn. (3.33)
27:             end for
28:             If the problem is a bi-objective DEED, determine the best $N_{P2}$ individuals from the
                parents and offspring based on the selection approach described in section 5.5.4
29:         end procedure
30:         Group selected individuals, $N_P \leftarrow N_{P1} + N_{P2}$
31:         Update $N_{P1}$ and $N_{P2}$ according to Eqn. (5.44)
32:     else
33:         set, $count_2 = count_2 + 1$
34:         if $count_2 \leq N_{gc}$ then
35:             Calculate average success rates of GA ($ASR_1$) and DE ($ASR_2$)
36:             if $ASR_1 > ASR_2$ then
37:                 Perform GA, considering $N_{P1} \leftarrow N_{P1} + N_{P2}$
38:             else
39:                 Perform DE, considering $N_{P2} \leftarrow N_{P1} + N_{P2}$
40:             end if
41:         end if
42:         if $count_2 = N_{gc}$ then
43:             Repeat step 4 and set again,$count_1 = count_2 = 0$
44:         end if
45:     end if
46: end for
```

5.5.2 GA-DE Search Operators

To update the individuals in GA-DE, either a GA or a self-adaptive DE search operators is used in various stages of evolution. Like the previous chapters, SBX and NUM are used in GA, and two self-adaptive mutation operators and one binomial crossover in DE because they showed superior performances for solving various DED problems in previous chapters. All these operators are discussed in sections 3.5.2 and 3.5.3 of chapter-3 for GA and DE search operators, respectively.

5.5.3 Heuristic for DED Constraints

As shown in Chapters 3 and 4, the solutions from an EA without heuristic are inferior to those of obtained from an EA with a heuristic. This was because a DED problem involves several difficult equality and inequality constraints, and the new solutions generated by an EA process may not satisfy all of them, especially during the early stages of the evolutionary process. To overcome this issue, a heuristic for repairing the infeasible individuals was proposed in chapter-3 for a thermal-based DED system and chapter-4 for an uncertain wind-thermal one. In this chapter, an improved and generalized heuristic is developed for a broad range of both single- and bi-objective, DED and DEED problems (e.g., thermal, hydro-thermal, solar-thermal and wind-thermal) involving both continuous and mixed-integer decision variables.

In this process, the $T-$hour load cycle is divided into T sub-problems, with production truly allocated among the committed units to meet the hourly load demand, starting from different random hours using the forward and backward slack generation approach. This heuristic simultaneously allocates both types of production (thermal and renewable) which is one of its main differences from the heuristic presented in chapter-3. Its pseudo code is shown in algorithm 5.2.

5.5.4 Selection Process

For the single objective DED problem, a greedy selection scheme is followed that discussed in Eqn. (3.33) of Chapter 3. To rank the chromosomes for the bi-objectives

Algorithm 5.2 Heuristic for DED and DEED constraints

```
Require: An infeasible individual, $\vec{y}$
 1: Tranform $\vec{y}$ into a form of $P$ matrix of size $T \times N$ as Eqn. 3.21, where $N$ is the number of generators
 2: Randomly select $t \in T$ and $P_t \in P$, and keep $t_0 = t$
 3: procedure START THE FORWARD PROCESS($t_0$ to $T$)
 4:     Set, $P_{i,t}^{max} = x_i^{max}, P_{i,t}^{min} = x_i^{min} i \in N$
 5:     while $t = T$ do
 6:         satisfy the generation limits as:
 7:         $$P_{i,t} = \begin{cases} P_{i,t}^{max} & \text{if } P_{i,t} > P_{i,t}^{max} \forall i \in N_T, N_H, N_W \\ P_{i,t}^{min} & \text{if } P_{i,t}, \leq P_{i,t}^{min} \forall i \in N_T, N_H, N_W \\ 1 & \text{if } 0.5 < P_{i,t} \forall i \in N_S \\ 0 & \text{if } P_{i,t} \leq 0.5 \forall i \in N_S \\ P_{i,t} & \text{otherwise} \end{cases} \quad (5.48)$$
 8:         Satisfy the equality constraints as:
 9:         for j=1:N do
10:             Select, $n_d \in \{N_T, N_W, N_H, N_S\}$ randomly
11:             if $n_d \in N_S$ then                    ▷ If $n_d^{th}$ unit is a solar unit
12:                 $P_{n_d,t} = \begin{cases} 0 & \text{if } P_{n_d,t} < 0.5 \\ P_{S,t} & \text{otherwise} \end{cases}$    ▷ Get available solar power at $t^{th}$ hour
13:             else
14:                 $P_{n_d,t} = \max\left[P_{n_d,t}^{min}, \min\left\{\left(P_{Dt} - \sum^{N}_{\substack{i=1 \\ i \neq n_d}} P_{i,t}\right), P_{n_d,t}^{max}\right\}\right]$
15:             end if
16:             if $\left|\sum_{i=1}^{N} P_{i,t} - (P_{D_t} + P_{losst})\right| \leq \varepsilon_g$ then
17:                 Break
18:             end if
19:         end for
20:         Update the upper and lower capacity limits, respectively:
21:         $P_{i,t+1}^{max} = min\,[P_i^{max}, (P_{i,t} + UR_i)],\ i \in N$
22:         $P_{i,t+1}^{min} = max\,[P_i^{min}, (P_{i,t} - DR_i)],\ i \in N$
23:         $t = t + 1$
24:     end while
25: end procedure
26: procedure START THE BACKWARD PROCESS($t_0 - 1$ to 1)
27:     Set, $t = t_0 - 1$
28:     while $t = 1$ do
29:         Update capacity limits as:
30:         $P_{i,t+1}^{max} = min\,[P_i^{max}, (P_{i,t} - UR_i)],\ i \in N$
31:         $P_{i,t+1}^{min} = max\,[P_i^{min}, (P_{i,t} + DR_i)],\ i \in N$
32:         Satisfy the equality constraints by following the steps from 6 to 19
33:         Set, $t = t - 1$
34:     end while
35: end procedure
```

DEED problems, firstly, the parents and offspring are grouped together and the best N_P individuals among them selected for the next generation. To do this, a popular constraint-handling approach with a non-dominated sorting (NDS) technique [20] is used in which an additional objective is considered based on the amount of relative CV. Then, a crowding sorting technique and non-dominated mechanism are used to preserve diversity and elitism among the population members. The advantages of having an additional objective for constrained optimization problems are explicitly demonstrated in [232].

5.6 Experimental Results

For the experimental study, several test problems involving thermal, hydro-thermal, solar-thermal and wind-thermal systems with up to a 24-hour planning horizon and a one-hour long time period from the literature are considered. Based on data availability, these problems can be solved as single and bi-objective with and without considering the power loss (P_{loss}), and are defined as follows:

- Case-1: single objective 5-unit thermal problems with and without P_{loss} [14];
- Case-2: single objective 10-unit thermal problems with and without P_{loss} [14];
- Case-3: a single objective 7-unit hydro-thermal problem without P_{loss} [17];
- Case-4: a single objective 19-unit solar-thermal system without P_{loss} [39];
- Case-5: a single objective 6-unit wind-thermal system with P_{loss} [137];
- Case-6: a bi-objective 7-unit hydro-thermal problem without P_{loss} [17], and
- Case-7: a bi-objective 19-unit solar-thermal system without P_{loss} [39].

For a fairer comparison, the problems' data are kept as in the literature [39, 137], and the GA parameters, probability of crossover and mutation, and distribution index (η) set to 0.9, 0.1 and 3, respectively. The N_P,N_g,NP_1^{min}, NP_1^{max} and N_{gc} for all cases are illustrated in Table 5.1. Thirty independent runs are performed for each test case and the solutions recorded and compared with results from state-of-the-art algorithms.

Table 5.1: Different parameters used in this chapter

Problem	N_P	N_G	NP_1^{max}	NP_1^{min}	N_{gc}
Case-1	100	1000	20	80	
Case-2	100	4000	20	80	
Case-3	200	500	40	160	
Case-4	100	1000	16	60	50
Case-5	100	1000	20	80	
Case -6	200	500	20	80	
Case-7	100	1000	20	80	

The algorithm is implemented on a desktop personal computer with a 3.4 GHZ Intel Core i7 processor and 16 GB of RAM using the Matlab (R2014a) environment and is run until the number of generations is higher than N_G (criterion-1) or the best fitness value is no longer improved in θ (where $\theta = 100$) generations (criterion-2).

5.6.1 Single Objective DED Problems

In this section, the single objective DED problems of cases-1 to case-5 are solved using the proposed GA-DE and other state-of-the-arts with and without considering the P_{loss}, as discussed below.

A Thermal DED

Firstly, the proposed GA-DE algorithm is applied to solve the 5- and 10-unit DED thermal systems (cases 1 and 2, respectively) with and without considering P_{loss}. Then, these problems are solved using the GA and DE independently considering the heuristic and are known as enhanced GA (E-GA) and enhanced DE (E-DE), as in previous chapter. To validate the results, the test problems are also solved using a well-known algorithm called the Evolution Strategy with Covariance Matrix Adaptation (CMA-ES) [233]. For this, a constrained problem is transformed into an unconstrained one using the penalty function approach, where the penalty coefficient is considered arbitrary as $1E + 3$. The code for CMA-ES is taken directly from the Web, where the sigma and stopping criteria are set as defaults. The results obtained from the GA-DE, E-GA, E-DE, CMA-ES and others in the literature are presented in Tables 5.2 to 5.5. in which STD represents the standard deviation of 30 random runs and NR indicates that the

Table 5.2: Summary of solutions for 5-unit system with P_{loss}

Method	Production cost ($)			STD
	Minimum	Average	Maximum	
SA [207]	47356	NR	NR	NR
APSO [208]	44678	NR	NR	NR
GA [200]	44862	44922	45894	NR
PSO [200]	44253	45657	46403	NR
ABC [200]	44046	44065	44219	NR
AIS [62]	44385	44759	45554	NR
H-PSO [206]	43223	43732	44252	274.95
CMA-ES [233]	43211.47	43720.20	44280.24	336.05
E-GA	42528.9	42580.6	42638.4	30.16
E-DE	42528.7	42571.2	42664.5	36.9
GA-DE	**42522.10**	**42547.60**	**42632.80**	**32.97**

Table 5.3: Summary of solutions for 10-unit system with P_{loss}

Method	Production cost ($)			STD
	Minimum	Average	Maximum	
EP [82]	1054685	1057323	NR	NR
EP-SQP [82]	1052668	1053771	NR	NR
MHEP-SQP [83]	1050054	1052349	NR	NR
DGPSO [83]	1049167	1051725	NR	NR
IPSO [209]	1046275	1048154	NR	NR
AIS [62]	1045715	1047050	1048431	NR
ECE [210]	1043989	1044963	1046805	NR
ABC [200]	1043381	1044963	1046805	NR
TVACIPSO [211]	1041066	1042118	1043625	NR
EBSO [212]	1038915	1039188	1039272	NR
CSAPSO [213]	1038251	1039543	NR	NR
SAMFA [214]	1037698	1037938	1039199	NR
MTLA [215]	1037489	1037712	1038090	NR
MIQP [14]	1038376	NR	NR	NR
CMA-ES [233]	1051937	1055172	1059457	2184.37
E-GA	1036460	1037020	1037430	251.83
E-DE	1036280	1036310	1036380	51.31
GA-DE	**1036240**	**1036280**	**1036360**	**44.28**

results are not reported in the literature. It is clear that GA-DE outperformed all the state-of-the-art algorithms for the all considered problems.

B Hydro-Thermal DED

In this section, a 7-unit hydro-thermal DED system [17] comprising 3 thermal and 4 hydro units is solved using the CMA-ES, E-GA, E-DE and proposed GA-DE algorithms

Table 5.4: Summary of solutions for 5-unit system without P_{loss}

Method	Production cost ($)			STD
	Minimum	Average	Maximum	
CMA-ES [233]	43034.78	43688.71	44510.21	575.63
E-GA	42524.4	42565.9	42630.8	26.77
E-DE	42523.6	42524.8	42621.6	28.87
GA-DE	**42517.00**	**42524.80**	**42615.80**	**24.49**

Table 5.5: Summary of solutions for 10-unit system without P_{loss}

Method	Production cost ($)			STD
	Minimum	Average	Maximum	
EP [82]	1048638	NR	NR	NR
SQP [82]	1051163	NR	NR	NR
EP-SQP [82]	1031746	1035748	NR	NR
MHEP-SQP [83]	1028924	1031179	NR	NR
AIS [62]	1021980	1023156	1024973	NR
GA [200]	1033481	1038014	1042606	NR
ABC [200]	1021576	1022686	1024316	NR
DE [99]	1036756	1040586	1452558	3225.8
CDE [99]	1019123	1020870	1023115	1310.7
MDE [104]	1031612	1033630	NR	NR
CSDE [216]	1023432	1026475	1027634	NR
Hybrid DE [104]	1031077	NR	NR	NR
HS [217]	1046726	NR	NR	NR
HHS [217]	1019091	NR	NR	NR
CE [210]	1022702	1024024	NR	NR
ECE [210]	1022272	1023335	NR	NR
PSO [200]	1027679	1031716	1034340	NR
IPSO [209]	1023807	1026863	NR	NR
ICPSO [218]	1019072	1020027	NR	NR
PSO-SQP [219]	1027334	1028546	NR	NR
ICA [220]	1018468	1019291	1021796	NR
H- PSO [206]	1018159	1019850	1021813	826.94
MIQP [14]	1016601	NR	NR	NR
CMA-ES [233]	1034484	1035843	1037202	1922
E-GA	1016360	1016710	1016880	221.11
E-DE	**1016160**	**1016260**	1016420	69.93
GA-DE	**1016160**	**1016200**	**1016280**	**38.82**

Table 5.6: Summary of solutions for 7-unit hydro-thermal system

Method	Production cost ($)			STD
	Minimum	Average	Maximum	
DE [17]	110810.00	NR	NR	NR
NSGA2 [234]	101659.00	112811.00	121685.00	5241.72
IDEA [234]	103433.00	109610.00	122391.00	5078.27
CMA-ES [233]	72165.03	72481.43	72797.83	447.45
H-NSGA2 [234]	71256.20	72131.00	73946.50	663.86
H-IDEA [234]	70309.00	71232.80	72186.90	515.88
E-GA	67955.30	68208.60	68613.00	198.46
E-DE	67502.20	67783.80	68134.60	227.53
GA-DE	**67335.20**	**67526.10**	**67896.70**	**120.31**

on the same platform. The results obtained are compared with those of each other and state-of-the-art algorithms. In Table 5.6, it is clear that the proposed approach is able to obtain the best results of all the algorithms.

C Solar-Thermal DED

In this section, a 19-unit solar-thermal mixed-integer nonlinear DED model from [39] which consists of 6 thermal and 13 solar units is solved using the E-GA, E-DE and proposed GA-DE algorithms. The discrete decision variables (i.e., generation from the solar unit) are handled as continuous ones and then rounded off in order to avoid different representations. It is also noted that the overall operating cost of the solar-thermal DED model depends on the percentage of solar share in actual production as the per unit solar cost considered is higher than the per unit fuel (e.g., coal) cost of a thermal generator [39]. Also, higher injections of the thermal generators produce higher gas emissions which incur an extra penalty cost for the additional equipment required to reduce environmental pollution. However, it is evident in Table 5.7 that, although the solar share of the proposed approach is only marginally lower than those of the others, the production cost of this method is much lower.

D Wind-Thermal DED

In this section, a wind-thermal DED problem consisting of 5 thermal and 160 wind farms for a 6-hour planning horizon with a one-hour time period is considered [137]. As in

Table 5.7: Summary of solutions for 19-unit solar-thermal system

Method	Production cost ($)			STD
	Minimum	Average	Maximum	
B-PSO [39]	944087.00	NR	NR	NR
E-GA	917211.98	917220.01	917217.69	3.04
E-DE	920873.41	922824.81	919626.45	2099.68
GA-DE	**915371.25**	**916061.31**	**916603.49**	**357.93**

Table 5.8: Summary of solutions for wind-thermal system

Method	Production cost ($)			STD
	Minimum	Average	Maximum	
CMA-ES [233]	803892	815891	830831	9360.24
DE [137]	798891	NR	NR	NR
PSO [137]	802386	NR	NR	NR
CPSO [137]	799258	NR	NR	NR
BPCDE [137]	795194	NR	NR	NR
E-DE	791028	791296	791523	122.27
E-GA	790772	791002	791883	221.55
GA-DE	**790525**	**790761**	**791177**	**113.23**

the other cases, this test problem are solved using CMA-ES, E-GA, E-DE and GA-DE, with their results and those from other methods in the literature presented in Table 5.8 showing that the proposed approach obtains better results than the others.

5.6.2 Bi-objective DEED Problems

For demonstrating the effectiveness of the proposed GA-DE algorithm for solving bi-objective DEED problems, in this section two standard benchmarks, (i) a 7-unit hydro thermal power system from [17]; and (ii) a 19-unit solar-thermal power system from [39], for a 24-hour planning horizon in one-hour time period are solved using our proposed and state-of-the-art algorithms with and without considering the heuristic, as follows:

1. Non-dominated sorting GA-II (NSGA-II) without heuristic,
2. Multi-objective DE (MODE) without heuristic,
3. NSGA-II with heuristic (H-NSGA-II),
4. MODE with heuristic (H-MODE), and
5. Proposed GA-DE with heuristic (GA-DE),

Table 5.9: Comparison of performances of algorithms for hydro-thermal DEED

Algorithm	HV (reference: [1,1])					Time
	Best	Mean	Median	Worst	STD	(sec)
NSGA-II	0.59	0.53	0.54	0.44	0.05	56.81
MODE	0.49	0.43	0.44	0.35	0.05	**48.91**
H-NSGA-II	0.84	0.81	0.81	0.79	0.01	237.82
H-MODE	0.81	0.77	0.78	0.71	0.03	232.55
GA-DE	**0.91**	**0.89**	**0.89**	**0.87**	**0.01**	234.41

A Hydro-Thermal DEED

In this section, a 7-unit bi-objective hydro-thermal DEED problem comprising 3 thermal and 4 hydro units is solved using the proposed and state-of-the-art algorithms on the same platform. Once the 30 random runs of each algorithm are completed, their hypervolume (HV) values are calculated based on their normalized fitness values as [235]:

$$f_{norm} = \frac{f - f_{ideal}}{f_{Nadir} - f_{ideal}} \tag{5.49}$$

where, f_{norm} and f are the normalized and actual function values, respectively, and f_{ideal}, and f_{Nadir} the ideal and nadir points [235] for this problem, respectively, which are found to be (7.17E+4,10.09) and (1.28E+5,142.95), respectively from all the runs of all the algorithms considered. The best, mean, median, worst, and standard deviation (STD) of the HV values obtained from algorithm with and without the heuristic are shown in Table 5.9. It is indicated that the proposed approach with the heuristic (H-GA-DE) obtains the best and most consistent results of all the algorithms in a reasonable computational time. The Pareto-frontiers of the best runs based on the HV values for all the algorithms are plotted in Fig. 5.2 which also shows the superiority of the proposed algorithm. In fact, the GA-DE approach obtains the best non-dominated solutions, both inclusive and exclusive of the heuristic, with H-GA-DE the best algorithm of all.

B Solar-Thermal DEED

To demonstrate the performances of the six algorithms, with and without the heuristic, on larger problems, in this section, a 19-unit solar-thermal DEED problem is solved that formulated as a mixed-integer, non-linear, bi-objective optimization one that minimizes

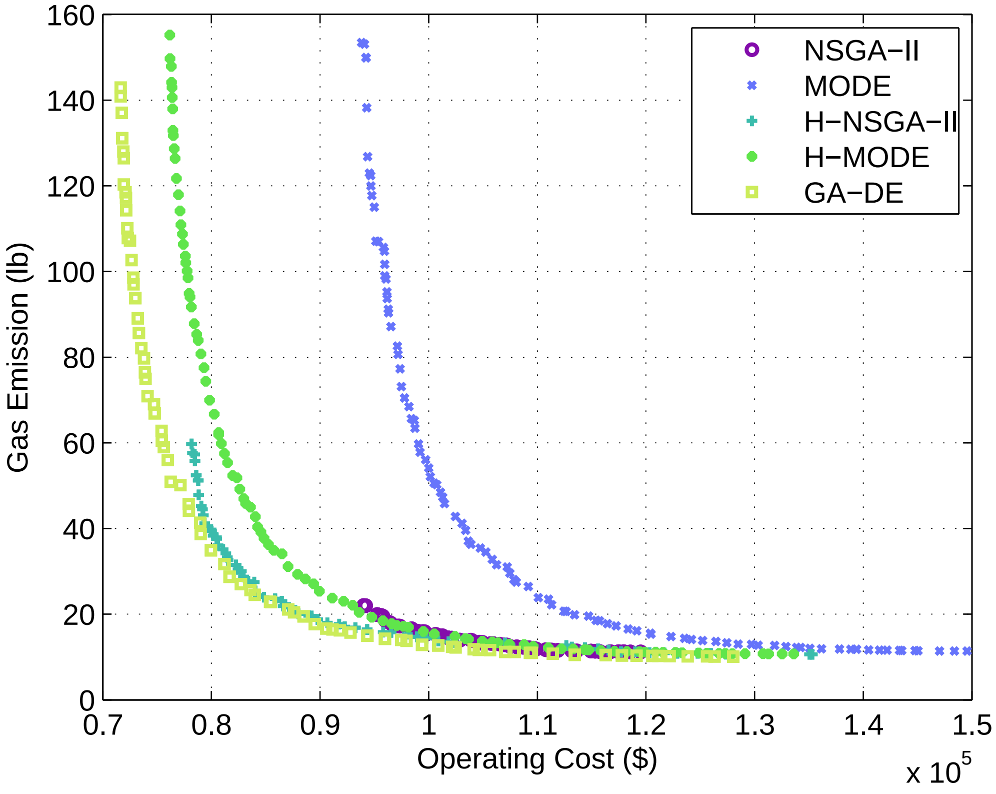

Fig. 5.2: Pareto-frontiers for hydro-thermal problem

both the operating costs and gas emissions. The binary decision variables of the solar units are handled as continuous ones and then rounded off in order to avoid different representations.

Once the 30 independent runs are completed, the functions' values are normalized according to Eqn. (5.49) based on nadir and ideal points, and found to be, (8.17E+5, 2.36E+5) and (3.08E+5, 2.0E+5), respectively. Subsequently, the HV of each run is calculated and the best, mean, median, worst and STD values presented in Table 5.10 which indicates that the proposed H-GA-DE obtains the best solutions of all the algorithms within a reasonable computational time.

The Pareto frontiers of the best runs based on the HV values are presented in Fig. 5.3 in which it is clear that including a heuristic significantly improves the performances of all the algorithms considered, with the proposed GA-DE the best in terms of obtaining non-dominated solutions. In fact, when the algorithms do not include the heuristic, as their numbers of feasible solutions are very limited, the range of Pareto frontiers is very

Table 5.10: Comparison of performances of algorithms for solar-thermal DEED

Algorithm	HV (reference: [1,1])					Time
	Best	Mean	Median	Worst	STD	(sec)
NSGA-II	0.18	0.17	0.17	0.15	0.01	64.47
MODE	0.21	0.20	0.21	0.18	0.01	**52.21**
H-NSGA-II	0.52	0.51	0.51	0.51	0.00	158.21
H-MODE	0.50	0.49	0.49	0.47	0.01	148.30
GA-DE	**0.56**	**0.55**	**0.55**	**0.54**	**0.00**	212.48

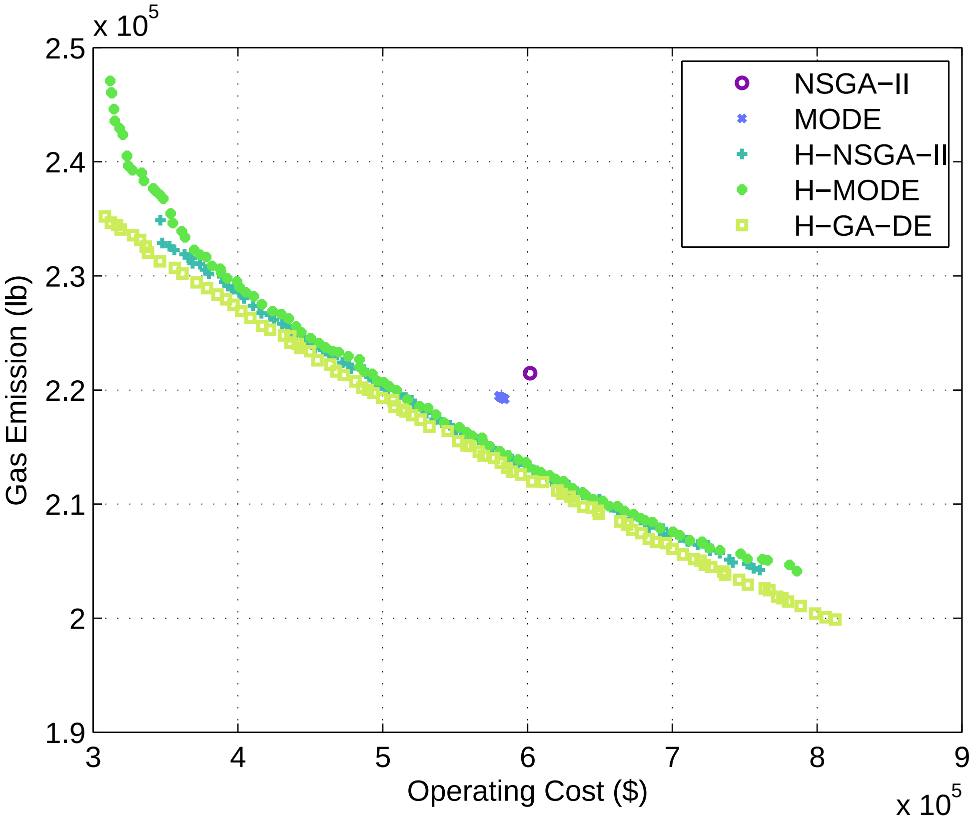

Fig. 5.3: Pareto-frontiers for solar-thermal problem

narrow. Conversely, when the heuristic is applied to rectify infeasible solutions towards a feasible direction, the algorithms quickly obtain non-dominated feasible solutions while simultaneously minimizing both objectives.

5.7 Statistical Comparison

In this section, the proposed GA-DE algorithm is statistically compared with-state-of-the-art ones. Based on the available data, the Wilcoxon non-parametric test results

Table 5.11: Wilcoxon test results for GA-DE versus E-DE, E-GA and CMA-ES

Algorithms	Criterion	Better	Similar	Worse	p	Decision
GA-DE vs E-DE	Best	6	1	0	0.027	+
	Mean	6	1	0	0.028	+
GA-DE vs E-GA	Best	7	0	0	0.018	+
	Mean	7	0	0	0.018	+
GA-DE vs CMA-ES	Best	6	0	0	0.028	+
	Mean	6	0	0	0.028	+

Table 5.12: Ranks of GA-DE, E-DE, E-GA and CMA-ES from Friedman test results for 7 instances based on best and average values

Criteria	GA-DE	E-DE	E-GA	CMA-ES
Best FV	**1.08**	2.08	2.83	4.00
Average FV	**1.08**	2.08	2.83	4.00

for GA-DE are compared against those for E-DE, E-GA and CMA-ES for the different problems including (i) 5-unit thermal with P_{loss}, (ii) 10-unit thermal with P_{loss}, (iii) 5-unit thermal without P_{loss}, (iv) 10-unit thermal without P_{loss}, (v) hydro-thermal, (vi) wind-thermal and (viii) solar-thermal are illustrated in Table 5.11. Note that the comparisons between GA-DE, and E-DE and E-GA are performed for all 7 systems but, between GA-DE and CMA-ES, for the six cases as CMA-ES is not a suitable method for solving a mixed-integer (solar-thermal) problem. Furthermore, all the comparisons are based on both the best and average FVs found in 30 runs to which, using a 5% significance level, assigning one of three signs (+, −, and ≈), where '+' means that GA-DE is significantly better than the other algorithm, '−' that it is significantly worse and '≈' that there is no significant difference between the two algorithms. According to Table 5.11, GA-DE is able to obtain better results than the other algorithms and, from a statistical perspective, is significantly better than the other methods.

In addition, the Friedman test is carried out to rank all the algorithms based on their best and average FVs, with the results for 7 and 4 instances shown in Tables 5.12 and 5.13, respectively, demonstrating that the proposed GA-DE algorithm is ranked 1^{st}.

Also, for the bi-objective DEED problems, a Friedman test is performed considering the HV of each run of each algorithm with their mean ranks (MRs) are listed on Table 5.14 which proved that the GA-DE is the best algorithm for both problems.

Table 5.13: Ranks of GA-DE, E-DE, E-GA, CMA-ES, AIS, ABC, PSO and GA from Friedman test results for 4 cases based on best and average FVs

Criteria	GA-DE	E-DE	E-GA	CMA-ES	AIS	ABC	PSO	GA
Best	**1.25**	1.75	3.00	6.00	6.00	4.50	6.00	7.50
Avg	**1.25**	1.75	3.00	4.00	6.00	5.00	7.50	7.50

Table 5.14: Friedman tests for the bi-objective problems

Alg.	Mean rank	
	Hydro-Thermal	Solar-Thermal
NSGA-II	1.60	1.00
MODE	1.40	2.00
H-NSGA-II	3.90	4.00
H-MODE	3.10	3.00
GA-DE	**5.00**	**5.00**

5.8 Parametric Analysis

This analysis evaluates the performances of some of the algorithm's parameters, including the effects of: (i) the proposed heuristic, (ii) N_P, (iii) NP_1^{min}, (iv) NP_1^{max}, and (v) the cycle or window size (WS) in terms of N_{g_c} that enables the better-performing algorithm to run independently. In addition, the computational costs of different algorithms for different problems are extensively analyzed with the simulation results compared based on different stopping criteria. To do this, the single objective DED problems are considered as their FVs (as single) are easy to comparable. Each test is conducted following the ceteris paribus strategy in which only one parameter is varied while all the others remain fixed at their best values [236].

5.8.1 Effect of Proposed Heuristic

In the proposed algorithm, a heuristic is used to convert any infeasible solutions into good-quality feasible ones. To demonstrate its effect, the algorithms are run with and without it, and the average fitness value over 30 independent runs of each variant recorded, as presented in Table 5.15. Note that, for the parametric analysis, the P_{loss} is not considered in cases 1 and 2. Based on the Table 5.15, it can be seen that the performance of GA-DE with the proposed heuristic dominates that without it. Also,

Table 5.15: Comparison of average results using different parameters

Problem	Without heuristic	With heuristic
Case-1	51886.4	**42542.9**
Case-2	1076540	**1016218**
Case-3	101659	**67748.8**
Case-4	infeasible	**908440.0**
Case-5	983831	**790794.1**

Table 5.16: Comparison of average results using different N_P

Cases	N_P	FV
	50	42568.4
Case-1	100	**42542.9**
	150	42575.4
	50	1016909
Case-2	100	**1016218**
	150	1016713
	100	68095.4
Case-3	200	**67748.8**
	300	67749.9
	50	916118.82
Case-4	100	**915371.25**
	150	915708.64
	50	791542.7
Case-5	100	**790794.1**
	150	791564.5

for the case-4, the algorithm without heuristic does not obtain a single feasible solution even after N_G generations.

5.8.2 Effect of N_P

In this section, using three different values of N_P for each case, the effect of N_P on different problems is analyzed. After 30 independent runs for each case, the average results are recorded and presented in Table 5.16. It is found that N_P values of 100, 100, 200, 100 and 100 are the best choices for cases 1, 2, 3, 4 and 5, respectively.

5.8.3 Effect of SPS_{min} and WS

The proposed algorithm is run considering NP_1^{min} = 10% and 30% of $N_P/2$ with WS set at values of 25, 50 and 100 generations, respectively. The average results from 30

Table 5.17: Comparison of results using different NP_1^{min} and WS

Problem	NP_1^{min}			WS		
	10%	20%	30%	25	50	100
Case-1	42559.3	**42542.9**	42556.5	42544.7	**42542.9**	42554.7
Case-2	1016616	**1016218**	1016591	1016498	**1016200**	1016555
Case-3	68023.8	**67748.8**	67913.8	67907.5	**67748.8**	67787.5
Case-4	918140.0	**908440.0**	921230.0	919590.0	**908440.0**	918540.0
Case-5	791840.5	**790794.1**	791525.3	791289.5	**790794.1**	791289.5

Table 5.18: Summary of computational costs for different problems

Problem	GA-DE		E-DE		E-GA		CMA-ES	
	No. FFEs	Time (min.)	No. FFEs	Time (min.)	No. FFEs	Time (min.)	No. FFEs	Time (min.)
5U without P_{loss}	92,300	4.94	63,500	4.25	66,500	4.70	129,81,602	127.91
5U with P_{loss}	100,000	6.82	40,600	3.97	78,600	6.25	126,85,700	119.12
10U without P_{loss}	393,200	12.11	265,200	11.70	326,100	12.80	323,30,922	462.60
10U with P_{loss}	400,000	13.34	347,600	12.07	341700	13.15	302,35,682	650.27
Hydro-thermal	60,000	6.38	60,000	6.20	60,000	7.35	230,58,440	1201.90
Wind-thermal	82,400	7.40	99,200	7.56	95,200	7.48	183,458	16.43
Solar-thermal	71,200	4.83	28,500	3.95	23,400	3.54	-	-

independent runs for each case are presented in Table 5.17. It is found that $NP_1^{min} =$ 20% of N_P and $WS = 50$ are the best values.

5.8.4 Effect of Stopping Criteria

In this section, the algorithms' performances are examined using three different stopping criteria of being allowed to run until (i) a predefined number of maximum fitness function evaluations (MaxFFEs) is reached, (ii) a predefined computational time is considered and (iii) the best FVs are no longer improved for θ consecutive generations.

For the analysis, the number of fitness function evaluations (FFEs) and computational cost for each problem required by the different algorithms to obtain the results in Tables 5.2-5.8 are summarized in Table 5.18. For a fair comparison, only the implemented algorithms (i.e., GA-DE, E-GA, E-DE and CMA-ES) are considered as the simulation time is highly dependent on their computational resources and coding efficiency.

Now, all the algorithms are run for up to the same number of $MaxFFEs$, the values of which for different problems are set according to those for GA-DE in Table 5.18. Based on 30 random runs, the computational costs and average FVs (AFVs) for

Table 5.19: Comparisons of different algorithms with same number of $MaxFFEs$

Problem	$FFEs$	GA-DE		E-DE		E-GA		CMA-ES	
		Time (min.)	AFV	Time (min.)	AFV	Time (min.)	AFV	Time (min.)	AFV
5U without P_{loss}	92,300	4.94	42524.80	4.35	42524.80	5.45	42565.90	0.50	49929.92
5U with P_{loss}	100,000	6.82	42547.60	6..27	42571.20	6.25	42580.60	1.45	49703.14
10U without P_{loss}	393,200	12.11	1016200.00	11.83	1016260.00	13.47	1016710.00	2.70	1052495.95
10U with P_{loss}	400,000	13.34	1036280.00	12.36	1036310.00	14.05	1037020.00	3.16	1069478.71
Hydro-thermal	60,000	6.38	67526.10	6.20	67783.80	7.35	68208.60	2.56	133561.43
Wind-thermal	82,400	7.40	790761.00	7.14	791296.00	8.37	791002.00	4.59	815977.01
Solar-thermal	71,200	4.83	916061.31	4.23	922824.81	5.24	917220.01	-	-

Table 5.20: Comparisons of different algorithms run for same computational time

Problem	Time	AFV		
	(min)	GA-DE	E-DE	E-GA
5-unit without P_{loss}	4.94	**42524.80**	42524.80	42577.30
5-unit with P_{loss}	6.82	**42547.60**	42571.20	42580.60
10-unit without P_{loss}	12.11	**1016200.00**	1016260.00	1016740.00
10-unit with P_{loss}	13.34	**1036280.00**	1036310.00	1037110.00
Hydro-thermal	6.38	**67526.10**	67783.80	68310.50
Wind-thermal	7.40	**790761.00**	791296.00	791118.00
Solar-thermal	4.83	**916061.31**	922824.81	917278.10

different approaches for different problems are presented in Table 5.19 in which it can be seen that CMA-ES is the fastest algorithm but obtains the worst quality of solutions. Of the three EAs, GA-DE is able to achieve the best solutions although it consumes slightly more computational time than the others.

Then, all the algorithms are run for up to the same computational time, with the results in Table 5.20 demonstrating that GA-DE performs best.

As previously mentioned, one of the stopping criteria is to run all the algorithms until there is no improvement in the best FVs for θ consecutive generations. The effect of this parameter is tested on GA-DE's performance for solving the 5- and 10-unit thermal (without P_{loss}), wind-thermal and solar-thermal DED systems. According to Table 5.21, it is better to set θ to a value of 100 or 200 rather 50 generations. However,

Table 5.21: Effect of θ

Criteria	θ	5-unit without P_{loss}			10-unit without P_{loss}		
		$FV(\$)$	Evolved Gen.	Time (min.)	$FV(\$)$	Evolved Gen.	Time (min.)
1	50	42535.8	268	1.23	1016420	1654	8.54
2	100	42524.80	923	4.94	1016260	3932	12.11
3	200	42524.80	1000	5.41	1016260	4000	13.05
		Wind-thermal			Solar-thermal		
Criteria	θ	$FV(\$)$	Evolved Gen.	Time (min.)	$FV(\$)$	Evolved Gen.	Time (min.)
1	50	790811	557	5.64	916254.49	572	3.82
2	100	790761	824	7.40	916061.31	712	4.83
3	200	790761	1000	8.78	916061.31	1000	6.08

as the computational time for GA-DE with $\theta = 100$ is less than that for GA-DE with $\theta = 200$, it is considered best to set θ to a value of 100.

5.8.5 Effect of Configuration for Updating N_{P1} and N_{P2}

As described earlier, the sub-population sizes of $\mathrm{N_{P1}}$ and $\mathrm{N_{P2}}$ are updated based on their normalized SUR as in Eqn. (5.45) and (5.44), respectively, with N_{P1} and N_{P2} remaining unchanged when both $\mathrm{SUR_{1,g}}$ and $\mathrm{SUR_{2,g}}$ are zero. However, if one SUR has quite a small value while the other is zero, there is a possibility that there will be a small bias towards N_{P1} based on Eqn. (5.44). To avoid such a situation, an alternative approach for updating N_{P1} and N_{P2} is tested in this section, in which a small Δ(here, Δ= 0.001) is added to both SUR as:

$$N_{P1} = \max\left[N_{P1}^{\min}, \min\left\{N_P \frac{SUR_{1,g} + \Delta}{(SUR_{1,g} + \Delta) + (SUR_{1,g} + \Delta)}, N_{P_1}^{\max}\right\}\right] \tag{5.50}$$
$$SUR_{1,g} \cup SUR_{2,g} \neq 0,\ g \in N_G$$

$$N_{P2} = N_P - N_{P1} \tag{5.51}$$

Table 5.22: Comparison of average results using different configurations

Criteria	5U without P_{loss}	5U with P_{loss}	10U without P_{loss}	10U with P_{loss}	Hydro-thermal	Wind-thermal	Solar-thermal
1	42524.8	42547.6	1016200.0	1036280.0	67526.1	790761.0	916061.3
2	42524.3	42546.9	1016270.0	1036270.0	67556.3	790772.0	917220.7

To demonstrate the effect of Eqns. (5.51) and (5.50), the performances of the proposed GA-DE algorithm is examined with N_{P1} and N_{P2} updated based on Eqns. (5.45) and (5.44) in criterion-1 and Eqns. (5.51) and (5.50), respectively in criterion-2.

Table (5.22) presents the average results for different test problems under both criteria which show that, those for criterion-2 deviate marginally from those in criterion-1. Therefore, although the technique for updating N_{P1} and N_{P2} has an impact on solution quality, it is not significant.

5.8.6 Effect of Switching Between GA and DE

As previously mentioned, GA-DE is a self-adaptive multi-EA in which individuals are switched dynamically between GA and DE during the evolutionary process. In this process, the sub-population sizes are increased for a well-performing algorithm and vice versa. In addition, the better-performing algorithm is run for a full cycle to evolve all individuals alone while the other is not run during that period. The changes in sub-population sizes of the two algorithms with the numbers of generations for the median run of all the test cases are presented in Fig. 5.4 to 5.8, in which it can be seen that GA performs better in the earlier stages for some cases, and DE for others.

Fig. 5.9 illustrates the percentages of individuals assigned to GA during the first 20 cycles for all cases. Note that those evolved by DE can be determined by subtracting the individuals assigned to GA from N_P. According to Fig. 5.9, neither GA nor DE is the better algorithm for solving the wide range of DED problems considered in this paper, and their performances can change during the evolutionary process. Therefore, configuring the best EA during the evolutionary process is a possible solution for obtaining better results.

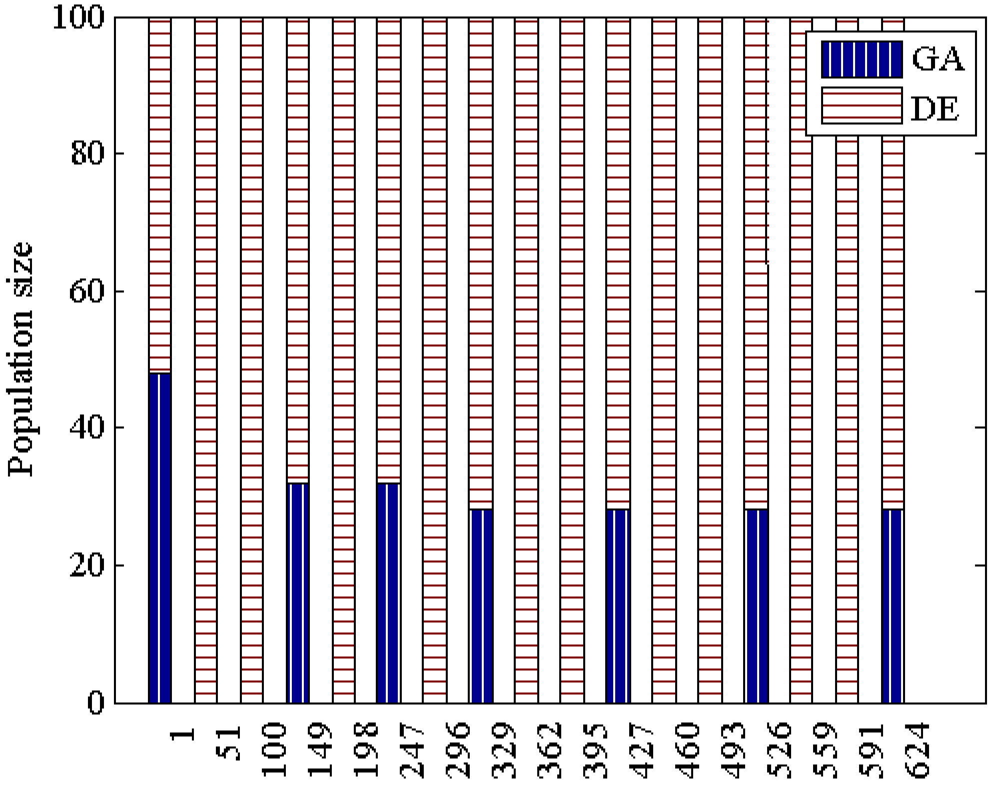

Fig. 5.4: Self-adaptive changes of N_{P1} and N_{P2} for 5-unit thermal system

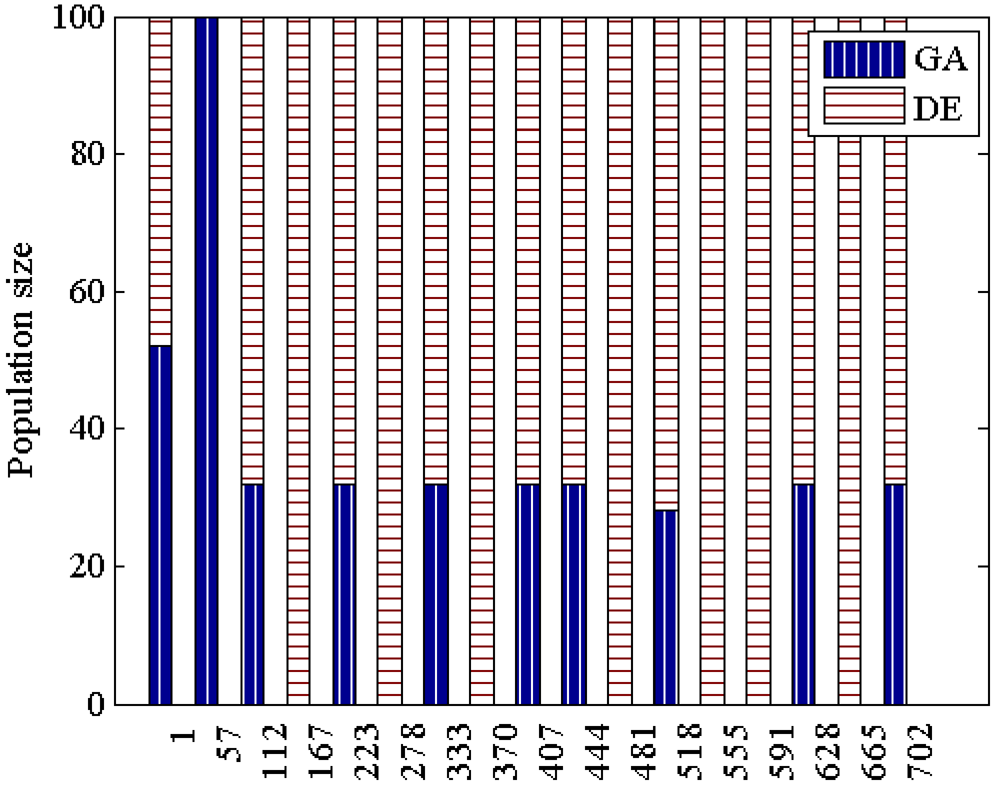

Fig. 5.5: Self-adaptive changes of N_{P1} and N_{P2} for 10-unit thermal system

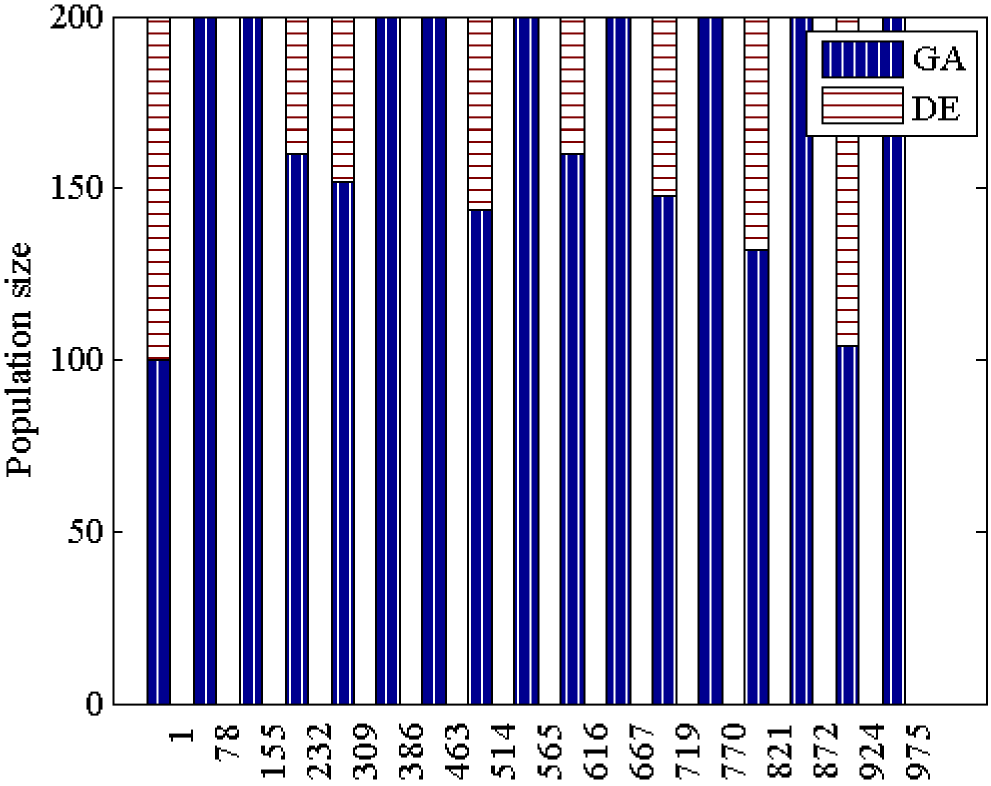

Fig. 5.6: Self-adaptive changes of N_{P1} and N_{P2} for hydro-thermal system

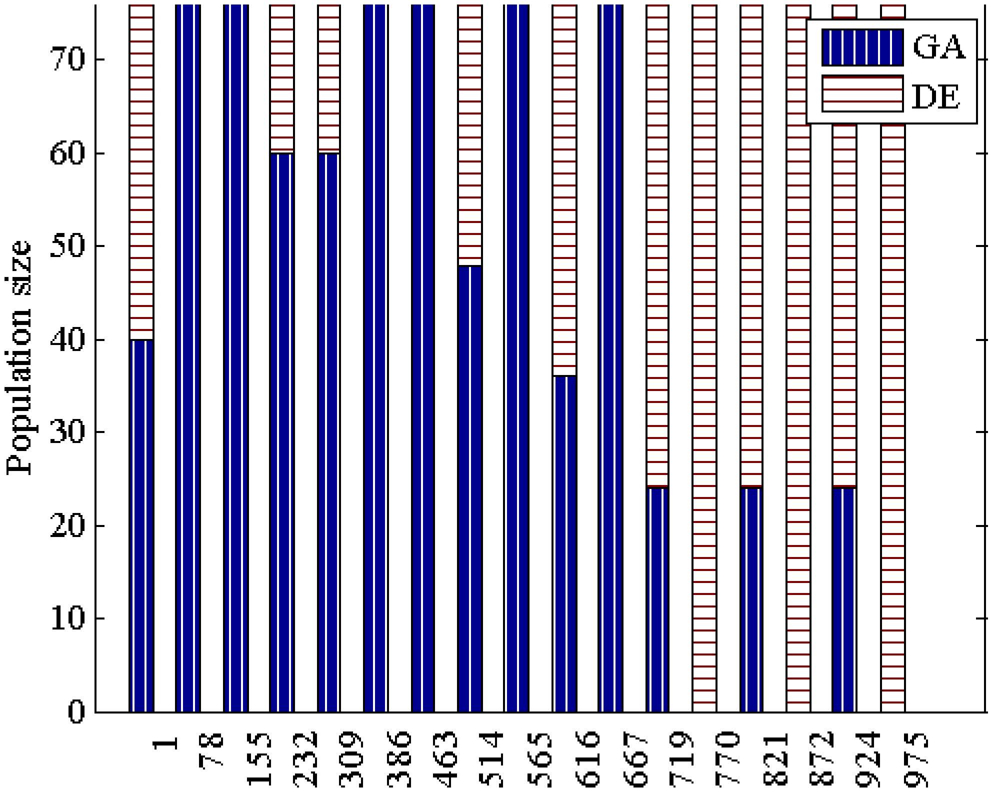

Fig. 5.7: Self-adaptive changes of N_{P1} and N_{P2} for solar-thermal system

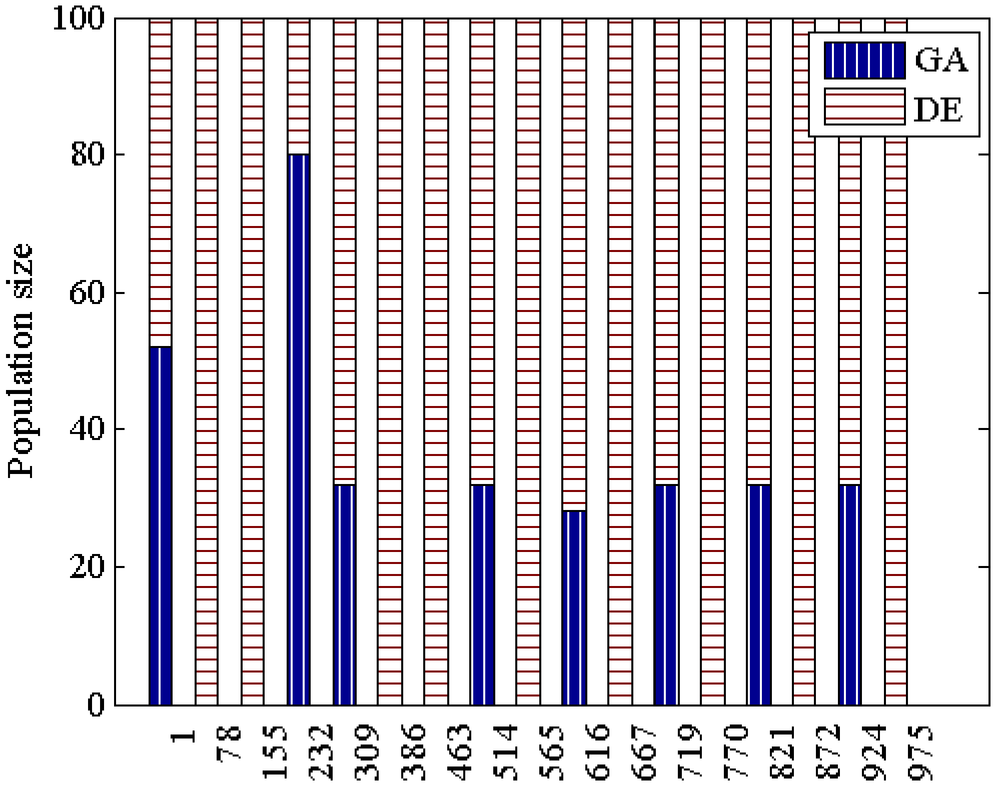

Fig. 5.8: Self-adaptive changes of N_{P1} and N_{P2} for wind-thermal system

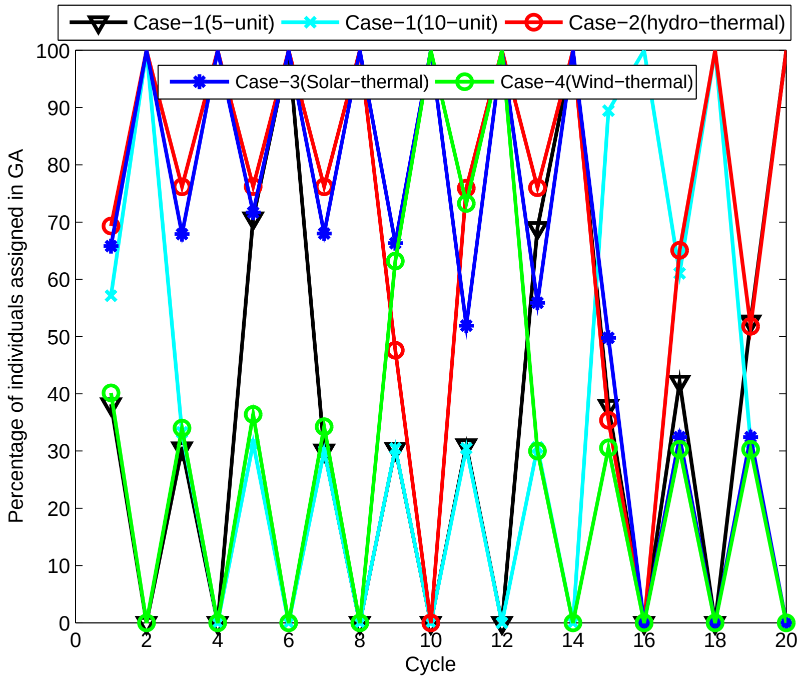

Fig. 5.9: The individuals are evolved by GA per cycle for different cases

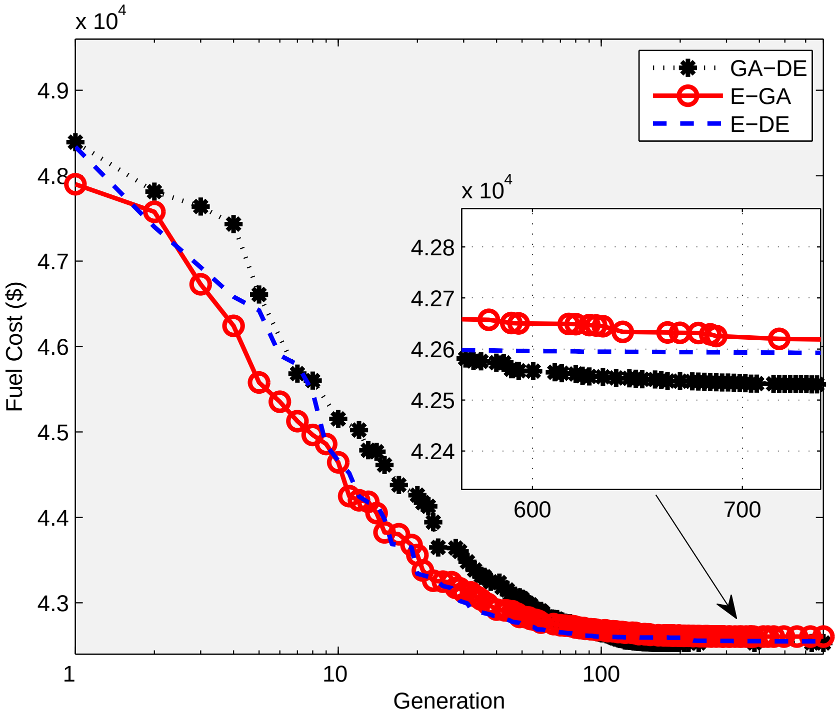

Fig. 5.10: Convergence plots for 5U with P_{loss}

The convergence patterns of different test problems for median runs presented in Fig. 5.10 to 5.15 demonstrate the advantages of the adaptive configuration of multi-EAs in that GA-DE converges faster than both E-GA and E-DE.

5.9 Chapter Summary

An evolutionary approach based on configuring two EAs, a GA and DE, for solving a wide range of single- and bi-objective DED and DEED problems, respectively, such as thermal, hydro-thermal, solar-thermal and wind-thermal systems, was presented in this chapter. In the algorithm's design, a self-adaptive mechanism for configuring the GA and DE during the course of evaluation based on the performances in previous generation (i.e., if an algorithm showed better performance, more individuals were evolved using it and vice versa), was presented. Once a prescribed number of generations (cycles), only the better algorithm was allowed to perform while, in the next cycle, both performed again and so on. In addition, the control parameters of the search operators were self-adaptively configured over the generations in order to achieve the best combinations on

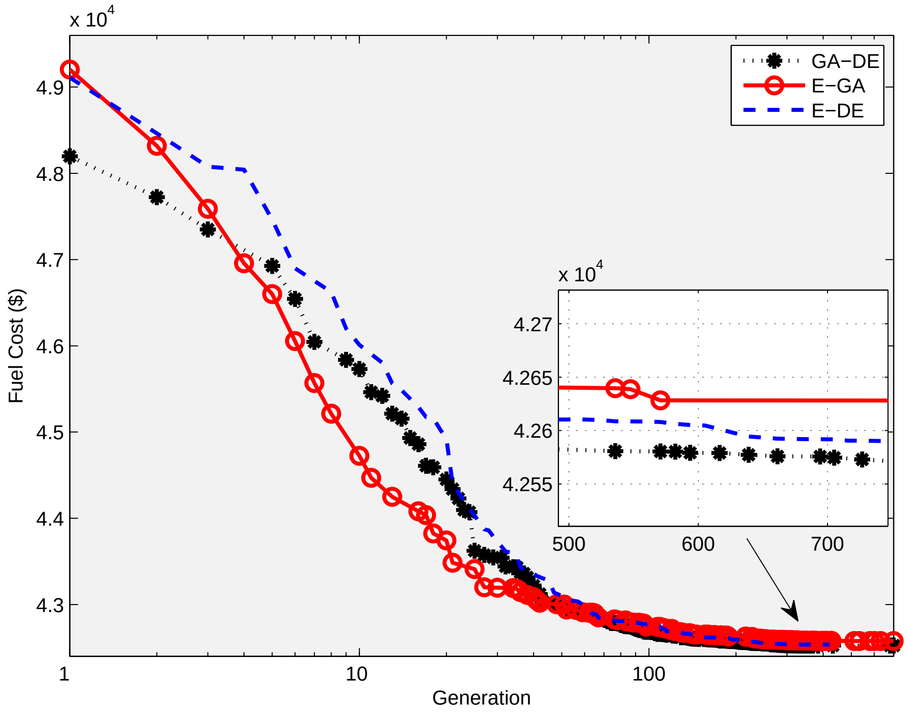

Fig. 5.11: Convergence plots for 5U without P_{loss}

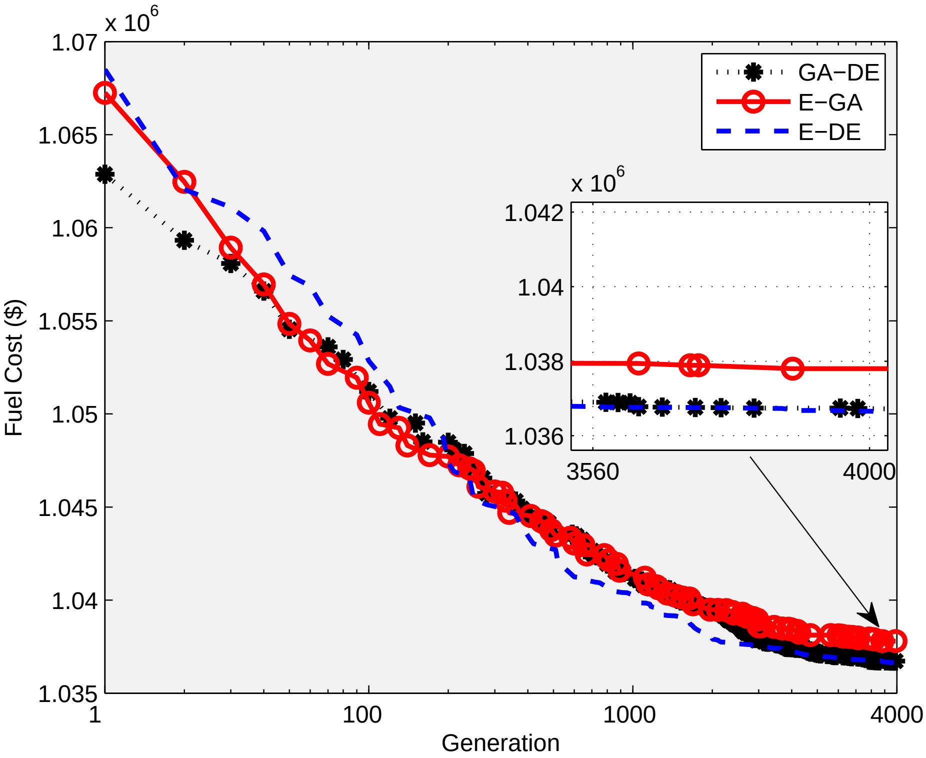

Fig. 5.12: Convergence plots for 10U with P_{loss}

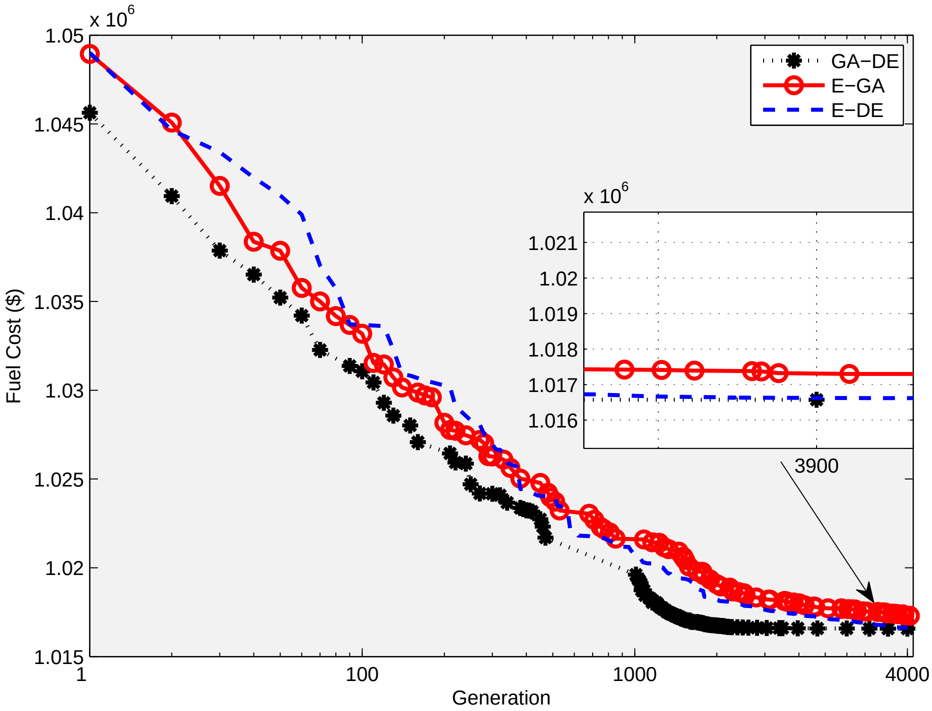

Fig. 5.13: Convergence plots for 10U without P_{loss}

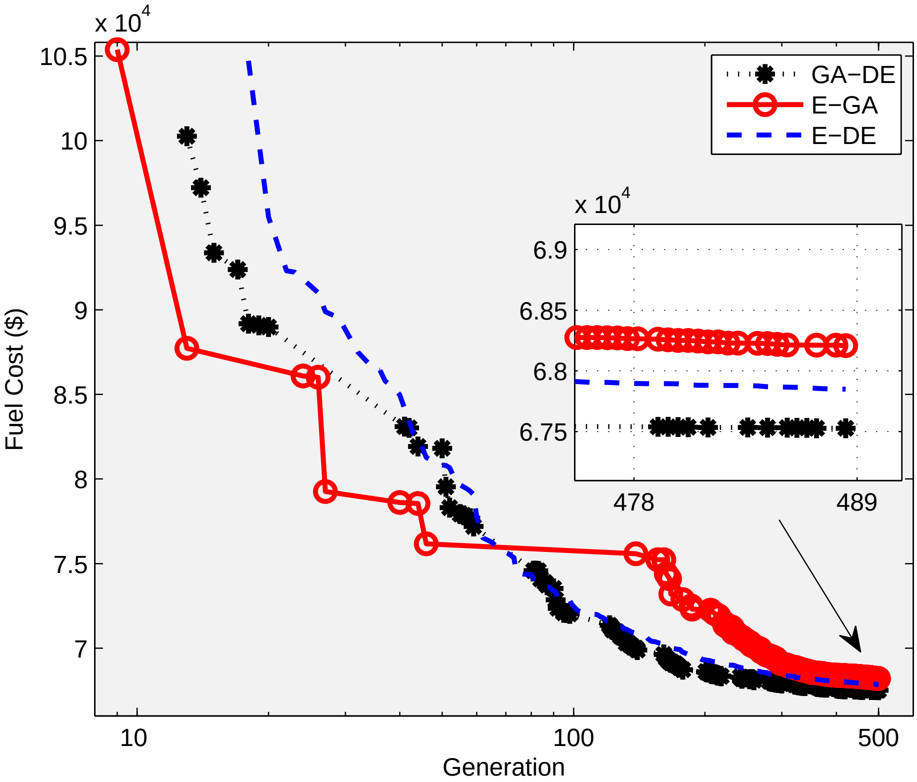

Fig. 5.14: Convergence plots for hydro-thermal DED system

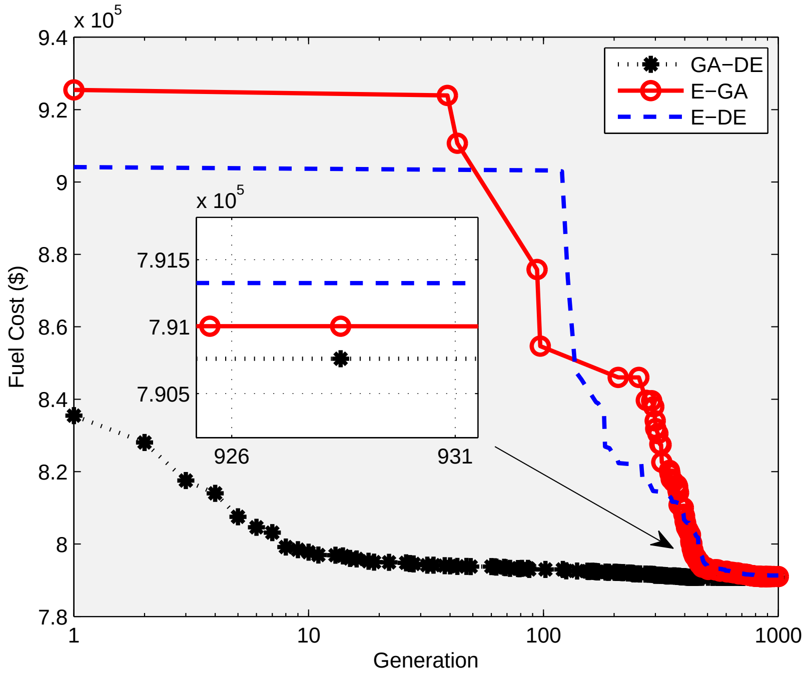

Fig. 5.15: Convergence plots for wind-thermal

a real-time basis with a heuristic technique employed to obtain feasible solutions from infeasible ones. The proposed framework was applied to different classes of DED and DEED problems, with the results showed that GA-DE was the best.

In Chapters 2, 3 and 4, efficient approaches for solving various DED and DEED problems by minimizing their operating costs and gas emissions are developed. However, it is also important in a real competitive energy market to maximize the individual profit of each participant. Therefore, in the next chapter, solution approaches for bidding problems that aim to maximize individual profits in an energy market are developed and discussed.

Chapter 6

EAs for Bidding Problems in Energy Market

This chapter discusses the importance of solving a bidding problem in an energy market. Then, problem descriptions, mathematical formulation and an overview of existing solution approaches with their drawbacks of this problem are presented. Subsequently, two co-evolutionary (CE) solution approaches one based on a genetic algorithm (GA) and other on a self-adaptive differential evolution (DE) are developed to solve this problem. Finally, the experimental results, parametric analyses and outcomes are discussed.

6.1 Introduction

As discussed in Chapter 2, during the last decade, the electricity markets in many countries have become decentralized and deregulated from monopolized to increase economic efficiency and reduce operational costs. In this scheme, the markets are being opened up to competition among both suppliers and consumers. In them, generator companies (GENCOs) and consumers simultaneously submit their bids to an independent system operator (ISO) that determines the market clearing price (MCP) and amount of electricity to be supplied by each winning bidder by solving a dispatch problem. As the

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The following articles have been published based on this chapter:

[1]. M. F. Zaman, S. M. Elsayed, T. Ray and R. A. Sarker, Co-evolutionary approach for strategic bidding in competitive electricity markets, ***Applied Soft Computing***, Volume 51, February 2017, Pages 1-22. [Key Sections: 6.3.1, 6.5.2, 6.5.3, 6.5.8 and 6.6.4]

[2]. M. F. Zaman, S. M. Elsayed, T. Ray and R. A. Sarker, Evolutionary algorithms for computing Nash equilibria in electricity markets, Evolutionary algorithms for computing Nash equilibria in electricity markets, ***IEEE Transactions on Evolutionary Computation*** (Under Review). [Key Sections: 6.3.2, 6.4, 6.5.5, 6.5.6, 6.5.7, 6.6.1, 6.6.2 and 6.6.3].

[3]. M. F. Zaman, S. M. Elsayed, T. Ray and R. A. Sarker, A co-evolutionary approach for optimal bidding strategy of multiple electricity suppliers, in ***IEEE Congress on Evolutionary Computation***, Vancouver, Canada, 2016.

profit of a bidder depends on both its own submitted bid and those of its rivals, each bidder optimizes its own bidding behavior with respect to those of its competitors while satisfying some power system constraints. As a high bid by a bidder may not be selected by the ISO while a lower one may not cover its own costs, to choose an appropriate bidding strategy for maximizing the profits of all bidders is a challenging economic game problem [52].

As discussed in Chapter 2, of different game-theory-based economic models, the Cournot and supply function equilibrium (SFE) are the most popular due to their realistic characteristics [189, 193]. In the former, the amount of power to be produced by each player is considered a strategic variable, while a linear function is used in the latter [189]. Each model is formulated as a bi-level optimization problem (details are provided later) which is very challenging to solve as it contains a nested optimization task within the constraints of another optimization problem. Also, as this problem becomes more complex in the presence of its difficult mathematical properties, such as multi-modality, non-convexity, non-differentiability and multiple solutions [24], it is inherently more difficult to solve than traditional optimization ones.

Although several approaches for solving this problem have been developed, as they determine a solution for each player iteratively in each iteration, approaching an overall solution is difficult even for a small problem and requires a long computational effort for a large one. Also, most of these methods aim to find a single solution whereas detecting multiple ones is more practical and challenging, with a few attempts having been made to solve such a discrete game problem. However, an energy market is a continuous one containing infinite sets of strategies that can be adopted by each player. Therefore, in this chapter, a CE approach for detecting multiple solutions in a single run involving continuous games with $N-$players is proposed.

6.2 Problem Description

In this section, a bidding problem in an energy market is described. It is formulated as a bi-level optimization problem with its objective in the upper level to maximize the profit of each bidder (either GENCOs or consumers) by anticipating the profit-maximization actions of its rivals [4]. In the lower level, the ISO solves an optimal power flow (OPF) problem to maximize the community social welfare (CSW) by scheduling the available generators based on the actions submitted by the GENCOs. The CSW is defined as the difference between the profits obtained by trading electricity to consumers and the expenses of purchasing it from GENCOs. The OPF problem is an extension of an economic dispatch (ED) one that considers the power transmission constraints, such as branch flows and capacity constraints. However, in practice, it is typically approximated by a more tractable 'DC-OPF' problem that focuses exclusively on real power constraints in a linearized form by simplifying some restrictions regarding voltage magnitudes, voltage angles, admittances and the reactive power [237]. In this thesis, the DC-OPF problem is used to represent an electrical power network which includes the constraints of active transmission power flows, transmission line (TL) capacities, active power generations, nodal voltage angles and active power demands.

The decision variables in the upper level are considered the bidding parameters of each bidder that can be varied within a given range while the lower level is the power output (PO) of each generator of each GENCO that maximizes the CSW. The objective function of the lower level is affected by the upper level's decision variables, for example, the cost function of a GENCO is controlled by its own interest that a bid is submitted. Once all the bidders submit their bids to the ISO, it solves the DC-OPF problem and determines the PO and MCP of each bidder. Then, the objective (profit) function of the upper level is calculated based on the PO, MCP and their actual production costs. However, the MCPs of all the bidders are the same when transmission congestions (TCs) are ignored but, if they are considered, vary significantly from location (or node) to location which is called the locational market price (LMP).

As previously mentioned, based on the bidding parameters, the problem can be formulated as SFE and Cournot models, as described below.

6.3 Problem Formulations

In this section, the mathematical formulations of the equilibrium models of an energy market, such as (i) SFE and (ii) Cournot game models are presented. However, both models consider some assumptions made are that each player (i) knows the market rules, (ii) has complete information about the actual generation costs of itself and its rivals, (iii) knows the range of its bidding parameters and those of its rivals from historical data, and (iv) knows the capacities of the TLs connected to the market [169].

6.3.1 Supply Function Equilibrium Model

In the equilibrium model, it is assumed that each GENCO has a single generator with the quadratic cost function:

$$C_i = a_i + b_i P_i + c_i P_i^2, \ \forall i \in I \tag{6.1}$$

where P_i is the generation output from i^{th} GENCO and I the number of GENCOs. Note that, in this research, it is assumed that each GENCO has a single generator that can be any type, such as thermal, hydro, solar or wind one. Then, the marginal cost (MC) of the i^{th} GENCO (generator) is:

$$MC_i = \frac{dC_i}{dP_i} = b_i + 2c_i P_i, \ \forall i \in I \tag{6.2}$$

Since each GENCO plays a game in the market, rather than submitting an actual marginal cost of Eqn. (6.2), a strategic quasi function (Eqn. (6.3)) called a linear supply function [189] is submitted to the ISO as:

$$B_i = b_i' + c_i' P_i, \ \forall i \in I \tag{6.3}$$

where B_i is the linear supply function of i^{th} generator and $\acute{b}_i$, $\acute{c}_i$ the quiescent cost coefficients of that generator.

The consumers' utility cost function (Y_j) is the quadratic inverse form [189]:

$$Y_j = d_j D_j - e_j D_j^2 \ \forall j \in J \tag{6.4}$$

where d_j, e_j are the coefficients of j^{th} strategic consumers' utility function, $D_j$the demand of that consumer and J the number of strategic consumers. The load demand function of the linear form is the inverse function with a negative gradient:

$$\frac{dY_j}{dD} = d_j - 2e_j D_j \ \forall j \in J \tag{6.5}$$

Again, as a strategic consumer, it plays with the quasi function in Eqn. (6.6):

$$L_j = d_j' - e_j' D_j \ \forall j \in J \tag{6.6}$$

where $\acute{d_j}, \acute{e_j}$ are quiescent coefficients of j^{th} demand curve.

Based on [189, 193], the bidding *parameterizations* can be selected in the following four ways.

1. *Intercept parameterization*: the strategic players adjust the intercepts of $\acute{b}_i, \ \forall i$ and $\acute{d_j}, \ \forall j$ of their marginal cost functions in Eqns. (6.3) and (6.6), respectively, to construct their profit-maximizing bids for submission to the ISO while keeping the slope constant as $\acute{c}_i = 2c_i, \ \forall i$ and $\acute{e}_j = 2e_j, \ \forall j$.
2. *Slope parameterization*: the strategic bids of the players are modeled by varying the slope of the marginal cost functions in Eqns. (6.3) and (6.6) with the values of $\acute{c}_i \forall i$ and $\acute{e_j} \forall j$, respectively, while keeping the intercepts constant as $\acute{b}_i = b_i, \ \forall i$ and $\acute{d}_j = d_j, \ \forall j$, respectively.
3. *Slope-and-intercept parameterization*: the players adjust both intercepts ($\acute{b}_i, \ \forall i$ and $\acute{d_j}, \ \forall j$) and slopes ($\acute{c}_i, \ \forall i$ and $\acute{e_j}, \ \forall j$) independently and simultaneously as their strategic variables to allow more degrees of freedom for choosing the strategic supply function.

4. *Slope intercept parameterization*: the strategic players adjust both the slopes and intercepts in the supply functions in Eqns. (6.3) and (6.6) for GENCOs and consumers, respectively, but in a fixed linear relationship between the true and quasi values of the marginal cost function. This can be interpreted as multiplying the marginal cost functions by arbitrary non-negative constants, say $k_{g_i} \forall i$ and $k_{d_j} \forall j$, in order to construct the supply function bids, as:

$$B_i = k_{g_i}(b_i + c_i P_i) \tag{6.7}$$
$$k_{g_i}^{min} \leq k_{g_i} \leq k_{g_i}^{max} \quad \forall i \in I$$

$$L_j = k_{d_j}(d_j - e_j D_j) \tag{6.8}$$
$$k_{d_j}^{min} \leq k_{d_j} \leq k_{d_j}^{max} \quad \forall j \in J$$

where B_i and L_j are the supply functions for the GENCO and consumer, respectively, $k_{g_i}$and k_{d_j} the coefficients of the supply functions in Eqns. (6.7) and (6.8), respectively, and $k_{g_i}^{min}$, $k_{g_i}^{max}$, and $k_{d_j}^{min}$, $k_{d_j}^{max}$ the minimum and maximum limits of $k_{g_i}$and k_{d_j}, respectively.

Due to the effectiveness of *'slope intercept parameterization'* in real life, it is used in this research with $k_{g_i} \forall i$ and $k_{d_j} \forall j$ the strategic variables for GENCOs and consumers, respectively. The strategic functions for GENCOs and consumers, respectively, as shown in Fig. 6.1 by dotted lines, represent the true supply functions and the solid lines the strategic supply ones obtained by multiplying the decision variables of $k_{g_i} \forall i$ and $k_{d_j} \forall j$.

A Formulation of ISO's Optimization Problem

Once the participants in the market submit their strategic supply functions, the ISO runs a DC-OPF problem to maximize the CSW subject to the power system's transmission constraints. The ramp rate constraints are ignored in this formulation as it is assumed that they are sufficiently high. Also, start-up and shut-down decisions are not

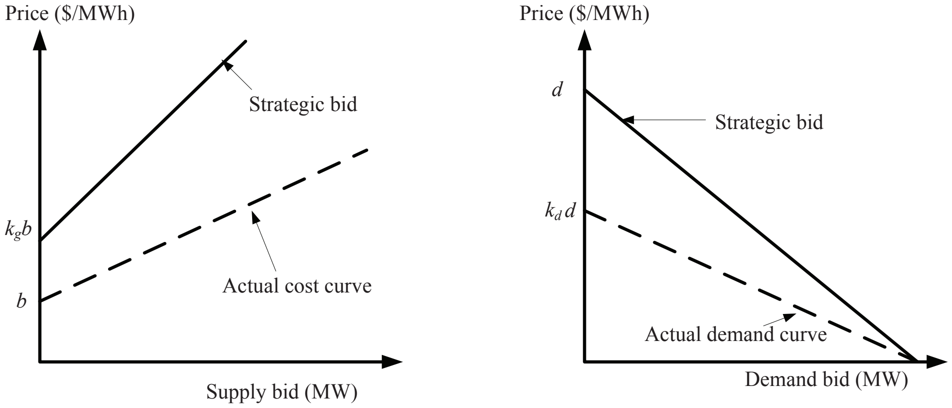

Fig. 6.1: Strategic bidding for supply and demand

considered as it is assumed that the on/off status of a unit is known a priori at the time of constructing bidding strategies [238]. Since the ISO receives strategic bids from each player, its objective function is represented by the quasi CSW that incorporates the strategic variables $k_{g_i} \forall i$ and $k_{d_j} \forall j$ as:

$$\text{Max} : \prod_{\text{ISO}} = \sum_{j=1}^{J} \left(d'_j D_j - \frac{1}{2} e'_j D_j^2 \right) - \sum_{i=1}^{I} \left(b'_i P_i + \frac{1}{2} c'_i P_i^2 \right) \tag{6.9}$$

with respect to: $P_i, D_j, \delta_k, i = 1, 2, ..., I; j = 1, 2, ..., J; k = 1, 2, ..., K$

Eqn. (6.9) represents the objective function of the ISO's DC-OPF problem in which it is equal to the consumers' benefit minus the generation costs considering the strategic bids. The DC-OPF problem has the following constraints when TCs are included.

1. Real power balance constraints for each node ($k = 1, 2, \ldots, K$):

$$\sum_{i=1}^{I_k} P_i - \sum_{j=1}^{J_k} D_j - PNetInject_k = 0 \tag{6.10}$$

$$\text{where } PNetInject_k = \sum_{km/mk \in BR} F_{km} \tag{6.11}$$

$$F_{km} = B_{km} \left(\delta_k - \delta_m \right) \tag{6.12}$$

2. Limits of real power flow through each branch ($km \in BR$):

$$|F_{km}| \leq F_{km}^{U} \tag{6.13}$$

3. Limits of real power of each generator ($i = 1, 2, \ldots, I$):

$$P_i^{\min} \leq P_i \leq P_i^{\max} \tag{6.14}$$

The above DC-OPF problem is a nonlinear and non-convex single-objective optimization problem, and generally represented by its first-order KKT conditions for solving using a conventional method [189]. Consequently, the LMPs, P_i, $i \in I$ from each GENCO, D_j, $j \in J$ of each consumer, transmission flows (F_{km}) and nodal voltage angles (δ_k) are calculated to simultaneously satisfy each market participant's first-order optimality conditions for maximizing their net benefits (KKT conditions) while clearing the market (supply = demand).

However, the lower level DC-OPF problem has to be optimized in every generation with the best solution is used in the evaluation of the objective function in the upper-level profit maximization problem. Therefore, an efficient technique is desired in solving the lower level problem to reduce the computational complexity of the bi-level optimization problem. This can be achieved by using a strictly convex quadratic programming (SCQP) technique for solving the lower level optimization problem [237, 239]. Such a technique can be only applied under the assumption that the objective function is quadratic, which has been satisfied of Eqn. (6.9). The SCQP-based DC-OPF problem is presented in the following subsection.

B Formulation of ISO's Optimization Problem based on SCQP

The DC-OPF problem can be represented as an SCQP one by eliminating the voltage angles using substitution in which the ISO's objective function of Eqn. (6.9) is subject to the equality constraints of the real power balance in Eqn. (6.10), is expressed as an SCQP and accumulates a soft penalty function of the sum of squared voltage angle differences as [237, 239]:

$$\text{Min}:\sum_{i=1}^{I}\left(\frac{1}{2}c_i'P_i^2+b_i'P_i\right)-\sum_{j=1}^{J}\left(d_j'D_j-\frac{1}{2}e_j'D_j^2\right)-\pi\left[\sum_{km\in BR}(\delta_k-\delta_m)^2\right] \tag{6.15}$$

where δ_k is voltage angle in radians at node/bus k with assuming a reference bus voltage angle of $\delta_1=0$, Eqn. (6.15) is reduced as:

$$\text{Min}:\sum_{i=1}^{I}\left(\frac{1}{2}c_i'P_i^2+b_i'P_i\right)-\sum_{j=1}^{J}\left(d_j'D_j-\frac{1}{2}e_j'D_j^2\right)-\pi\left[\sum_{1m\in BR}\delta_m^2+\sum_{km\in BR,k\geq 2}(\delta_k-\delta_m)^2\right] \tag{6.16}$$

subject to:

$$\sum_{i=1}^{I_k}P_i-\sum_{km/mk\in BR}B_{km}\left(\delta_k-\delta_m\right)=\sum_{j=1}^{J_k}D_j\ \forall k=1,2,\cdots,K \tag{6.17}$$

$$-B_{km}\left(\delta_k-\delta_m\right)\geq -F_{km}^U\ \forall k,m=1,2,\cdots,K \tag{6.18}$$

$$B_{km}\left(\delta_k-\delta_m\right)\geq -F_{km}^U\ \forall k,m=1,2,\cdots,K \tag{6.19}$$

$$P_i\geq P_i^{\min}\ \forall i=1,2,\cdots,I \tag{6.20}$$

where B_{km}, F_{km} and F_{km}^U are the susceptance, TL flow and maximum capacity of the TL connected to nodes k to m, respectively, K the number of nodes, I_k and J_k the numbers of generators and consumers, respectively at the k^{th} node.

To efficiently solve the above optimization problem, a matrix representation of the objective function in Eqn. (6.16) and constraints in Eqns. (6.17) to (6.20) is developed as:

$$\text{Min: } f(x)=\frac{1}{2}\mathbf{x}^T\mathbf{G}\mathbf{x}+\mathbf{f}^T\mathbf{x} \tag{6.21}$$

$$\text{subject to: } \mathbf{C}_{in}\mathbf{x}^T \geq \mathbf{b}_{in} \tag{6.22}$$

$$\mathbf{C}_{eq}\mathbf{x}^T = \mathbf{b}_{eq} \tag{6.23}$$

Details of the coefficients, such as $\mathbf{G}$, $\mathbf{f}$, $\mathbf{C_{in}}$, $\mathbf{b_{in}}$, $\mathbf{C_{eq}}$ and $\mathbf{b_{eq}}$ of Eqns. (6.21) to (6.23) are shown in Appendix B. Note that, for the variable notations, a boldface one indicates that it is a matrix or vector and a normal italic one a scalar.

C Formulating Optimization Problem of Each Player

Once the lower-level SCQP problem is solved, the values of P_i, D_j, λ_{P_i}, λ_{D_i} and F_{km} $\forall i, j, k$ are calculated based on their primal and dual variables in the KKT representation shown in Appendix C. Then, the upper-level optimization problems of the strategic firms, in which individual profits are maximized, are solved given the revenue minus the true generation cost as:

$$\begin{gathered} Max: \ \pi_i(k_{g_i}) = \lambda_{P_i} P_i - C_i(P_i) \\ k_{g_i}^{min} \leq k_{g_i} \leq k_{g_i}^{max}, \forall i \in I \end{gathered} \tag{6.24}$$

$$\begin{gathered} Max: \ \pi_j(k_{d_j}) = Y_j(D_j) - \lambda_{d_j} D_j \\ k_{d_j}^{min} \leq k_{d_j} \leq k_{d_j}^{max}, \forall j \in J \end{gathered} \tag{6.25}$$

where π_i and π_j are the profits of the GENCO and consumer, respectively. As the variables P_i, D_j, λ_{P_i}, λ_{D_i} are produced by the SCQP problem given in Eqns. (6.21) to (6.23), they can be expressed as implicit functions of the players' bidding strategies as $\mathbf{k}_g = \{k_{g1}, k_{g2}, \ldots, k_{gI}\}$ and $\mathbf{k}_d = \{k_{d1}, k_{d2}, \ldots, k_{dJ}\}$. Therefore, they should satisfy the KKT conditions of the ISO optimization problem.

6.3.2 Cournot Model

The formulation of Cournot game is very similar to that of SFE with the exception is the bidding parameter in which, in the Cournot game, a player (say, n) uses its variable $P_i \, i = n$ as the bidding variable to maximize its profits with respect to the other players, $P_i \, i = 1, 2, \ldots, I; \; i \neq n$ as [174]:

$$\pi(P_i) = \lambda_{P_i} P_i - C_i(P_i), \, \forall i = 1, 2, ..., I \qquad (6.26)$$
$$\text{where } C_i(P_i) = a_i + b_i P_i + c_i P_i^2$$

$$P_i^{min} \leq P_i \leq P_i^{max} \; \forall i \in I \qquad (6.27)$$

where the amount of electricity P_i is the decision strategic variable for this model of the i^{th} generator with $\lambda_{P_i} \forall i$ determined by the Lagrange multiplier of the equality constraints in Eqn. (6.29) of the lower level DC-OPF problem, which is the simplest version of above DC-OPF one as:

$$\text{Max: } \sum_{j=1}^{J} (d_j D_j - e_j D_j^2) \qquad (6.28)$$

$$\text{subject to: } \sum_{i=1}^{I_k \in I} P_i - F_{km} = \sum_{j=1}^{J_k \in J} D_j \qquad (6.29)$$
$$\text{where } F_{km} = \sum_{km/mk \in BR} B_{km} \left(\delta_k - \delta_m\right)$$

$$-F_{km}^U \leq F_{km} \leq F_{km}^U \; \forall k, m = 1, 2, ..., K \qquad (6.30)$$

Like SFE model, $(d_j, \, e_j)$ and D_j are the coefficients of the demand function and electricity demand of the j^{th} consumer, respectively, J the number of consumers, and δ_k the voltage angle (in radians) at node $k, \forall k \in K, \; k \neq 1$ as δ_1 considered the reference bus with a fixed value of 0.

6.4 Solution Approach

As discussed in Chapter 2, solving the SFE and Cournot models has gained a great deal of attention over the last decade. As both involve difficult mathematical properties in the objective function, including multi-modality, non-convexity and non-differentiability, compared with classical techniques, various evolutionary algorithms (EAs) are now generating interest in the research community for solving this problem. In many of them, a conventional iterative (IT) approach is used to determine the optimal bidding strategies of all participating players, with each strategy updated sequentially by one in an iteration to maximize its profit while those of its rivals remain unchanged. This process continues until the bidding strategy of a player improves, with the algorithm terminated as soon as a Nash equilibrium (NE) is reached. The NE is a stable state of a game in which a player cannot improve its profit unilaterally given that the actions of its rivals remain unchanged [47].

6.4.1 Motivation

As previously mentioned, most existing methods solve the bidding problems of bidders one after the other which may take too long when there are many bidders and is one of the issues addressed in this chapter. Also as, in most of the abovementioned methods, game-based bidding strategies are used, the bids are represented as discrete quantities, such as bidding high, medium or low, with the payoff matrices easily determined by computing all possible combinations of the strategies. However, in reality, as a player in an energy market submits its bid within a given range, as the size of the payoff matrix becomes infinite, it is impossible to evaluate all the combinations [13]. Moreover, current methods determine a single NE which is not adequate for an energy market as, even if it is perfect, the possibilities of there being other equilibria cannot be ignored [24]. Therefore, to address the abovementioned issues, in this chapter, two CE approaches those detect multiple solutions in a single run are implemented.

6.5 Proposed Co-evolutionary Approach

In this section, the proposed CE algorithms are presented for solving the bidding problem of an energy market to maximize the individual profit. The algorithms also determine multiple NEs in a single run by anticipating the actions of each player on those of the others. In them, two CE algorithms are designed based on two variants of EAs, such as self-adaptive DE (called CE-DE) and GA (called CE-GA), considering $N-$subpopulations for $N-$players are developed in which, in each subpopulation, the actions of a player (say, x) are optimized with respect to those of its rivals. In the initial generation, N_P actions of each subpopulation are randomly assigned based on Eqn. (6.31) and then evaluated. As, to evaluate an individual of a player ($n \in N$), it is necessary to know the set of best individuals (let x_n^*, $n = 1, 2, \ldots, N$) of its rivals, it is initially assumed that the initial individuals are the best individuals of the other players, that is, $x_n^* \in x_n$, $n = 1, 2, .., N$. Once all the individuals in a subpopulation are evaluated, the Nash non-dominated sorting (NNDS) algorithm derived from well known fast non-dominated sorting (NDS) mechanism [20] is run to determine their ranks, as shown in Algorithm 6.6. Subsequently, the best individuals of a player are updated based on the first non-dominated rank ($nd\_rank = 1$) and their FVs, as described in subsection 6.5.5. In subsequent generations, the offspring are generated by evolving the parents using either a self-adaptive DE (variant-1) or real coded GA (variant-2) with this process continuing until a stopping criterion is met. The pseudo-code of the proposed CE solution approach is shown in Algorithm 6.3 and details of its components provided in subsequent subsections.

6.5.1 Initial Generation

A CE algorithm starts with a number of subpopulations, each of which has N_P random individuals. Considering that N players participate in a game, each of which has its own sub-population, an individual in the $n-$subpopulation is initialized as:

Algorithm 6.3 CE solution approach

```
Require: $N_P$, $N_G > 1$ and $N$
 1: Set $g = 0$
 2: Randomly generate initial individuals in each subpopulation using Eqn. (6.31)
 3: Set random best individuals, as $x_n^* \subseteq x_n \forall n$
 4: for $n = 1 : N$ do
 5:     Evaluate $FVs$ of all $N_P$ individuals using the Algorithm-6.4
 6:     Determine the rank of the individuals with updating best ones ($x_n^*$) by performing
        NNDS, in Algorithm-6.6.
 7: end for
 8: for $g = 1 : N_G$ do     ▷ $g$ and $N_G$ is the current and maximum generation number,
    respectively.
 9:     for $n = 1 : N$ do
10:         for $p = 1 : N_P$ do
11:             Replace the redundant individuals as in section 6.5.6
12:             Generate a child $y_{n,p}$ by evolving $x_n$ using either GA or DE operators
13:             Evaluate $FVs$ of both $x_{n,p}$ and $y_{n,p}$ using Algorithm-6.4.
14:             Accept $x_{n,p}$ or $y_{n,p}$ based on Algorithm-6.5.
15:         end for
16:         Repeat step 6
17:     end for
18:     Terminate, if a stopping criterion is met, described in section 6.5.5
19: end for
```

$$x_{p,n} = x_{\min}^n + (x_{\max}^n - x_{\min}^n)\ \mathrm{LHS}(N_P) \tag{6.31}$$

$$p = 1, 2, \ldots, N_P,\ n = 1, 2, \ldots, N$$

where $x_n \in [(k_g, k_d), P]$ are the decision variables for the SFE (subsection 6.3.1) and Cournot (subsection 6.3.2) models, respectively. The minimum (x_{min}) and maximum (x_{max}) limits are found from their respective limits. The number of players (N) depends on the problem size, that is, $N = I,\ I+J$, for the Cournot, and SFE models, respectively. $LHS(N_P)$ represents the N_P random individuals generated using LHS as described previous section.

6.5.2 Evaluation

As previously mentioned, the objective function of a player is to maximize its own profit by modifying its bidding action with respect to those of its rivals. From the profit functions of Eqns. (6.24) to (6.26), it can be seen that, when a player evaluates its own fitness function, the values of the others must be known. Therefore, the FFE of an individual in a subpopulation ($p \in N_P$) for a player ($n \in N$) depends on both its own and its opponents' bidding actions. Since selecting rivals' bidding actions is difficult, the sets of best bidding actions found in the previous generation is used. This process is illustrated by an example that assumes the market has two strategic players: the individuals of player-1 in generation $g+1$ are evaluated by taking the set of best bidding actions of player-2 from its previous generation (g); if there is more than one but less than N_P best individuals, to evaluate all of those of player-1 in generation $g+1$, its rivals' strategies are randomly chosen ensuring that each performs at least once. For an $N-$player game, the FFEs of N_x individuals of a player in subpopulation$-n$ are presented in Algorithm 6.4.

Algorithm 6.4 The process of FFEs of single player

```
Require: $x_{i,n}$   $i = 1, 2, ..., N_x$ and $n \in N$
Require: A set of best bidding actions of $n^{th}$ player's rivals, as $\{x_k^*\}$,   $k = 1, 2, ..., N$,   $k \neq n$
Determine the size of each $\{x_k^*\}$, as $N_{best_k} = \text{size}(\{x_k^*\})$,   $k = 1, 2, ..., N$,   $k \neq n$
for $i = 1 : N_x$ do
    Set an empty vector, $\overrightarrow{xo} = \varnothing$   ▷ $xo$ represents operating $x$ and $\varnothing$ an empty set
    for $k = 1 : N$ do
        if $k \neq n$ then
            Update, $\overrightarrow{xo}_k = x_{k,r}^*$, where, $\mathbb{Z}r \in [1, N_{best_k}]$
        else                                                   ▷ take the current individual
            Update, $\overrightarrow{xo}_k = x_{i,k}$
        end if
        Evaluate FV by supplying a $\overrightarrow{xo}$ to the respective player's profit function
    end for
    Update, $x_{i,k} = \overrightarrow{xo}_k$   $k = 1, 2, ..N$
end for
Return, $FVs$ and $x$
```

6.5.3 Update Bidding Actions

To update the bidding actions of each player, a GA and DE are used for the CE-GA and CE-DE algorithms, respectively. The search operators GA and DE are discussed in sections 3.5.2 and 3.5.3, respectively.

6.5.4 Selection

To select an individual, a greedy scheme is used in which the fittest (according to the FVs) of two candidates, a parent and its child, is chosen. However, as the problem considered in this study involves maximizing the profits of a number of players ($N > 1$), a direct greedy method is not appropriate. Therefore, the new selection criteria described below are proposed.

Consider an $N-$player game with a player's parent and offspring are x_1 and x_2, respectively and a set of best actions of its rivals, y^*. The payoffs for x_1 and x_2 are $FV(x_1, y^*)$ and $FV(x_2, y^*)$, respectively, assuming an operator, M where $M(x_1, x_2) = FV(x_1, y^*) > FV(x_2, y^*)$ represents the number of players that benefit if a player uses a x_1 strategy compared with when that player uses of x_2 with the same best bidding actions of its rivals, *i.e.*, y^*. Then, the potential relationships between x_1 and x_2 are:

1. $M(x_1, x_2) = N$: x_1 is strictly non-dominated by x_2
2. $M(x_2, x_1) = N$: x_2 is strictly non-dominated by x_1
3. $M(x_1, x_2) = M(x_2, x_1) \neq N$: neither is x_1 strictly non-dominated by x_2 nor x_2 strictly non-dominated by x_1

Proposition 1. *A strictly non-dominated solution is a global NE.*

***Proof*.** Let $x^* \in x$ be a solution strictly non-dominated by another solution, $x_1 \in x$. Suppose that, x^* is not a global NE, but, x_1 is an equilibrium *i.e.*, there must be at least one player, $n \in N$ that benefits when using x_1 but not x^*, as:

$$M(x_1, x^*) = FV(x_1, y^*) > FV(x^*, y^*) \geq 1 \tag{6.32}$$

However, $M(x_1, x^*) = 0$ when x^* is strictly nondominated by x_1 which means that x^* is a global NE.

As for criterion-3, neither solution is a global NE, the self-benefit criteria is used to select the individuals in order to drive the solutions towards the global NE space;

for example, if $FV(x_1, y^*) = [10, 8]$, $FV(x_2, y^*) = [9, 10]$ and the operating player is $n = 1$, since $FV_n(x_1, y^*) > FV_n(x_2, y^*)$ (*i.e.*, $10 > 9$), x_1 survives to the next generation. Details of these criteria for selecting an individual from a parent (x_1) and its child (x_2) are provided in Algorithm 6.5.

Algorithm 6.5 Criteria for selecting parent or child

```
Require: A parent, $x_1$, and a child, $x_2$, with their FVs, as $FV(x_1, y^*)$ and $FV(x_2, y^*)$,
         respectively
Require: $n \leftarrow$ Index of player is currently operating
Determine, $M(x_1, x_2)$ and $M(x_2, x_1)$
if $M(x_1, x_2) = N$ then                                  ▷ parent is good
    $x = x_1$                                              ▷ select parent
else if $M(x_2, x_1) = N$ then                             ▷ child is good
    $x = x_2$                                              ▷ select child
else if $FV_n(x_1, y^*) > FV_n(x_2, y^*)$ then   ▷ is FV of $n^{th}$ player better for parent?
    $x = x_1$                                              ▷ select parent
else                                     ▷ the FV of $n^{th}$ player better for child
    $x = x_2$                                              ▷ select child
end if
Return, $x$
```

6.5.5 Ranking Individuals

Once all the better-performing individuals in a subpopulation are selected, they are further ranked to determine the best ones for evaluating the next generations. This is achieved using Algorithm 6.6 which is developed based on the concept of the NDS approach [20] and called the NNDS.

Algorithm 6.6 Ranking individuals using NNDS

```
Require: The individuals, $x$ of a subpopulation, $n$
Determine $nd\_rank(x)$ using the NDS approach [20]
Take the $n^{th}$ player's individuals, $x_n \subset x$
Set, $X = \varnothing$ and $xBest = \varnothing$          ▷ $\varnothing$ is a symbol for the empty set
for $k = 1 : \max(nd\_rank)$ do
    Get, $x_{n,k} \subset x_n$ based on the $k^{th}$ $nd\_rank$
    Update, $x_{n,k} = \text{sort}(x_{n,k})$ based on $n^{th}$ player's $FVs$
    Update, $X = [X, x_{n,k}]$
    if $k = 1$ then                                ▷ Update the best individuals
        $xBest_n = xn_k$
    end if
end for
Return, $x \leftarrow X$ and $x^* \leftarrow xBest$
```

In the NNDS, firstly, the individuals are ranked based on the conventional NDS approach which means that those better for all players receive nd_rank=1 and those worse for all players a maximum nd_rank, and so on, as explained in following example.

1. x_1 is non-dominated by x_2 if $M(x_1, x_2) > M(x_2, x_1)$, *i.e.*, $nd\_rank(x_1) = 1$ and $nd\_rank(x_2) = 2$
2. x_2 is non-dominated by x_1 if $M(x_2, x_1) > M(x_1, x_2)$, *i.e.*, $nd\_rank(x_2) = 1$ and $nd\_rank(x_1) = 2$
3. x_1 and x_2 are indifferent if $M(x_1, x_2) = M(x_2, x_1)$, *i.e.*, $nd\_rank(x_1) = nd\_rank(x_2) = 1$

To determine the best set of actions of each player, the individuals with $nd\_rank = 1$ is sleeted. These solutions are actually the NEs found so far, as proven in proposition-2.

Proposition 2. *The solutions with* $nd\_rank = 1$ *are NE*s.

Proof. Suppose that $x^* \in x$ is a solution with $nd\_rank = 1$ but not an NE. Let $x_1 \in x$ be another solution with $nd\_rank > 1$ but an NE, *i.e.*, there must be at least one player that obtain a benefit using x_1 rather than x^*, such as:

$$M(x_1, x^*) = FV(x_1, y^*) > FV(x^*, y^*) \geq 1 \tag{6.33}$$

However, it is necessary that $M(x_1, x^*) = 0$ satisfies the conditions of the NNDS approach. Therefore, $M(x^*, x_1) = FV(x^*, y^*) > FV(x_1, y^*) \geq 1$ which indicates that x^* is an NE because $\nexists x_1 \in x$, $x_1 \neq x^*$ such that $M(x_1, x^*) > M(x^*, x_1)$.

6.5.6 Maintaining Diversity

As, if there are redundant individuals in a subpopulation, which is possible, the performance of the optimization algorithm can be affected. Any redundant individual is replaced by a random solution generated using Eqn. (6.31). To allow the algorithm to concentrate on high-quality solutions during the later stages of the evolution, the process continues until the algorithm reaches half the N_G.

6.5.7 Stopping criteria

In this study, two stopping criteria are considered:

1. the maximum number of generations (N_G) is reached; and
2. both the maximum number of generations is reached to $N_G/2$ and the best bidding actions are no longer improved for a predefined number of generations, θ.

Criteria 1 and 2 affect the run time and solution optimality, respectively. When only criterion 1 is used, N_G is difficult to define because different systems have different convergence characteristics. Therefore, when both criteria 1 and 2 are used simultaneously, the solution optimality is possibly guaranteed [240].

6.5.8 Solution Approaches for Lower-Level Optimization Problem

As seen in section 6.3, a nonlinear DC-OPF optimization problem is required to solve when a profit function of the bidding problem in Eqns. (6.24), to (6.26) is evaluated. This problem is used in the lower level of the competitive bi-level SFE model and treated as a single-objective optimization problem in a non-competitive market. For verification purposes, it is solved using three different approaches, such as (i) a classical IP optimization technique, (ii) a real-coded GA, and (ii) a self-adaptive DE. A brief description of an IP method is described in section 2.7.1 while the operators of GA and DE presented in sections 3.5.2 and 3.5.3, respectively.

6.6 Experimental Study

For the experimental study, the wide range of game-based bidding problems of the real-life electricity markets are solved. Besides, to verify the proposed methods in solving the different games, four standard test functions are considered. The considered problems are:

1. four standard test functions;

2. a Cournot model of the *IEEE* 2-bus system; and
3. a SFE model of the *IEEE* 3- and 30-bus systems.

Each test problem is solved using the proposed CE approaches based on (i) GA (called the CE-GA) and (ii) DE (called the CE-DE) algorithms. Also, to validate these methods, two conventional iterative (IT) line search algorithms [174], one based on GA (called IT-GA) and the other on DE (called IT-DE) [241] are adopted. In them, in each iteration, a player optimizes its bidding strategy given its rivals have fixed actions. To start a game, each player randomly chooses its action assuming that random strategies are used by the other players and then optimizes its own action with respect to those of the other players. In the following generations, either GA or DE search operators are used to generate a better-quality strategy from its parents. Once a player obtains its optimal bidding strategy, the first iteration is over. Then, the next player begins to optimize its own strategy using the same process while considering the best bidding strategies of its rivals found so far. This iterative process is terminated when either no player is able to change its action in θ generations or the maximum number of iterations ($MaxIt$) is reached.

The GA parameters, the probabilities of crossover and mutation, are set to 0.9 and 0.1, respectively. Based on the empirical analysis discussed in subsection 6.6.3, the values of θ, N_P, N_G, and $MaxIt$ are set to 5, 40, 100 and 10, respectively. Thirty independent runs are performed for each test case and the solutions recorded, with the median one based on the average profits reported. Moreover, the NEs obtained by the CE algorithms are verified by performing a Gambit simulation [242] in which the final results consider the pure strategies of the players, with their payoff matrices further evaluated to determine all the equilibrium points through configuring the Gambit software as “Compute all Nash Equilibria” [242][13].

6.6.1 Test Problems

In this subsection, four standard continuous test functions are solved, each of which has two competitive players that optimize their decision variables within a range to maximize their own profits with respect to those of their rivals [172, 229]. Four test functions are considered: (i) the Cournot model of duopoly; (ii) the partnership game; and (iii) and (iv) examples from [172], with their respective payoff functions:

$$\begin{aligned} \pi_i(q_i, q_j) &= q_i(24 - (q_i + q_j) - 5) \\ 0 \le q_i \le 100&, \forall i, j = 1, 2;\ i \neq j \end{aligned} \tag{6.34}$$

$$\begin{aligned} \pi_i(q_i, q_j) &= p_c/2 - q_i^2 \\ 0 \le q_i \le 4&, \forall i, j = 1, 2,\ i \neq j \\ p_c &= 4(q_1 + q_2 + 0.2q_1q_2) \end{aligned} \tag{6.35}$$

$$\begin{aligned} \pi_1 &= q_1 \\ \pi_2 &= (0.5 - q_1)q_2 \\ 0 \le q_1 &\le 0.5 \quad 0 \le q_2 \le 1 \end{aligned} \tag{6.36}$$

$$\begin{aligned} \pi_i = \frac{1}{4}(q_i + q_j)(100 - q_i) - (100 - q_i)(200 - \\ q_i - 0.001q_iq_j) \\ 0 \le q_i \le 100, \forall i, j = 1, 2,\ i \neq j \end{aligned} \tag{6.37}$$

where π_i is the profit (payoff) of the i^{th} player and q_1 and q_2 the strategic variables optimized to maximize π_i, $i \in \{1, 2\}$. The analytical results obtained of their resulting NEs are $(5, 5)$, $(1.25, 1.25)$, $(0.5, 0 \sim 1)$, and (48.98, 48.98) for test problems 1, 2, 3 and 4, respectively [172].

Now, these problems are solved using the CE-GA, CE-DE, IT-GA and IT-DE algorithms and their results for bidding actions and payoffs illustrated in Fig. 6.2 to 6.5, respectively. It can be seen that the IT algorithms find a single NE and the CE-based

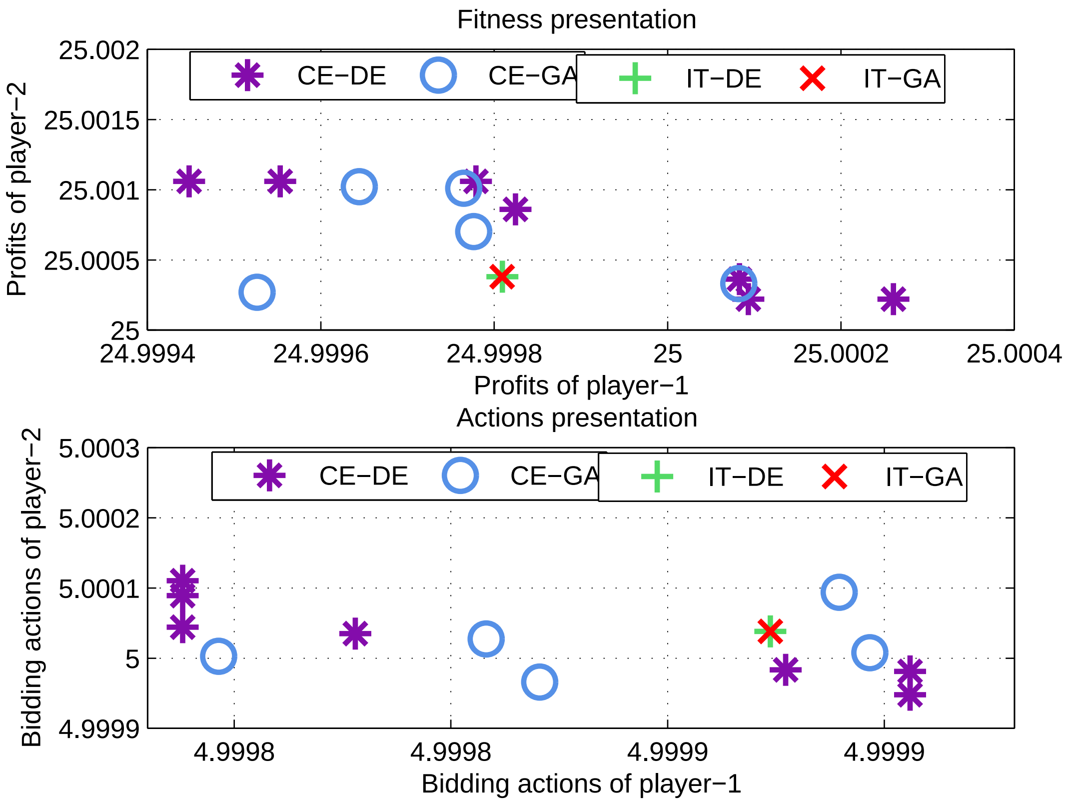

Fig. 6.2: Profits and actions obtained by CE and IT approaches for test problem-1

ones several. Also, the CE based algorithms maximize their payoff values than those of the IT ones, with CE-DE obtaining the best results in terms of maximizing profits.

To demonstrate the performances of the CE algorithms, their results are compared for detecting a number of NEs (nNEs), the FFEs they require for each run and their simulation times with those of the IT algorithms, as presented in Table 6.1, with the results showing that the CE algorithms require fewer FFEs than the IT ones and CE-DE is the best of all the algorithms. Moreover, the CE-DE identifies the maximum numbers of NEs for all test functions while the IT based approaches find one.

6.6.2 Bidding Problems

As previously mentioned, the game-based bidding problem is formulated as a bi-level optimization problem with the upper-level profit maximization of each individual bidder solved using the proposed CE-GA and CE-DE, and conventional IT-GA and IT-DE algorithms. To solve the lower-level DC-OPF problem, a suitable algorithm among three

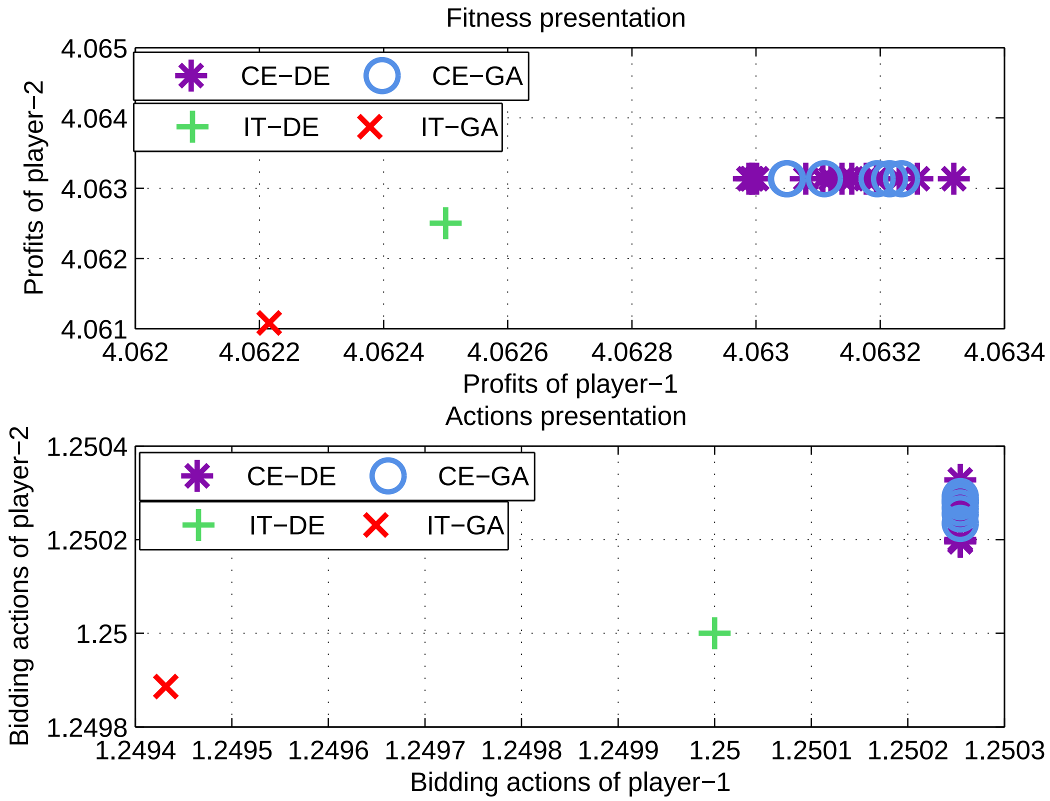

Fig. 6.3: Profits and actions obtained by CE and IT approaches for test problem-2

Table 6.1: Summary of results for test functions

		Algorithms			
		IT-GA [241]	IT-DE [241]	CE-GA	CE-DE
Test problem-1	FFEs	41050	41050	16080	**10160**
	Time (sec.)	8.16	6.91	3.36	**3.29**
	nNE	1	1	5	**7**
Test problem-2	FFEs	27366	27366	16080	**13520**
	Time (sec.)	7.45	4.36	3.24	**3.12**
	nNE	1	1	6	**14**
Test problem-3	FFEs	27366	27846	16080	**16080**
	Time (sec.)	7.32	6.34	3.47	**3.31**
	nNE	1	1	14	**40**
Test problem-4	FFEs	41050	31927	16080	**9900**
	Time (sec.)	11.14	5.22	3.37	**3.29**
	nNE	1	1	4	**10**

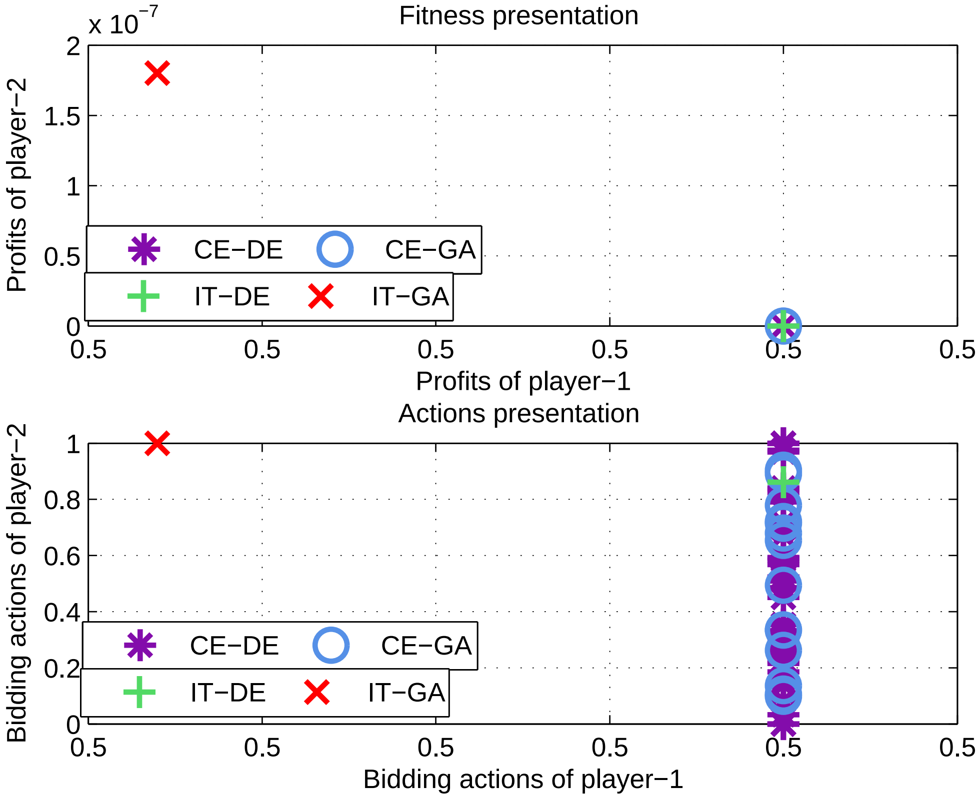

Fig. 6.4: Profits and actions obtained by CE and IT approaches for test problem-3

considered ones, such as , IP, GA and DE is determined. Because, if the lower level algorithm provides a local solution and/or takes long time to compute, the higher level CE based algorithms cannot perform well. Therefore, at first, the market is considered non-competitive, all the participating GENCOs and consumers are considered as non-strategic with their bidding coefficients set to 1 [47]. In other words, neither GENCOs nor consumers are allowed to maximize their profits but, rather, always play with their true marginal cost and demand functions in Eqns. (6.2) and (6.5) for GENCOs and consumers, respectively. Therefore, as this bi-level problem has no longer upper level, it becomes a single-objective optimization one of DC-OPF problem, which aims to maximize the CSW, and is solved using the (i) E-GA, (ii) E-DE and (iii) IP algorithms. Since the smaller number of generators are involved in the bidding problem, the best parameters of GA and DE those found in previous Chapter in solving 5-unit thermal problem of Table 5.1 are used for solving the DC-OPF one, and the $MaxIt$ set to a value of 1000 for IP algorithm.

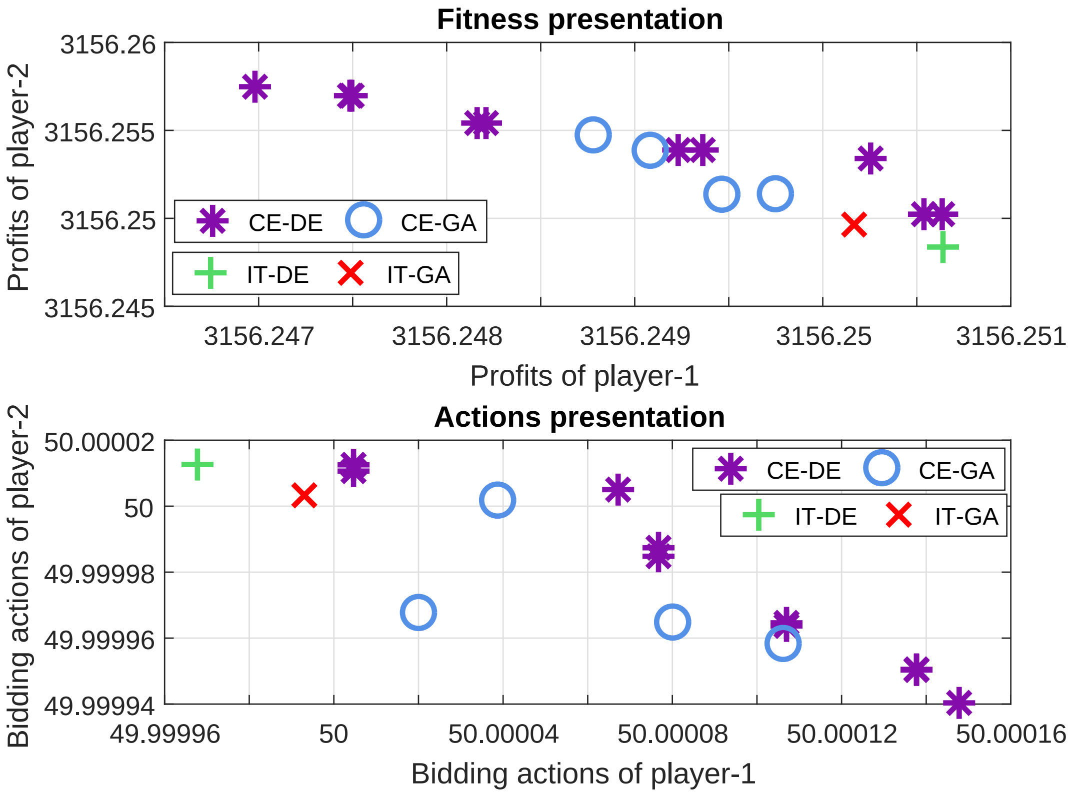

Fig. 6.5: Profits and actions obtained by CE and IT approaches for test problem-4

After 30 independent runs of each algorithm for solving each energy market;s problem, their average results and the results in the literature, such as those from EBA [47], BA [47], PSO [47], GA [47] and NCP [243], including the CSW and computational time, are presented in Table 6.2. Note that, for solving DC-OPF problem using IP method, the developed matrix representation in Eqns. (6.21) to (6.23) for the SCQP problem is used while if they are solved using GA and DE algorithms, a non-convex formulation of Eqns. (6.15) to (6.20) is used. The simulation results for the DC-OPF problem for considered bidding problems are presented in Table 6.2 in which, the profits of each algorithm are quite similar while the computational time of IP is much lower than those of the others.

As the lower level of the problem has to be optimized in every generation, to be used in the evaluation of the objective function in the upper one, which is computationally expensive to solve using an EA, the IP method with the SCQP formulation is used to solve the lower level problem in the bi-level bidding problem. For all problems, the $MaxIt$ is set to the value of 1000.

Table 6.2: Caparisons of different algorithms for solving lower-level DC-OPF problems

Algorithm	2-bus		3-bus		30-bus	
	CSW	Time	CSW	Time	CSW	Time
	($)	(sec.)	($)	(sec.)	($)	(sec.)
EBA [47]	NR	NR	**6212.05**	0.96	NR	NR
BA [47]	NR	NR	6212.05	0.96	NR	NR
PSO [47]	NR	NR	6212.05	0.96	NR	NR
GA [47]	NR	NR	6212.05	0.96	NR	NR
NCP [243]	NR	NR	6212.10	NR	NR	NR
E-GA	10000.04	27.14	6212.06	47.08	**18453.88**	94.09
E-DE	**10000.09**	25.58	6212.06	30.09	**18453.88**	62.28
IP	10000.00	**0.01**	6212.06	**0.01**	**18453.88**	**0.08**

For solving the bidding problems using the proposed CE-DE and CE-GA algorithms, each problem considers the following three cases.

- Case I: consumers are non-strategic, and TLs ignored
- Case II: consumers are non-strategic, and TLs considered
- Case III: consumers are strategic, and TLs considered

A strategic customer is one that can participate in the bidding process which increases the number of players in that game while, in a non-strategic customer game, the number of players is reduced to the number of GENCOs with customers only able to buy a predefined amount of electricity from the market. Also, if the problem considers the capacity constraints of a TL, the optimization space of the problem becomes discrete which means that it has multiple NEs [24]. Details of each test problem are provided below.

A IEEE 2-bus system

At first, a modified IEEE 2-bus Cournot game is solved which qualitatively similarly to the California model [174] shown in Fig. 6.6. Its formulation is discussed in subsection 6.3.2 and, for cases I and II, F_{12}^{U} is set to 80 and 55 MW, respectively [174].

For case I, a strategy of $(148, 148)$ with the payoff of $(1.39E{+}3, 1.39E{+}3)$ is found in [174] as well as obtained from the conventional IT-DE and IT-GA algorithms. The CE-DE and CE-GA algorithms determine several NEs with a fixed payoff, as shown in Fig.

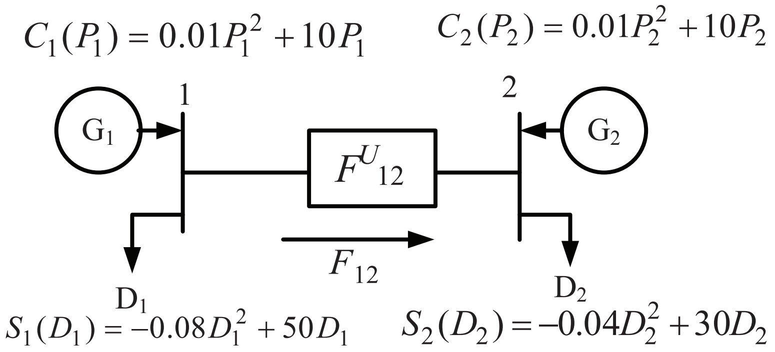

Fig. 6.6: 2 bus Cournot model

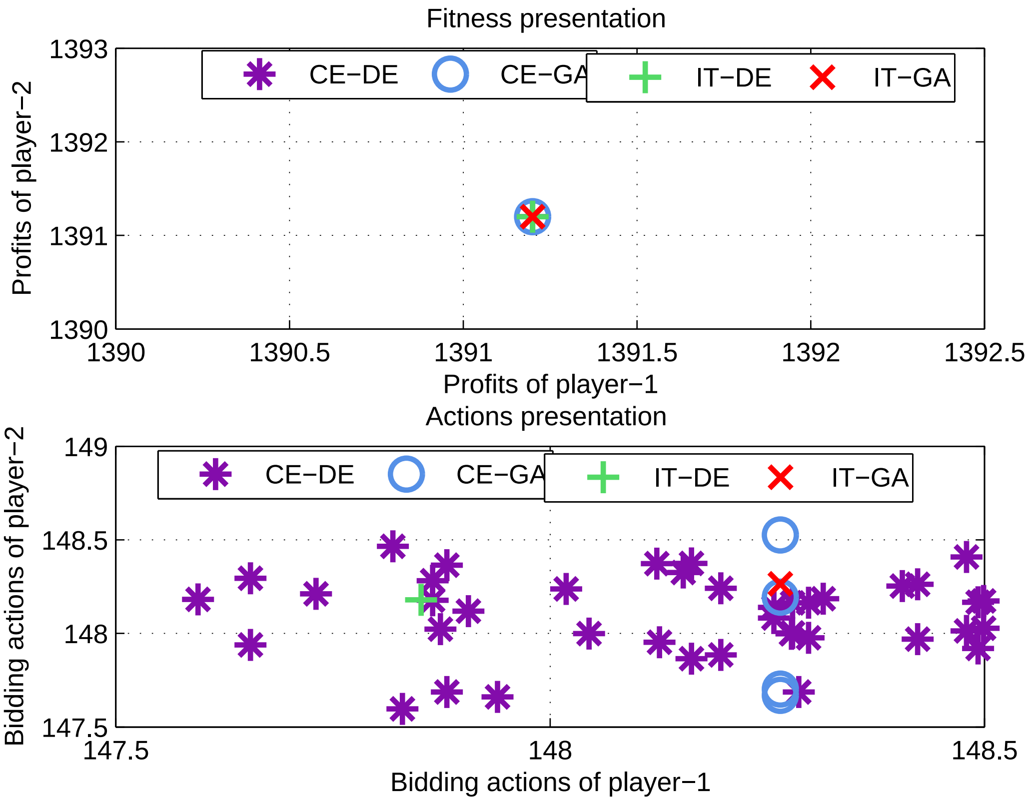

Fig. 6.7: Profits and actions obtained by CE and IT approaches for IEEE 2-bus system (case I)

6.7. For case II, although the local search algorithms obtain different NEs of (148, 148), (92, 136) and (153, 136) from different runs, it is proven that, except for (148, 148), the solutions are local NEs [174]. On the other hand, the proposed CE algorithms obtain a number of NEs, as shown in Fig. 6.8, all of which are verified by the Gambit simulation.

By comparing the FFEs and simulation times of the IT- and CE-based algorithms

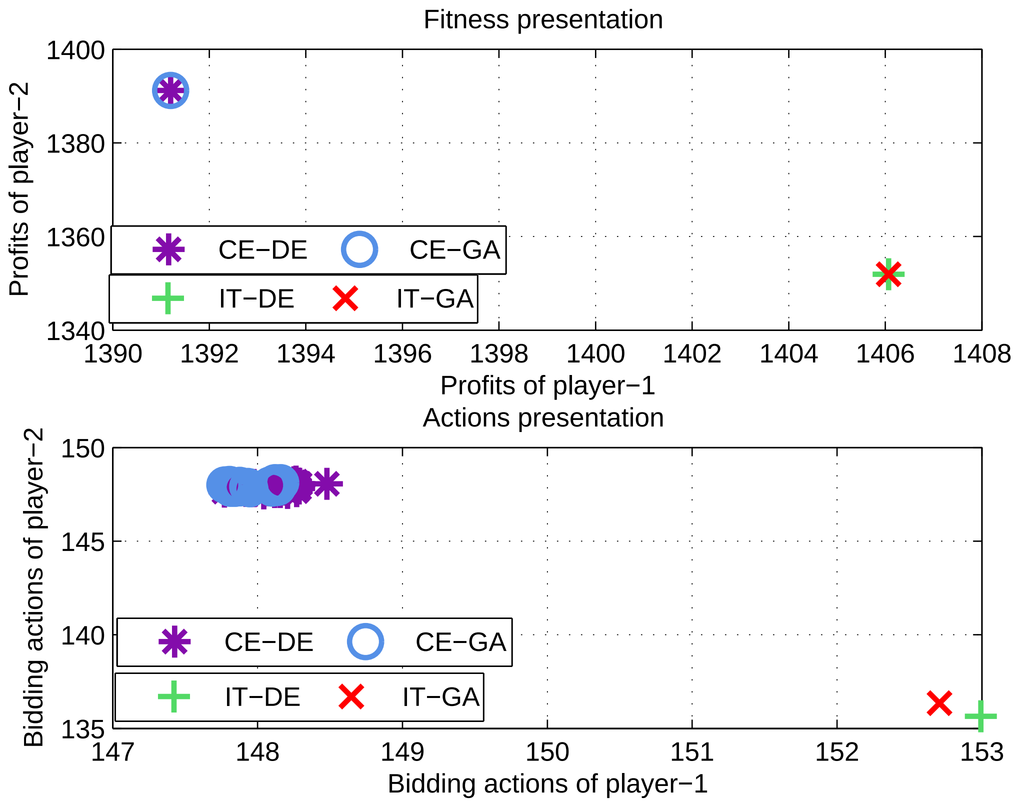

Fig. 6.8: Profits and actions obtained by CE and IT approaches for IEEE 2-bus system (case II)

Table 6.3: Summary of results for IEEE 2 bus system

Algorithm	Case I			Case II		
	FFEs	Time (min.)	nNE	FFEs	Time (min.)	nNE
IT-GA [241]	41040	9.10	1	45600	10.84	1
IT-DE [241]	45560	9.05	1	48560	11.46	1
CE-GA	16080	3.63	4	16080	3.81	15
CE-DE	16080	2.61	40	16080	3.30	40

for cases I and II, as shown in Table 6.3, it is proven that the proposed CE algorithms are very efficient, even after obtaining multiple NEs, with CE-DE the best in terms of its nNEs, FFEs and computational time.

B IEEE 3-bus system

The *IEEE* 3-bus test system is formulated as a SFE model assuming that the bidding action involves the cost coefficients of the respective generator and consumer as $k_g \in$

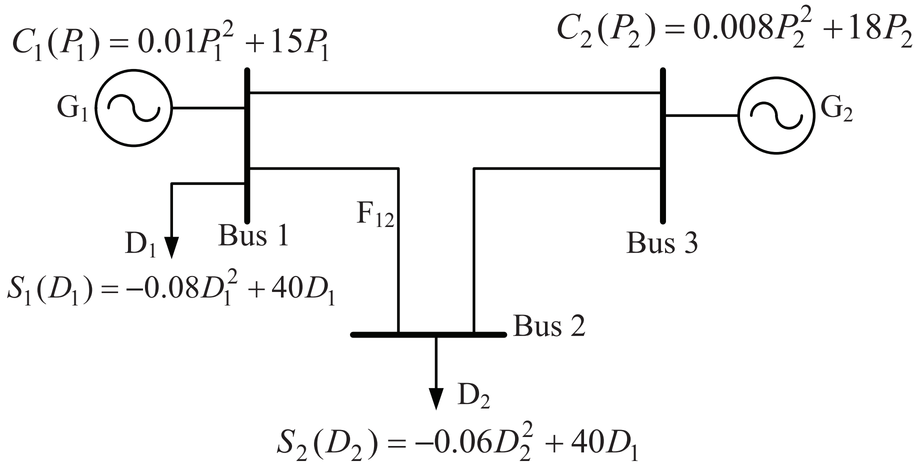

Fig. 6.9: IEEE 3 bus system

$[1.0, 2.5]$, and $k_d \in [0.1, 1.0]$, respectively [47]. Its mathematical formulation is provided in subsection 6.3.1 and its parameters depicted in Fig. 6.9 which shows that it consists of two generators at nodes 1 and 3, two consumers at nodes 1 and 2, and three TLs considered lossless with equal reactance values of $x = 0.002$. The TL capacity of F_{12}^U is set to 500 MW for case I and 25 MW for cases II and III while the capacity limits of the other TLs are ignored.

Once cases I and II of this system are solved using the CE- and IT- based algorithms, their final results as well as those of the state-of-the-art algorithms, such as GA, PSO, Bat-inspired algorithm (BA), enhanced BA (EBA) [47] and mixed nonlinear complementarity problem's algorithm (NCP) [243] are illustrated in Fig. 6.10 and 6.11, respectively, with the proposed CE approaches obtaining multiple equilibria. Nevertheless, it is seen in the Gambit software that the solutions of other algorithms are rejected (*i.e.*, not an NE) by the CE algorithms' results.

For case III, as the consumers participate in the bidding market, there are four players. Since it is difficult to present the results visually, the obtained mean values of the bidding actions and payoffs from each algorithm are tabulated in Table 6.4. One can observe that the results are very consistent. The numbers of FFEs, computational times and nNEs presented in Table 6.5 for all three cases indicate that CE-DE is the best algorithm.

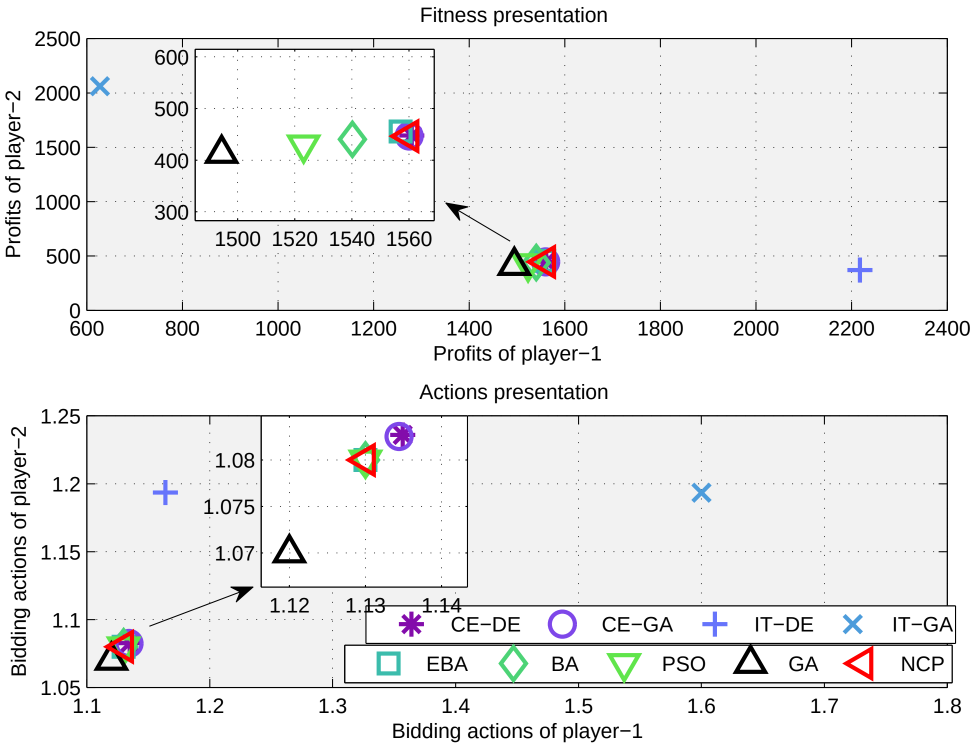

Fig. 6.10: Profits and actions obtained by CE and IT approaches for IEEE 3-bus system (case I)

Table 6.4: Bidding actions and payoffs obtained by CE and IT approaches for IEEE 3-bus system (case III)

Alg.	Actions				Payoff			
	P-1	P-2	P-3	P-4	P-1	P-2	P-3	P-4
IT-GA [241]	1.36	1.18	0.92	0.82	762.36	1093.81	1988.80	1634.91
IT-DE [241]	1.31	1.16	0.90	0.78	766.58	861.24	2117.16	1657.94
CE-GA	1.31	1.16	0.90	0.78	766.98	859.96	2120.15	1656.04
CE-DE	1.31	1.16	0.90	0.78	766.66	861.39	2116.60	1658.40

Table 6.5: Summary of results for IEEE 3-bus system

Alg.	Case I			Case II			Case III		
	FFEs	Time (min.)	nNE	FFEs	Time (min.)	nNE	FFEs	Time (min.)	nNE
IT -GA[241]	45600	5.70	1	27361	2.02	1	54720	4.27	1
IT -DE[241]	45600	4.49	1	27360	1.95	1	54720	4.04	1
CE-GA	**16080**	1.19	3	16080	1.19	**3**	32160	2.33	4
CE-DE	**16080**	**1.17**	**4**	**13040**	**0.95**	**3**	**18080**	**1.31**	**16**

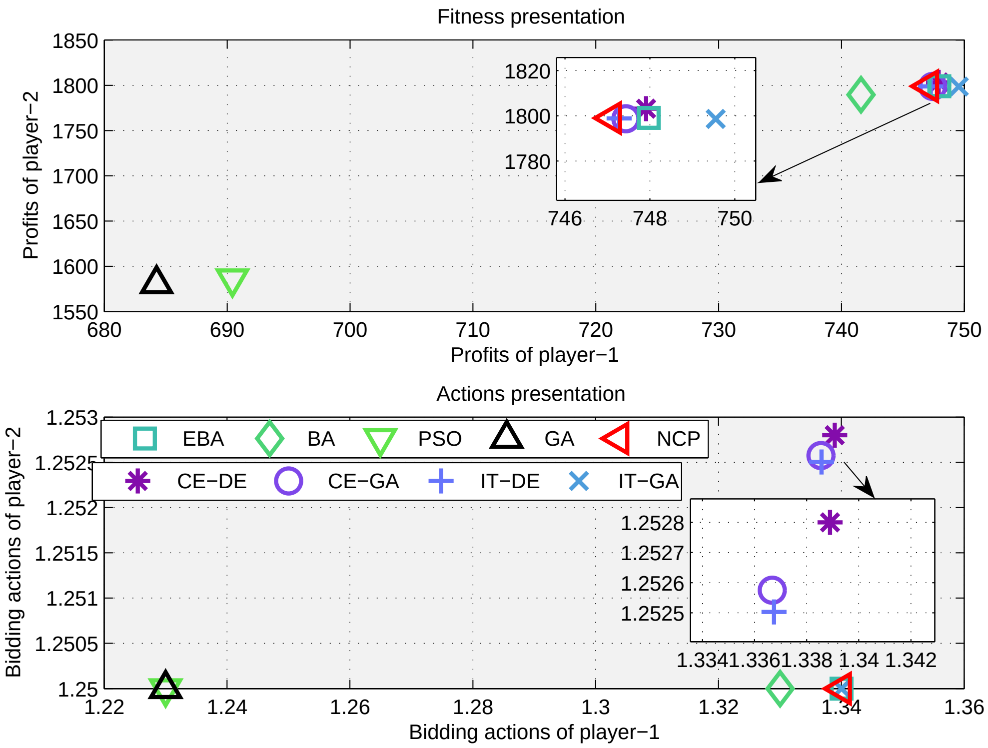

Fig. 6.11: Profits and actions obtained by CE and IT approaches for IEEE 3-bus system (case II)

C IEEE 30-bus system

To demonstrate the effectiveness of the proposed algorithms for a large system, the *IEEE* 30-bus test system, which has up to 26 competitive players with 6 generators, 20 loads, 41 lines and 30 buses, is considered with all the TLs lossless and their reactance values set to 0.001. The system data and schematic diagram are described in [244]. The TLs' capacity limits are ignored for case I while, for cases II and II, $F^U_{6,8}$, $F^U_{17,12}$ and $F^U_{10,17}$ are set to 10, 8 and 10, respectively, and the bidding coefficients of the generators and consumers $k_g \in [1.0, 2.5]$, and $k_d \in [0.1, 1.0]$, respectively. All the cases are solved using all the algorithms, with a summary of their results presented in Table 6.6 which demonstrates that there is a global NE in case I and multiple ones in cases II and III. However, to obtain these equilibria, conventional methods take longer and require more FFEs than the proposed CE-based approaches. Comparing CE-GA and CE-DE, again, CE-DE is best in terms of nNEs, FFEs and computational times for all cases.

Table 6.6: Summary of results for IEEE 30-bus system

Alg.	Case-I			Case-II			Case-III		
	FFEs	Time (min.)	nNE	FFEs	Time (min.)	nNE	FFEs	Time (min.)	nNE
IT -GA[241]	95760	12.37	1	95760	13.13	1	592800	82.06	1
IT -DE[241]	82080	10.44	1	82080	10.71	1	592840	81.70	1
CE-GA	48240	6.88	1	48240	6.75	13	209040	28.25	16
CE-DE	48240	6.05	1	29520	3.89	21	209040	27.93	40

Table 6.7: Effect of N_P on CE-DE

Problem	$N_P = 20$				$N_P = 40$				$N_P = 60$			
	$MFVs$	FFEs	Time	nNEs	$MFVs$	FFEs	Time	nNEs	FFEs	$MFVs$	Time	nNEs
1	25.00	6521	0.05	4	25.00	10160	0.05	7	25.00	15480	0.05	7
2	4.06	4680	0.03	4	4.06	13520	0.05	14	4.06	16440	0.05	14
3	0.25	8040	0.06	20	0.25	16080	0.06	40	0.25	24120	0.08	60
4	3.16E+03	5160	0.04	6	3.16E+3	9900	0.05	10	3.16E+03	14280	0.05	10
IEEE 2	1.39E+03	8040	1.67	20	1.39E+3	16080	3.3	40	1.39E+03	24120	4.90	60
IEEE 3	1.27E+03	7160	0.58	2	1.27E+3	13040	0.95	3	1.27E+03	18120	1.28	5
IEEE 30	842.81	13800	1.31	14	842.83	29520	3.89	21	842.76	40680	3.84	20

6.6.3 Parametric analysis

In this subsection, the robustness of the proposed CE approaches is evaluated in terms of the means of the mean FVs (MFVs) of all the players, nNEs and run times (in minutes) by analyzing the parameters (i) N_P, (ii) stopping criteria and (iii) convergence plots. To do this, the best-performing algorithm, CE-DE, is used to solve the test problems for case II by following a *ceteris paribus* strategy in which only one parameter is varied while all the others remain fixed to their best values. Then a statistical comparison between IT- and CE-based algorithms with their convergence characteristics are presented.

A Effect of N_P

Three different values of N_P are used to solve the test problems considered, with their results presented in Table 6.7 demonstrating that all their MFVs are almost the same. However, in terms of nNEs, CE-DE with $N_P = 20$ is inferior to CE-DE with $N_P = 40$ and $N_P = 60$ although the computational times and FFVs are much higher for $N_P = 60$. Therefore, it can be stated that N_P does not affect the algorithm's capability to obtain the best MFV, with its value of 40 saving computational time and producing good results.

Table 6.8: Effect of θ on CE-DE

Problem	$\theta = 2$				$\theta = 5$				$\theta = 10$			
	$MFVs$	FFEs	Time	nNEs	$MFVs$	FFEs	Time	nNEs	FFEs	$MFVs$	Time	nNEs
1	25.00	9840	0.04	7	25.00	10160	0.05	7	25.00	12400	0.05	7
2	4.07	10320	0.04	6	4.06	13520	0.05	14	4.06	14480	0.06	14
3	0.25	16080	0.07	40	0.25	16080	0.06	40	0.25	16080	0.07	40
4	3.16E+03	9040	0.04	7	3.16E+3	9900	0.05	10	3.16E+03	10800	0.05	10
IEEE 2	1.39E+03	16080	3.32	40	1.39E+3	16080	3.3	40	1.39E+03	16080	3.54	40
IEEE 3	1.28E+03	9200	0.68	3	1.27E+3	13040	0.95	3	1.28E+03	16080	1.23	3
IEEE 30	842.83	28560	3.03	12	842.83	29520	3.89	21	842.76	35280	3.92	21

Table 6.9: Effect of N_G on CE-DE

Problem	$N_G = 50$				$N_G = 100$				$N_G = 200$			
	$MFVs$	FFEs	Time	nNEs	$MFVs$	FFEs	Time	nNEs	FFEs	$MFVs$	Time	nNEs
1	25.00	8080	0.04	6	25.00	10160	0.05	7	25.00	17040	0.07	9
2	4.07	8080	0.04	13	4.06	13520	0.05	14	4.06	17040	0.07	14
3	0.25	8080	0.04	40	0.25	16080	0.06	40	0.25	32080	0.14	40
4	3.16E+03	8080	0.04	7	3.16E+3	9900	0.05	10	3.16E+03	17040	0.07	11
IEEE 2	1.39E+03	8080	1.74	40	1.39E+3	16080	3.3	40	1.39E+03	32080	6.69	40
IEEE 3	1.28E+03	8080	0.62	2	1.27E+3	13040	0.95	3	1.27E+03	18000	1.32	3
IEEE 30	842.96	24240	2.46	12	842.83	29520	3.89	21	842.74	51120	5.16	21

B Effect of stopping criteria

As previously discussed in subsection 6.5.7, this study uses two different stopping criteria, θ and N_G, the effects of those are analyzed. Firstly, three different θ values (2, 5 and 10) are tested and present their results in Table 6.8 which indicate that they do not have a significant impact on the quality of solutions (MFVs) but higher values increase the computational time. Also, as it is seen that the nNEs are almost the same for θ values of 5 and 10, it is wise to choose one of 5.

Using the best value of $\theta = 5$, CE-DE is run with three different N_G, *i.e.*, 50, 100 and 200, to solve the same problems. The results presented in Table 6.9 indicate that the performance of this algorithm slightly improves when N_G is increased and as, obviously, the computational time also increases, $N_G = 100$ is selected.

C Detection of NE

In this subsection, the process of determining NEs in different generations by solving the *IEEE* 2-bus system for case II using the best-performing algorithm CE-DE is illustrated, with a few samples of some results for nNEs and their locations illustrated in Fig. 6.12. It can be seen that, in the first few generations, the actions of the players are distributed over the optimization area. Then, each subpopulation subsequently seeks its

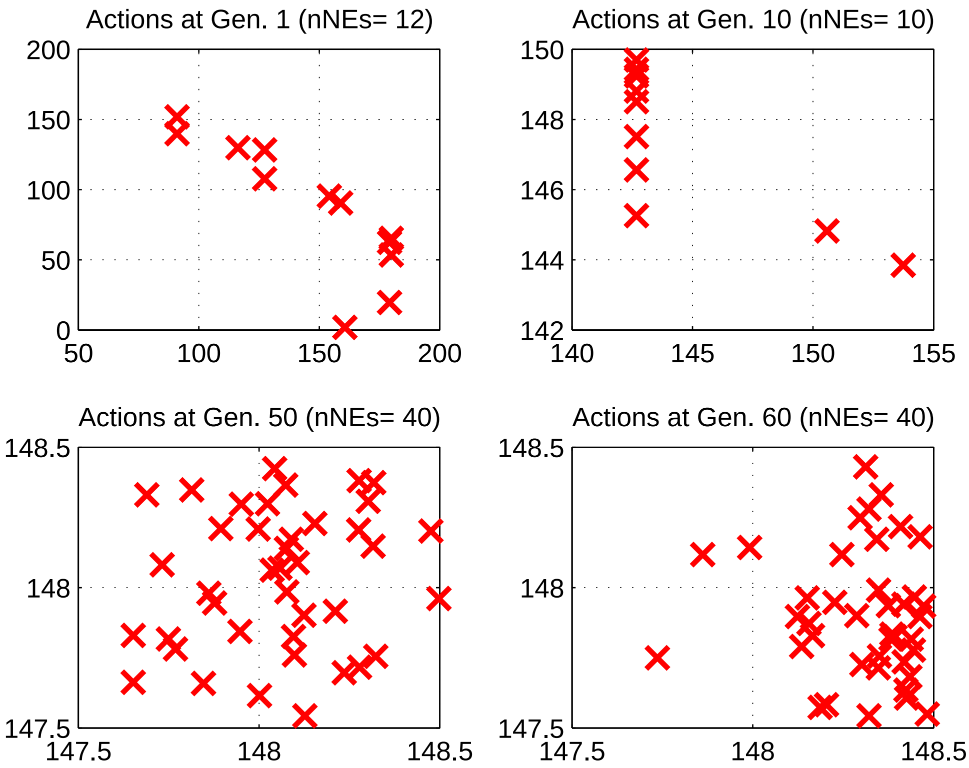

Fig. 6.12: NEs obtained in different generations

own best propagation with respect to its rivals' best actions. After a few generations, the algorithm obtains all the equilibria points which later verified by the professional Gambit software. This means that, although the algorithm initially treats some solutions as NEs, finally, the true NEs are only kept in the solutions.

6.6.4 Comparison CE and IT based Algorithms

In this subsection, the proposed CE based algorithms are statistically compared with those of traditional CE based algorithms. Firstly, an ANOVA test in randomized complete block designs procedures is performed as the number of objective functions (treatments) is more than one. Here, the treatments (samples) are considered the profits of all the players, CSWs and computational times for all considered problems with their case studies, and four algorithms, such as IT-GA, IT-DE, CE-GA and CE-DE considered as a block. The null and alternative hypothesizes are defined, respectively, as:

Table 6.10: ANOVA analysis for all the considered test problems

	SS	df	MS	F	$P-$value	F_{crit}	Comments
Algorithms	4.01E+04	3	1.34E+04	4.36	0.0047	2.62	$F > F_{crit}$
Treatments	2.41E+10	196	1.23E+08	40136.57	0.00	1.21	$F > F_{crit}$
Error	1.80E+06	588	3.06E+03				
Total	2.41E+10	787	1.23E+08				

$$H_0 : \alpha_1 = \alpha_2 = \alpha_3 = \cdots = \alpha_k = 0 \tag{6.38}$$

$$H_1 : \text{ At least one of the } \alpha_i \text{is not equal to zero} \tag{6.39}$$

where α_i is the effect of the i^{th} treatment. The null hypothesis H_0 is tested at the 5% level of significance, that assumes, all the algorithms provide the solutions with the same mean value. The test results of 'sum of squares (SS)', 'degree of freedom (df)', 'mean square (MS)', computed F and critical F_{crit} with the $P-$values for both algorithms and treatments are presented in Table 6.10. From the results, the smaller the $P-$values (< 0.05) and the meeting the constraint $F > F_{crit}$ demonstrate the evidence to against the null hypothesis, H_O. Therefore, the solutions from the all algorithms are not equal, at least one of the mean is different. However, the ANOVA test does not provide the information where the actually differences lies or which one is better [245].

To determine the individual algorithm's effect, a Wilcoxon sign test is performed in the samples solutions of all players from all considered problems for four algorithms. The comparisons are performed based on the average profits of all players, using a 5% significance level. The results are shown in Table 6.11, in which found that the $P-$values of all the sets of comparisons are less than 0.05, indicating that there is a significant difference between the solutions from any two algorithms. Also, it is found that the CE-based algorithms obtain better solutions than those of IT-based ones. In addition, the Friedman test is carried out to rank all the algorithms, as shown in Tables 6.12, with the results demonstrating that the proposed CE-DE algorithm is ranked 1^{st}, followed by CE-GA, IT-DE and IT-GA. Furthermore, a sample box plot for the 30-bus (case III) system for player 1 is depicted in Fig. 6.13 that illustrates the performance of the

Table 6.11: Wilcoxon test results for IT-DE, IT-GA, CE-DE and CE-GA

	Better	Similar	Worse	$P-$value
IT-DE vs. IT-GA	88	70	42	0.001
IT-DE vs. CE-DE	51	70	79	0.018
IT-DE vs. CE-GA	52	75	73	0.044
IT-GA vs. CE-DE	46	70	84	0.001
IT-GA vs. CE-GA	44	70	86	0.000
CE-DE vs. CE-GA	84	70	46	0.001

Table 6.12: Ranks of IT-DE, IT-GA, CE-DE and CE-GA from Friedman test results

IT-DE	IT-GA	CE-DE	CE-GA
2.51	2.82	**2.24**	2.44

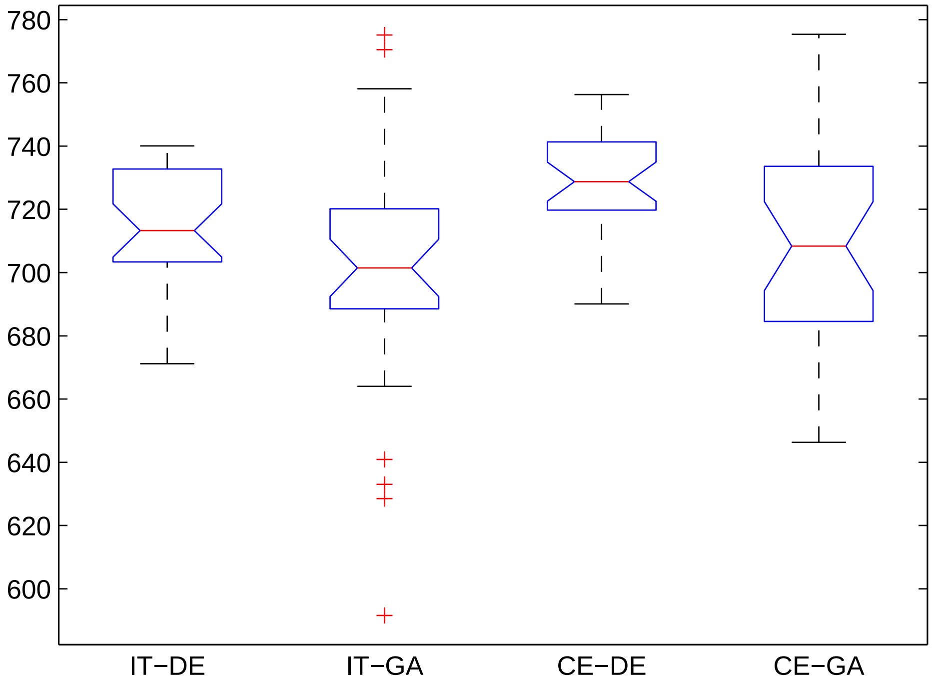

Fig. 6.13: A sample boxplot of the profits of player-1 of IEEE 30-bus system (case III)

proposed CE-DE algorithm for obtaining highest mean results with a smaller standard deviation.

The performances of the proposed CE approaches are also explored by comparing their convergence characteristics with those of the IT based methods. The *IEEE* 3-bus test problem for case III is solved using the CE-DE and IT-DE algorithms with

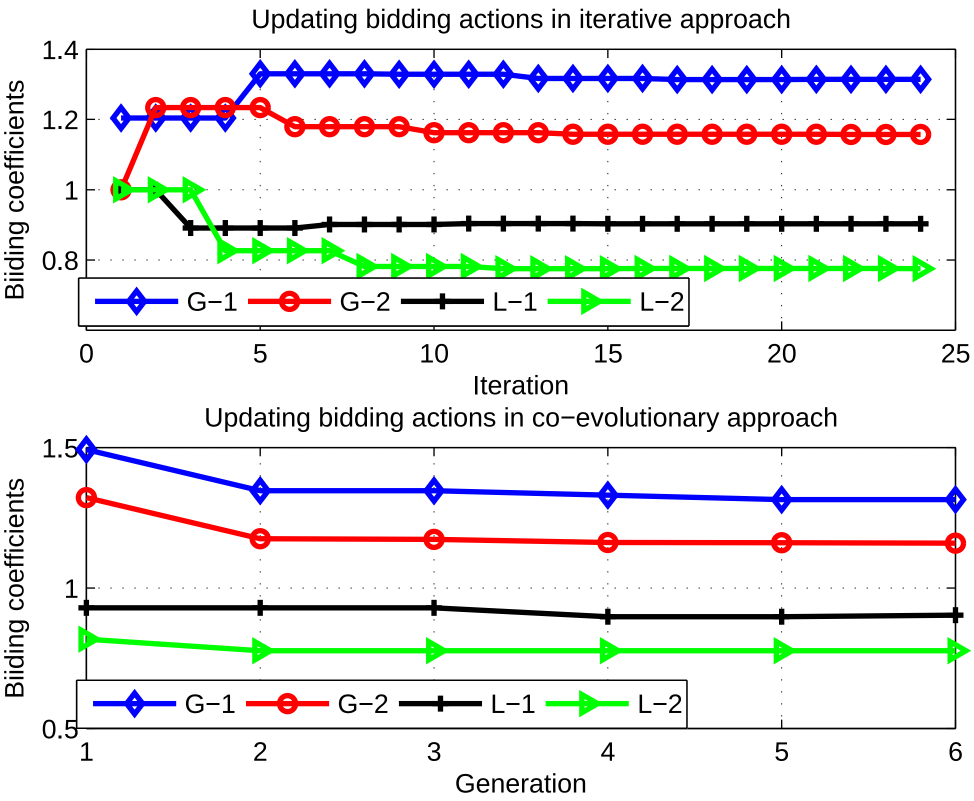

Fig. 6.14: Convergence characteristics of bidding actions for both GENCOs and consumers in IT-DE and CE-DE algorithms

the convergence patterns of their bidding coefficients shown in Fig. 6.14. It can be seen that the IT-DE takes 25 iterations to converge while the CE-DE converges in only six generations and, even after 4, obtains the best solution. This is because an IT approach determines the best bidding action for each bidder sequentially while the CE one determines them for all bidders simultaneously.

6.7 Chapter Summary

The objective of this Chapter was to develop the solution approaches for the bidding problems of an energy market where both GENCOs and consumers participate in a bidding process to maximize their individual profits by optimizing their own bidding behaviors while anticipating those of others. The market was represented as a non-cooperative game with aiming to determine NE. It was formulated as a bi-level optimization problem in which the lower level maximizes the CSW by solving a DC-OPF problem using the developed two EAs and a classical optimization technique. In the upper level, either self-adaptive DE or GA was used to maximize an individual bidder's profit, with multi-populations considered for multiple bidders in which each sub-population represented a player that co-evolved with the others and evaluated its own best propagation considering the best individuals from the other subpopulations. Therefore, in a few generations, the best bidding strategies of all players were obtained. Moreover, to determine multiple NEs in a single run, a new ranking technique for determining the best individuals in a subpopulation was developed, with two propositions proven to justify that the best solutions obtained from the proposed technique were the actual NEs.

To validate the results, two conventional methods were also implemented and their results compared by solving a number of benchmark problems, including four standard test functions and three real-world energy market problems. Comparisons of the simulation results revealed that the CE-based approaches had merit in terms of their nNEs detected, FFEs and computational times, with CE-DE the best of all the algorithms.

Chapter 7

Conclusions and Future Research Directions

This chapter presents a summary of the research carried out for this thesis, discusses its findings and suggests possible future research directions.

7.1 Summary of Research Conducted

In this thesis, the importance of solving different types of power system optimization problems, particularly dynamic economic dispatch (DED) and bidding ones, in electricity generation and distribution was discussed. The DED was used to minimize the production cost by allocating daily load demands to the operating generators while satisfying various technical and environmental constraints. In the bidding problem, the individual profits of an energy market were maximized by determining the optimal action of each participant with respect to those of the others and the market's constraints. The primary objective of this study was to develop an algorithmic framework for solving these problems that could be applicable for real-world power system operations.

The framework for the developed solution approaches was divided into several steps. Firstly, for solving real-world thermal generator-based DED problems, two efficient evolutionary algorithms (EAs), a self-adaptive differential evolution (DE) and genetic algorithm (GA) were developed. In them, a new heuristic technique for repairing infeasible individual was proposed. The mathematical model and solution approaches were extended to consider uncertain wind generators in a DED model, with the uncertainties due to variable wind speeds and load demands for a one-week period incorporated. Another heuristic technique for handling these uncertainties and the large number of equality constraints of a DED problem for the time period of one week with one-hour time spans were developed. Then, the proposed method was further extended to establish a general evolutionary framework for the automatic configuration of GA and DE for solving a wide range of both thermal and renewable-based DED problems. Later, these problems, which were formulated as bi-objective dynamic economic and emission dispatch (DEED) ones with their objectives to simultaneously minimize both the fuel costs and greenhouse gas emissions, were solved. Finally, two co-evolutionary (CE) solution approaches, one based on a self-adaptive DE and the other on a GA, for the bidding problem were developed with the aim of determining multiple solutions in a single run.

The proposed solution approaches were applied to a number of DED, DEED and bidding problems. The first three were used to solve various types of single- and bi-objective DED and DEED problems, such as thermal, hydro-thermal, solar-thermal and wind-thermal systems with and without considering gas emissions as a second objective. The CE algorithms were applied to the bidding problems considering two different equilibrium models, each with three cases: (i) the generators were strategic but the consumers non-strategic and the constraints of the transmission lines (TLs) ignored; (ii) the generators were strategic, the consumers non-strategic and the TLs considered; and (iii) both the generators and consumers were strategic with the TLs considered. For comparison purposes, some state-of-the-art algorithms were also implemented to solve the above problems. Several parametric and statistical analyses of each algorithm for each problem were performed. The experimental results and findings obtained from each approach are summarized below.

7.1.1 EAs for Thermal DED Problems

In Chapter 3, the importance of solving a real-life thermal-based DED problem in electricity generation was discussed. The goal of this chapter was to develop an appropriate solution approach for a practical thermal based DED problem. Therefore, the objective (cost) function of a DED problem was considered non-smooth, non-convex and multi-modal which is common in a real-life thermal generator due to the valve-point effect (VPE). Also, electricity transmission losses and ramp constraints were included in the formulation of the DED problem.

Two enhanced EAs based on (i) a GA and (ii) self-adaptive DE with a heuristic technique, namely E-GA and E-DE, respectively, were proposed to solve these problems. The control parameters of DE were self-adaptively adjusted in each generation while a non-uniform mutation was used in GA to avoid premature convergence. To satisfy the large number of equality constraints in a DED problem, a new heuristic technique that decoupled a T-hour problem into a T number of periodic sub-problems and allocated the hourly load demand to the generators using forward and backward slack-generation approaches was proposed. It repaired any infeasible individual into a feasible one which led to a great improvement in the algorithms' performances. The performance of the proposed algorithms were validated by solving seven benchmark problems taken from different studies in the literature. Also, the effects of the various important parameters used in the proposed algorithms were explicitly investigated. Based on the analysis of results and convergence plots, it could be concluded that the heuristic enhanced the performances of the two EAs considered in this thesis, with E-DE the best of all the algorithms for solving thermal-based DED problems.

7.1.2 EAs for Wind-thermal DED Problems

In Chapter 4, a non-linear, constrained and complex DED model of an uncertain wind-thermal power system, in which uncertainties due to variable wind speeds and electricity demands were considered in its formulation, was presented. This problem was re-formulated as a scenario-based wind-thermal DED one considering some additional constraints (e.g. transient ramp violations) for generating one-day solutions, in periodic order, on consecutive days. These constraints helped to reduce any unwanted electricity shortfall during the transition period from the last hour of one operating day to the first hour of the next. Hundreds of possible scenarios with uncertain wind speeds and variable load demands were generated for a seven-day period using Gaussian distributions with means and standard deviations obtained from historical data.

To solve such uncertain DED problems, two solution approaches based on (i) a self-adaptive DE and (ii) real-coded GA with a new heuristic were designed. The heuristic was used to meet the large numbers of equality and inequality constraints in a DED problem under the uncertain environment. It transformed an infeasible solution into a feasible one which satisfied periodic demands, and capacity and ramp limit constraints over a seven-day horizon. Two uncertain DED problems consisting of 5- and 10-unit wind-thermal generators, with their uncertainties represented by 100 realistic scenarios generated based on Australian wind speed and electricity demand data, were solved using the proposed solution approaches and a state-of-the-art algorithm considering two different heuristics. The results obtained were compared with each other and those in the literature. It was evident that the proposed methods provided scheduling with a zero penalty cost and lower production cost than traditional methods, with the E-GA performing best.

7.1.3 Evolutionary Framework for DED and DEED Problems

In Chapter 5, the importance of solving various types of DED and DEED problems in power system operations was discussed. Comprehensive descriptions of the mathematical formulations for thermal, hydro-thermal, wind-thermal and solar-thermal systems were presented. The uncertainties of renewable sources were formulated as penalty functions and added to the objective one. The objective of a single-objective DED problem was to minimize the overall operating costs, including the fuel and environmental ones, of thermal generators, the operational costs of renewable sources, and the under- and over-estimated costs of any uncertainties. The objectives of a bi-objective DEED problem were to simultaneously minimize the costs of both their operations and greenhouse gas emissions.

Motivated by the two proposed algorithms presented in Chapters 3 and 4, a general evolutionary framework for the automatic configuration of GA and DE that could solve a wide range of both single- and bi-objective DED and DEED problems was designed, with the algorithm called GA-DE. In it, random individuals from the initial population were evaluated in parallel through two different sub-populations, one using GA and the other DE. Although the initial sub-population sizes were the same, they were dynamically varied in each generation based on the performance of each EA in previous generations. After a predefined number of generations (also called a cycle), only the better-performing algorithm was allowed to run alone for a subsequent cycle. After that cycle was completed, both algorithms were run again for another cycle using the same sub-population size. The process was continually repeated until a stopping criterion was met. Also, a self-adaptive mechanism was used to determine the best set of control parameters for the mutation and crossover operators of DE in each generation of the evolutionary process. Moreover, a heuristic technique was employed to improve the convergence rate of each algorithm by rectifying infeasible individuals towards feasible directions. Different types of single- and bi-objective DED and DEED problems, respectively, were solved using the proposed and state-of-the-art algorithms. Several parametric and statistical analyses were carried out to demonstrate the effects of different parameters used in the algorithm. A comparison indicated that the proposed algorithm consistently performed better than all the others, with the heuristic greatly enhancing all their performances.

7.1.4 Co-evolutionary Approaches for Bidding Problems

Chapter 6 presented a bidding problem for maximizing the individual profits of both generator companies (GENCOs) and customers in an energy market in which they optimized their own bidding behaviors while anticipating those of others. The market was represented as a non-cooperative game with a supply function equilibrium (SFE) and a Cournot model that aimed to determine a Nash equilibrium (NE). Both models were formulated as bi-level optimization problems with each bidder's profit maximized at the higher level and the overall cost minimized at the lower level. In the upper level, once all the bidders provided their bids to an independent system operator (ISO) in a competitive environment, in the lower level, a DC-optimal power flow (DC-OPF) problem was solved which determined the market price and quantity for each bidder. Based on these two values, the profits (objective function in the upper level) of the bidders were calculated.

A bidding strategy could be either discrete or continuous. In a discrete one, each bidder determined its optimal bid (NE) from a set of known ones using the traditional min-max game theory approach. However as, in this study, the realistic bidding parameters were considered continuous and the payoff functions non-smooth, non-convex and multi-modal, the bidding problem considered might have had multiple equilibria, i.e., multiple NEs.

Two CE solution approaches based on (i) a self-adaptive DE and (ii) a GA were developed to solve such a bidding problem that formulated as a bi-level optimization problem. For verification purposes, the lower-level DC-OPF problem was solved using three algorithms, an interior point (IP), DE and GA, and the upper level one, two EAs (GA and DE). Each algorithm considered multi-populations for multiple bidders in which each sub-population represented a player (bidder) that co-evolved with the others and sought its best propagation considering the best individuals from the other sub-populations. Also, to determine multiple solutions (i.e., multiple NEs) in a single run, a new ranking technique for determining the best individuals in a sub-population was developed. In it, two propositions were given to justify that the best solutions obtained from the proposed techniques were the actual NEs. Moreover, two well-known conventional iterative (IT) solution methods, IT-DE and IT-GA, were implemented to analyze the effectiveness of the proposed CE algorithms. Their performances were validated by solving four standard test functions and three IEEE bidding problems. Comparisons of the simulation results with both each other and those in the literature revealed that the CE approaches had merit in terms of quality and reliability, with that based on DE the best method for a bidding problem.

7.2 Research Findings

The proposed algorithms were tested on different bidding, DED and DEED problems over a 24-hour planning horizon with one-hour long periods. The results obtained were compared with those from different state-of-the-art algorithms in the literature. After analyzing them, the key outcomes found were as follows.

- A real-parameter enhanced GA with a non-uniform mutation and a self-adaptive enhanced DE exhibited superior performances for solving DED, DEED and bidding problems.
- The heuristic repair scheme greatly improved the quality of solutions by transforming infeasible individuals into feasible ones while solving DED and DEED problems.

- Selecting the DE's control parameters using the self-adaptive mechanism enabled it to obtain the best solution quickly.
- The performance of the non-uniform mutation of GA was better than those of other mutation operators, such as polynomial and chaotic ones.
- Incorporating some additional constraints in an uncertain DED problem helped to minimize any electricity shortfall due to a disturbance in the system.
- Efficient solution approaches could schedule uncertain generators in such a way that they could operate in a periodic order on subsequent days.
- When solving different DED problems using the E-GA and E-DE algorithms, the former performed well for the wind-thermal and the latter for the thermal DED problems.
- For a wide range of single-objective DED and bi-objective DEED problems, higher-quality solutions were obtained with the proposed evolutionary framework (i.e., GA-DE) than the state-of-the-art algorithms, including the developed E-GA and E-DE ones.
- Although the numbers of fitness function evaluations (FFEs) consumed by GA-DE were marginally higher than those by E-DE and E-GA in some cases and much lower than those of a state-of-the-art algorithm (CMA-ES) in all cases, it produced the best-quality solutions. The main reason for GA-DE's higher numbers of FFEs was that it did not meet the stopping criterion (no improvements noticed in the last 100 generations) at the same stage in the evolutionary process as the other algorithms that became stuck in local optima which indicated that it was able to maintain much better diversity.
- When the same number of maximum FFEs was set as the stopping criterion for all algorithms, the GA-DE obtained better-quality solutions with reasonable computational times than E-DE and E-GA while, although the simulation times of CMA-ES were the minimum in all instances, the quality of its solutions was significantly degraded.

- For a fixed computational time, the GA-DE was found to be the best algorithm followed by E-DE and E-GA.
- For the multi-objective DEED problems, the Pareto frontiers obtained by the GA-DE algorithm were clearly better than the solutions from the state-of-the-art algorithms.
- The complexity of the bi-level bidding problems was reduced by solving the lower-level DC-OPF problem using a strictly convex quadratic programming (SCQP) approach.
- For solving the bidding problem using the proposed CE and conventional IT-based methods, it was revealed that the CE one was the fastest. This was because an IT approach determined the best bidding action for each bidder sequentially while the CE ones determined that for all bidders simultaneously.
- The CE methods obtained the best results in terms of individual profits and community social welfare (CSW).
- The CE methods obtained multiple NEs in continuous strategic games. The theoretical analyses confirmed that the results obtained were NEs which were verified using the professional Gambit software.

7.3 Future Research Directions

The mathematical models and solution approaches developed in this thesis could be extended in the following ways.

1. Although the data used for each problem considered were taken from different studies in the literature, solving a practical problem using industrial data would be interesting.
2. Although the DED problems were solved considering a 24-hour planning horizon with one-hour intervals which could be shortened, if necessary, without modifying the algorithm, solving them with five-minute intervals using more sensitive data (frequent changes) for real-time scheduling could be worthwhile.

3. Although uncertainties due to wind speeds and variable load demands were incorporated in the DED model, other uncertainty factors, such as the disruption of a generator and/or physical fault in a transmission line could be considered.

4. The generalized framework for the various types of DED and DEED problems could be extended by considering other EAs and configuring two or more of them. Also, using more than one evolutionary operator in a single EA could be worth investigating.

5. The framework could be used to solve other power system optimization problems, such as security-constrained ED (SCED) and OPF ones.

6. As all the solution approaches developed used some random individuals in the initial population, they took a long time to reach their final solutions. Therefore, an appropriate method for generating initial individuals for each algorithm could be implemented.

7. Although the diversity of individuals was maintained by injecting some random individuals, another method for balancing convergence and diversity could be developed.

8. The performances of the enhanced EAs for solving thermal-based DED problems could be improved by adding a local search technique.

9. For solving bidding problems, a number of aspects could be further investigated. First and foremost, although the cost function of a generator was considered quadratic, it could be represented as piece-wise non-linear, non-convex and non-smooth to align with reality. Secondly, the market model developed based on a single period could be extended to multi-period demands of 24 hours with five-minute to one-hour intervals. Finally, in this study, it was assumed that each bidder had incomplete information about the bidding strategies of its rivals but perfect information about their cost structures. This could be further extended by considering that they have incomplete information of both. Furthermore, solving the problem in a completely distributed manner is another possible direction for future work.

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Appendix A

Data of Test Systems

In this chapter, the data for all the test problems are provided.

A.1 Thermal System

In this section, the data for the 5 and 10 thermal systems are presented while the data for the 30, 100 and 150 units can be found by duplicating the 10-unit system of 3, 10 and 15 times, respectively.

A.1.1 5-Unit

The characteristics of the generators, load demand and corresponding P_{loss} coefficients (B) for the 5-unit thermal system are presented in Tables A.1, A.2 and A.3, respectively.

Table A.1: Characteristics of generators in 5-unit thermal system

Unit	P_{min}	P_{max}	a	b	c	d	e	UR	DR
	MW	MW	$\$/h$	$\$/MWh$	$\$/(MW)^2h$	$\$/h$	rad/MW	MW/h	MW/h
1	10	75	25	2	0.008	100	0.042	30	30
2	20	125	60	1.8	0.003	140	0.04	30	30
3	30	175	100	2.1	0.0012	160	0.038	40	40
4	40	250	120	2	0.001	180	0.037	50	50
5	50	300	40	1.8	0.0015	200	0.035	50	50

Table A.2: Load demand for 5-unit system

t (hour)	1	2	3	4	5	6	7	8	9	10	11	12
P_D (MW)	410	435	475	530	558	608	626	654	690	704	720	740
t (hour)	13	14	15	16	17	18	19	20	21	22	23	24
P_D (MW)	704	690	654	580	558	608	654	704	680	605	527	463

Table A.3: P_{loss} coefficients (B) of 5-unit system

0.000049	0.000014	0.000015	0.000015	0.000020
0.000014	0.000045	0.000016	0.000020	0.000018
0.000015	0.000016	0.000039	0.000010	0.000012
0.000015	0.000020	0.000010	0.000040	0.000014
0.000020	0.000018	0.000012	0.000014	0.000035

Table A.4: Characteristics of generators in 10-unit thermal system

Unit	P_{min}	P_{max}	a	b	c	d	e	UR	DR
	MW	MW	$\$/h$	$\$/MWh$	$\$/(MW)^2h$	$\$/h$	rad/MW	MW/h	MW/h
1	150	470	958.2	21.6	0.00043	450	0.041	80	80
2	135	460	1313.6	21.05	0.00063	600	0.036	80	80
3	73	340	604.97	20.81	0.00039	320	0.028	80	80
4	60	300	471.6	23.9	0.0007	260	0.052	50	50
5	73	243	480.29	21.62	0.00079	280	0.063	50	50
6	57	160	601.75	17.87	0.00056	310	0.048	50	50
7	20	130	502.7	16.51	0.00211	300	0.086	30	30
8	47	120	639.4	23.23	0.0048	340	0.082	30	30
9	20	80	455.6	19.58	0.10908	270	0.098	30	30
10	55	55	0.00951	22.54	692.4	380	0.0943	30	30

Table A.5: Load demand for 10-unit system

t (hour)	1	2	3	4	5	6	7	8	9	10	11	12
P_D (MW)	1036	1110	1258	1406	1480	1628	1702	1776	1924	2072	2146	2220
t (hour)	13	14	15	16	17	18	19	20	21	22	23	24
P_D (MW)	2072	1924	1776	1554	1480	1628	1776	2072	1924	1628	1332	1184

Table A.6: P_{loss} coefficients (B) of 10-unit system

0.0087	0.00043	-0.00461	0.00036	0.00032	-0.00066	0.00096	-0.0016	0.0008	-0.0001
0.00043	0.0083	-0.00097	0.00022	0.00075	-0.00028	0.00504	0.0017	0.00054	0.0072
-0.00461	-0.00097	0.009	-0.002	0.00063	0.003	0.0017	-0.0043	0.0031	-0.002
0.00036	0.00022	-0.002	0.0053	0.00047	0.00262	-0.00196	0.0021	0.00067	0.0018
0.00032	0.00075	0.00063	0.00047	0.0086	-0.0008	0.00037	0.00072	-0.0009	0.00069
-0.00066	-0.00028	0.003	0.00262	-0.0008	0.0118	-0.0049	0.0003	0.003	-0.003
0.00096	0.00504	0.0017	-0.00196	0.00037	-0.0049	0.00824	-0.0009	0.0059	-0.0006
-0.0016	0.0017	-0.0043	0.0021	0.00072	0.0003	-0.0009	0.0012	-0.00096	0.00056
0.0008	0.00054	0.0031	0.00067	-0.0009	0.003	0.0059	-0.00096	0.00093	-0.0003
-0.0001	0.0072	-0.002	0.0018	0.00069	-0.003	-0.0006	0.00056	-0.0003	0.00099

A.1.2 10-Unit

The characteristics of the generators, load demand and P_{loss} coefficients (B) for the 10-unit problem are presented in Tables A.4, A.5 and A.6, respectively.

Table A.7: Characteristics of thermal generators in hydro-thermal system

Unit	P_{min}	P_{max}	a	b	c	d	e
	MW	MW	$\$/h$	$\$/MWh$	$\$/(MW)^2h$	$\$/h$	rad/MW
1	20	175	10	2	0.0037	18	0.037
2	40	300	10	1.75	0.0175	16	0.038
3	50	500	20	1	0.0625	14	0.04
4	20	175	10	2	0.0037	18	0.037
5	40	300	10	1.75	0.0175	16	0.038

Table A.8: Characteristics of hydro generators in hydro-thermal system

Unit	C_1	C_2	C_3	C_4	C_5	C_6	V_H^{min}	V_H^{max}	V^{ini}	V^{end}	X_H^{min}	X_H^{max}	P_H^{min}	P_H^{max}
1	-0.0042	-0.42	0.03	0.9	10	-50	80	150	100	120	5	15	0	500
2	-0.004	-0.3	0.015	1.14	9.5	-70	60	120	80	70	6	15	0	500
3	-0.0016	-0.3	0.014	0.55	5.5	-40	100	240	170	170	10	30	0	500
4	-0.003	-0.31	0.027	1.44	14	-90	70	160	120	140	6	20	0	500

Table A.9: Reservoir inflows ($\times 104\, m^3$)

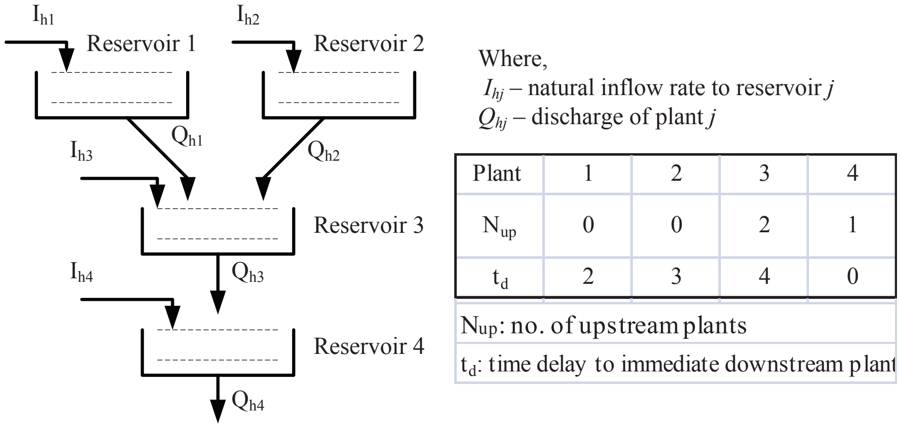
Hour	Reservoir				Hour	Reservoir				Hour	Reservoir			
	1	2	3	4		1	2	3	4		1	2	3	4
1	10.0	8.0	8.1	2.8	9	10.0	8.0	1.0	0.0	17	9.0	7.0	2.0	0.0
2	9.0	8.0	8.2	2.4	10	11.0	9.0	1.0	0.0	18	8.0	6.0	2.0	0.0
3	8.0	9.0	4.0	1.6	11	12.0	9.0	1.0	0.0	19	7.0	7.0	1.0	0.0
4	7.0	9.0	2.0	0.0	12	10.0	8.0	2.0	0.0	20	6.0	8.0	1.0	0.0
5	6.0	8.0	3.0	0.0	13	11.0	8.0	4.0	0.0	21	7.0	9.0	2.0	0.0
6	7.0	7.0	4.0	0.0	14	12.0	9.0	3.0	0.0	22	8.0	9.0	2.0	0.0
7	8.0	6.0	3.0	0.0	15	11.0	9.0	3.0	0.0	23	9.0	8.0	1.0	0.0
8	9.0	7.0	2.0	0.0	16	10.0	8.0	2.0	0.0	24	10.0	8.0	0.0	0.0

Table A.10: Load demand for hydro-thermal system

t (hour)	1	2	3	4	5	6	7	8	9	10	11	12
P_D (MW)	750	780	700	650	670	800	950	1010	1090	1080	1100	1150
t (hour)	13	14	15	16	17	18	19	20	21	22	23	24
P_D (MW)	1110	1030	1019	1060	1050	1120	1070	1050	910	860	850	800

A.2 Hydro-Thermal System

For the 7-unit hydro-thermal system, the characteristics of the thermal and hydro generators are presented in Tables A.7 and A.8, respectively, the hydro reservoir configuration with delay times in Fig. A.1, the reservoir inflow rates in Table A.9 and the 24-hour load demands in Table A.10.



Where,
I_{hj} – natural inflow rate to reservoir *j*
Q_{hj} – discharge of plant *j*

Plant	1	2	3	4
N_{up}	0	0	2	1
t_d	2	3	4	0

N_{up}: no. of upstream plants
t_d: time delay to immediate downstream plant

Fig. A.1: Hydraulic system network

Table A.11: Characteristics of thermal generators in solar-thermal system

Unit	P_{min}	P_{max}	a	b	c	d	e	α	β	γ	η	δ	UR	DR
	MW	MW	$\frac{\$}{h}$	$\frac{\$}{MWh}$	$\frac{\$}{(MW)^2h}$	$\frac{\$}{h}$	$\frac{rad}{MW}$	$\frac{lb}{h}$	$\frac{lb}{MWh}$	$\frac{lb}{(MW)^2h}$	$\frac{lb}{h}$	$\frac{1}{MW}$	$\frac{MW}{h}$	$\frac{MW}{h}$
1	100	500	0.007	7	240	0	0	13.86	0.33	0.00419	0	0	80	120
2	50	200	0.0095	10	200	0	0	13.86	0.33	0.00419	0	0	50	90
3	80	300	0.009	8	220	0	0	40.27	-0.55	0.00683	0	0	65	100
4	50	150	0.009	11	200	0	0	40.27	-0.55	0.00683	0	0	50	90
5	50	200	0.008	10.5	220	0	0	42.90	-0.51	0.00461	0	0	50	90
6	50	120	0.0075	12	190	0	0	42.90	-0.51	0.00461	0	0	50	90

Table A.12: Power ratings and per unit rates of solar plants

Unit	1	2	3	4	5	6	7	8	9	10	11	12	13
$P_r(MW)$	20	25	25	30	30	35	35	40	40	40	40	40	40
$U_{cost}(\$/kWh)$	0.22	0.23	0.23	0.24	0.24	0.25	0.26	0.27	0.27	0.275	0.28	0.28	0.28

Table A.13: Sample data of solar radiation, temperature and power demand

Hour	1	2	3	4	5	6	7	8	9	10	11	12
$Si(W/m^2)$	0	0	0	0	5.4	101	253.7	541.2	530.4	793.9	1078	1125.6
$T_{amb}(^0c)$	30	29	28	28	28	28	29	31	33	34	35	36
$T_{ref}(^0c)$	35	33	31	31	31	31	33	37	41	43	45	47
$P_D(MW)$	955	942	953	930	935	963	989	1023	1126	1150	1201	1235
Hour	13	14	15	16	17	18	19	20	21	22	23	24
$Si(W/m^2)$	1013.5	848.2	726.7	654	392.9	215.1	38.5	0	0	0	0	0
$T_{amb}(^0c)$	37	37	37	38	38	37	35	34	34	33	32	32
$T_{ref}(^0c)$	49	49	49	51	51	49	45	43	43	41	39	39
$P_D(MW)$	1190	1251	1263	1250	1221	1202	1159	1092	1023	984	975	960

A.3 Solar-Thermal System

For the mixed-integer solar-thermal problem, the characteristics of the thermal generators and solar plants are presented in Tables A.11 and A.12, respectively, and the load demands and temperatures for a 24-hour period in Table A.13.

Table A.14: Characteristics of thermal generators in wind-thermal system

Unit	P_{min}	P_{max}	a	b	c	d	e	α	β	γ	η
	MW	MW	$\frac{\$}{h}$	$\frac{\$}{MWh}$	$\frac{\$}{(MW)^2h}$	$\frac{\$}{h}$	$\frac{rad}{MW}$	$\frac{lb}{h}$	$\frac{lb}{MWh}$	$\frac{lb}{(MW)^2h}$	$\frac{lb}{h}$
1	30	400	100	15	0.12	260	5.2	911.8	2.094	0.05859	0.1
2	100	600	200	18	0.04	280	6.3	613.1	-5.457	0.04266	1
3	100	650	100	10	0.06	300	8.6	628.5	-4.116	0.03669	1
4	250	800	200	18	0.04	270	9.8	542.6	-8.55	0.0238	1
5	300	1000	100	15	0.05	380	4.2	461.3	-9.712	0.01153	1

Table A.15: Ramp characteristics of thermal generators in wind-thermal system

Unit	UR	DR	DR^0	UR^1	T_{min}^{on}	T_{min}^{off}	P_0	T_0
	$\frac{MW}{h}$	$\frac{MW}{h}$	$\frac{MW}{h}$	$\frac{MW}{h}$	h	h	MW	h
1	100	100	50	100	4	3	260	3
2	100	100	80	160	3	3	400	5
3	120	120	80	160	4	4	320	3
4	200	180	100	200	4	3	480	3
5	200	200	100	300	4	3	600	6

Table A.16: P_{loss} coefficients (B) of thermal generators in wind-thermal system

7.075	-1.005	-1.865	-1.975	-1.585	-0.36
-1.005	11.355	0.055	-1.07	-1.475	-0.51
-1.865	0.055	7.295	2.905	0.08	-0.945
-1.975	-1.07	2.905	3.96	0.395	-1.03
-1.585	-1.475	0.08	0.395	1.61	-0.535
-0.36	-0.51	-0.945	-1.03	-0.535	3.14

Table A.17: P_{loss} coefficients (B) of thermal generators in wind-thermal system

Time (h)	1	2	3	4	5	6
$\mu(m/s)$	12.1	14.07	8.52	10.23	4.86	6.52
$\sigma(m/s)$	7.03	9.29	5.13	6.85	2.91	4.28
$P_D(MW)$	1900	1952	2260	2330	2406	2026

A.4 Wind-Thermal System

For the wind-thermal system, the characteristics of the thermal generators and their P_{loss} coefficients are presented in Tables A.14 to A.16, respectively, and the hourly load demand and wind speed with a standard deviation error in Table A.17.

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Appendix B

SCQP Formulation

In this section, for the DC-OPF SCQP problem, the coefficients of the objective function in Eqn. (6.21) and constraints in Eqns. (6.22) and (6.23) are described.

B.1 Depiction of Objective Function

The decision variable of the objective function in Eqn. (6.21) is:

$$x = [P_1, P_2, ..., P_I, \delta_2, \delta_2, ..., \delta_K, q_1, q_2, ..., q_J]^T_{(I+K+J-1)\times 1} \tag{B.1}$$

and the coefficient:

$$G = \begin{bmatrix} U_g & 0 & 0 \\ 0 & W_{rr} & 0 \\ 0 & 0 & U_d \end{bmatrix} \in \Re_{(I+K+J-1)\times(I+K+J-1)} \tag{B.2}$$

where $\mathrm{U_g}$ and $\mathrm{U_d}$ are the generators' and consumers' quadratic matrices, respectively, as:

$$\left[U_{g_{m,n}}\right]_{(I\times I)} = \begin{cases} c'_m & \text{if } m = n \\ 0 & \text{otherwise} \end{cases} ; \forall m, n = 1, 2, \ldots, I \tag{B.3}$$

$$\left[U_{d_{m,n}}\right]_{(J\times J)} = \begin{cases} e'_m & \text{if } m = n \\ 0 & \text{otherwise} \end{cases} ; \forall m, n = 1, 2, \ldots, J \tag{B.4}$$

Parameter $\mathbf{W_{r\mathit{r}}}$ is the reduced form of the weight matrix ($\mathbf{W}$) that can be defined as the voltage and angle difference of each node as:

$$W = 2\pi\left(w_{mn}\right) \in \Re_{(K\times K)} \tag{B.5}$$

$$\text{where, } w_{mn} = \begin{cases} -E_{mn} & if\ m \neq n \\ \sum^{K}_{\substack{k=1 \\ k\neq m}} E_{mk} & if\ m \equiv n \end{cases} \tag{B.6}$$

where $E \in \Re_{(K\times K)}$ is the branch connection matrix defined as:

$$E = \begin{cases} 1 & \text{if either } km\text{or } mk \in BR \\ 0 & \text{otherwise} \end{cases} \tag{B.7}$$

Once the W matrix is found, the reduced weight matrix (W_{rr}) is determined after removing the first row and column, *i.e.,* excluding the slack bus ($k = 1$).

The linear argument ($\mathbf{f}$) in Eqn. (6.21) is determined as:

$$f = \begin{bmatrix} b' & 0 & d' \end{bmatrix} \in \Re_{1\times(I+J+K-1)} \tag{B.8}$$

Comparing the original (6.15) and quasi (6.21) objective functions, it is seen that the latter provides a positive definite quadratic form, with at least one non-zero component strictly positive scalar which may indicate that the optimization problem could be satisfied by the first-order optimality of KKT conditions [237]. The KKT representation of the problem is shown in Appendix C.

B.2 Depiction of Constraints

The coefficients of the inequality constraint in Eqn. (6.22) are defined as:

$$C_{in} = \begin{bmatrix} C_g & O_g \\ O_d & C_d \end{bmatrix} \in \Re_{(2K+2I+J)\times(I+J+K-1)} \tag{B.9}$$

where,

$$C_g = \begin{bmatrix} O_t & -DA_r \\ -O_t & DA_r \\ I_p & O_p \\ -I_P & -O_p \end{bmatrix} \in \Re_{(2K+2I)\times(I+K-1)} \tag{B.10}$$

where, $\mathbf{O_t}$, $\mathbf{O_p}$, $\mathbf{O_d}$ and $\mathbf{O_g}$ are zero matrices of sizes $K \times I$, $I \times (k-1)$, $J \times (I+K-1)$ and $(2K+2I) \times J$, respectively, while $\mathbf{I_p}$ is the identity matrix of size $(I \times k-1)$. The diagonal matrix, $\mathbf{D}$, reduced adjacency matrix $\mathbf{A_r}$, and diagonal adjacent matrix of the load demand, $\mathbf{C_d}$ are determined as:

$$[D_{m,n}]_{(K\times K)} = \begin{cases} B_{m,n} & \text{if } m = n \\ 0 & \text{if } m \neq n \end{cases}, \ \forall m,n = 1,2,\ldots,K \tag{B.11}$$

$$A = \begin{bmatrix} \hbar(1,\mathrm{BI}_1) & \hbar(2,\mathrm{BI}_1) & \ldots & \hbar(K,\mathrm{BI}_1) \\ \hbar(1,\mathrm{BI}_2) & \hbar(2,\mathrm{BI}_2) & \cdots & \hbar(K,\mathrm{BI}_2) \\ \vdots & \vdots & \ddots & \vdots \\ \hbar(1,\mathrm{BI}_N) & \hbar(2,\mathrm{BI}_N) & \cdots & \hbar(K,\mathrm{BI}_N) \end{bmatrix} = \Re_{(I\times K)} \tag{B.12}$$

$$\hbar(i,\mathrm{BI}_n) = \begin{cases} +1 & \text{if } BI_n \text{ takes the form } ij \in BR \text{ for some node } j > i \\ -1 & \text{if } BI_n \text{ takes the form } ji \in BR \text{ for some node } j < i \\ 0 & \text{otherwise} \end{cases}$$
$$i = 1,...,K; n = 1,...,I \tag{B.13}$$

Then, the reduced adjacency matrix, $\mathbf{A_r}$ is calculated after deleting the first row and column of the $\mathbf{A}$ matrix, with the load adjacent to the diagonal matrix determined as:

$$\left[C_{d_{m,n}}\right]_{(J\times J)} = \begin{cases} 1 & \text{if } m = n \\ 0 & \text{if } m \neq n \end{cases}, \ \forall m,n = 1,2,\ldots,J \tag{B.14}$$

The coefficient on the right-hand side in Eqn. (6.22) $\mathbf{b_{i}}_{n}$ can be calculated as:

$$b_{in} = \begin{bmatrix} F & F & P_{min} & P_{max} \end{bmatrix}^T \tag{B.15}$$

$$\text{where } F = \left[F_1^U, \cdots, F_K^U\right]_{(1\times K)} \tag{B.16}$$

$$P_{min} = \left[P_1^{\min}, P_2^{\min}, \cdots, P_I^{\min}\right]_{(1\times I)} \tag{B.17}$$

$$P_{max} = [P_1^{\max}, P_2^{\max}, \cdots, P_I^{\max}]_{(1\times I)} \tag{B.18}$$

The coefficients of the equality constraints in Eqn. (6.23) $\mathbf{C_{e}}_{q}$ and $\mathbf{b_{e}}_{q}$ are determined as:

$$C_{iq} = \begin{bmatrix} \coprod_g & Y_{bus}^r & \coprod_d \end{bmatrix} \in \Re_{(K,I+J+K-1)} \tag{B.19}$$

where $\coprod_g$ and $\coprod_g$ are the matrices indicating the locations of the generators and loads, respectively, which are defined as:

$$\coprod_g = \begin{bmatrix} \exists\,(1 \in I_1) & \exists\,(2 \in I_1) & \cdots & \exists\,(I \in I_1) \\ \exists\,(1 \in I_2) & \exists\,(2 \in I_2) & \cdots & \exists\,(I \in I_2) \\ \vdots & \vdots & \ddots & \vdots \\ \exists\,(1 \in I_K) & \exists\,(2 \in I_K) & \cdots & \exists\,(I \in I_K) \end{bmatrix}_{(K\times I)} \tag{B.20}$$

$$\text{where, } \exists\,(i \in I_k) = \begin{cases} 1 & \text{if } i \in I_k \\ 0 & \text{if } i \notin I_k \end{cases} \tag{B.21}$$

$$\coprod_{d} = \begin{bmatrix} \perp(1 \in J_1) & \perp(2 \in J_1) & \cdots & \perp(J \in J_1) \\ \perp(1 \in J_2) & \perp(2 \in J_2) & \cdots & \perp(J \in J_2) \\ \vdots & \vdots & \ddots & \vdots \\ \perp(1 \in J_K) & \perp(2 \in J_K) & \cdots & \perp(J \in J_K) \end{bmatrix}_{(K \times J)} \tag{B.22}$$

$$\text{where, } \perp(j \in J_k) = \begin{cases} -1 & \text{if } j \in J_k \\ 0 & \text{if } j \notin J_k \end{cases} \tag{B.23}$$

The impedance matrix (Y_{bus}) is calculated as:

$$Y_{bus} = \begin{bmatrix} \sum_{k \neq 1}^{K} B_{1,k} & -B_{1,2} & \cdots & -B_{1,K} \\ -B_{2,1} & \sum_{k \neq 2}^{K} B_{2,k} & \cdots & -B_{2,K} \\ \vdots & \vdots & \ddots & \vdots \\ -B_{K,1} & -B_{K,2} & \cdots & \sum_{k \neq K}^{K} B_{K,k} \end{bmatrix} \in \Re_{(K \times K)} \tag{B.24}$$

Then, the reduced impedance matrix (Y_{bus}^{r}) is obtained from the Y_{bus} matrix after removing the first row. Note that the coefficient of the equality constraints in Eqn. (6.23) , $\mathbf{b_{e}}_q$ is a zero matrix of size ($K \times 1$).

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Appendix C

KKT Conditions of SCQP Problem

The ISO's SCQP problem can be summarized as:

$$\text{Minimize: } f(\text{x}) \tag{C.1}$$

$$\text{subject to: } g_{in}(x) = b_{in} - C_{in}x^T \leq 0 \ \forall in \in IN \tag{C.2}$$

$$h_{eq}(x) = b_{eq} - C_{eq}x^T = 0 \ \ \forall eq \in EQ \tag{C.3}$$

where g and h are the inequality and equality constraints, respectively, and IN and EQ their active numbers, respectively. Note that the number of equality constraints is exactly the same as the number of buses for a power system network. Based on [246], the KKT conditions are:

$$\nabla f(x) + \sum_{in=1}^{IN} u_{in} \nabla g_{in}(x) + \sum_{eq=1}^{EQ} \lambda_k \nabla h_{eq}(x) = 0 \tag{C.4}$$

$$u_{in} g_{in}(x) = 0 \ \ \forall in = 1, 2, \cdots, IN \tag{C.5}$$

where $u_{in} \forall in$ is a non-negative scalar and λ the scalar dual variables for the inequality and equality constraints, respectively. After differentiating Eqn. (C.4) with respect to all the primal and dual variables, a well-known matrix equation ($\mathbf{A}y$=$\mathbf{b}$) is found, where $\mathbf{y} = \left[\mathbf{x^T}, u_1, \ldots, u_{IN}, \lambda_1, \ldots, \lambda_{EQ}\right]^T$. The process for determining $\mathbf{y}$ is explicitly described in [246, 247].

Once $\mathbf{x}$ and $\lambda_k, \forall k = 1, 2, \ldots, K$ are known, the PD by each generator (P_i), load dispatch by each consumer (q_j), LMP of each node ($\lambda_{P_i} \forall i$, $\lambda_{d_j} \forall j$) and branch flows (F_{km}) are calculated as:

$$P_i = x_i \;\; \forall i = 1, 2, \cdots, I \tag{C.6}$$

$$q_j = x_{I+K+j} \;\; \forall j = 1, 2, \cdots, J \tag{C.7}$$

$$\lambda_{P_i} = \lambda_i \;\; \forall i \in I_K \tag{C.8}$$

$$\lambda_{d_j} = \lambda_j \;\; \forall j \in J_K \tag{C.9}$$

$$F = S * PNetInject \tag{C.10}$$

$$\text{where } S = (D * A_r) * B_{rr}^{-1} \tag{C.11}$$

$$PNetInject = B_{rr} * \delta \tag{C.12}$$

$$\delta_k = x_{I+k} \quad \forall k = 1, 2, \cdots K \tag{C.13}$$

where $\mathbf{B}_{\mathbf{r}r}$ is found from the $\mathbf{Y}_{\mathbf{b}us}$ matrix after deleting the first row and column.