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Novel Hybrid Optimization Methods for the Solution of the Economic Dispatch of Generation in Power Systems

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Doctor of Philosophy Dissertation

NOVEL HYBRID OPTIMIZATION METHODS FOR THE SOLUTION OF THE ECONOMIC DISPATCH OF GENERATION IN POWER SYSTEMS

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ABSTRACT

The economic dispatch of generation in power systems is one of the most important optimization problems for both the generating companies competing in a free electricity market and the systems operator in charge with a fair handling of transactions between electricity suppliers and their customers. The fuel cost component is still the major part of the variable cost of electricity generation, directly reflected in the electricity bills. Fine tuning in modelling the cost function, together with the right solution adopted to solve the problem, may lead to significant savings per year in large power system networks.

Economic dispatch aims at allocating the electricity load demand to the committed generating units in the most economic or profitable way, while continuously respecting the physical constraints of the power system. Typically, the economic dispatch problem is a highly non-linear optimization problem and there are a significant number of constraints that need to be respected, thus making economic dispatch a computationally intensive task. This problem needs to be solved continuously at time intervals ranging from minutes to half an hour, depending on the utility practice and the electricity market it operates in.

This dissertation proposes a novel heuristic-hybrid optimization method/algorithm particularly suited to large dimensional, complex optimization functions. The algorithm proposed is called GAAPI and is an hybridization between two optimization techniques: a special class of ant colony optimization for continuous domains entitled API and a genetic algorithm (GA). The algorithm adopts the downhill

behavior of API (a key characteristic of optimization algorithms) and the good spreading in the solution space of the genetic algorithm. GAAPI improves the overall search capability of the two constituent algorithms, while maintaining robustness in the solution and fast computational capabilities.

GAAPI is tested using twenty benchmark optimization functions. The results are analyzed in terms of both the quality of the solution and the computational efficiency; it is shown that the proposed GAAPI algorithm is capable of obtaining highly robust, quality solutions in a reasonable computational time, compared to a number of similar algorithms proposed in the literature.

The proposed algorithm is applied to the problem of the economic dispatch in power systems. Four IEEE test power systems having different sizes and complexities are used to validate the effectiveness and applicability of the algorithm for solving the economic dispatch problem in its different formulations. Due to the fast computational capabilities of the proposed algorithm, it is envisioned that it becomes an operations tool for both the generation companies and the TSO/ISO. The main advantages of the optimization tool proposed are its flexibility in adding more constraints with minimum transformations in the approach, its reduced computational time, and the robustness of the solution.

This dissertation also investigates a number of technical and economic challenges a power system may encounter when variable, partially predictable generation resources share a significant amount in the load covering. In specific, this work includes a study for the dispatch challenges in isolated power systems with a high share of renewable generation, such as wind. The power system of Cyprus has been used as a case study for the application of this methodology and solutions to overcome the dispatch challenges in such isolated power systems are proposed.

ΠΕΡΙΛΗΨΗ

Η οικονομική κατανομή της παραγωγής στα συστήματα ηλεκτρικής ενέργειας είναι ένα από τα πιο σημαντικά προβλήματα βελτιστοποίησης, τόσο για τις εταιρείες παραγωγής οι οποίες ανταγωνίζονται στην ελεύθερη αγορά ηλεκτρικής ενέργειας, όσο και για τον διαχειριστή του συστήματος ο οποίος είναι υπεύθυνος για τη δίκαιη διαχείριση των συναλλαγών μεταξύ των παροχέων ηλεκτρικής ενέργειας και των καταναλωτών. Το κόστος καυσίμου παραμένει το πιο σημαντικό μέρος του μεταβλητού κόστους παραγωγής ηλεκτρικής ενέργειας και ανακλάται απευθείας στους λογαριασμούς ηλεκτρικής ενέργειας. Μικρές αλλαγές στη μοντελοποίηση της συνάρτησης κόστους μαζί με την υιοθέτηση της σωστής μεθοδολογίας επίλυσης του προβλήματος μπορούν να οδηγήσουν σε σημαντικές εξοικονομήσεις ανά έτος.

Το πρόβλημα της οικονομικής κατανομής στοχεύει στον καταμερισμό της ζήτησης ηλεκτρικού φορτίου στις δεσμευμένες μονάδες παραγωγής, με τον πιο οικονομικό ή επικερδή τρόπο, ενώ ταυτόχρονα ικανοποιούνται όλοι οι φυσικοί περιορισμοί του συστήματος ηλεκτρικής ενέργειας. Συνήθως, το πρόβλημα της οικονομικής κατανομής είναι ένα άκρως μη-γραμμικό πρόβλημα βελτιστοποίησης, ενώ υπάρχει ένας σημαντικός αριθμός περιορισμών οι οποίοι πρέπει να ικανοποιούνται. Οι πιο πάνω παράγοντες καθιστούν το πρόβλημα της οικονομικής κατανομής ένα υπολογιστικά απαιτητικό πρόβλημα. Επιπλέον, αυτό το πρόβλημα απαιτείται να επιλύεται συνεχώς σε χρονικά διαστήματα που κυμαίνονται από δευτερόλεπτα μέχρι μισή ώρα, ανάλογα με τις πρακτικές κάθε εταιρείας και την αγορά ηλεκτρισμού στην οποία επιχειρεί.

Αυτή η διατριβή προτείνει ένα καινοτόμο ευρεστικό-υβριδικό αλγόριθμο

βελτιστοποίησης, ο οποίος είναι ιδιαίτερα κατάλληλος για συναρτήσεις ελτιστοποίησης οι οποίες είναι σύνθετες και μεγάλες σε διαστάσεις. Ο αλγόριθμος που προτείνεται ονομάζεται GAAPI και είναι υβριδοποίηση μεταξύ δυο τεχνικών βελτιστοποίησης: μιας ειδικής τάξης βελτιστοποίησης βασιζόμενη σε συμπεριφορές αποικιών μυρμηγκιών (API) και ενός γενετικού αλγορίθμου (GA). Ο καινοτόμος αλγόριθμος εκμεταλλεύεται την συμπεριφορά κατάβασης του API (η οποία είναι σημαντικό χαρακτηριστικό για οποιοδήποτε αλγόριθμο βελτιστοποίησης) και την καλή εξάπλωση στο χώρο λύσεων του γενετικού αλγόριθμου. Ο αλγόριθμος GAAPI βελτιώνει την ικανότητα εξερεύνησης των δυο συνιστώντων αλγορίθμων, ενώ διατηρεί την στιβαρότητα στη λύση και παρέχει ταχείς υπολογιστικές δυνατότητες.

Ο GAAPI εξετάστηκε χρησιμοποιώντας είκοσι πρότυπες συναρτήσεις βελτιστοποίησης. Τα αποτελέσματα αναλύονται αναφορικά με την ποιότητα της λύσεως και την υπολογιστική απόδοση. Δεικνύεται ότι ο προτεινόμενος αλγόριθμος GAAPI είναι ικανός να επιτυγχάνει λύσεις υψηλής στιβαρότητας και ποιότητας εντός λογικού υπολογιστικού χρόνου, συγκρινόμενος με αριθμό αλγορίθμων που προτείνονται στη βιβλιογραφία.

Ο προτεινόμενος αλγόριθμος εφαρμόζεται στο πρόβλημα της οικονομικής κατανομής στα συστήματα ηλεκτρικής ενέργειας. Χρησιμοποιούνται τέσσερα δοκιμαστικά συστήματα του Ινστιτούτου Ηλεκτρολόγων και Ηλεκτρονικών Μηχανικών (IEEE), τα οποία έχουν διαφορετικά μεγέθη και πολυπλοκότητες, για να επικυρωθεί η αποτελεσματικότητα και η εφαρμοσιμότητα του αλγορίθμου σε διάφορες διατυπώσεις. Λόγω των ταχέων υπολογιστικών του δυνατοτήτων, ο προτεινόμενος αλγόριθμος οραματίζεται να χρησιμοποιηθεί ως ένα εργαλείο λειτουργίας τόσο για τις εταιρείες παραγωγής όσο και για τους διαχειριστές του συστήματος μεταφοράς. Τα κύρια πλεονεκτήματα του προτεινόμενου εργαλείου βελτιστοποίησης είναι η ευελιξία στην προσθήκη περαιτέρω περιορισμών με ελάχιστες τροποποιήσεις στην προσέγγιση, ο μειωμένος υπολογιστικός χρόνος και η στιβαρότητα της λύσης.

Αυτή η διατριβή εξετάζει επίσης αριθμό τεχνικών και οικονομικών προκλήσεων τις οποίες μπορεί να αντιμετωπίσει ένα σύστημα ηλεκτρικής ενέργειας όταν υπάρχει σημαντική διείσδυση μεταβλητών, μερικώς προβλεπτών πηγών παραγωγής. Συγκεκριμένα, αυτή η εργασία συμπεριλαμβάνει μια μελέτη για τις προκλήσεις κατανομής σε απομονωμένα συστήματα με υψηλή διείσδυση ανανεώσιμων πηγών ενέργειας, όπως η αιολική. Το σύστημα της Κύπρου έχει χρησιμοποιηθεί ως περιπτωσιακό μοντέλο για την εφαρμογή αυτής της μεθοδολογίας, ενώ προτείνονται λύσεις για να υπερπηδηθούν οι προκλήσεις κατανομής παραγωγής σε τέτοια απομονωμένα συστήματα ηλεκτρικής ενέργειας.

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Book Chapters

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LIST OF SYMBOLS

A_{ant}	Amplitude of the search space of the ant
a_i, b_i *and* c_i	The constant, linear and quadratic fuel-cost coefficients of unit *i*
a_{ij}, b_{ij}, c_{ij}	Cost coefficients of generator *i* for the fuel type *j*
A_{site}	Amplitude of the search space of the site
a_w, b_w, c_w	Coefficients of the fuzzy membership function that defines the security level of the system in terms of wind power penetration
B_{ij}, B_{i0}, *and* B_{00}	The B-loss coefficients
CDF	Cumulative Distribution Function
C_w	Penalty cost for not using all the available wind power
CW	Coefficient for the associated cost for the security level
$\{c_k\}$	An arbitrary decreasing sequence
DR_i and UR_i	Down and up-rate limit of the ith generator, respectively
E	Emissions' function
e(ns)	Consecutive failures in the search of the site
e_i *and* f_i	Coefficients responsible to model the rippling effect of the opening of the admission valves in the function of the cost of fuel (defined for unit *i*)
E^{max}	Maximum allowable amount of total pollutants for the entire system
F	Feasible region of variable *x*
F(x)	Aggregated function

FOP	Probability of full outage
$f(x)$	Objective function
G	Fitness score function
G_{ij} and B_{ij}	Transmission line conductance and susceptance between bus i and bus j, respectively
G_{ant_i}	Age of the ant i
g_k	Conductance of the k^{th} line that connects bus i to bus j
GT	Gas turbine
$h_k(x)$ and $g_l(x)$	Equality and inequality constraints, respectively
$Ibest_i^k$ and $Gbest_i^k$	The best positions of individual i up to iteration k and the best position of the swarm relative to individual i, respectively
IC	Incremental cost of generation
$\boldsymbol{J}$	Search space (discrete domain)
$LOLE$	Loss of load expectation per year
LSI	Number of load shedding incidents per year
M	Total number of intervals in the day-ahead market
$M(f,c)$	The mean of $f(x)$ on the level set $\boldsymbol{S_0}$ according to the sequence c
MC	Marginal cost of generation
N	Initial position of the nest in the feasible solution space
$N(\mu, \sigma^2)$	Gaussian random variation with mean μ and variance σ
N_{ants}	Total number of search agents
NB	Number of buses in the power network

NG	Number of generators in the power system committed for dispatch
NL	Number of transmission lines
NP	Number of pollutants taken into account
N_{POZ}	Number of prohibited zones of unit i
ns	Number of sites memorized by each ant
Ns	Total number of sites one ant can memorize
NWF	Number of wind turbines
OC	Operational cost of the power system
P	Total number of consecutive failures until a site is deleted from the memory of the ant
P_c	Probability of crossover
P_D	Load power demand
P_{Di} and Q_{Di}	Real and reactive power demand of the i^{th} bus, respectively
PF	Pareto-front
Pf_i	Penalty coefficient for the i^{th} constrained function
P_i	Output power of the i^{th} generating unit
P_i^{min} and P_i^{max}	Lower and upper bound of generation of unit i, respectively
$P_i^{l_j}$ and $P_i^{u_j}$	Lower and upper bounds of the prohibited zone j of unit i, respectively
P_i^t	Output power of generator i in the dispatch interval t
P_{Loss}	Transmission losses
P_m	Probability of mutation

POP	Probability of partial outage
popRCGA	Counter for the number of individuals added into the population of the RCGA algorithm
PopSize	Population size
Pt	Profit of the generating company
PWF_k	Estimated power output of the k th cluster of wind farms
Q_i	Reactive power generated at the i^{th} bus
rand(.), c_1 and c_2	Randomly generated number
$R_m^{\,u}$	The total profit (revenue) of both generating companies and electricity consumers in the interval m of the day-ahead market, when the day-ahead retail price is $u(m)$
$\boldsymbol{S}$	Search space (continuous domain)
$\boldsymbol{S_0}$	The solution space of all better solutions than the current nest position
s_k	Individual k of the population
$S_{k,j}$	Element j of the individual k
SL	Security level of the power system under consideration
S_l	Thermal limit of the line
sp	Selling price per MWh produced
SRi	Fraction of total spinning reserve of the power system to be allocated to the unit i
SSR	Total spinning reserve of the power system

ST	Steam turbine
T_{ant_i}	Maximum number of iterations between two consecutive movements of the ant *i*
T_i	Current number of iterations after the last movement of the ant *i*
$Unif$	A uniform distribution between the lower and the upper bound
U_i^{min} and U_i^{max}	Minimum and maximum water discharge limits of the hydro unit *i*, respectively
$u(m)$	Retail price in the dispatch interval m of the day-ahead market
$\|V_i\|$	Voltage magnitude at bus *i*
V_i^k	Velocity of individual *i* in iteration *k*
W	The actual generation of wind power
W_{av}	Total available wind power
w_j	The emissions-to-cost conversion factor for emissions type *j*
$WP_{i,k}$	Power output of wind turbine *i* of cluster *k*
X_i^k	Position of individual *i* in iteration *k*
X_i^{min} and X_i^{max}	Minimum and maximum level of the reservoir of the hydro unit *i*, respectively
x	Decision vector
$\tilde{x}$	An ε-optimal solution
x^*	Global optimal solution
$x^{min} and\ x^{max}$	Lower and upper bound vectors, respectively, delimitating the feasible solution space

(x^t, y^t)	Pair of two vectors in float representation from generation t
z_j	Offset value that guarantees the minimum amount of variance
α	Ratio of the blend crossover
$\alpha_{ji}, \beta_{ji}, \gamma_{ji}$	The constant, linear and quadratic coefficients of the emissions of fuel type j emitted by unit i, respectively
β_j	Constant of proportionality
$\Delta(W\text{-}PD)$	Estimated mean variation of aggregated wind power and load values over the dispatch interval
δ_i	Voltage angles at bus i
E	A sufficiently small number
η_t	Deviation from the estimated mean
$\theta(s_k)$	Fitness score of the individual s_k
λ	Lagrange multiplier
μ *and* μC	Security level and associated cost for the security level, respectively
$\mu(\mathbf{S_0})$	Lebesgue measure of $\boldsymbol{S_0}$
φ_{ij} *and* λ_{ij}	Exponential coefficients of the emissions function applied to generator i and pollutant j
Ω	Weight parameter
Π^{min} and Π^{max}	Minimum and maximum thresholds for the security level
ΠC^{min} and ΠC^{max}	Minimum and maximum thresholds for the associated cost of security

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Chapter 1

Introduction

1.1 Electricity as a vital commodity

Electricity became a vital commodity in our modern times. Almost every other commodity around us relies on electricity, from light systems, heating, cooling, water systems, communication, and transportation to a wide range of industrial processes. More than fifteen percent of energy consumed worldwide refers to electricity, but this percent is much higher in developed countries and tends to increase. Moreover, electricity consumption is highly correlated with the economic growth. In the past three decades, the electricity consumption worldwide almost tripled as a consequence of economic growth.

The vital impact of electricity on our daily lives is especially noticed when sudden interruptions in the continuous electricity supply occur. Moreover, sudden, uncontrolled, wide-scale power outages may result in high societal and economic threats. Just to mention in brief several notable blackouts which occurred during the last decade around the world and their impacts in terms of the number of people affected:

the blackout in Java-Bali, Indonesia affected more than a hundred million people in September 2005; in November 2009 the blackout in Brazil and Paraguay affected about ninety million people, while in September 2003 a widespread blackout affected all Italy (except two of its islands) for about twelve hours and part of Switzerland for about three hours; the blackout in Northeast USA and Southeast Canada in 2003 left forty million people in the dark [1].

Electricity is usually produced by large power plants which use coal, heavy fuel oil, natural gas, hydro or nuclear fission as primary energy source and transform it into electrical power. Besides these technologies which have been used in power systems for decades, renewable energy sources such as wind, solar thermal and solar photovoltaics, biomass and micro-hydro are increasingly being utilized into the modern power systems. Each of the technologies mentioned above have a couple of economic, technical and societal advantages and disadvantages. The fossil fuel and nuclear technologies, on one hand, have the disadvantages of using finite resources with unequal distribution of fuel supplies between regions (creating possibilities for exercising political influence), and they are pollutant (emission of greenhouse gases or nuclear waste). On the other hand, they represent affordable, reliable and well controllable technologies for electricity supply at a large scale. Renewable sources of energy have the advantage of being an unlimited resource (especially wind and solar), and may lead to a reduced dependency on imported fuel. However, they have economic and technical disadvantages, such as that they are still more expensive than conventional generation and they are mostly less controllable since their primary energy cannot be controlled (with the exception of hydro, geothermal and biomass). Therefore, the integration of renewable energy sources into the power system poses technical and economic challenges.

To reach the consumers (also known in power systems as *loads*) which are widely spread on large areas, electricity is usually transported and delivered through electrical networks (transmission and distribution networks which differ by means of the voltage level). A schematic representation of electricity supply chain is presented in Figure 1.1.

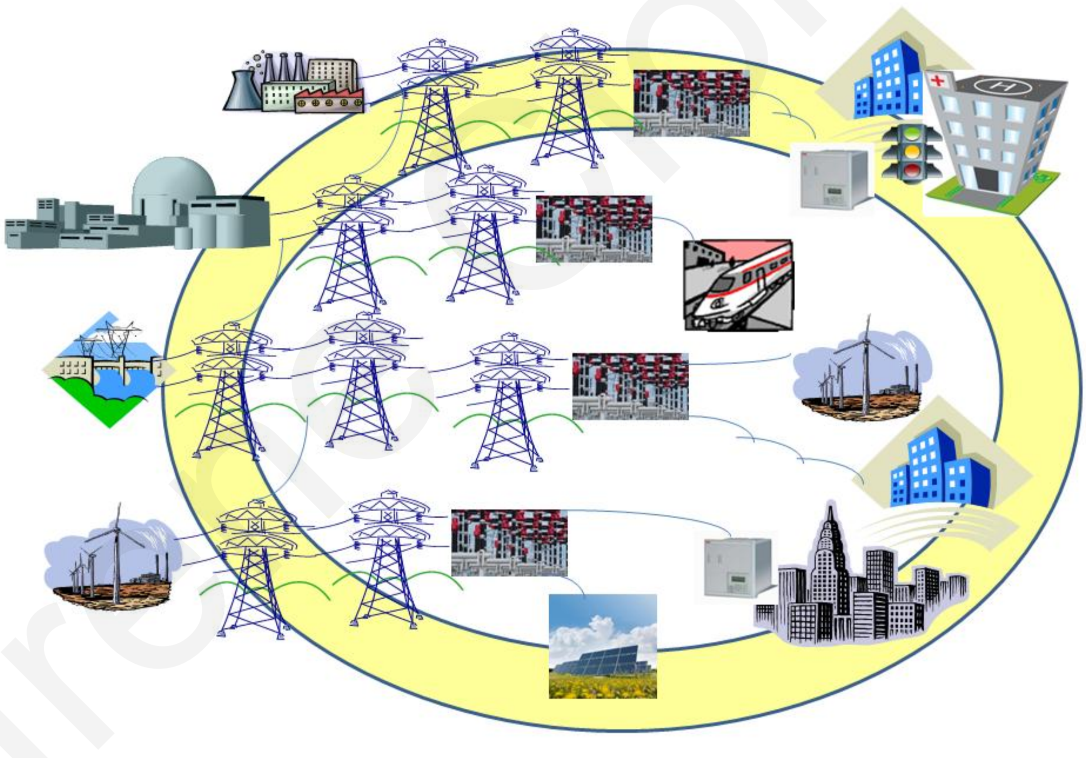

Figure 1.1 Pictogram of the electricity supply chain

Electric energy is critically important in our daily lives, and its need is growing year after year with a faster or slower rate, depending on the economic growth and societal development. Sustainable and reliable generation of electricity is required, while societal, economic and engineering constraints need to be met. Moreover, compared to other vital commodities such as water or food, electricity has a number of particularities which make it a special commodity: it cannot be economically stored, has no substitutes, and requires near perfect, instantaneous balance between generation and demand. Thus, it is worth saying that the power system operation and management is one of the most challenging problems to solve. Parts of these challenges are to be addressed in this work.

1.2 Economic dispatch in power system operation

In general, the power generation problem is based on three different sets of decisions which are dependent on the length of the planning time horizon. The first set consists of the long-term decisions (years) where the decision variables to be determined are the capacity, type, and number of power generators (units) to own. In the medium term (days to months), one needs to decide how to schedule (commit) the existing units for the planning horizon. And finally, in the short term (minutes to hours), the goal is to efficiently determine the amount of power that each committed unit need to produce in order to meet the real-time electricity demand. In general, the long-term problem is identified as the power expansion problem, the medium-term problem is identified as the unit commitment (UC) problem, and the short-term problem is called the economic dispatch (ED) or generator allocation problem. Note that the mid-term problems may refer also to the maintenance scheduling, when the time horizon is in the range of one year. In this case, the short-term problems refer to both UC and ED, and their time horizon is in the range of weeks to minutes.

A pictorial understanding of the main power system operation problems, their time frame and questions they answer is given in Figure 1.2 below.

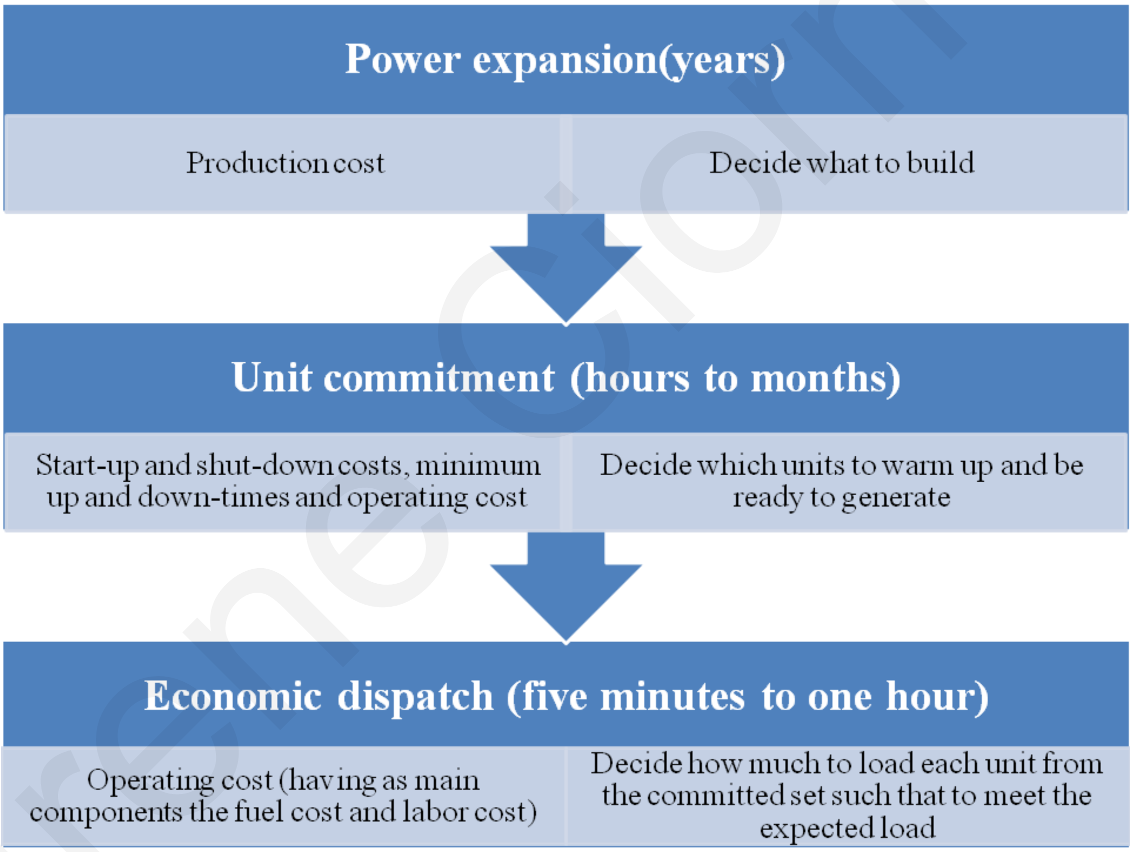

Figure 1.2 Overview of the main power system operation problems

One of the main challenging aspects of power systems operation is that electrical energy cannot be economically stored in significant amounts. Thus, electrical power must be consumed at the same moment it is generated. For a reliable supply of power it is therefore essential to maintain the balance between demand (total system load including transmission and distribution line losses) and generation. It is in principle possible to maintain the power balance by adjusting both generation and demand, but historically, mostly the central generation units have been used to follow the demand at all times. The operation of power systems is therefore critically dependent on the capabilities of generators for balancing the load. In reality, one may say that any electric power system is never at its equilibrium. This happens first of all due to the stochastic nature of the demand, due to unplanned equipment failures, or due to stochastic power generation.

Due to the diversity in the characteristics and operation properties of different power generation units in a power system network, scheduling of these generation units is needed based on load forecasts and the economics and technical characteristics of the available generation units. This involves the calculation of the optimal selection of units for power generation (UC) and the optimal loading of the selected generators for subdivisions of time of the initial commitment time span (ED). The main difference between the ED and the UC problems is that the ED assumes that there is a set of units (say *NG* units) already connected to the system. On the other hand, the UC problem assumes that having a set of *MG* available units and assuming as known a forecasted load, determine which are the optimal subsets of the complete set of *MG* units which will satisfy the load in the most economical way? Note that the number of total available units (*MG*) is not always identical to the total number of committed units

(*NG*). The units not committed form the so called “cold reserve”. Important parameters in unit commitment include start-up and shut-down costs, minimum up and down-times and operating cost. The economic dispatch performs the actual distribution of the total load between committed units, which is optimized for each operating state while taking into account all economic and technical aspects of the units. The cost component which is the most important in the economic dispatch case is the operating cost. The operating cost is dominated by the fuel cost, although labor is also a key component. Thus, the goal of power system economic dispatch is to minimize the fuel cost (or in other words, to maximize system efficiency and minimize system losses that cannot be billed or pass on to customers). From the output of UC and ED an estimation of the associated use of fossil fuels and emission of greenhouse gases can be calculated as well. In summary, in order to reach the goal of economic dispatch, first one needs to develop relationships between the cost of power output and the operating costs.

Unit commitment and economic dispatch problems rely on forecasted values for the load demand determined for each dispatch interval. When stochastic power generation such as wind is part of the power system portfolio, the UC and ED problems are highly challenging due to the variability and limited predictability of this generation, which come on top of existing variations and uncertainties of the load. For the operation of power systems with significant amounts of stochastic renewables, the importance of conventional generation will remain or may increase even further in order to guarantee a reliable power supply.

1.3 Motivation and objectives

In power systems planning and operation, the optimal allocation of power output among the committed generating units, termed economic dispatch (ED), is one of the most important optimization problems. In practice, due to the power generation diversity, the power plants have different fuel and operational costs, they are not located at the same electrical distance from the centre of loads, and under normal operating conditions the generation capacity is more than the total load demand and transmission losses. Thus, there are many options for scheduling generation [2]. Moreover, it is widely recognized that a proper scheduling of the available generating units may lead to significant savings per year (billions of Dollars/Euros for large utilities) in production costs [3].

Just analyzing a simple example may give a hint of what economic dispatch means in terms of utility savings. The following example is based on the principle of equal incremental fuel cost, which will be detailed in Chapter 2. In short, the incremental fuel cost (IC) is an indicator of how much it will cost to operate a generator which produces one additional MW of power, and has as unit Euros per megawatt hour (€/MWh). Let us assume a case where there is a power system with two generators characterized by linear incremental fuel costs $IC_1 > IC_2$. That means that for an additional 1 MW, the operating cost of the first generator is more than the operating cost of the second generator. Assume an ideal system where there are no transmission line losses, and no generator limits and if the objective is to minimize the total operation cost, which always is the business case, then it is reasonable to reduce the power output at generator one and, in return, increase the output of generator two.

In real power systems, the economic dispatch problem is highly nonlinear due to the fuel-power characteristic of the modern thermal units (e.g. units with multiple admission valves) or due to the power system operation constraints (e.g. power flow and transmission losses in the network) and discontinuity due to a number of technical constraints which may affect each individual unit such as generation limits (maximum generation capacity and minimum stable generation), flexibility (the power output can be adjusted within limits, or there are inflexible units such as nuclear where the power output cannot be adjusted due to technical reasons), or prohibited operating zones (zones on the power output characteristic which must be avoided due to thermal instability of the unit). The non-detailed formulation of the problem due to the necessary assumptions made is leading to limitations in the modelling of real-world, large scale power systems.

This dissertation aims at proposing solutions for a more accurate model of the ED problem in power system generation which takes into account its nonlinearities and nonconvexities, as well as the partial predictability of power generation from renewable sources such as wind, while respecting at all times the physical constraints of the power network. The fuel cost curve allows us to look at a wide range of economic dispatch practice such as total operating cost of a system, incremental cost and minute by minute loading of a generator. Further, the power system modeling and economic dispatch procedure highly reflect the fact that the power grid system is fast becoming a computerized control system. By taking this approach, we are aiming at a much higher operating precision and less human error.

The algorithms proposed in this dissertation are characterized by the accuracy and robustness of the solution, while computational effort is reduced compared to other similar recently developed methods. Moreover, one of the algorithms proposed in the dissertation can easily be applied to any other large scale optimization problem having high nonlinearities.

Nowadays, renewable energy, and especially wind energy, draws much attention for both governments and the power engineering community as a viable clean energy alternative to classical, coal or oil-fuel burning power plants. However, wind generation brings technical and economic challenges to be addressed, especially in power systems with limited flexibilities. Such flexibilities refer to interconnections to other power systems, the existence of hydropower plant and/or combined heat and power (CHP) units in the generation mix, and the presence of flexible consumers (consumers which can reduce or increase their load according to the needs of the power system dispatcher). The dissertation also stresses the dispatch challenges that the power system dispatchers may face in operating isolated systems with a high share of renewable generation and limited flexibilities, in particular the power system of Cyprus. Solutions to part of these challenges are proposed.

In summary, the main objectives and contributions of this dissertation are as follows:

- to identify dispatch challenges in the future power system architecture; the focus of this objective is to analyze the transformations in the economical and technical organization of the modern power systems and to identify the impact and challenging aspects on the dispatch of generation;
- to determine suitable models and mathematical formulations for the economic dispatch problem according to the new power system architecture; the focus of this objective is to determine how to represent the objective mathematically and what is the accuracy of this formulation (limitations and assumptions under which the system is represented);
- to develop approximate search algorithms which can provide suitable solutions for the more accurate models proposed (nonconvex in nature) for the economic dispatch problem; the focus of this objective is to find the mathematical/algorithmic tool to be used to obtain the objective defined above and to interpret what does solving the set of equations help us to decide;
- to propose solutions which may overcome part of the dispatch challenges in isolated power systems with a high share of power supplied by renewable energy sources.

1.4 Dissertation Outline

This dissertation is structured in six parts. They are briefly introduced below.

Chapter two discusses the possible formulations of the economic dispatch problem. This chapter looks at and classifies the different formulations of the problem according to the optimization targets that are to be followed.

Typically, the objective of the economic dispatch problem is to find the real power scheduling of each power plant or at each power producer (in the energy market context), such that to minimize the operation cost (total fuel cost), while continuously respecting the operating/physical constraints of the power network. This is done by minimizing (maximization can be translated into a minimization problem as well) the selected objective functions while maintaining an acceptable system performance in terms of generating capability limits and the output of the compensating devices.

The objective functions, also commonly known as *cost functions*, may refer to economic costs or profits, system security, environmental emission costs, or other objectives. Active and reactive power planning may be considered for the economic operation of the power systems. A detailed description of the various forms of objective functions and the constraints considered in the ED problem is summarized in this chapter. The optimization problem may be a linear, quadratic, or non-convex constrained optimization problem based on the mathematical approximation model used; consequently, the methodologies to solve this optimization problem can vary significantly.

Chapter three analyzes and discusses the methodologies proposed in the power system community to solve different approaches of the economic dispatch problem. The methodologies used to solve the economic dispatch problem vary widely according to different approaches in formulation. Therefore, a variety of methodologies and algorithms has been developed to accomplish the solution of the optimal economic dispatch problem, according to the utility generation mix and their particular constraints and needs in terms of modeling accuracy. The methods vary from relatively simple analytical or graphical methods, to highly complex and theoretically complicated approaches. This chapter summarizes the classical and modern algorithms proposed in the last three decades and classifies them into analytical, computational intelligence, and hybrid methods. The chapter also presents a summary of the most common testing platforms (benchmark test systems) for the surveyed algorithms. A concluding discussion emphasizes the advantages and disadvantages in adopting different solutions together with their appropriate usage according to the model adopted in formulation of the economic dispatch problem.

Chapter four introduces the novel algorithm of GAAPI which aims at being a robust optimization tool for unconstrained continuous optimization problems. This algorithm is appropriate for optimization problems whose decision variables take values from the real – number domain. The GAAPI algorithm was created by combining some unique characteristics of two other powerful meta–heuristic algorithms: a real coded genetic algorithm (RCGA) and a special type of ant colony based algorithms for continuous domains (API). An empirical validation of the algorithm is carried out for twenty widely known challenging benchmark functions. It was proven that in most of the test cases (15 out of 20), GAAPI provided satisfactory or optimum solutions, with very little computational effort compared to other powerful methods of its class. The algorithm is recommended for large, complex problems with a dimensionality greater than 30.

Chapter five proposes the application of the new developed GAAPI algorithm to the constrained optimization problem of economic dispatch in power systems. The proposed algorithm was redesigned in such a way that the various power system constraints may be modeled and respected. It was also shown that starting from the solution obtained for the quadratic cost function (Lagrange multipliers method), the search space is reduced, and implicitly the computational effort is reduced. The strategy for handling the constraints is to always generate feasible solutions and work only with these feasible solutions during the search process of API, while the RCGA algorithm may allow infeasible solutions which are further controlled by an aggregated penalty objective function. This constraint handling method is therefore a hybrid one. The proposed solution was then empirically validated on a number of standard IEEE test systems. It was proven that the GAAPI for ED always find comparable or better solutions in a number of independent trials, while always satisfying the constraints, as compared to other methods available in the power systems literature. Further, through the test cases presented, its superiority in robustness is evident: it has a high probability to reach the global or quasi-global solution, especially in nonconvex formulations. GAAPI converges smoothly to the global, avoiding fast convergence that may lead to local optima.

Chapter six addresses the technical and economic challenges of isolated power systems with variable, partially predictable generation such as wind. Also, the impact of wind generation on the economic dispatch is discussed. Further, solutions to partially overcome the dispatch challenges are proposed, while directions for further research are discussed. In this chapter a real case study (the power system of Cyprus) in considered for the analysis of economic and technical challenges in dispatching isolated power systems with stochastic generation such as electricity generation from wind parks and limited flexibility. A brief enumeration of the challenges resulted from the study is: (i) there may be an increase in reserve demand (which can go up to 20% increase) especially in the valley load periods which coincide with high instant penetration of wind power; (ii) an increase in frequency of ramping in the case of fast units which can be translated into shortening the maintenance period intervals for those units and therefore higher maintenance costs per year and also increase in failure risk of those units; (iii) wind power curtailment may be advised by the system operator when a large error between predicted and realized wind occur.

In this chapter, two solutions are proposed to overcome some of the above mentioned challenges. One refers to the reformulation of the ED problem as a multi/bi-objective optimization where the cost of generation and the security level of the system are optimized simultaneously. The other one addresses the importance of the ramp rate limits in the formulation of the ED problem, especially when more variability takes place during intra-hour dispatch. The last solution refers to a stochastic ED formulation where the ramping constraints are depicted as linear stochastic functions. Moreover, when a forecasting program is run before each ED call, better integration of wind energy is expected, as suboptimal solutions and eventually wind curtailment are avoided.

Chapter seven: the last chapter of the dissertation refers to concluding remarks and to future directions of research in the field of power generation dispatch.

Chapter 2

Economic dispatch: Approaches

2.1 Introduction

In general, the generation scheduling problem is identified as the economic dispatch problem (also known as *generator allocation* or *optimal loading*). The economic dispatch problem is concerned with selecting the best output level for all generators which are committed in the system. It can be a subproblem of the unit commitment problem, or an independent problem to be solved at a time interval (known as *the dispatch interval*), which typically ranges from five minutes to one hour, depending on the utility. The ED problem answers the question: what should the output power of each committed unit be during each dispatch interval such that to ensure secure electricity supply for a specific load demand in the most economical way?

The possible formulations of the economic dispatch problem are discussed in this chapter. Typically, the objective of the economic dispatch problem is to find the real power scheduling of each power plant or at each power producer (in the energy market context), such that to minimize the operation cost (total fuel cost), while continuously respecting the operating/physical constraints of the power network. This is done by minimizing (maximization can be translated into a minimization problem as well) the selected objective functions while maintaining an acceptable system performance in terms of generating capability limits and the output of the compensating devices. The objective functions, also commonly known as *cost functions*, may refer to economic costs or profits, system security, environmental emission costs, or other objectives. Active and reactive power planning may be considered for the economic operation of the power systems. This dissertation focuses on active power dispatch.

The economic dispatch problem may be formulated in terms of the energy market context (e.g., monopoly or liberalized), in terms of the approximation used for the objective function, in terms of the assumptions related to load dynamics, and in terms of the constraints considered. Despite the type of formulation, the generic economic dispatch problem is in essence a constrained optimization problem of the general form given below:

$$\begin{aligned} &\textit{Optimize } f(x) \qquad x \in R^n \\ &s.t.\ h_k(x) = 0, \text{ with } k=1\ldots K \\ &g_l(x) \leq 0, \text{ with } l=1\ldots L \end{aligned} \tag{2.1}$$

where, $f(x)$ is the objective function to be minimized or maximized, and $h_k(x)$ and $g_l(x)$ are the equality and inequality constraints imposed by the physical limitations of the system. K and L denote the number of the equality and inequality constraints considered in the problem.

A summary of various formulations of the economic dispatch problem is pictured in Figure 2.1. Detailed description of the various forms of objective functions and the constraints considered in the ED problem is presented in the following parts of this chapter. The optimization problem may be a linear, quadratic, or non-convex constrained optimization problem based on the mathematical approximation model used; consequently, the methodologies to solve this optimization problem can vary significantly.

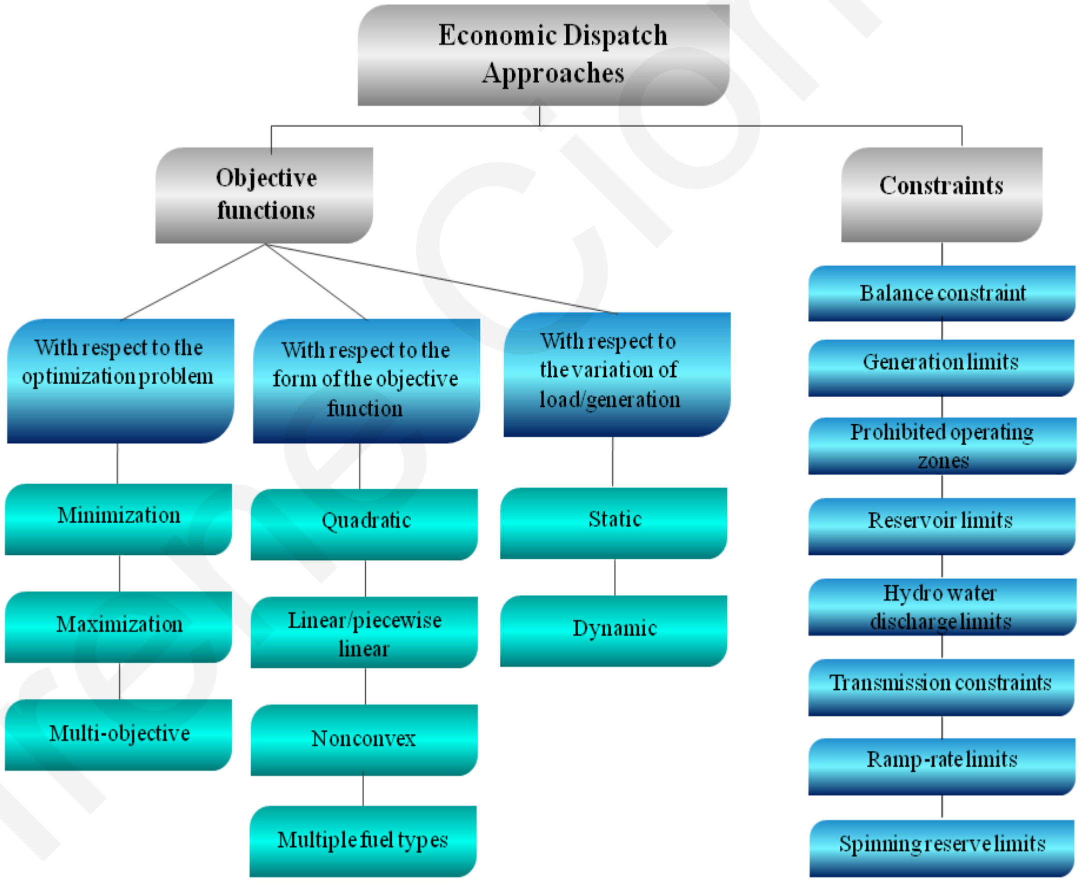

Figure 2.1 Summary of the economic dispacth approaches

2.2 Objective Function Formulations

The objective function to be optimized in the ED problem refers mainly to the generation cost. Generation costs may be subdivided into capital costs (those required to erect the plant) and operating costs (those required to actually produce electric power, which in turn have two main components: the fuel cost and the labor cost). These costs may vary widely with different technologies: for example, nuclear and some hydroelectric units have high capital costs and low operating costs, while natural gas generators have low capital costs and higher operating costs. It is important to note that both the capital and the operating costs may differ from country to country for the same technology.

It is widely accepted that generator operating costs are those to be taken into account for the economic dispatch formulation [2, 4-7]. These costs are typically represented by up to four different curves: 1) input/output (I/O); 2) fuel-cost curve; 3) heat-rate curve; and 4) incremental cost curve [2, 5, 8].

In the context of the electricity market, the objective function of the economic dispatch problem refers to the overall profit of the economic players in the market (generation, retailers, and consumers). This profit is very sensitive to electricity price volatility in different time intervals (the *day-ahead retail price* refers to a time-slot in the day-ahead market; and the *real-time retail price* refers to a time-slot of the balancing market/real time-scheduling market), as well as to the market agents behavior [9-11].

2.2.1 Formulation with Respect to the Optimization Problem

It is possible to formulate the objective function as a minimization, maximization, or multi-objective problem. In the context of the energy market framework, all three formulations may coexist.

a. Minimization problem

The allocation of generation to the generating units is performed in such a way as to minimize the cost of power generation:

$$\begin{gathered} Minimize\ Operational\ Cost\ (OC) \\ s.t.\ h_k(x) = 0, \text{ with } k=1\ldots K \\ g_l(x) \leq 0, \text{ with } l=1\ldots L \end{gathered} \tag{2.2}$$

where, OC is the cost of generation in the load following group of committed units, while h_k and g_l are the equality and inequality sets of constraints as defined in (2.1). The detailed mathematical approximation of the OC is described by (2.8), (2.10), (2.11), and (2.12) below.

b. Maximization problem

Each actor in the energy market aims at maximizing its profit. Profit maximization is not always identical with the minimization of the operational cost. In the energy market context, the GENCOs no longer have the obligation to serve the demand; therefore, they may choose to generate less than the demand. This fact allows more flexibility and makes the ED problem under a deregulated environment more complex. Moreover, the profit depends, not only on the cost, but also on the revenue. If the revenue increases more than the cost does, then the profit will increase. This problem is formulated as,

$$\begin{gathered} Maximize\ Profit\ (P_t) \\ s.t.\ h_k(x) = 0, \text{ with } k=1\ldots K \\ g_l(x) \leq 0, \text{ with } l=1\ldots L \end{gathered} \tag{2.3}$$

where P_t is the profit of the generating company (difference between the selling price and the cost of generation). The profit is given by,

$$P_t = \sum_{i=1}^{NG} P_i * sp - OC \ \ (€/h) \tag{2.4}$$

where, P_i is the output power of the i^{th} generating unit, *sp* is the selling price per MW produced (which is taken as constant during the dispatch interval), and *NG* is the number of generators in the power system committed for dispatch. The operational cost and the profit are generally expressed in monetary currency per hour. Both Euro (€) and US Dollar ($) currencies have been arbitrarily chosen in this dissertation.

Recent advances in economic dispatch under a deregulated energy market may consider a model with both supply (SSM) and demand side management (DSM). Generation and demand offers are highly sensitive to forecasted electricity prices, while also correlated to the behavior of other market participants. Thus, one can distinguish two classes of opportunistic users: non-persistent (users which leave the power market if they find that the current electricity price, in the time frame they are acting, is unacceptable) and persistent (they wait for the next acceptable price corresponding to the next time frame of the market)[10]. The objective function implies maximization of the overall profit which refers to both generation and demand sides. Thus, the profit P_t from (2.4) is written as,

$$P_t = \sum_{m=1}^{M} R_m^u \ (€/\mathrm{h}) \tag{2.5}$$

where, R_m^u is the total profit (revenue) of both generating companies and electricity consumers in the interval *m* of the day-ahead market, when the day-ahead retail price is *u*(*m*), and *M* is the total number of intervals in the day-ahead market. Due to the probabilistic nature of the generation and the demand sides, R_m^u is determined as an approximate (expected) value of a random variable. Thus, R_m^u depends on the exact stochastic models assumed for wind generation and the energy demand of the consumer. Also note that the optimization problem related to (2.5) is subject to the timeframe of generation/consumption in the day-ahead or balancing electricity markets.

c. Multi-objective problem

The multi-objective problem as referenced in economic dispatch approaches may refer to i) the minimization of generation cost and maximization of the security level of operating the system, when variable generation from renewable sources take part into the economic dispatch process [11-13]; or ii) the minimization of both generation cost and emissions (duality problem), when emissions regulations play a significant role in the load following operation [4, 14-20]. The multi-objective problem is therefore formulated as,

$$Minimize\ (OC)\ and\ Maximize\ Security\ Level\ (SL) \tag{2.6}$$

or

$$Minimize\ (OC)\ and\ Minimize\ Emissions\ (E) \tag{2.7}$$

where, *SL* is the security level of the power system under consideration; it can be estimated using different reliability parameters (e.g., the loss of load availability per year [12, 21, 22]) and can be modeled as a linear or quadratic approximation. The emissions function (*E*) can be seen as a tax paid for emissions produced by each kWh output [23, 24] and can therefore be included in the operational cost optimization function; or, as the total amount of emissions produced by the thermal generation mix under dispatch (in tons/h) and included in the constraints [19-21, 23-28]. A simplified representation of the *OC* and *E* can be found in (2.8) and (2.10), and (2.9), respectively.

2.2.2 Formulation with Respect to the Form of the Objective Function

The most common representations in the ED formulation are the quadratic cost of generation, the linear or piecewise linear function, the nonconvex cost of generation, and the multiple fuel types.

a. Quadratic cost of generation (variable fuel cost)

Smooth quadratic (convex) function approximations of the unit input-output characteristics provide the basis for most classical economic dispatch techniques. The objective function may be represented as a second order polynomial in the form,

$$OC = \sum_{i=1}^{NG} (a_i + b_i P_i + c_i P_i^2) \ (€/\mathrm{h}) \tag{2.8}$$

where, P_i is the output of the generating unit i and the terms a_i, b_i and c_i, are the constant, linear and quadratic fuel-cost coefficients of unit i. The quadratic representation is the most common approach when modeling the operational cost of any thermal power plant.

The quantitative function of the emissions is typically represented (mainly for simplification) as a quadratic [19-21, 23] or linear function [19-21, 23, 25-27],

$$E = \sum_{j=1}^{NP} w_j \sum_{i=1}^{NG} \alpha_{ij} + \beta_{ij} P_i + \gamma_{ij} P_i^2 \ \ (€/h) \tag{2.9}$$

where, NP refers to the number of pollutants taken into account; the terms α_{ij}, β_{ij}, γ_{ij} are the constant, linear and quadratic coefficients of the emissions of fuel type j emitted by unit i, respectively, and they are expressed in (tons/h), (tons/MWh), and (tons/(MW)^{2}h), respectively; w_j is the emissions-to-cost conversion factor for emissions type j, and is expressed in (€/tons).

In the deregulated energy market context, and assuming nondiscriminatory access to the transmission facilities, the variable cost to be optimized can be seen as an aggregation between the variable fuel cost (2.8) and the wheeling cost (which reflects the use of the transmission facility for every power transaction). The most common wheeling cost function is determined based on a DC power flow model [29].

b. Linear or piecewise linear function

Many utilities prefer to represent their generator cost functions as single- or multiple-segment linear cost functions [2, 5, 8], as illustratively presented in Figure 2.2.

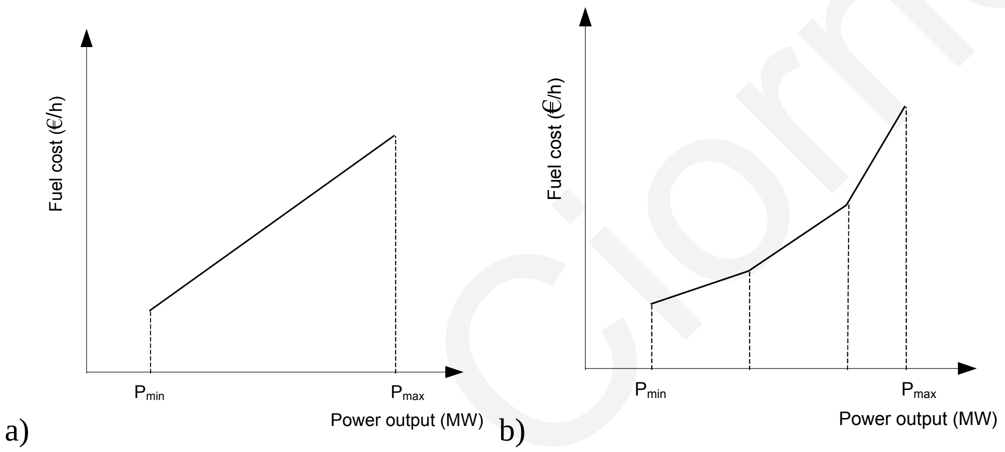

Figure 2.2. Linear or piecewise linear generator cost function: a) single-segment representation; b) multiple-segment representation.

In the energy market framework, the *incremental cost* (*IC*) or *marginal cost* (*MC*) *of generation* is one of the most important quantities in operating a power system, representing the cost of producing the next increment of power (next MWh). At least theoretically, the MC should be the bidding price into the market of any power producer (GENCO), together with the physical limitations of their generator portfolios [8]. Therefore, the TSO responsible with the energy market balance will solve the dispatch problem using the above mentioned IC (MC), together with the wheeling (transmission) cost (WC) [30]. Assuming a quadratic representation of the fuel cost, the IC can be written as,

$$IC_i = \frac{dOC_i}{dP_i} = b_i + 2c_iP_i \ (€/\mathrm{MWh}) \tag{2.10}$$

Linear components to incorporate risk evaluation due to wind energy variability in generation can be added to the generic fuel cost function [12], or to the power wheeling cost component [31]. According to [30], there are four methods to evaluate the power wheeling cost: the postage stamp method, the megawatt mile method, the contract path method, and the marginal cost method. All the above mentioned methods assume linear approximations and only the approaches differ.

c. Nonconvex cost of generation

Modern thermal units have multiple fuel admission valves that are used to control the power output of the unit. The generator cost function is obtained from data points taken during "heat run" tests, when input and output data is measured as the unit is slowly varied through its operating region. As each steam admission valve in a turbine starts to open, it produces a rippling effect on the unit curve. These "valve-points" are illustrated in Figure 2.3 for a five-valve steam turbine unit.

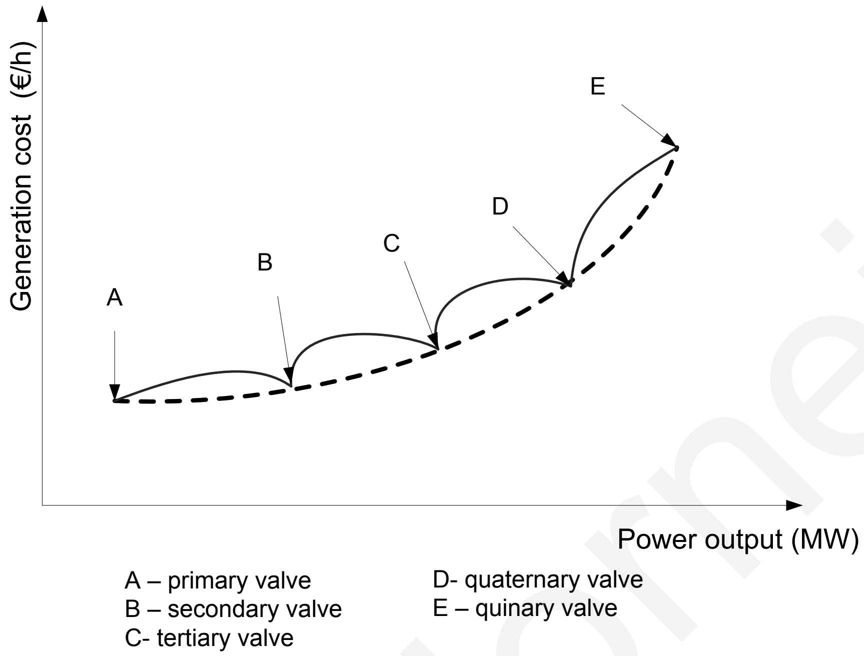

Figure 2.3 Nonconvex cost of generation for a five-valve steam turbine unit

The valve point effect is modeled by adding a sinusoidal component to the quadratic approximation of the fuel cost function [32-49],

$$OC = \sum_{i=1}^{NG} a_i + b_i P_i + c_i P_i^2 + \left| e_i \sin\left(f_i\left(P_i^{min} - P_i\right)\right)\right| \ \ (€/\mathrm{h}) \qquad (2.11)$$

where, e_i and f_i are the fuel-cost coefficients of unit i responsible to model the rippling effect of the opening of the admission valves and P_i^{min} is the minimum accepted output power of unit i.

A power generation system may also use combined cycle units (CC), formed by a series of single-cycle gas turbines in conjunction with some heat recovery steam generators (HRSG), as peak load serving units [50]. In this case, the ED problem with CC units has a mixed continuous-discrete optimization incremental cost function as depicted in Figure 2.4.

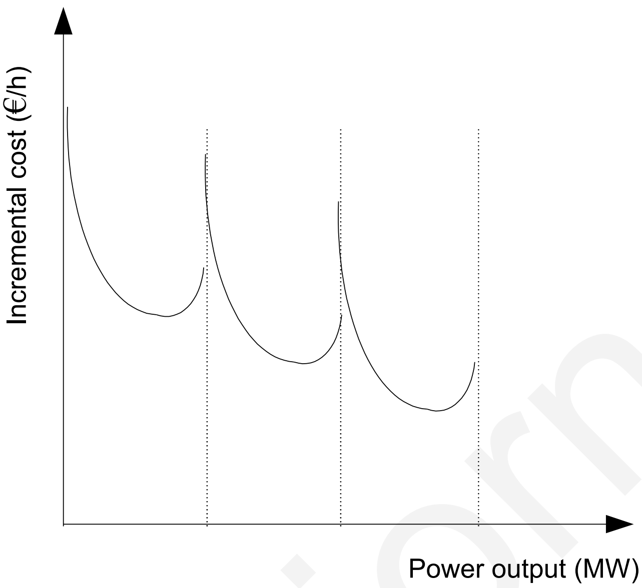

Figure 2.4. Incremental cost curve for a CC unit with three gas turbines and one HRSG

d. Multiple fuel types

Some modern thermal units can burn different types of fuels at different stages of operation [43]. Therefore, their corresponding generation cost should be expressed as follows,

$$OC_i(P_i) = \begin{cases} a_{i1} + b_{i1}P_i + c_{i1}P_i^2 & fuel\ 1, \quad P_i^{max} \le P_i \le P_{i1} \\ a_{i2} + b_{i2}P_i + c_{i2}P_i^2 & fuel\ 2, \quad P_{i1} \le P_i \le P_{i2} \\ \quad \cdots & \quad \cdots \quad\quad\quad \cdots \\ a_{i1} + b_{i1}P_i + c_{i1}P_i^2 & fuel\ k, \quad P_{i(k-1)} \le P_i^{max} \end{cases} \quad (€/\mathrm{h}) \qquad (2.12)$$

where, a_{ij}, b_{ij}, c_{ij} are the cost coefficients of generator i for the fuel type j, and P_i is the power output of generator i.

Most of the formulations in (2.8), (2.10), (2.11) and (2.12) suggest that the thermal power plants ensure the load following regulation. This is true for the majority of the power systems, but in some power systems combined cycle (CC), hydropower plants and wind farms can also participate in the economic dispatch operation. As the fuel component is the most significant part of the operation cost, wind and hydro participation will not influence the objective cost function, but only the system constraints.

2.2.3 Formulation with Respect to Load/Generation Variations

The economic dispatch problem may be formulated as a static or dynamic optimization problem.

a. Static economic dispatch (ED)

In this formulation, the temporal component is ignored, as presented in (2.8), (2.10), (2.11), and (2.12).

b. Dynamic economic dispatch (DED)

In the dynamic formulation of the economic dispatch problem, the changes in the load (in the context, load may refer either to the power consumption or to the aggregated load which is read as the difference between the power consumption and the power generated from wind) are taken into account over a specific time interval (dispatch period) which usually lasts for 24 hours. Therefore, a temporal component is considered in the problem formulation. Compared to the static formulation of the problem, the dynamic formulation approach has a "look ahead capability" [51]. Typically, the ramp rate constraints distinguish the dynamic economic dispatch (DED) problem from the traditional, static economic dispatch [14, 32, 33, 52-59]. These constraints are also called “dynamic constraints”. The dynamic economic dispatch may also have a convex or nonconvex function of cost of generation, while the constraints can be the same as in the static approach.

Optimal dynamic dispatch is a variation of DED where the generation of a power system is modeled in terms of a continuous-time or discrete-time control system [60, 61]. For a recent survey on the dynamic economic dispatch formulation and solutions, the reader is invited to study a recent survey of Xia and Elaiw [51].

2.3 Constraints formulation

In power systems operation a number of physical (mechanical, thermal, and capacity) constraints must be continuously respected to ensure the reliable and secure operation of the system. The generic economic dispatch formulation takes into account most of the following limits and constraints.

a. System Demand and Generation Balance

The total electric power generation has to meet the total electric power demand plus the power losses in the transmission lines. Hence,

$$P_D + P_{Loss} - \sum_{i=1}^{NG} P_i = 0 \tag{2.13}$$

where, P_D is the load power demand, P_{Loss} represents the transmission losses, and P_i is the output power of unit i out of NG total units in the system. The balance constraint is usually expressed in terms of real power. Demand side power can be seen as an uncertain measure in the context of energy markets which allow demand side management (opportunist users) [62].

b. Generation Limits

For stable operation, the real power output of each generator is restricted by lower and upper limits as follows,

$$P_i^{min} \leq P_i \leq P_i^{max}\ (MW) \tag{2.14}$$

where, P_i^{min} and P_i^{max} are the lower and the upper bound of generation of unit i.

c. Prohibited Operating Zones

Modern generators with valve point loading may have many prohibited operating zones [13]. Therefore, in practical operation, when adjusting the generation output P_i of unit i, operation in the prohibited zones must be avoided. The feasible operating zones of unit i can be described as,

$$\begin{array}{l} P_i^{min} \leq P_i \leq P_i^{l_1} \\ P_i^{u_{j-1}} \leq P_i \leq P_i^{l_j}, \qquad j = 1,..,N_{POZ} \\ P_i^{u_j} \leq P_i \leq P_i^{max} \end{array} \tag{2.15}$$

where, N_{POZ} is the number of prohibited zones of unit i; $P_i^{l_j}$ and $P_i^{u_j}$ are the lower and upper bounds of the prohibited zone j of unit i, respectively.

d. Reservoir Storage Limits

When hydro units are part of the generation dispatch pool, restrictions imposed by the limits of their storage reservoirs must be considered,

$$X_i^{min} \leq X_i \leq X_i^{max} \; (m^3) \tag{2.16}$$

where, X_i^{min} and X_i^{max} are the minimum and the maximum level of the reservoir of the hydro unit *i*.

e. Hydro Water Discharge Limits

Each hydropower plant can discharge a limited quantity of water in a predefined time interval (the dispatch period), and therefore,

$$U_i^{min} \leq U_i \leq U_i^{max} \; (m^3/time\ interval) \tag{2.17}$$

where, U_i^{min} and U_i^{max} are the minimum and the maximum water discharge limits of the hydro unit *i*.

f. Transmission Constraints

The following constraints are derived from the OPF formulation and are also usually called network constraints as they relate to the power balance in the system.

$$Q_i - Q_{Di} - |V_i| \sum_{j=1}^{NB} |V_j| \, [G_{ij} \sin(\delta_i - \delta_j) - B_{ij} \cos(\delta_i - \delta_j)] = 0 \tag{2.18}$$

$$P_i - P_{Di} - |V_i| \sum_{j=1}^{NB} |V_j| \left[G_{ij} \cos(\delta_i - \delta_j) + B_{ij} \sin(\delta_i - \delta_j)\right] = 0 \qquad (2.19)$$

where, i = 1,..., NB; NB is the number of buses; Q_i is the reactive power generated at the i^{th} bus; P_{Di} and Q_{Di} are the i^{th} bus real and reactive power demand, respectively; G_{ij} and B_{ij} are the transmission line conductance and susceptance between bus i and bus j, respectively; $|V_i|$ and $|V_j|$ are the voltage magnitudes at bus i and bus j, respectively; and δ_i and δ_j are the voltage angles at bus i and bus j, respectively.

The power flow solution gives all the bus voltage magnitudes and angles. The real power losses in the transmission system can then be derived as,

$$P_{Loss} = \sum_{k=1}^{NL} g_k \left[V_i^2 + V_j^2 - 2V_iV_j \cos(\delta_i - \delta_j)\right] \ (MW) \qquad (2.20)$$

where, NL is the number of transmission lines and g_k is the conductance of the k^{th} line that connects bus i to bus j.

However, a common practice is to express the total transmission losses either as a quadratic function of the power output of generating units (known as *Kron's loss formula*), or through a simplified linear formula [3]. The Kron's loss formula is,

$$P_{Loss} = \sum_{i=1}^{NG} \sum_{j=1}^{NG} P_i B_{ij} P_j + \sum_{i=1}^{NG} B_{i0} P_i + B_{00} \ (MW) \qquad (2.21)$$

where, B_{ij}, B_{i0}, and B_{00} are the B coefficients which are assumed to be constant. Reasonable accuracy can be expected when the actual operating conditions are close to the case at which these coefficients were computed. To determine the coefficients for a new case study, a power flow program must be run in advance.

Security limits are part of the transmission constraints and they refer to the secure operation of the power system, i.e. the apparent power flow through the transmission line (S_l) is restricted by its upper limit. Hence,

$$S_l \leq S_l^{max}, l = 1, \dots, NL \ \ (MVA) \tag{2.22}$$

where, *NL* represents the number of lines in the system.

g. Ramp Rate Limits

Increasing or decreasing the output generation of each unit is restricted to an amount of power over a time interval due to the physical limitations of each unit. The generator ramp rate limits change the effective real power operating limits as follows:

$$\max\left(P_i^{min}, P_i^{t-1} - DR_i\right) \leq P_i^t \leq \min(P_i^{max}, P_i^{t-1} + UR_i) \ (\mathrm{MW/h}) \tag{2.23}$$

where, P_i^{t-1} is output power of generator *i* in the previous dispatch (which took place at time *t-1*); and P_i^t is the output power of generator *i* in the current dispatch interval *t*; the terms DR_i and UR_i are the down-rate and up-rate limit of the i^{th} generator, respectively, and it is measured in terms of the increment of power over the dispatch time period (MW/time-period).

h. Spinning Reserve

A minimum spinning reserve value is imposed to each unit in order to have primary frequency response to load variations. The spinning reserve constraint can have linear or multiple-segment characteristics (e.g., pumped storage for negative spinning reserve requirements). The spinning reserve constraint can be represented as,

$$\sum_{i=1}^{NG} SR_i \geq SSR \ (MW) \tag{2.24}$$

where, SR_i is the fraction of total spinning reserve of the power system (*SSR*) allocated to the unit *i*.

i. Tie Line Limits

For multi-area generation scheduling, the TSO must take into account the limitations of the transmission capacity between areas. A relation similar to (2.19) can be used [63]. Constraints (2.14) to (2.17) and (2.20) to (2.23) are the physical system operating limits, and are usually called engineering constraints [64].

j. Emission Constraints

Emissions can be taken into account either as part of the objective function or as constraints [23, 25, 26]. The total emissions of all generating units can be expressed as a polynomial function of active power output [15, 16, 30],

$$E = \sum_{i=1}^{NG} \sum_{j=1}^{NP} \alpha_{ij} + \beta_{ij} P_i + \gamma_{ij} P_i^2 + \varphi_{ij} e^{\lambda_{ij} P_i} \leq E^{max} \ (tons/h) \tag{2.25}$$

where, φ_{ij} and λ_{ij} are the exponential coefficients of the emissions function of pollutant *j* applied to generator *i*, and E^{max} is the maximum allowable amount of pollutants for the entire system. It should be noted that the total amount of emissions also depends on the load level. The typical pollutants taken into consideration refer to NO_x, CO_2, SO_2, particles, or thermal pollutants. The emission coefficients differ with different thermal power plant technologies and with the age of the units.

2.4 Chapter Summary

This chapter is an attempt to keep track of the classical and modern economic dispatch formulations. In economic dispatch practices there are many choices for setting the operating points of generators. These choices are highly dependent on the variables that affect operational costs, such as the generator characteristics, the distance from the load, type of fuel, load capacity and transmission line losses. By including these variables one will be able to perform economic dispatch and inter-connect generators to minimize operating costs and costs due to other system characteristics. This chapter presented a detailed description of the various forms of objective functions and the constraints considered in the ED problem.

The generator cost is typically represented by four curves, namely: Input/Output (I/O), heat rate, fuel cost and incremental cost curve. Generator cost curves are not smooth, and they are generally represented by quadratic functions and piecewise linear functions. However, nonlinearities due to generation characteristics (modern generators with multiple valves, combined cycle units), nonlinearities in equality and inequality constraints, and increased unpredictability due to large renewable generation, call for better approximation models that can provide satisfactory accuracy compared to the real system operation.

Typically, the objective of the economic dispatch problem is to find the real power scheduling of each power plant or at each power producer (in the energy market context), such that to minimize the operation cost (total fuel cost), while continuously respecting the operating/physical constraints of the power network. This is done by minimizing (maximization can be translated into a minimization problem as well) the selected objective functions while maintaining an acceptable system performance in terms of generating capability limits and the output of the compensating devices.

The objective functions, also commonly known as cost functions, may refer to economic costs or profits, system security, environmental emission costs, or other objectives. Active and reactive power planning may be considered for the economic operation of the power systems. The optimization problem may be a linear, quadratic, or non-convex constrained optimization problem based on the mathematical approximation model used; consequently, the methodologies to solve this optimization problem can vary significantly.

Chapter 3

Economic dispatch: Methodologies

3.1 Introduction

The methodologies used to solve the economic dispatch problem vary widely according to different approaches in formulation. Therefore, a variety of methodologies and algorithms has been developed to accomplish the solution of the optimal economic dispatch problem, according to the utility generation mix and their particular constraints and needs in terms of modeling accuracy. The methods vary from relatively simple analytical or graphical methods, to highly complex and theoretically complicated approaches. This chapter summarizes the classical and modern algorithms proposed in the last three decades and classifies them into analytical, computational intelligence, and hybrid methods. The chapter also presents a summary of the most common testing platforms (benchmark test systems) for the surveyed algorithms. A concluding discussion emphasizes the advantages and disadvantages in adopting different solutions together with their appropriate usage according to the model adopted in formulation of the economic dispatch problem.

A pictorial summary of the methodologies used to solve the economic dispatch problem in power system is given in Figure 3.1.

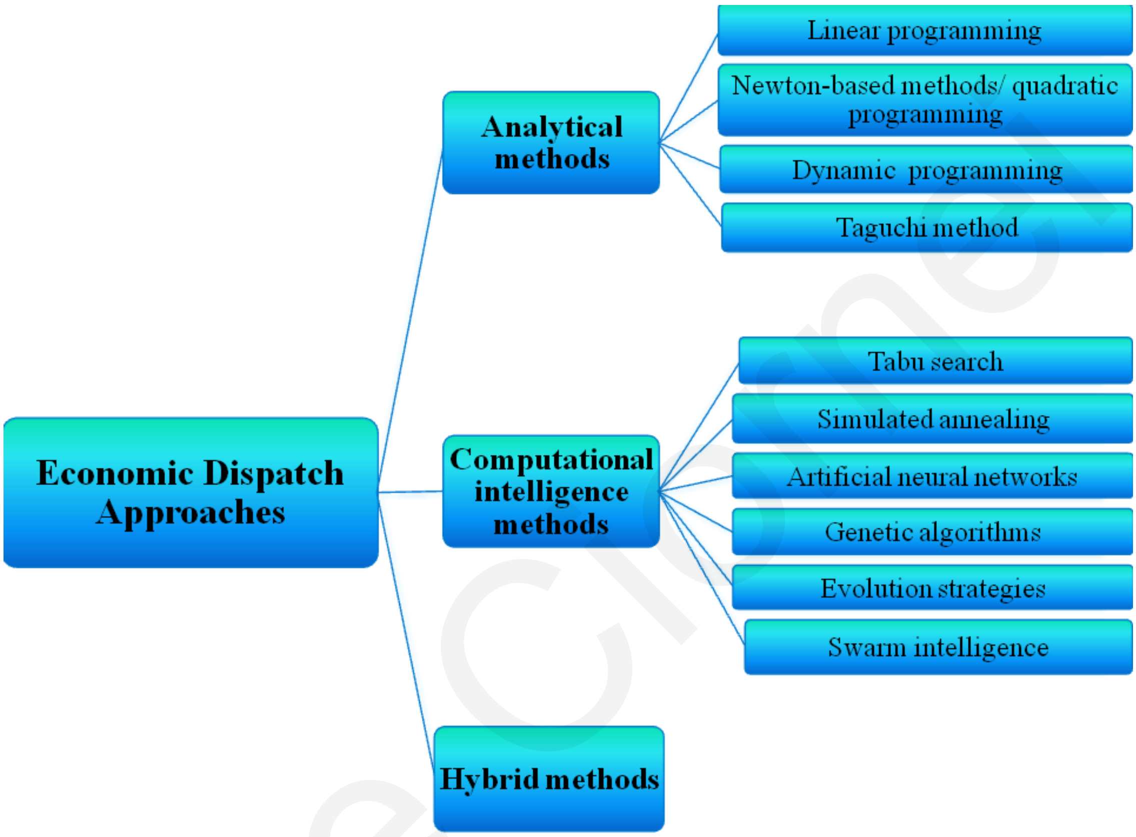

Figure 3.1 Summary of the methodologies used to solve the economic dispatch problem

3.2 Benchmark test systems

A number of test benchmark systems (IEEE based test systems or real power networks) have been used to test different solution approaches for the ED problem. The test systems vary from small test systems with three generators up to 40-generator test systems. A summary of these most common benchmark power systems is presented in

Table 3.1. The cost function characteristics in the ED formulation, the best solution reported so far in the literature (minimum cost of generation), and appropriate references for the test systems are main entries of the table.

Table 3.1. Test systems for the economic dispatch problem

Test system	Characteristics	Power Demand (MW)	Minimum cost of generation(a) ($/h)	References
3-gen	VPE, NC	850	8234.0	[38, 40, 45, 50, 65-67]
6-gen	QCF; NC	1263	15275.93	[35, 65]
	QFC;TL		15446.02(b)	[35, 39, 65, 68]
	QFC; POZ, TL		15443.24	[35-37, 68-72]
	combination of VPE, PWC and QCF; CCCP units, RRL	283.4	697.73	[36, 73]
10-gen	PWC; MF	2400	481.6	[38, 74, 75]
	VPE; MF; NC	2700	624.1273	[39, 43]
13-gen	VPE; no TL	1800	17938.95	[36, 43, 44, 47-49, 66, 69, 76, 77]
	VPE; TL; no constraints to units 11 and 12	2520	24164.04	[36, 37, 43, 44, 49, 72, 76]
	VPE; no TL; the output of units 11 and 12 are fixed to 75 MW, and 60 MW, respectively		24246.60	[36, 49, 67, 76]
	VPE; TL; no constraints to units 11 and 12		24540.06	[36, 77]

Test system	Characteristics	Power Demand (MW)	Minimum cost of generation[a] ($/h)	References
15-gen	QCF; POZ; TL	2650	32480.91	[36, 45, 65]
	QCF; POZ; no TL		33048.33	[36, 77, 78]
	QFC; POZ; no TL; SR;		32507.5	[45, 79]
	QCF; POZ; TL	2630	32393.23	[35, 36, 65, 68]
20-gen	QCF; TL	2500	62421.16	[67, 78, 80, 81]
40-gen	VPE, NC	10500	121501.14	[36-39, 43, 44, 46, 47, 65, 66, 69, 72, 77, 82]
Crete Power system	18-gen with QCF, TL	400	29731.03	[36, 83]
	19-gen; TL		32015.42	[36]
Hellenic power system	32- CCCP units; LCF; TL; unit 26 has fixed output	6300	227582.29	[36]
Taiwan power	40 gen; with 3 CC units;QCF;	5320 - 8708	5994532-11269335	[50]

gen: generators; LCF: linear cost function; QCF: quadratic cost function; CCF: cubic cost function; PWC: piecewise cost function; VPE: valve point effect considered; POZ: prohibited operating zones considered; RRL: ramp rate limits; CCCP: combined cycle co-generation plant; TL: transmission losses considered; MFQ: multiple fuels, quadratic; MFN: multiple fuels, nonconvex VPE; NC: no complexity (no TL, no POZ, no RRL). Notes: (a) refers to the best solution reported so far in the literature reviewed in this paper; (b) balance mismatch >0.6 MW.

3.3 Analytical Methods

Many electric utilities prefer analytical optimization methods to determine the optimal solutions for diverse practical planning problems, due to their deterministic approach they guarantee to find the optimum solution (if it exists) in a finite number of operations. The optimum solution here shall be read as a local optimum approximate solution. These analytical methods usually refer to approximate solutions obtained by variations of linear programming techniques or quadratic, gradient based methods.

A simple example

In essence, the most common industry approach is the simplified ED formulation which reads as follows. Having a portfolio of *NG* generating units committed for power production, and each one is characterized by a fuel cost function of the form (3.1) or (3.2), determine the best set of P_i while respecting the balance between generation and demand (3.3). Some extended formulations may also include transmission losses into the balance constraint (3.4), the generator limits (3.5). The transmission losses are generally approximated with a linear or with a quadratic function like in (3.6).

$$OC = \sum_{i=1}^{NG} (a_i + b_i P_i + c_i P_i^2) \ (€/\mathrm{h}) \tag{3.1}$$

$$IC_i = \frac{dOC_i}{dP_i} = b_i + 2c_i P_i \ (€/\mathrm{MWh}) \tag{3.2}$$

$$P_D - \sum_{i=1}^{NG} P_i = 0 \tag{3.3}$$

$$P_D + P_{Loss} - \sum_{i=1}^{NG} P_i = 0 \tag{3.4}$$

$$P_i^{min} \leq P_i \leq P_i^{max} \ (MW) \tag{3.5}$$

$$P_{Loss} = \sum_{i=1}^{NG} \sum_{j=1}^{NG} P_i B_{ij} P_j + \sum_{i=1}^{NG} B_{i0} P_i + B_{00} \ \ (MW) \tag{3.6}$$

The solution for this simplified approach is as follows: starting from the cost function of each generator (3.1), determine the incremental cost of each generator (3.2). Thus, having a simple power system with two committed generating units to cove a load demand of 500 MW determine which is the optimal way of loading each unit. Each unit is characterized by a production cost OC_1 and OC_2, respectively.

$$\mathrm{OC}_1 = 600 + 20P_1 + 0.01P_1^2 \ (€/\mathrm{h}) \tag{3.7}$$

$$\mathrm{OC}_2 = 300 + 15P_2 + 0.03P_2^2 \ (€/\mathrm{h}) \tag{3.8}$$

Therefore we have a minimization problem with one equality constraint. Using the Lagrange multiplier method, we first redefine the problem as an unconstrained optimization by forming the Lagrangean:

$$L(P, \lambda) = \sum_{i=1}^{2} OC_i \, (P_i) + \lambda(P_D - \sum_{i=1}^{2} P_i)$$

The necessary conditions for a minimum are:

$$\frac{dOC_1(P_1)}{dP_1} - \lambda = 20 + 0.02P_1 - \lambda = 0 \tag{3.9}$$

$$\frac{dOC_2(P_2)}{dP_2} - \lambda = 15 + 0.06P_2 - \lambda = 0 \tag{3.10}$$

$$500 - P_1 - P_2 = 0 \tag{3.11}$$

Therefore, we need to solve a system of three linear equations (3.9), (3.10) and (3.11), which in a matrix form looks like,

$$\begin{bmatrix} 0.02 & 0 & -1 \\ 0 & 0.06 & -1 \\ -1 & -1 & 0 \end{bmatrix} \begin{bmatrix} P_1 \\ P_2 \\ \lambda \end{bmatrix} = \begin{bmatrix} -20 \\ -15 \\ 500 \end{bmatrix} \tag{3.12}$$

The solution of this system is,

$$\begin{bmatrix} P_1 \\ P_2 \\ \lambda \end{bmatrix} = \begin{bmatrix} 312.5\ MW \\ 187.5\ MW \\ 26.2\ \text{€/MWh} \end{bmatrix} \tag{3.13}$$

When to the previous example we add another constraint, such as the generation limits, the optimal solution can be found based on the same equal incremental cost of each generating unit, through an iterative process which minimizes the error between the sum of generation output of the entire set of the committed units and the load demand, while checking the constraint of generator limits at each iteration. If the limits are exceeded, freeze any generator beyond its upper limit to its P_i^{max}, and any generator below its lower limit to P_i^{min}; extract these values from the total load and solve again the balance of the remaining set of generators, always checking for new limits.

a. Linear Programming Methods

One of the most widespread optimization methods in practical planning applications is linear programming. The use of piecewise linear cost curves for the formulation of the operational cost function results in a separate variable for each segment in the curve. Linear programming methods are attractive to operation researchers, because they include the system constraints in their formulation and they have no convergence problems as they solve the problem in its primal form. Three major linear programming based methods were introduced for the solution of the ED problem in the last twenty years: a) *Simplex method* [64, 84], b) *Interior point methods* [54, 85-93] and c) *Mixed integer linear programming* [8, 94]. Moreover, Lagrangean approaches to deal with constraints may be part of the solution strategy [64, 84, 91]. Simplex linear optimization methods deal with searching a set of feasible solutions placed on the vertex of the feasible convex polyhedron and then walking along edges of the polyhedron to vertices with successively better values of the objective function until the optimum is reached. Interior point based methods, contrary to the Simplex method, reach an optimal solution by traversing the interior of the feasible region, and have proved to be more efficient in practice, especially for large systems. Further to the efficiency in terms of computational effort, interior point methods do not need a feasible starting point [89].

The application of linear programming techniques was based on either the transformation of the quadratic approximation of the generation cost into piecewise linear format, or the use of the incremental cost, ignoring a number of constraints in the first stage and correcting the solution in further stages if the constraints considered were violated [85, 88]. Decomposition of the whole problem into subproblems with the use of the Benders or Dantzig-Wolfe decomposition principle [85, 91, 95] may be used to simplify the solution procedure.

In [92] a nonlinear primal-dual interior point method is applied to solve the extended optimal power flow model of a pool-bilateral electricity market. The objective function of the dispatch model in deregulated markets comprises a linear approximation of the generation cost, a linear approximation of the transmission losses and a linear approximation of a penalty cost for the deviation of the vector of the contracted power from the proposed values.

In [96], contingency constraints (reserve constraints) are taken into account, in addition to the standard economic dispatch formulation, in order to incorporate the impact of an outage or loss of generation of any single generating unit. The Simplex method is used to solve the linear formulation of the ED problem with implicit lower and upper generation constraints.

b. Quadratic Programming/Newton Based Methods

One of the most popular methods to solve the ED problem is the Lagrange multipliers (LM) method, also called “Lambda iteration method” [2, 5, 8, 27]. This algorithm is based on quadratic programming approaches (gradient methods) and a Lagrange multipliers aggregation procedure to reduce constrained optimization problems to an unconstrained form. Kuhn-Tucker optimality conditions must be applicable [2]. The method requires existence of first derivatives of the objective function as well as linear characteristics of the constraints. An analytical approach over the LM method is given in [97]. Using the duality theory, the authors prove that, for a set of assumptions, Kuhn-Tucker conditions might be omitted and no iterative algorithm is needed to determine the optimal primal and dual solution of the problem, but only $2n$ function evaluations are needed (where n is the number of unknown variables in the optimization problem). In [98] a graphical representation of the LM method is presented. In [99] the Lagrange multipliers method is extended for prohibited operating zones constraints, using penalty factors to discourage operation in the forbidden zone. In [100], the LM method was applied to solve an environmental constrained ED problem with quadratic approximation of the emissions function.

Similar algorithms to the LM method are quadratic interior point approaches [101], and Newton based (quadratic programming) search methods applied to solve the generic ED problem [25-27, 33, 41, 102-106]. In [105], the transmission wheeling cost is included into the objective function of the GENCO. A decomposition technique is applied to determine individual wheeling current from the line flow, and to determine the utilization factors for each transaction in every transmission facility of the power system, using a power flow model. Then, the estimated wheeling cost is combined with the fuel cost to form the objective function of the ED model. Moreover, the fuel cost was represented in this case as a cubic function.

Cogeneration dispatch using two aggregated LM methods is presented in [107]. In a first approximation, λ is set to a large value such that all units operate at their maximum capacity, and then the output power of the units with the highest incremental cost is progressively reduced until balance between generation and load is met concomitant with a heat dispatch procedure. In [108], a direct search gradient based method is proposed to solve the generic and multi-area ED with transmission capacity constraints. The direction of search is chosen according to the increase or decrease in the operation cost of independent generating units. The handling of prohibited operating zones in the classical LM is treated in [79]. “Advantageous” sub-regions in the solution space are defined for prohibited zone violations to trigger the solution to a feasible point. The authors use a cost penalty, similar to that in [99] to define the “advantageous spaces”.

c. Dynamic Programming

In power engineering optimization, dynamic programming (DP) was mainly used for discrete optimization problems such as unit commitment. However, there have been attempts to solve the ED problem with piecewise linear cost of generation [2, 5, 8]. The dynamic programming solution to the ED problem is characterized by stages, where each generating unit is associated with a stage. It is assumed that each generator cost function and the load demand are expressed as discrete MW steps with a constant step size. The main advantage of DP compared to the LM method is that no restrictions on the generation cost function are needed [53]. In [109] DP is used to determine the optimal generation allocation through a hydropower plant mix, with non-convex flow slope characteristics. A network flow approach is used in [110] to solve the multi-area economic dispatch problem with a significant number of constraints such as spinning reserve, emission constraints, transmission losses, and tie-line limitations.

d. Taguchi Method (TM)

The Taguchi method is a statistical theory-based optimization method, similar to an experimental design approach, which involves a step by step search in a subset of all possible combinations of parameter values. Here, parameters refer to the unknown variables of the objective function (e.g., the vector of the power outputs of the generators in the system). The subset of explored solutions is chosen such that sufficient information is extracted with respect to evaluation characteristics.

To solve the ED problem with a nonconvex cost function and multiple fuels, in [38] it is proposed to use the Taguchi method with orthogonal arrays. The method consists of choosing, at first, a number of discrete values (between the generation limits) selected in ascending order, which are called "levels". Then, an orthogonal array is formed as a set of combinations of different levels that the generation output may have, such that two rules are respected: a) each output level of each generator appears the same number of times in every column of the array, and b) each combination of generators between any two columns appears the same number of times. Therefore, for a given number of levels (q), and number of generators (n), the number of tests (combinations) to be explored in the orthogonal array is much smaller than the total number of combinations (q^n) when the array formation rules are adopted. After each array evaluation (cycle test) a minimum generation cost is found, and a "trend parameter" which counts the contribution of each level in the evaluation process of the cost function is calculated. According to the "trend parameter", new levels are chosen for the next array formation. The algorithm procedure is repeated until a satisfactory balance mismatch between load and generation is achieved.

3.4 Computational Intelligence Methods

Computational intelligence approaches are increasingly being used for the solution of highly nonconvex global optimization practical problems [36, 45, 111-113]. Computational intelligence based algorithms have the advantage (if successful) of finding the near global optimum solution much faster than many analytical based methods, and they do not require that the objective functions and the constraints be differentiable and continuous. However, their inability to guarantee convergence [112] causes skepticism for some real life system applications.

A number of different classes of computational intelligence algorithms have been proposed to solve the generic quadratic and the non-convex ED problems in both regulated and deregulated energy markets. Such methodologies include: *Tabu Search, Simulated Annealing, Artificial Neural Networks, Genetic Algorithms, Evolution Strategies*, and *Swarm Intelligence Optimization.* A brief description of the general approaches related to these optimization techniques is provided below.

a. Tabu Search

The Tabu search algorithm is in fact a multiple-local search method that uses memory (called “Tabu list”) to avoid reevaluation of visited solutions: once a potential solution has been determined, it is marked as "Tabu" so that the algorithm does not visit that possibility again [45]. In [114] an improved Tabu search algorithm (ITS) with flexible memory system is proposed to solve the ED problem with nonconvex generation cost. In order to avoid the entrapment in a local minimum an “ideal of distance" to the fitness is calculated such that to accelerate the algorithm convergence. The authors apply a parallel search technique to reduce the dependence of the convergence rate on the initial condition. A parallel Tabu search (PTS) algorithm, implemented on a system with 32 processors is proposed in [115]. The solution to the ED (quadratic and nonconvex) formulation with ramp rate limits uses a neighborhood decomposition technique to split the search space into subspaces (“subneighborhoods”) and a competitive selection subroutine to update the best solution achieved by search subspaces.

b. Simulated Annealing

Simulated annealing (SA) is a powerful optimization method especially used in combinatorial problems. It is inspired from the physical process of successively overheating and cooling a solid to increase its strength. In optimization, better solutions can be obtained following a step by step transitioning from an equilibrium state to another until the minimum “energy” of the system is reached. In [116] the simulated annealing method is applied to solve the generic ED problem with a quadratic cost function. Initially the losses are ignored, and later they are incorporated in the algorithm using the “B-loss” formula. In [117] the method is used to determine the optimal generation dispatch of a generation mix of wind and thermal power plants. In [84], SA is used to determine the optimal trajectory of the generation dispatch considering the thermal stress constraints of the generating units.

c. Artificial Neural Networks

Artificial neural networks (ANNs) are computational models which simulate biological neural networks in both structure and functionality. Generally, ANNs are adaptive systems that capture the dynamic changes of the system they try to model, and they evolve to the target in a “learning” manner. ANN programming is more common for system control, forecasting applications, and pattern recognition applications. However, ANNs have also been used to solve combinatorial and continuous optimization problems such as the ED problem [74, 75, 80, 81, 118-120]. In [55] a redispatch approach based on the Hopfield neural network is proposed to solve the dynamic economic dispatch (DED) problem. The solution methodology is divided into two stages: a lambda-iteration method is first used to obtain a first approximation of the static ED problem and then, a Hopfield neural network redispatch technique is applied for the DED problem. In [42] ANNs are applied to the real-time optimal generation dispatch of thermal units, considering environmental constraints, operational requirements and network losses. The algorithm uses penalty factors derived from a Newton-Raphson power flow subroutine to incorporate system load changes.

d. Genetic Algorithms

Genetic algorithms (GA) are a special class of evolutionary optimization approaches (algorithms which imitate the principles of natural evolution based on survival). The main idea behind genetic algorithms is to improve a set of candidate solutions for a problem by using several genetic operators inspired from genetic real life evolution mechanisms. Genetic operators are the variation mechanisms that generate new candidate solutions, similar to the parent solutions (solutions from a previous generation), but including some differences. Usually, the genetic operators used are *selection*, *crossover*, and *mutation*. The selection operator makes sure that the best member from a population survives. Crossover generates two new individuals (offspring) from two parent solutions, based on certain rules such as mixing them with a given probability. Mutation takes an individual and randomly changes a part of it with a certain probability [121]. The representation of a solution in a GA is typically based on a list of discrete [72] tokens, often bits (genome), but it can be extended to graphs, lists, or real-valued vectors. The crossover operator plays a significant role in GAs.

Different approaches to solve both the quadratic and the nonconvex ED problem using GA based algorithms have been proposed [16, 40, 43, 82, 83, 122-125]. In [16] a niched Pareto genetic algorithm (NPGA) is proposed for the solution of a multiobjective environmental/economic dispatch (EED) problem. The method uses a hierarchical clustering technique in order to provide the decision maker with a simple and manageable architecture of the Pareto-optimal non-dominated solutions of the multiobjective EED problem. In [18] a fuzzy logic controller is proposed to adaptively adjust the crossover probability and mutation rate during the GA optimization process. In [40] two different GA binary encoding techniques are proposed and compared to solve the ED problem with valve point effect. GA is used in [43] to solve the practical ED problem with valve point effect and multiple fuels. The proposed algorithm uses an evolutionary direction operator called "multiplier updating" to deal with the equality and inequality constraints and a migration operator to make the search more effective. In [83] a real-coded GA with varying operator probabilities is used to solve the generic convex ED problem with network constraints. A floating point number representation is used to overcome the decision of how many bits should be used for encoding in the case of binary-GA applications. In [126] a GA technique is used to determine the optimum integration of renewable technologies in power systems.

e. Evolution Strategies

Evolution or evolutionary (both terms appear in the literature) strategies (ESs) were first developed in Germany in the 60s and were focused on solving complex, continuous optimization problems; later, they were extended to discrete optimization [127]. Evolution strategies are part of the same class of optimization approaches as GAs, called the Evolutionary Algorithms (EA) or evolutionary computation (EC) class. The main difference between GAs and ESs is in the representation of the solution, the type of selection, and the mutation scheme. ESs use the representation that best fits the problem domain (most often real vectors). All *n* parents are mutated (typically no crossover) to create *n* new children. Therefore, in the current generation, a total of *2n* candidates are set from which only the *n* most fit candidates are kept, where *n* is the number of individuals in a population of candidate solutions. Mutation schemes can also be adaptive [128].

Different improvements and adaptations of the generic evolution strategy were proposed to solve the classical single- or multi-objective ED, or the practical nonconvex ED problem [15, 28, 50, 66, 71-73, 76, 77, 129-131].

In [28] the environmental economic dispatch (EED) problem was solved using an ES with a Gaussian mutation, stochastic tournament selection scheme, as well as an acceleration technique for faster convergence and robustness of the search. The acceleration technique is based on examining the loading of all units in the sense that the units which are found to be close to one of their extreme operating limits are shifted to the corresponding limit. Pereira-Neto *et al*. [72] proposed an ES for the solution of the economic dispatch problem with noncontinuous and nonconvex cost functions. The economic dispatch problem takes into account nonlinear generator characteristics such as ramp-rate limits and prohibited operating zones in the power system operation. Abido [15] uses ES to solve a multi-objective environmental/economic electric power dispatch (EED) problem. His algorithm, entitled Pareto-based Multi-Objective Evolutionary Algorithm (MOEA) gives the solution in the form of the pareto-optimal front. A feasibility check procedure has been superimposed on MOEA to restrict the search to the feasible region of the problem space.

In [130] an ES which uses both recombination (crossover) and mutation operators to create offspring is proposed to solve the ED problem with a non-convex valve point effect generation cost function, prohibited operating zones, ramp rate limits, and transmission losses considered. In [73] an EP technique is proposed for the solution of the optimal power flow (OPF) problem with non-smooth fuel functions, like quadratic, piece-wise, valve point loading, and combined cycle cogeneration plants. To avoid premature convergence, the authors propose an adaptive mutation, which non-linearly changes with respect to the number of generations. In [76] a "real-parameter quantum evolutionary algorithm" is proposed to solve the DED problem. Each solution string is represented as a two dimensional floating point array with each element representing the output of one generating unit, in a particular time interval. The real numbers are scaled to be between 0 and 1, as in quantum computing representation (q-bits), with 0 representing the minimum generation limit and 1 the maximum generation limit for the corresponding generator. In [77] an EP approach, entitled self-tuning hybrid differential evolution (self-tuning HDE), is used to determine the solution of the ED problem with valve point effect, ramp rate limits, and prohibited operating zones. The self-tuning HDE uses the concept of the 1/5 success rule of evolution strategies (ESs) to accelerate the search for the global optimum. Another modified differential evolution (MDE) approach is proposed in [131] to solve the dynamic economic dispatch (DED) problem with valve-point effects taken into account. In contrast to the penalty function method, a constraints-handling method is used to guide the solution search to the feasible region quickly.

In [132] a comparison of various evolutionary algorithms (EA) is given, such as real coded GA, particle swarm optimization (PSO) and differential evolution (DE), which are used to solve the ED problem valve-point effect and multiple fuel options (with both quadratic and non-smooth approximations). A "parameter-less constraint-handling scheme" is proposed, instead of the classical penalty aggregation fitness function used in ESs methods to handle constraints. The constraint-handling scheme consists of using different comparisons between feasible and infeasible solutions. Precisely, if the solutions are feasible (have zero constraint violation), their comparison measure is their value on the objective function; otherwise, if the comparison is between infeasible solutions then they are evaluated according to their constraint violations alone. Hence, the objective function and the constraint violations are not combined in creating a new solution and thus, the use of weights for an aggregated single objective function is avoided.

f. Swarm Intelligence Optimization

Swarm intelligence optimization refers to optimization models based on the "collective" or social behavior in sharing information between individuals within a group for completing tasks [133]. Such models include ant colony optimization (ACO), particle swarm optimization (PSO), bird flocking, animal herding, or fish schooling [134]. In this section reference will be made only to the first two approaches.

The behavior of ants for finding the shortest path to the food was first modeled for optimization purposes in [135]. In this algorithm (the ACO algorithm), initially each ant searches randomly different paths towards the food. Later on, each artificial ant constructs one solution according to the amount of pheromone (information) deposited on the ground by other members of the colony who previously followed the same path.

Therefore, a set of artificial ants cooperate in the solution of a problem by exchanging information via pheromone deposited along the edges of a graph. Another type of ant search developed for continuous optimization problems, entitled API, was proposed in [136].

Ant colony optimization is more common for discrete optimization problems than for continuous ones [67]. However, the classical or modified ACO has been applied to solve continuous optimization problems such as the ED problem [67, 137, 138]. In [67] a chaotic ant swarm optimization (CASO) is used for the solution of the classical ED with transmission losses and generation limits. The search behavior of the ant colony is initially “chaotic”, and more organized as the search evolves (the chaotic behavior of the individual decreases gradually, and is taken into account using an “organizational variable”).

In the PSO case, the swarm behavior can be modeled with simple information rules based on two important operators: cognitive operator (“individual velocity”), which express the own experience of each individual, and social operator (“global velocity”), which express the entire community experience [36, 113]. An illustrative vectorial presentation of the search mechanism in particle swarm optimization is given in Fig. 3.2 (adapted from [46]), to understand how each particle evolves during the search. The equations that describe the transitioning scheme of each particle in the search mechanism are,

$$V_i^{k+1} = \omega V_i^k + c_1 rand_1\left(Ibest_I^k + X_i^k\right) + c_2 rand_2(Gbest_i^k - X_i^k) \qquad (3.14)$$

$$X^{k+1} = X^k + V_i^{k+1} \tag{3.15}$$

where, V_i^k is the velocity of individual i in iteration k; ω, c_1, and c_2 are weight parameters; X_i^k is the position of individual i in iteration k; $Ibest_i^k$ and $Gbest_i^k$ store the best positions (solutions) of individual i and of the group respectively, until iteration k; X_i^{k+1} is the next position occupied by individual i after modifying its velocity.

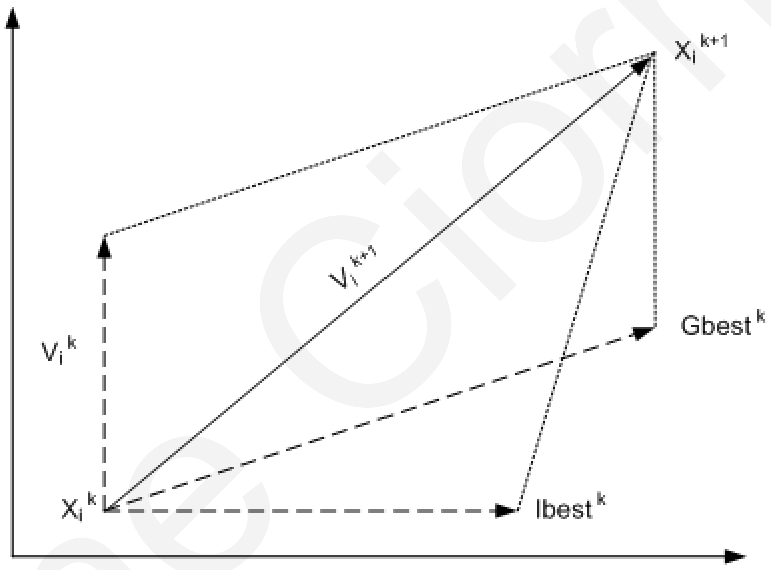

Figure 3.2. The search mechanism of particle swarm optimization [46]

Park *et al.* [46] used the particle swarm optimization (PSO) technique to solve the practical ED problem with nonconvex cost functions and multiple fuels. A constraint treatment mechanism is used for both the initialization and updating processes, such that always feasible candidate solutions are examined during the search procedure. Also, a search-space reduction strategy is adopted to accelerate the optimization process when the search is not improving after a predefined search period. The search space is “dynamically adjusted” (increased or reduced) according to the distance between the generating boundaries of unit *i* and the global position of the swarm, up to the current iteration.

In [65], a self-organizing hierarchical particle swarm optimization (SOH_PSO) is proposed for the solution of the practical ED problem. Time-varying acceleration coefficients are included in the classical PSO mechanism to avoid premature convergence to sub-optimum solutions.

In [48] quantum mechanics and Monte Carlo approaches are used to derive the transitioning equations for the movement of particles in the solution space. Equations (3.14) and (3.15) remain the same. However, *Ibest* and *Gbest* are calculated using Schrödinger’s equation from quantum mechanics for the motion of microscopic particles, which is based on the harmonic oscillator principle.

In [139], the classical quadratic ED problem with prohibited operating zones and ramp rate limits is solved using eight combinations of PSO search. The classical equations of the PSO ((3.14) and (3.15)) are transfigured in that the two random functions $rand_1$ and $rand_2$ are now combinations of Gaussian probability distribution and/or chaotic sequences functions. In this context, [139] proposes improved PSO approaches for solving EDPs that take into account nonlinear generator features such as ramp-rate limits and prohibited operating zones in the power system operation.

3.5 Hybrid Methods

Hybrid methods are the merger of two or more optimization algorithms to improve the overall performance of a single optimization technique [13, 20, 32, 33, 44, 45, 68-70, 78, 140-145]. The main goal of developing hybrid methods is to achieve an improvement in terms of complexity and computational effort reduction, on one hand, and to increase the accuracy and robustness of the solution, on the other hand.

Thus, in [37], simulated annealing and particle swarm optimization techniques form the hybrid SA-PSO model, which solves the practical ED problem with valve point effect, ramp rate limits, and prohibited operating zones. The particle swarm optimization is the main search algorithm and SA is used as a “judgment operator” for the velocity update process. Thus, if the fitness value of the next value (position) of each particle calculated using (3.14) and (3.15) is better than the fitness of the previous position, then the particle moves to this new position; otherwise, an SA probabilistic criterion is used to decide on whether to allow this movement. In [44] a combination of a genetic algorithm (GA) with a sequential quadratic programming (SQP) technique is proposed for the solution of the DED problem with valve-point effects considered. GA is the main search algorithm, and SQP is used as a “local optimizer to fine-tune the region explored by GA”. For the SQP, the authors use an approximation, differentiable, entropy-type function instead of the fuel cost defined in (3.10), in order to maintain the valve point effect. More specifically, the hybrid method uses SQP as a fourth operator to generate offspring in the GA process, together with the common selection, crossover, and mutation. In [20], a fuzzy logic strategy is combined with PSO to solve the multi-objective EED problem. The proposed method is entitled fuzzified multi-objective particle swarm optimization (FMOPSO). In [13] a hybrid optimization method is presented that combines the PSO with chance-constrained programming to solve the generic ED problem of cascaded hydroelectric plants. In [142] an improved differential evolution (IDE) is combined with Shor's r-algorithm to solve the DED problem with valve-point effects taken into account. The evolution algorithm is used as a based level search (conducts the direction towards the optimal global region), and the Shor's r-algorithm as local search (fine tuning) to reach the optimal solution. In [68] ant colony API search and GA are combined to form a hybrid GAAPI model which solves the practical ED problem. Here API is the main search mechanism, keeping the "hill climbing behavior" of constantly improving the solution, while the GA is used to deal with the diversity of solutions explored. In [144] a fuzzy clustering-based particle swarm optimization (FCPSO) algorithm has been proposed to solve the EED problem. An external repository is used to keep a record of the nondominated particles found along the search process, and the fuzzy clustering technique to manage the size of this repository (eliminates from time to time similar solutions, such that the dimension of the repository is kept between the predefined limits).

3.6 Chapter summary

This chapter is an attempt to keep track of the classical and modern methodologies related to the economic dispatch problem. Even though many and excellent advances have been made in the classical formulation of the problem using analytical based optimization methods, the conclusion of the majority of the literature surveyed is that, with a few exceptions, these methods suffer from certain drawbacks. Such drawbacks include: (i) the non-detailed formulation of the problem due to the necessary assumptions made, leading to limitations in the modelling of real-world, large scale power systems; (ii) poor convergence characteristics and slow execution when a large number of variables is considered; (iii) getting stuck in local optima. However, a number of advantages may make them preferred, especially in the industry community, such as that they have been proven to provide stable approximate solutions (mature mathematical programming techniques where optimality is rigorously demonstrated) and that they may take advantage of existing sparsity techniques to handle large-scale systems.

Nonlinearities due to generation characteristics (modern generators with multiple valves, combined cycle units), nonlinearities in equality and inequality constraints, and increased unpredictability due to large renewable generation, call for optimization methods that can provide satisfactory results in terms of computational effort, accuracy, and robustness of the solution. The competition in energy generation, together with the environmental concerns and their governmental regulations, complicate the economic dispatch problem even further. In the near future, combined energy carriers such as electricity, gas, heat, and hydrogen production may ask for an integrated solution in terms of dispatch of resources. Computational intelligence based methods can cope with these nonlinearities and discontinuities in the solution space, giving good approximate solution in reasonable computational time regardless of the dimension of the system. However, one of the main drawbacks of computational intelligence methods is their sometimes lack of consistency in solution and no guarantee that the solution obtained is the global optimum. The above mentioned remarks are derived from the surveyed literature.

The preference in using one method over another depends on the designer sense of optimality and the level of acceptance or definition of a “good” model or solution. This is totally in agreement with the no free lunch theorem concept [146] which states that “all algorithms that search for an extremum of a cost function perform exactly the same, when averaged over all possible cost functions” [147].Different needs are to be addressed in the near future, with solutions accompanied by solid theoretical and test results, as well as tools for actual implementation of economic dispatch methodologies, especially considering both the demand side and the generation side uncertainties, as well as the benefits of smart grid technologies. A common dispatch methodology or standard with respect to variable renewable energy sources that penetrate the generation mix needs to be developed. A theoretical proof of convergence and robustness of the computational intelligence methods is required in order to gain the confidence of industry engineers. Further, the future industry application economic dispatch may transition from a single objective to a highly multi-objective optimization problem, especially considering environmental concerns and a multi-carrier energy industry. The impact of uncertainty in generation and the impact of market structure to the economic dispatch approach need a closer examination.

Chapter 4

GAAPI: Efficient Solution for Global Continuous Optimization

4.1 Introduction

Global optimization refers to the procedure of finding approximate solutions, which are considered the best possible solutions, to objective functions [148]. Ideally, the approximation is optimal up to a small constant error, for which the solution is considered to be satisfactory. In general, there can be solutions that are locally optimal, but not globally optimal; this situation appears more frequently when the dimension of the problem is high and when the function has many local optima [112]. Consequently, global optimization problems are typically quite difficult to be solved exactly, especially in the context of nonlinear problems or combinatorial problems. Global optimization problems fall within the broader class of nonlinear programming (NLP). It should be noted that approximation algorithms are increasingly being used for problems where exact polynomial algorithms are known but are computationally expensive due to the dimensionality of these problems. In the last three decades, a significant research effort was focused on the development of effective and efficient stochastic methods that could reach the nearest global optimal solution. In this class of methods, evolutionary computation (EC) is one of the favorite methodologies, using techniques that exploit a set of potential solutions (called a population) in order to detect the optimal solution through cooperation and competition among the individuals of the population [149]. These techniques often find the optima for difficult optimization problems faster than traditional adaptive stochastic search algorithms. The most frequently used population-based EC methods include evolutionary strategies (ES) [149-151], genetic algorithms (GAs) [121, 152, 153], evolutionary programming (EP) [154], clustering methods [155], ant colony optimization (ACO/API) [136, 156], and particle swarm optimization (PSO) [157].

One of the issues that probabilistic optimization algorithms might face in solving global, highly nonconvex optimization problems is premature convergence. One of the causes of premature convergence of evolutionary based algorithms is the lack of diversity. In nature, the diversity is ensured by the variety and abundance of organisms at a given place and time. The same principle (different type of solutions at one moment in the iterative search process) is used in computational intelligence for optimization algorithms [158].

Another issue of probabilistic approaches in optimization is related to their lack of advanced search capability around the global solution. Several studies have shown that incorporating some knowledge about the search space can improve the search capability of evolutionary algorithms (EAs) significantly [159]. In particular, the hybridization of EAs with local searches has proven to be very promising [160, 161].

The efficiency of natural ecosystems is based on the many ways of interaction between species and/or members of the same species, in order to reach the species goal or the equilibrium of the ecosystem. The algorithm proposed in this work, improves both the diversity and the “hill climbing” consistency. This is achieved by combining genetic algorithms and API. The main proposed algorithm in this dissertation, named GAAPI, underlines the best behavior of the foraging strategy of API (downhill characteristics by continuously looking for a better prey) and of GAs (good spreading in the solution space by using its operators: selection, crossover, and mutation).

GAAPI has been designed to find the near global optimum solution for nonlinear, unconstrained and constrained problems. The main strategy of the algorithm is a modified API; the modifications are mentioned in the description of the algorithm in the following section of this chapter. Genetic algorithm operators are used in the information sharing process of each ant, to ensure that the trapping in local minima has a probability near zero.

4.2 API + RCGA = GAAPI

This section of the chapter describes in detail the proposed GAAPI algorithm. First, an introduction of the two main components of the GAAPI algorithm is provided. The first component, the API algorithm, is the core of the proposed method; the second component is the real coded genetic algorithm (RCGA) with emphasis on GA operators modified such that an improved balance between exploration and exploitation in the search procedure is maintained. Also, the main differences between API and GAAPI are underlined.

4.2.1 API Algorithm

The API algorithm was inspired by the behavior of a type of ants (pachycondyla apicalis ants) which live in the Mexican tropical forest near the Guatemalan border. Colonies of these ants comprise around 20 to 100 ants. The foraging strategy of the pachycondyla apicalis ants can be characterized by the following description. First, these ants create their hunting sites which are distributed relatively uniformly within a radius of approximately 10 m around their nest. In this way, using a small mosaic of areas, the ants cover a rather large region around the nest. Second, the ants intensify their search around some selected sites for prey. Pachycondyla apicalis ants use a recruitment mechanism called tandem running, in which pairs of ants, one leading and one following, move toward a resource. In this foraging process, these ants use their memory of the visual landmark (map of the terrain encountered in their previous search) rather than pheromone trails (chemical signals) encountered in other ant species. After capturing their prey, the ants will move to a new nest via the tandem running recruitment mechanism, to begin a new cycle of foraging. Based on the natural behavior of pachycondyla apicalis ants described in [162], Monmarché *et al.* proposed an API algorithm (short for apicalis) for the solution of optimization problems [163]. Despite the good performance of the algorithm, further research shows that API has poor use of the memory that generally characterizes ant colony systems [164].

The nest (N) initially takes a random position in the feasible search space $[x^{min}, x^{max}]$, where $x^{min} = [x_1^{min}, x_2^{min}, \dots, x_n^{min}]$ and $x^{max} = [x_1^{max}, x_2^{max}, \dots, x_n^{max}]$ are the lower and upper bound vectors for each dimension, respectively, delimitating the feasible solution space in $\boldsymbol{R}^n$ (n is the dimension of the problem). Therefore, $N = (N_1, N_2, \dots, N_n)$ is the initial position of the nest in the feasible solution space. Then, the feasible solution space $[x^{min}, x^{max}]$ is divided into smaller solution spaces with different amplitudes (defined as a percentage of the search space) from the initial domain, where overlapping is allowed. Figure 4.1 shows how the initial solution space is divided into smaller search spaces. The example in Figure 4.1 is given for a two dimensional search space. This approach is the one adopted by Monmarché in his thesis when proposing the API algorithm [163]. The approach is quite similar to later adaptations of ACO for continuous domains proposed in [165].

The amplitudes for search space division change dynamically. The formula used to determine the search amplitude of each agent (ant) is given by,

$$A_{ant} = \left(1 - \frac{k}{N_{ants}}\right) G_{ant_i} \tag{4.1}$$

where, A_{ant} is the radius from the nest N, delimitating the solution space ant i can cover; k is the current index (iteration of the search loop) of ant i, N_{ants} is the total number of search agents, and G_{ant_i} is the age of the ant and it is a parameter that increases as ant i performs its tasks with time, and is computed by,

$$G_{ant_i} = \frac{T_i}{T_{ant_i}} \tag{4.2}$$

This parameter was inspired from the real behavior of pachycondyla apicalis ants described in [162]. T_i is the current number of iterations after the movement of the ant i, and T_{ant_i} is the maximum number of iterations between two movements of the ant i_i.

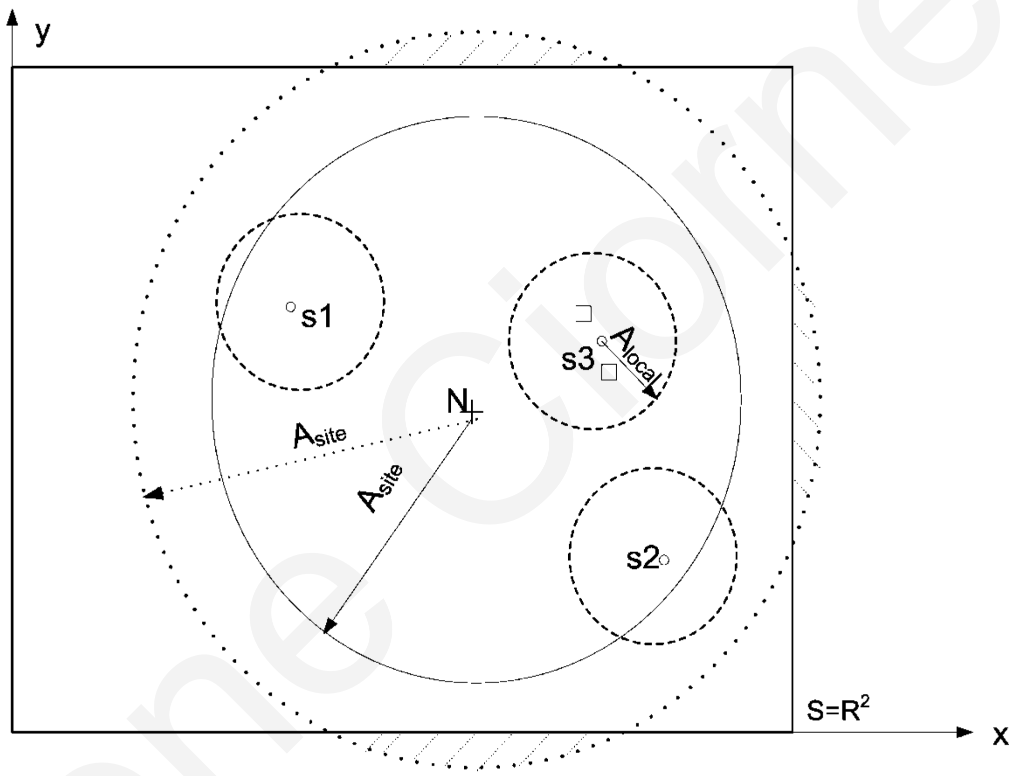

Figure 4.1 Search space division according to API strategy

In Figure 4.1 above, $\boldsymbol{S} = \boldsymbol{R}^2$ denotes a bi-dimensional solution space; s_1, s_2, s_3 are sites randomly generated around the nest N, and their maximum allowed distance from the nest being given by A_{ant}. The small squares denote local explorations of the site (points situated at a maximum distance of A_{site} from the center of site s) [136].

A short step-by-step description of API is given in Table 4.1.

Table 4.1 API algorithm

1. ***Initialization*****:** set the algorithm parameters
2. ***Generation of new nest*** (exploration)
3. ***Exploitation***

3.1. ***Intensification search*****:**

FOR each ant

IF the number of hunting sites in its memory is less than a predefined number

THEN create a new site in its neighborhood and exploit the new site

ELSEIF the previous site exploitation was successful

THEN exploit the same site again

ELSE exploit a probabilistically selected site (among the sites in its memory)

End (if)

End (for)

3.2. ***Erase sites:*** from the memory of ants erase all sites that have been explored unsuccessfully more than a predefined consecutive number of times

3.3. ***Information sharing*****:**

Choose two ants randomly and exchange information between them. The information exchanged is the best site in their memory at the current iteration

3.4. ***Nest movement*****:**

IF the condition for nest movements is satisfied, go to step (4)

ELSE, go to step (3.1)

End (if)

4. ***Termination test*****:**

IF the test is successful, STOP

ELSE, empty the memory of all ants and go to step (2)

END

The initialization of algorithm parameters (step 1) refers to setting the number of ants, the number of hunting sites each ant can memorize (search), the number of times one ant accepts to go back to an unsuccessful site (a site where the solution was not improved compared to the previous search in the same site), and to the maximum number of nest movements. The nest is moved in a new position only if at least one ant found a better solution than the current position of the nest or if the number of unsuccessful search cycles (at the end of step 3 the solution is not improved compared to the current nest position) reached a predefined number. The algorithm stops when either the total number of nest movements was reached, or the number of unsuccessful search cycles reached the limit.

4.2.2 RCGA Algorithm

The real-coded genetic algorithm (RCGA) is inspired from the float representation of the evolutionary strategy approach. Real-coded genetic algorithms work with real number representation, therefore there is no other structure of the chromosomes, but floating vectors whose size is the number of variables of the optimization problem to be solved. This form of GA has the advantage of eliminating coding and decoding procedures needed in the binary representation of GA, thus using real-value object representation. For most applications of GAs in constrained optimization problems, the real coding is used to represent a solution to a given problem. This is one of the reasons that it has been adopted for hybridization with API in this work.

Genetic algorithms start searching the solution space by initializing a population of random candidates for the solution. Every individual in the population undergoes genetic evolution through crossover and mutation. The selection procedure is conducted based on the fitness of each individual. By using elitist strategy, the best individual in each generation is ensured to be passed to the next generation. The elitist selection operator creates a new population by selecting individuals from the old populations, biased towards the best individuals. The chromosomes, which produce the best optimal fitness, are selected for the next generations.

Crossover is the main genetic operator, which swaps chromosome parts between individuals. Crossover is not performed on every pair of individuals, its frequency being controlled by a crossover probability (P_c). This probability should have a large value for a higher chance of creating offspring with genome appropriate to the parents. The blend crossover (denoted as *BLX-alpha*) is the operator adopted in this work, due to its interesting property: the location of the child solution depends on the difference in the parent solutions. In other words, if the difference between the parent solutions is small, the difference between the child and parent solutions is also small. This property is essential for a search algorithm to exhibit self-adaptation. Thus, the BLX-alpha proceeds by blending two float vectors (x^t, y^t) using a parameter $\alpha = [0{,}1]$, where t denotes the index of the generation. The resulting children (x^{t+1}, y^{t+1}) are equal to $x_i^{t+1} = (1 - \alpha_i)x_i^t + \alpha_i y_i^t$, and to $y_i^{t+1} = \alpha_i x_i^t + (1 - \alpha_i)y_i^t$, respectively.

The next operator is mutation and its action is to change a random part of the string representing the individual. Mutation probability should be quite low, relative to the crossover probability, so that only a few elements in the solution vector undergo the mutation process. If the probability of mutation is high, then the offspring may lose too many of the characteristics of the parents and may lead to divergence in the solution. Uniform mutation was adopted in this work. The algorithm is repeated for several generations until one of the individuals of the population converges to an optimal value (until the weighted average change in the fitness function value over all generations is less than a threshold/tolerance) or the required number of generations is reached. A step-by-step description of the RCGA is given below.

Table 4.2 RCGA algorithm

---

1. ***Initialize the population*:**

$S_{Init}=(s_1;\ s_2;\ \ldots;\ s_{\text{PopSize}})=(x^{(1)};\ x^{(2)};\ \ldots\ ;\ x^{(PopSize)})$, where $x^{(k)} = Unif\left(x^{min}, x^{max}\right)^{(k)}$, and k=1, …, *PopSize*

2. ***Determine the fitness score of the population and select parents according to their fitness score (the individuals with the highest fitness are selected as parents)*:** $\theta(s_k)= G(f(s_k))$

3. ***Variance assignment*:**

3.1. Apply blend ***crossover***, with probability P_c: $s_k = s_{k+m}$

3.2. Apply ***mutation*** operator, with probability P_m: $s_{k+m,j} = S_{k,j} + N(0, \beta_j{*}\theta(s_k) + z_j)$, $j = 1,\ldots, k$

4. ***Determine the fitness score of each variance*:**

Each variance s_{i+m} is assigned a fitness score $\theta(s_{k+m}) = G(f(s_{k+m}))$.

5. ***Rank the solution*** in descending order of $\theta(s_k)$

6. ***Repeat*:** Go to step 3 until an acceptable solution has been found or the available execution time is exhausted.

In Table 4.2,

- *PopSize* is the population size at the current iteration, s_k is the individual k of the population, with k = 1,..., *PopSize*. *Unif* is a uniform distribution between in the lower and the upper bounds of each i dimension of individual k as presented in (4.4), and m is the number of potential parents (which is less or equal to the population size);

- $\theta(s_k)$ from item 2 above is the fitness score of the individual s_k, G denotes the fitness score function, and f is the real fitness or optimization function. The fitness score function adopted in this paper is the inverse of the fitness function to be optimized. In case of minimization problems, the individual is considered to be the most fitted if it has the smallest value of the optimization function. In case of maximization problems the fitness score is given by the fitness function;
- $S_{k,j}$ from item 3 above is the element j of the individual k, $N(\mu, \sigma^2)$ is the Gaussian random variate with mean μ and standard deviation σ; β_j is a constant of proportionality to scale $\theta(s_k)$, and z_j is the offset that guarantees the minimum amount of variance.

The equation from item 3.1 above ($s_k = s_{k+m}$), shall be read as follows: after crossover, a new individual is formed (s_{k+m}), which is added at the end of the current population of parents (whose dimension is m). If a randomly generated number is higher than the probability of crossover (P_c) of the k^{th} individual in the current population, then the newly formed individual (s_{k+m}) replaces the k^{th} individual in the next generation. The same applies to item 3.2, in which the mutation operator is applied with a probability of mutation P_m to each gene j of each individual k.

4.2.3 GAAPI Algorithm

To eliminate the shortcomings and the insufficient robustness of the global search ability of the API algorithm, a GAAPI algorithm that incorporates some favourable features of GA and API algorithms has been developed. The idea in GAAPI is to keep the algorithm focused towards continuous improvement of the solution, while avoiding getting trapped in local optima. Therefore, the API algorithm was intended to be the core of the GAAPI (keeping the search targeted towards improvement in the solution) while RCGA was intended to provide the escape mechanism from local optima when API is trapped. Thus, when API is at the search level of sites (the lowest search level) and continuously improves the solution, RCGA is in a passive mode. In this passive mode, the population of RCGA is formed by all the best solutions generated by API at the ant level only (there are no sites to be forgotten). When API is slow in improving the solution (there are sites to be forgotten due to failure in improving the solution), RGCA switches to an active role. This time, its population uses the information of forgotten sites as well (the population is more heterogeneous than in the former case), and thus the solution generated by the RCGA has more chances to be far from the local optimum in which the API was trapped.

The key modifications in API to form the new GAAPI algorithm are summarized below.

1. ***Generation of New Nest***: After initialization, only the best solution found since the last nest move has the opportunity to be selected as a new nest to start the next iteration. The "hill climb" property is not very strong in this case, so the trapping in local minima is avoided.

2. ***Exploitation with API***: Initially, each ant checks its memory. If the number of hunting sites in its memory is less than a predefined number, it will generate a new site in the small neighborhood of the center of its current hunting site, save it to its memory, and use it as the next hunting site. Otherwise, one of the sites in its memory is selected as the hunting site. The ant then performs a local search around the neighborhood of this hunting site. If this local exploitation is successful, the ant will

repeat its exploration around the site until an unsuccessful search occurs; otherwise (if the previous exploration was unsuccessful), the ant will select an alternative site among its memorized sites. This process will be repeated until a termination criterion is reached. The termination criterion used in this phase is that the procedure will stop automatically once the number of successive unsuccessful explorations reaches a predefined value, or there is no improvement after a number of iterations. A schematic representation of the search mechanism of API is given in Figure 4.2; where, *ns* represents the counter for the number of sites memorized by each ant; *e*(*ns*) is the counter for consecutive failure in site search; *Ns* is the total number of sites one ant can memorize; *popRCGA* is the counter for the number of individuals added into the population of the RCGA algorithm; *P* is the predefined number of allowed consecutive search failures in one site before it is deleted from the memory of the ant.

2.1. ***Information sharing with RCGA***: In order to keep diversity in the solution space, *information sharing* is performed using a simple RCGA method. A random site is chosen in the memory of a randomly chosen ant, and it is replaced by the new RCGA solution. This can be seen as a form of communication. The RCGA procedure involves a population formed by the currently best hunting sites in the memory of all ants as well as the forgotten (erased) sites. The best solution obtained after one set of GA operations (selection, crossover, mutation), replaces the chosen site in the memory of the selected ants. This technique is applied before moving the nest to the best position so far. The RCGA contains the forgotten sites in order to keep diversity in the population. The RCGA operators are set as follows: *Blend crossover* operator (BLX-α) [121] with a probability of 0.3, and a value of α set to 0.366 [30]; a *uniform mutation* with a mutation probability set to 0.35; *Elitism*: the two best individuals are retained with no modifications in the population of the next generation, such that the strongest genes up to this point are retained.

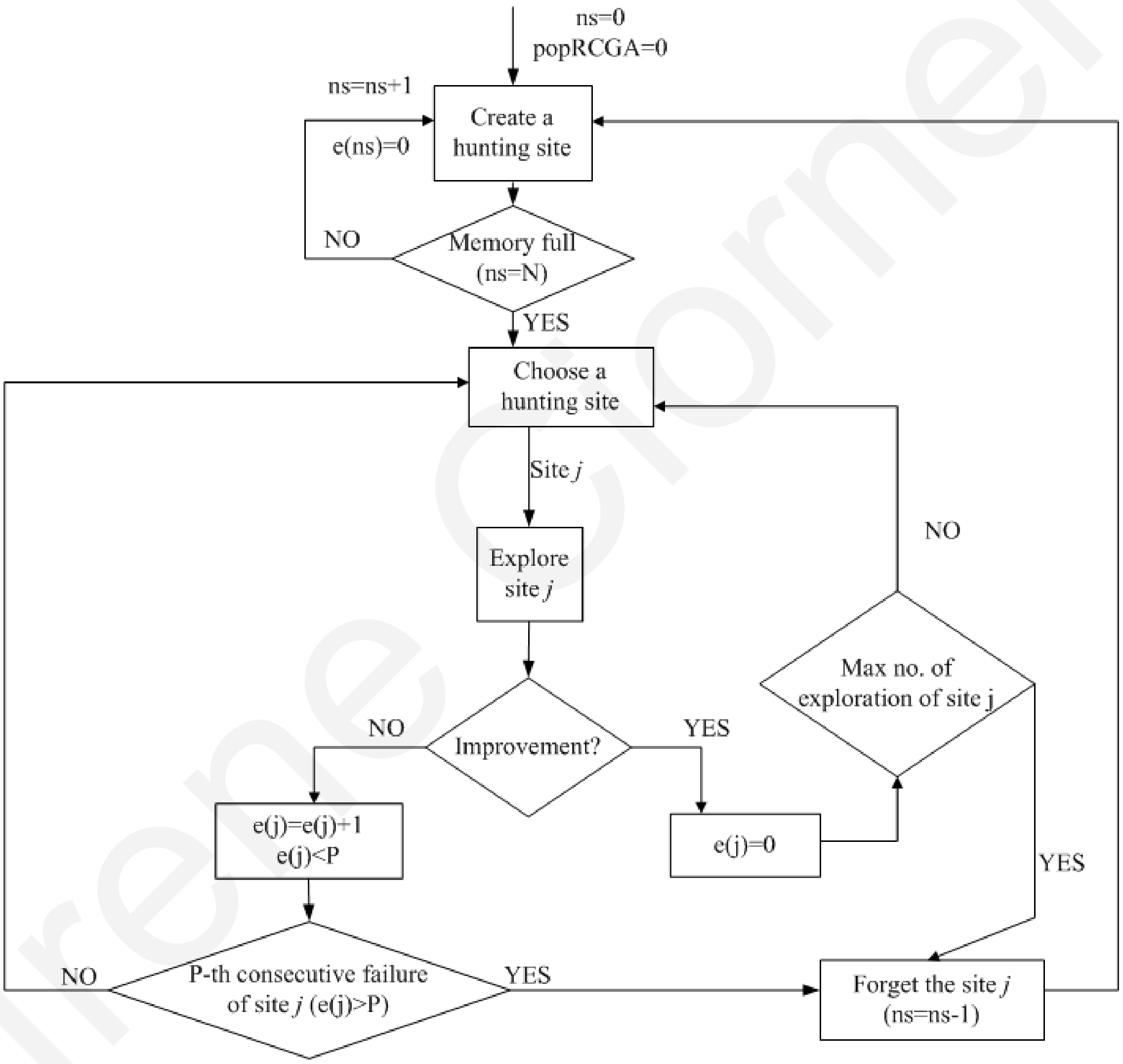

Figure 4.2 API search mechanism as used in the GAAPI algorithm

GAAPI has a well established balance between exploration (with API and RCGA) and exploitation (API). API keeps the algorithm focused towards the global optimum, moving the nest position (the point where exploitation starts) only in the best solution found so far, while RCGA helps the ants to use useful information of less explored regions (forgotten sites) The strong influence of API with its “down-hill” (gradient descending) behavior may increase the speed of convergence towards the global when compared to other powerful global search techniques such as PSO, EAs or GAs, where the exploration behavior may play a strong role. Figure 4.3 shows the GAAPI algorithm in the form of a flowchart, demonstrating the key steps of the process.

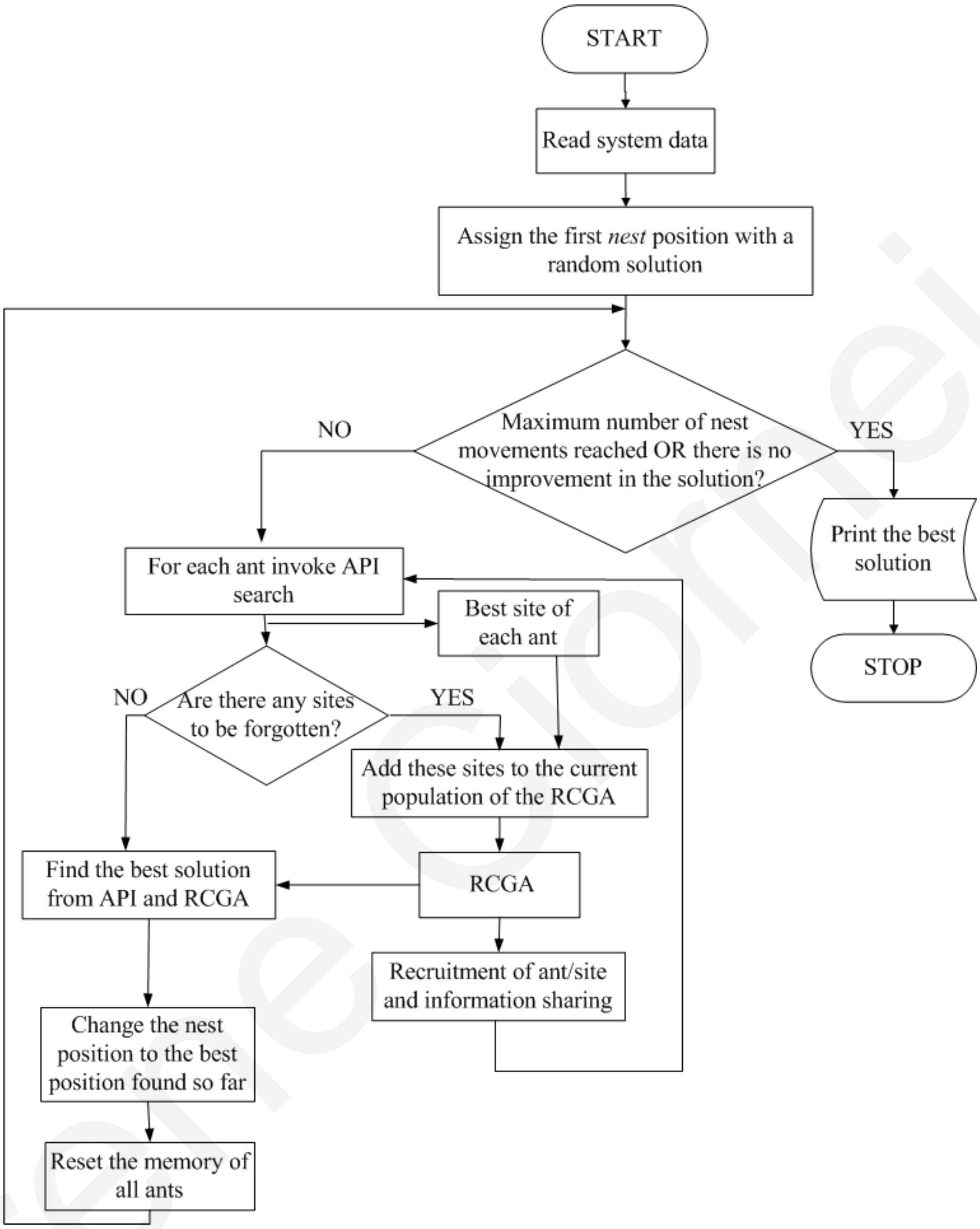

Figure 4.3 GAAPI flowchart

4.3 Proof of convergence

The problem of optimal search begins with an object of interest (target) which the searcher wishes to find. The target is assumed to be located either at a point in

Euclidean *n*-space ($\boldsymbol{S}$) or in one of a possibly infinite collection of cells *j*. The search space $\boldsymbol{S}$ is called continuous, and the search space $\boldsymbol{J}$ is called discrete. While the target's position is unknown, it is assumed that there is a probability distribution, known to the searcher, for the target's position at time t_0. It is assumed that the target is stationary (does not change position in time).

a. Definitions

D1. An ***unconstrained optimization problem*** (**UCOP**) can be formulated as a minimization of an objective function of the form,

$$Minimize\ f(x), x = (x_1, x_2, \dots, x_n) \in \boldsymbol{S} \tag{4.3}$$

where, $\boldsymbol{S} \subseteq \boldsymbol{R}^n$ defines the search space of the optimization problem, which is an *n*-dimensional space bounded or not by the parametric constraints,

$$x^{min} \leq x_i \leq x^{max}, \forall\ i = 1, \dots, n \tag{4.4}$$

Thus, $\boldsymbol{S} = [x^{min}, x^{max}]$

where, $x^{min} = [x_1^{min}, x_2^{min}, \dots, x_n^{min}]$ and $x^{max} = [x_1^{max}, x_2^{max}, \dots, x_n^{max}]$.

D2. A **constrained optimization problem** (**COP**) can be formulated as a minimization of an objective function of the form,

$$Minimize\ f(x), x = (x_1, x_2, \dots, x_n) \in \boldsymbol{S} \cap \boldsymbol{F} \tag{4.5}$$

where, $\boldsymbol{S}$ is as defined in (4.3) and $\boldsymbol{F}$ is the feasible region of variable x, and reads as $F = \{x \in \boldsymbol{R}^n | \, g_i(x) \leq 0, j = 1, 2, \dots, m\}$; $g(x)$ represents the vector constraints of the optimization problem.

b. Assumptions

In this part of the dissertation we are particularly interested in unconstrained optimization problems, and thus it is assumed that the set $\boldsymbol{S}$ is wide enough such that,

$$\boldsymbol{S} \supseteq \boldsymbol{S_0} = \{x \in \Re^n | \, f(x) \leq c\} \tag{4.6}$$

for a sufficiently large real number c.

Suppose that $x^* = (x_i^*, x_2^*, \dots, x_n^*)$ is a globally optimal solution and $\varepsilon > 0$ is a sufficiently small number. If a candidate solution $\tilde{x} = (\tilde{x}_1, \; \tilde{x}_2, \dots, \tilde{x}_n)$ satisfies

$$|\tilde{x}_i - x_i^*| \leq \epsilon, \forall i = 1, \dots, n \tag{4.7}$$

or

$$|f(\tilde{x}) - f(x^*)| \leq \epsilon \tag{4.8}$$

then, $\tilde{x}$ is called an *ε-optimal solution* of the problem defined in (4.5).

Further, it is assumed that the function $f(x)$ is continuous on $\boldsymbol{S}$, and that $\boldsymbol{S} \cap \boldsymbol{S_0}$ is a nonempty and compact set for a real number c.

For the GAAPI algorithm, $\boldsymbol{S_0}$ and c defined in (4.6) have the following interpretation: $\boldsymbol{S_0}$ is the solution space of all better solutions than the current nest position (N) found by the ant colony during the current search, and $c = f(N)$ is the evaluation of the objective function in the current position of the nest.

Let c be a constant satisfying $c > f^*$, where $f^* = \min_{x \in \boldsymbol{S}} f(x)$. The set $\boldsymbol{S_0}$ defined in (4.6) is called a *level set f(x)*, and can be characterized by the following mean,

$$M(f,c) = \frac{\int_{\boldsymbol{S_0}} f(x)dx}{\mu(\boldsymbol{S_0})} \tag{4.9}$$

$M(f,c)$ is called the mean of $f(x)$ on the level set $\boldsymbol{S_0}$, where $\mu(\boldsymbol{S_0})$ is the Lebesgue measure of $\boldsymbol{S_0}$ [166]. If $\{c_k\}$ is an arbitrary decreasing sequence with the limit f^* ($\{c_k\} \rightarrow f^*$) and lower bound f^*, then $M(f, c_k)$ is a decreasing sequence with lower bound f^*. Moreover, this limit does not depend on the choice of $\{c_k\}$.

Using the same logic as in [166] and [167] the following assumptions are set up:

Assumption (A1): $f(x)$ is continuous on $\boldsymbol{S_0}$.

Assumption (A2): There is a real number c such that $\boldsymbol{S_0}$ is a nonempty and compact set.

Lemma 1: Under the assumptions (A1) and (A2), if $\boldsymbol{S} \cap \boldsymbol{S_0} \neq \emptyset$ and $\mu(\boldsymbol{S} \cap \boldsymbol{S_0}) = 0$, then c is the globally optimal value of $f(x)$ on $\boldsymbol{S}$ and $\boldsymbol{S} \cap \boldsymbol{S_0}$ is the set of globally optimal solutions.

Lemma 2: Under the assumptions (A1) and (A2), the following conclusions may be made:

- If $c > f^*$, then $M(f,c) \leq c$. If $c_1 > c_2 > f^*$, then $M(f,c_1) \geq M(f,c_2) \geq f^*$

• f^* is the globally optimal function value if and only if $M(f,f^*)=f^*$

• If $\lim_{k\to\infty} f^k = f^*$, then $\lim_{k\to\infty} M(f, f^k) = M(f, f^*)$.

Thus, under the assumptions (A1) and (A2) and following the Lemmas 1 and 2, the probability to end up in an ε-optimal solution by using the GAAPI algorithm goes to one as the number of iterations (nest movements) goes to infinity, in the GAAPI algorithm.

4.4 Algorithm Validation

Besides the theoretical proof of convergence of the proposed GAAPI algorithm under the specific assumptions, also the performance of the proposed algorithm for continuous a set of hard global optimization problems is empirically investigated as well. The investigation covers a set of twenty benchmark test functions, widely used in the scientific literature to test optimization algorithms. Note that most of these test functions have many local minima and therefore they are challenging enough for performance evaluation.

a. Test Functions

The proposed GAAPI algorithm aims to be a solution in solving a large class of continuous unconstrained and constrained global optimization problems. Therefore, in order to validate the proposed algorithm, twenty functions were chosen as benchmark test functions [161, 163, 166, 168, 169].

Table 4.3 Characteristics of the test functions

Test Function	Search space	Global minimum	Dimension (n)
F1	$[-500, 500]^n$	-12569.5	30
F2	$[-5.12, 5.12]^n$	0	30
F3	$[-32, 32]^n$	0	30
F4	$[-600, 600]^n$	0	30
F5	$[-50, 50]^n$	0	30
F6	$[-50, 50]^n$	0	30
F7	$[0, pi]^n$	-99.2784	100
F8	$[-pi, pi]^n$	0	100
F9	$[-5, 5]^n$	-78.3324	100
F10	$[-5, 10]^n$	0	100
F11	$[-100, 100]^n$	0	30
F12	$[-1.28, 1.28]^n$	0	30
F13	$[-10, 10]^n$	0	30
F14	$[-100, 100]^n$	0	30
F15	$[-100, 100]^n$	0	30
F16	$[-5, 5]^n$	-1.03163	2
F17	[-5, 10]x[0, 15]	0.398	2
F18	$[-2, 2]^n$	3	2
F19	$[-5, 5]^n$	0.000308	4
F20	$[0, 1]^n$	-3.32	6

The functions chosen are test functions widely used in the scientific literature to test global optimization algorithms and to deduce conclusions regarding their performance. The basic parameters of all twenty test functions are listed in Table 4.3, including the search space limits, their dimensions and their global minimum (which is known). The equations that describe the twenty benchmark test functions are given in the Appendix (Section A1). Table 4.4 presents few descriptive characteristics of a class of six very popular and highly challenging test functions among those twenty. The corresponding 3D plots of this class of the most popular test functions are also given in the Appendix.

Table 4.4 Characteristics of six genertic benchmark functions

Function	Name of the function	Description
F2	Rastrigin	A highly multimodal function. The location of the deep local minima is regularly distributed. The global minimum is in x* = 0 and f(x*) = 0.
F3	Ackley	A multimodal function with deep local minima. The global minimum of this function is x* = 0 and f(x*) = 0. The variables of this function are independent.
F4	Grienwangk	A multi-modal function, having the global minimum in x* = 0 and f(x*) = 0. There is significant interaction between its variables due to the product term.
F10	Rosenbrock	A unimodal function, that has its global minimum at x* = (1, 1, …, 1) and f(x*) = 0. This function has many interactions between some of its variables.
F11	Spherical	A very simple unimodal function, that has its global minimum at x* = 0 and f(x*) = 0. This function has no interaction between its variables.
F14	Quadratic	It is a variation of the spherical function but with many interactions between its variables. The global minimum is located at x* = 0 and f(x*) = 0.

b. Parameter values for GAAPI

The values of the parameters of GAAPI that have been used for the global optimization of the twenty test functions are given below.

- The *population size* of RCGA is variable and depends on the current iteration and the number of unsuccessful sites memorized until the recruitment process. In the case of the initial iteration, the population has five individuals: the first and second best up to the first call of RCGA and three other individuals chosen randomly from all the sites of all ants. In the case of subsequent iterations, the population composition is like the first iteration only if no forgotten sites appear up to that point.

- *Blend crossover* operator (BLX-α) with a probability $P_c = 0.3$; the value of α was set to 0.366.
- *Uniform mutation* with a mutation probability $P_m = 0.35$.
- *The number of ants* in the API colony was set to 100.
- *The number of sites* each ant can search and memorize was set to 3.

The maximum number of explorations of the same site was set to 30. For a number of functions which have many local minima very near to each other (F5, F7, F16, F17, and F20), the maximum number of explorations was set to 500. The number of consecutive unsuccessful visits at one site before being deleted from the memory of the ant was set to 5 (or 40 for the functions cited above).

c. Empirical performance

The GAAPI algorithm was implemented in MATLAB 7.a on a Pentium IV personal computer with a 3.6 GHz processor and it was executed in 50 independent runs for each test function, in order to keep the same base of comparison with other similar algorithms. The following qualitative indicators were recorded: the minimum function value denoted by MIN, the maximum function value denoted by MAX, the average function value denoted by MEAN, the standard deviation denoted by STD, the average CPU time of 50 independent runs denoted by CPU and the mean number of function evaluations denoted by M_num_fun. The last two indicators give a fair indication about the effectiveness of the algorithm in real problems. All these indicators are generally accepted measures of performance when referring to heuristic global optimization algorithms. Note that CPU time together with the PC platform on which the algorithm was executed, is only provided for comparison purposes to other works which used this indicator. However, this parameter is subject to hardware platform capabilities on which the algorithm is run, and may not be the best choice of comparison of computational performance. The use of ***M_num_fun*** is emphasized in this dissertation instead.

Table 4.5 gives the qualitative performance results for the twenty test functions. In most of the benchmark functions GAAPI proved its consistency, having the lowest standard deviation as compared to the other methods and the lowest mean number of function evaluations and CPU time. The mean number of function evaluations (*M_num_fun*) is the average of the total number of function evaluations during a predefined number of independent runs of the algorithm. In other words, if we denote with nF_i the number of function evaluations in the i^{th} independent run of the proposed algorithm and we have a total of M runs which we take into account in our evaluation process, then the mean number of function evaluations is,

$$M\_num\_fun = \frac{\sum_{i=1}^{M} nF_i}{M} \tag{4.10}$$

Table 4.5 Performance of GAAPI over the 20 test functions

Function	MIN	MAX	MEAN	STD	CPU (s)
F1	-12569.5	-12568.3	-12569.4	0.2618	30.5867
F2	1.02E-06	0.028603	0.005046	0.0074	27.0671
F3	0.000163	0.187231	0.038933	0.0545	18.2644
F4	2.2E-05	1.027464	0.077839	0.2250	37.2827
F5	3.65E-10	1.72E-08	2.73E-06	1.1E-06	22.4786
F6	2.23E-07	0.33526	0.068774	0.1102	42.2726
F7	-39.7847	-24.5752	-37.4486	4.7103	24.2658
F8	1.4E-07	1.441302	0.149302	0.3299	401.7522
F9	-78.3323	-78.331	-78.3322	0.0003	37.9272
F10	4.18E-05	0.257584	0.040124	0.0707	35.5866
F11	6.67E-09	0.063028	0.010741	0.0176	35.6439
F12	1.28E-05	0.0132	0.0037	0.0030	17.0035
F13	0.001297	0.244238	0.055812	0.0546	37.5640
F14	0.000537	9.408785	2.292226	3.2218	39.5760
F15	0.000298	0.047323	0.01266	0.0134	30.7023
F16	6.94E-10	1.24E-05	1.36E-06	3.05E-06	23.8269
F17	10.22525	10.22532	10.22526	1.47E-05	27.8655
F18	3.002442	7.805611	3.703591	1.2472	27.2073
F19	0.051743	0.051869	0.051756	3.08E-05	27.9693
F20	-22.231	-22.231	-22.231	1.45E-05	29.0590

In most of the cases, the number of function evaluations to reach a solution very near to the global solution is 10 to 50 times less than the other methods used for comparison. For seven of the most popular and difficult functions, GAAPI obtained the best global solution fast and accurately (F1, F5, F8-F12).

GAAPI responds very well, particularly for complex functions with higher dimensionality (N = 100 or 30, such as in F1–F7, F9–F15, and F18). However, the algorithm did not perform satisfactorily for test functions F16 (Fig. 4), F17 (Fig. 5), F19, and F20. This may be due to the flatness characteristics of these functions (many local minima at the same level). In this validation analysis the GAAPI algorithm was executed for all twenty functions using the same termination criterion: the algorithm stops if no improvement occurs after twenty consecutive nest movements. The initials of the algorithms referenced in this work are presented in Table 4.6. A brief description of some of these algorithms is presented in [166].

Table 4.6 Notations of the algorithms used for comparison

Notation	Description
ALEP	Evolutionary programming with adaptive Levy mutation
FEP	Fast evolutionary programming Cauchy mutation
OGA/Q	Orthogonal genetic algorithm with quantization
HTGA	Hybrid Taguchi – genetic algorithm
EDA/L	Hybrid estimation of distribution algorithm
M-L	Modified mean-level-set method proposed in [166]
LEA	Level-set evolution and Latin squares algorithm
CEP	Conventional evolutionary programming
HPSO-TVAC	Hierarchical particle swarm optimization with time-varying acceleration coefficients
CPSO-H6	Hybrid cooperative particle swarm optimization, API – special class of continuous domain ant colony optimization search based on the Monmarché approach [136]
ACAGA	Hybrid algorithm combining ant colony algorithm with genetic algorithm for continuous domain optimization problems [170]

Table 4.7 provides a comparison of the computational time required for GAAPI and other heuristic methods for determining the global optimal solution. Results on other methods are obtained from [166]. It is shown that GAAPI is faster compared to the other methods; in some cases it is considerably faster. As the computational effort is very important, especially to actual problems that need to be solved in real time,

GAAPI may be considered as a useful optimization tool based on the computational time required determining the global optimum.

Table 4.7 Comparison to other heuristic methods with respect to CPU time

Function	Algorithm used and CPU time (s)			
F1	HTGA	CPSO-H6	LEA	GAAPI
	689.30	658.70	656.30	30.59
F2	HTGA	CPSO-H6	LEA	GAAPI
	607.50	557.70	557.20	27.07
F3	ALEP	CPSO-H6	LEA	GAAPI
	359.30	326.80	326.10	18.26
F4	HTGA	CPSO-H6	LEA	GAAPI
	373.80	368.10	365.60	37.28
F5	HTGA	CPSO-H6	LEA	GAAPI
	378.60	369.80	368.50	22.48
F6	HTGA	CPSO-H6	LEA	GAAPI
	381.20	363.70	359.10	42.27
F7	HTGA	CPSO-H6	LEA	GAAPI
	765.20	719.60	660.80	24.27
F8	ALEP	CPSO-H6	LEA	GAAPI
	689.40	503.40	493.40	401.75
F9	ALEP	CPSO-H6	LEA	GAAPI
	782.70	685.80	612.30	37.93
F10	HPSO-TVAC	CPSO-H6	LEA	GAAPI
	594.50	501.10	443.80	35.59
F11	HTGA	CPSO-H6	LEA	GAAPI
	312.50	242.60	240.20	35.64
F12	HTGA	CPSO-H6	LEA	GAAPI
	318.40	243.70	242.40	17.00
F13	HTGA	CPSO-H6	LEA	GAAPI
	322.60	243.00	240.80	37.56
F14	HTGA	CPSO-H6	LEA	GAAPI
	328.40	244.60	241.30	39.58
F15	HTGA	CPSO-H6	LEA	GAAPI

Function	Algorithm used and CPU time (s)			
	334.20	243.10	242.20	30.70
F16	HTGA	ALEP	LEA	GAAPI
	31.60	31.10	30.80	23.83
F17	HTGA	ALEP	LEA	GAAPI
	31.10	31.10	30.60	27.87
F18	HTGA	ALEP	LEA	GAAPI
	35.40	34.00	33.50	27.20
F19	HTGA	ALEP	LEA	GAAPI
	121.20	102.00	101.30	27.97
F20	CPSO-H6	ALEP	LEA	GAAPI
	67.70	66.60	66.20	29.06

Tables 4.8 to 4.11 show a comparison between the performance of GAAPI and the performance of other heuristic algorithms, for all twenty test functions used for the present analysis. Each table compares the performance of each algorithm (if the results are available, and only for the functions tested) and provides the mean number of function evaluations (M_num_fun), the best value determined by each algorithm (M-best), and the standard deviation for 50 independent runs of each algorithm. Further, the optimal value of each test function is provided.

It should be noted that in the literature selected for comparison for the purposes of this work, the same number of function evaluations for each algorithm was not available. Thus, this measure is used only to sustain a quasi-comparison on the speed of convergence of different heuristic algorithms toward a near global solution denoted as the best-mean solution over a number of independent runs.

Table 4.8 Comparison to other heuristic methods for F1 to F5

Function	Algorithm	M_num_fun	M-best	Std	Opt-F
F1	ALEP	150000	-11469.2	58.2	-12569.5
	FEP	900000	-12554.5	52.6	
	OGA/Q	302116	-12569.45	6.44E-4	
	HTGA	163468	-12569.46	0	
	EDA/L	52216	-12569.48	N/A	
	M-L	655895	-5461.826	275.15	
	LEA	287365	-12569.45	4.83E-4	
	ACAGA	N/A	-12569.48	4.12E-3	
	GAAPI	26510	-12569.5	5.77E-7	
F2	ALEP	150000	5.85	2.07	0
	FEP	500000	0.046	0.0012	
	CEP	250000	4.73	N/A	
	OGA/Q	224710	0	0	
	HTGA	16267	0	0	
	HPSO-TVAC	200000	0.044	0.19	
	CPSO-H6	200000	0.778	N/A	
	EDA/L	75014	0	N/A	
	M-L	305899	121.7575	7.75	
	LEA	223803	2.10E-8	3.3E-18	
	API	N/A	2.32	N/A	
	ACAGA	N/A	2.53E-6	3.62E-6	
	GAAPI	24714	1.02E-6	4.58E-9	
F3	ALEP	150000	0.019	0.001	0
	FEP	150000	0.018	0.021	
	CEP	250000	7.49E-4	N/A	
	OGA/Q	112421	4.4E-16	3.9E-17	
	HTGA	16632	0	0	
	CPSO-H6	200000	2.7E-12	N/A	
	EDA/L	106061	4.1E-15	N/A	
	M-L	121435	2.5993	0.094	
	LEA	105926	3.2E-16	3.0E-17	
	API	N/A	2.22E-3	N/A	
	ACAGA	N/A	4.69E-6	7.12E-5	
	GAAPI	19592	0.000163	9.1E-7	
F4	ALEP	150000	0.024	0.028	0
	FEP	200000	0.016	0.022	
	CEP	250000	2.52E-7	N/A	
	OGA/Q	134000	0	0	

Function	Algorithm	M_num_fun	M-best	Std	Opt-F
	HTGA	20999	0	0	
	HPSO-TVAC	200000	0.01	0.001	
	CPSO-H6	200000	0.0524	N/A	
	EDA/L	79096	0	N/A	
	M-L	151281	0.11894	0.0104	
	LEA	130498	6.10E-6	2.5E-17	
	GAAPI	29647	2.2E-05	2.05E-8	
F5	ALEP	150000	6.0E-6	1.0E-6	0
	FEP	150000	9.2E-6	3.6E-6	
	OGA/Q	134556	6.01E-6	1.15E-6	
	HTGA	66457	1.0E-6	0	
	EDA/L	89925	3.6E-21	N/A	
	M-L	146209	0.2105	0.0360	
	LEA	132642	2.42E-6	2.27E-6	
	GAAPI	60297	3.65E-10	1.82E-11	

For the first five functions GAAPI found the near global solution in much less computational time and/or mean number of function evaluations (up to twenty times less) for all of the functions under analysis in this table. Also, GAAPI found the best solution among all algorithms for two of the functions (F1 and F5), while for the other three functions GAAPI practically found the global optimum (the error was less than 10^{-4}). It should be noted that the values for the API and ACAGA algorithms given in Tables 4.8 and 4.10 were obtained from [163] and [170] respectively.

Table 4.9 Comparison to other heuristic methods for F6 to F10

Function	Algorithm	M_num_fun	M-best	Std	Opt-F
F6	ALEP	150000	9.80E-05	1.20E-05	0
	FEP	150000	1.60E-04	7.30E-05	
	OGA/Q	134143	1.87E-04	2.62E-05	
	HTGA	59003	0.0001	0	
	EDA/L	114570	3.49E-21	N/A	
	M-L	147928	1.51E+00	2.25564	
	LEA	130213	1.73E-04	1.21E-04	
	GAAPI	26895	2.23E-07	3.06E-03	
F7	OGA/Q	302773	-92.83	0.02626	-99.3
	HTGA	265693	-92.80	0	
	EDA/L	169887	-94.3757	N/A	
	M-L	329087	-23.9754	0.62875	
	LEA	289863	-93.01	0.02314	
	GAAPI	21235	-39.7847	0.100521	
F8	OGA/Q	190031	4.67E-07	1.29E-07	0
	HTGA	186816	5.87E-05	8.33E-05	
	EDA/L	124417	3.29E-08	N/A	
	M-L	221547	25877.8	1739.75	
	LEA	189427	1.63E-06	6.527E-07	
	GAAPI	28778	1.40E-07	2.33E-02	
F9	OGA/Q	245930	-7.83E01	6.29E-03	-78.3
	HTGA	216535	-78.303	0	
	EDA/L	153116	-78.3107	NA	
	M-L	251199	-35.8099	0.89146	
	LEA	243895	-78310	6.13E-03	
	GAAPI	28701	-78.3323	1.38E-05	
F10	OGA/Q	167863	0.752	0.114	0
	HTGA	60737	0.7	0	
	HPSO-TVAC	200000	9.855	6.725	
	EDA/L	128140	4.32E-03	N/A	
	CPSO-H6	200000	0.194	N/A	
	M-L	137100	2935.93	134.8186	
	LEA	168910	0.5609	0.1078	
	GAAPI	29171	4.18E-05	5.03E-03	

Table 4.10 Comparison to other heuristic methods for F11 to F15

Function	Algorithm	M_num_fun	M-best	Std	Opt-F
F11	ALEP	150000	6.32E-04	7.60E-05	0
	FEP	150000	5.70E-04	1.30E-04	
	CEP	250000	3.09E-07	N/A	
	OGA/Q	112559	0	0	
	HTGA	20844	0	0	
	HPSO-TVAC	120000	0.01	N/A	
	M-L	162010	3.19123	0.29463	
	LEA	110674	4.73E-16	6.22E-17	
	API	N/A	6.65E-06	N/A	
	GAAPI	29199	6.67E-09	1.89E-04	
F12	CEP	250000	9.42	N/A	0
	OGA/Q	112652	6.30E-03	4.07E-04	
	HTGA	20065	0.001	0	
	M-L	124982	1.703986	0.52155	
	LEA	111093	5.14E-03	4.43E-04	
	GAAPI	4149	1.28E-05	7.21E-07	
F13	FEP	200000	0.0081	7.70E-04	0
	CEP	250000	1.99E-03	N/A	
	OGA/Q	112612	0	0	
	HTGA	14285	0	0	
	M-L	120176	9.7416	0.463769	
	LEA	110031	4.25E-19	4.24E-19	
	ACAGA	N/A	2.58E-05	4.17E-05	
	GAAPI	30714	0.001297	2.01E-02	
F14	ALEP	150000	0.04185	5.97E-02	0
	FEP	500000	0.016	0.014	
	CEP	250000	0.612	N/A	
	OGA/Q	112576	0	0	
	HTGA	26469	0	0	
	CPSO-H6	200000	2.63E-66	N/A	
	M-L	155783	2.21994	0.50449	
	LEA	110604	6.78E-18	5.43E-18	
	ACAGA	NA	2.26E-07	1.75E-6	
	GAAPI	31792	0.000537	3.1932	
F15	FEP	500000	0.3	0.5	0
	CEP	250000	0.323	N/A	
	OGA/Q	112893	0	0	
	HTGA	21261	0	0	

Function	Algorithm	M_num_fun	M-best	Std	Opt-F
	M-L	125439	0.55755	4.00E-02	
	LEA	111105	2.68E-16	6.26E-17	
	GAAPI	31040	0.000298	4.01E-03	

For the next group of functions (F11 to F15), for the first two functions GAAPI obtained the best solution reported so far; for the next three functions (F13 to F15) GAAPI obtained a near global optimum solution. For F13, GAAPI obtained better solutions than the FEP, CEP and M-L algorithms, and better CPU time/ mean number of function evaluations than all the other algorithms. However, OGA/G, HTGA, ACAGA and LEA had a better minimum solution. For F14, GAAPI outperformed ALEP, FEP, CEP and M-L, but OGA/G, HTGA, CPSO-H6, ACAGA and LEA performed better than GAAPI. For F15, LEA, OGA/Q, HTGA and LEA outperformed GAAPI in terms of the best solution found so far; however, the GAAPI solution was near the global optimum in faster computational time.

For the last group of five test functions, GAAPI obtained a good solution for F18. However, its performance for the other four test functions was not satisfactory. The main reason for this failure is the flatness of these objective functions around the global minimum, and due to the termination criterion of the GAAPI to stop when no improvement occurs after a number of consecutive nest movements. However, this termination criterion is very powerful to limit the computational effort.

Table 4.11 Comparison to other heuristic methods for F16 to F20

Function	Algorithm	M_num_fun	M-best	Std	Opt-F
F16	ALEP	3000	-1.031	0	-1.031
	FEP	10000	-1.03	4.90E-07	
	M-L	13592	-1.02662	5.27E-03	
	LEA	10823	-1.03108	3.36E-07	
	GAAPI	27241	6.94E-10	1.40E-07	
F17	FEP	10000	0.398	1.50E-07	0.398
	M-L	12703	0.403297	8.83E-03	
	LEA	10538	0.398	2.65E-05	
	GAAPI	29625	10.22525	5.43E-07	
F18	ALEP	3000	3	0	3
	FEP	10000	3.02	0.11	
	M-L	16325	3.048855	0.0603749	
	LEA	11721	3.00003	6.25E-05	
	GAAPI	29625	3.002442	2.85E-05	
F19	FEP	400000	5.00E-04	3.20E-04	3.08E-4
	M-L	186768	1.34E-03	2.98E-04	
	LEA	55714	3.51E-04	7.36E-05	
	GAAPI	28654	0.051743	8.45E-07	
F20	FEP	20000	-3.27	0.059	-3.32
	M-L	92516	-3.12696	0.067397	
	LEA	28428	-3.301	7.83E-03	
	GAAPI	29302	-22.231	3.87E-07	

4.5 Chapter Summary

In this chapter a new algorithm, called GAAPI, was introduced as a solution to global unconstrained continuous optimization problems. This algorithm is appropriate for optimization problems whose decision variables take values from the real – number domain. The GAAPI algorithm was created by combining some unique characteristics of two other robust meta–heuristic algorithms: RCGA and API.

It was proven that in most of the test cases (15 out of 20 benchmark functions) GAAPI provided satisfactory or optimum solutions, with very little computational effort. The algorithm is recommended for large, complex problems with a dimensionality greater than 30. For seven benchmark functions GAAPI gave the best solution reported so far in the literature, with less number of function evaluations (10 to 50 times less than other powerful methods). The best solution was found for complex functions with high dimensionality (n = 30 or n = 100) (seven test functions). For eight other test functions with high dimensionality (n = 30) GAAPI gave near global optimal solutions with much less computational effort. However, for a small class of functions (five benchmark functions), having mainly small dimensionality (n = 2, n = 4 or n = 6), GAAPI failed to find the global optimum solution. The main reason for this failure is the flatness of the objective function around the global minimum.

There are at least two main reasons why GAAPI performs better than other powerful heuristic techniques. First, the balance in exploration and exploitation given by the two chosen algorithms API and GA is one of the reasons. API has a strong influence targeting the search towards a continuously improved solution (the nest is moved only in the best solution found at each iteration by its ants), while GA has an active role in the solution search, only when API reduces its speed of convergence (the solution does not improve much from one iteration to another, or there are many failures in exploiting different sites). This balance in exploration and exploitation increases the chances of a faster convergence towards the global optimum, while other methods such as PSO, EAs, or GAs have a strong exploration component. The second reason is the choice of crossover and mutation functions in RCGA. These influence the activeness or passiveness of GA in the GAAPI search. A different crossover (for example, an arithmetic real coded crossover) would maintain GA active at each nest movement, which may lead to solution divergence. The same may happen if the mutation probability is higher than the crossover probability.

Other hybridization techniques of API with variances of evolutionary algorithms may further improve the quality of the solution in difficult global optimization problems, but a difficulty in implementation could appear due to the complicated forms of the operators to be used. There may be value in comparing analytically the search behavior of GAAPI and other search models for ACO-GA hybridization techniques or in the association of API with other evolutionary algorithms used for some applications in continuous global optimization. There may also be value in concentrating on comparisons of GAAPI to other hybridization schemes which relate to GA and local search mechanisms. This study focused mainly on continuous domain optimization problems, so further work can be addressed to see the applicability of the proposed algorithm to discrete as well as constrained optimization problems.

Chapter 5

GAAPI: Integrated solution for economic dispatch in power systems

5.1 Introduction

This chapter proposes the application of the developed GAAPI algorithm to the constrained optimization problem of economic dispatch in power systems. First, the formulations of the economic dispatch problem to which GAAPI is proposed as a solution are introduced. Second, the adaptations needed in the GAAPI algorithm for constrained optimization are presented. Last, the proposed solution is empirically validated on a number of standard IEEE test systems.

5.2 Economic dispatch: modeling

In this work we call *mathematical model* any system of functions, equations, equalities and inequalities which define the optimization problem intended to be solved. In specific, for the economic dispatch in power systems, combinations of different formulations of the objective function together with different sets of constraints taken into account can form distinct models of the problem. Thus, this section summarizes the mathematical models used in this work for the analysis of the economic dispatch problem in its various aspects. From the large number of formulations available in the recent literature for the economic dispatch of generation in power systems (see Chapter 2), only some of them were elaborated in the current work due to their practical meaning (e.g., modern generators have multiple admission valves, and therefore their output characteristic is no longer quadratic), as well as for comparison purposes (e.g., use of the quadratic approximation of the objective function or neglecting the network constraints) of the GAAPI algorithm with other similar techniques. The critical "must be respected" network constraints used in the formulations adopted for analysis in this dissertation are also described in detail with emphasis on their importance in practice. A summary of the mathematical characteristics of the economic dispatch models used for the applicability of GAAPI is given in Table 5.1.

Table 5.1 Characteristics of the mathematical ED models used to test GAAPI

Name of the model	Characteristics
Simplified model	The simplest model of the ED problem: quadratic single objective function and one equality linear constraint
Convex constrained model	Complex model: quadratic single objective function with nonlinear equality and inequality constraints
Nonconvex constrained model	More complex model: nonconvex single objective function with nonlinear equality and inequality constraints

a. Simplified model

The first model called *the simplified model* is one of the first approaches used to describe mathematically the optimization problem of economic dispatch. It refers to the case when the ED problem is stated as a single objective minimization problem. The cost of fuel (the optimization objective) is represented as a quadratic polynomial, and only the balance constraint is taken into account in this model, all others been neglected. The reason for the existence of this simplified model is that, when the transmission distances are very small and the load density is very high, transmission losses can be neglected, which is the case of this model, when the system configuration or the impedances of the transmission lines are not taken into account. In brief, the simple ED model assumes that all generators and loads are connected to a single bus, as presented in Figure 5.1.

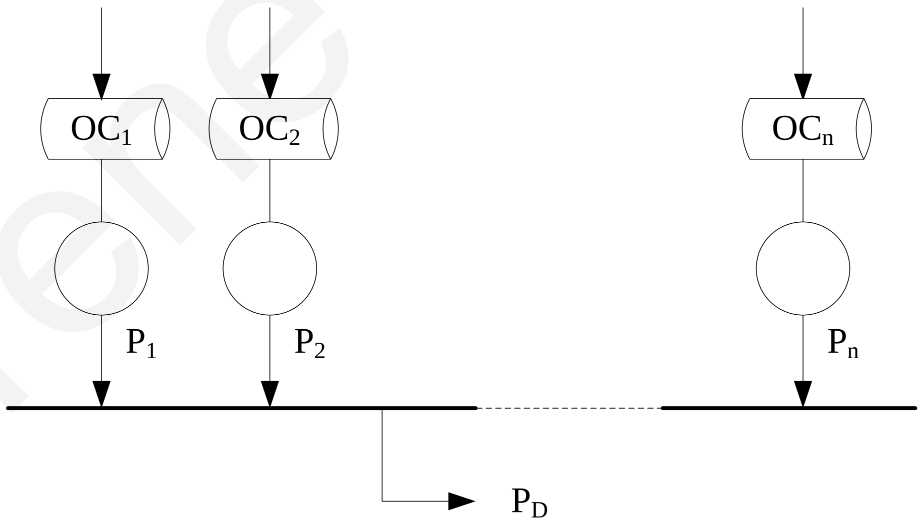

Figure 5.1 The simple economic dispatch model (Simplified model)

This model is mathematically formulated as,

$$\min OC = \sum_{i=1}^{NG} a_i + b_i P_i + c_i P_i^2$$

Subject to,

$$P_D - \sum_{i=1}^{NG} P_i = 0 \qquad (5.1)$$

$$P_i \geq 0$$

The above model is used in this work mainly for comparison to other analytical or heuristic approaches previously used by other authors to solve this specific problem. It was also used as a measure of confidence of the GAAPI convergence and accuracy of the solution in the early stages of the development of the proposed algorithm. As an example, for small size test systems, such as two or three generator power systems the global solution of the ED problem stated in (5.1) is known (it may be determined analytically). Therefore, it is enough but not sufficient, in the first stages of algorithm testing, to verify if the algorithms that are developed and analyzed in this dissertation converge to this known global solution.

b. Convex constrained model

The second model in this dissertation refers to *the convex constrained model* that is described mathematically below. This is the most common model used in the literature to validate different methodologies or algorithms to solve the economic dispatch problem. The model is a minimization problem which uses a quadratic approximation of the objective function (the sum of the cost of fuel of each generating unit) and a number of constraints from the balance and transmission losses, to the prohibited operating zone constraints. In large interconnected power networks, where power is transmitted over long distances with low load density areas, transmission losses are a major factor which affects the optimum dispatch of generation. Therefore, this model takes into account the power system network architecture by considering the real power losses through the transmission lines for transmitting the electrical energy from the source (generating unit) to the destination (power consumer).

The convex constrained model differs from the simple ED model presented in the previous section mainly with regards to the number of constraints taken into account. The transmission losses are generally approximated with a quadratic function of the power output of the units committed in the dispatch procedure. The coefficients of the quadratic approximation of the transmission losses are set up as constants after a previous run of a power flow model of the system.

As can be observed in (5.2), the second model under analysis in this dissertation is more complex and difficult to approach than the simplified model, due to nonlinearities and recurrence in the approximation of the transmission losses on one hand, and due to noncontinuities in the constraint of the prohibited operating zones, on the other hand. The model is described mathematically below. $[B_{ij}]$ is a square matrix of dimensions NG by NG, $[B_{i0}]$ is a column vector with NG components, and B_{00} is a real constant, all representing the "B-loss" coefficients which are assumed to be constant over the economic dispatch run; DR_i and UR_i refer to the down-ramp rate of unit i and up-ramp rate of unit i, respectively.

$$\min OC = \sum_{i=1}^{NG} a_i + b_i P_i + c_i P_i^2$$

Subject to,

$$P_D + P_{Loss} - \sum_{i=1}^{NG} P_i = 0,$$

$$P_i^{min} \leq P_i \leq P_i^{max}$$

$$\max\left(P_i^{min}, P_i^0 - DR_i\right) \leq P_i \leq \min(P_i^{max}, P_i^0 + UR_i) \tag{5.2}$$

$$\begin{aligned} &P_i^{min} \leq P_i \leq P_i^{l_1} \\ &P_i^{u_{j-1}} \leq P_i \leq P_i^{l_j}, \qquad j = 1, \ldots, N_{POZ} \\ &P_i^{u_j} \leq P_i \leq P_i^{max} \end{aligned}$$

$$where\ P_{Loss} = \sum_{i=1}^{NG} \sum_{j=1}^{NG} P_i B_{ij} P_j + \sum_{i=1}^{NG} B_{i0} P_i + B_{00}$$

c. Nonconvex constrained model

The third model refers to *the nonconvex constrained model* for the economic dispatch problem. This model is an extension of the convex constrained ED model, because only the form of the objective function differs. This model takes into account the rippling effect of the multiple steam admission valves of the modern thermal units, which is known in the power system literature as "the valve point effect". When modelling this effect, an extra sinusoidal term is added to the quadratic approximation of the classical cost of generation. This rippling effect due to the steam admission valves is also linked to the prohibited operating zones constraints, as presented in detail in Chapter 2.

A schematic representation of the constrained ED models (both convex and nonconvex) is presented in Figure 5.2.

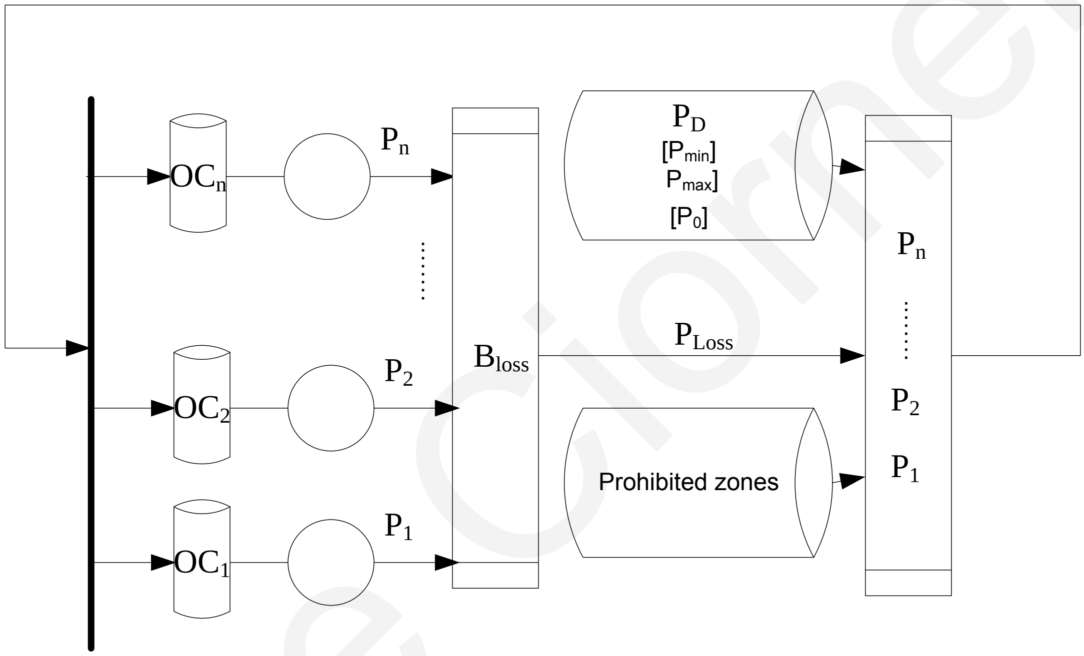

Figure 5.2 Representation of both convex and nonconvex constrained models

The nonconvex constrained model for the ED problem is a more accurate model than the previous two models, and it closely represents the architecture of actual power systems. Despite the fact that this model does not explicitly represent hydro or combined cycle (CC) units, the model does not lose generality. Hydro units add just another "generating" limit constraint (the reservoir limits), and the CC units include other non-continuities, which may be incorporated into the prohibited operating zones constraints. The mathematical description of the nonconvex constrained ED model is given by,

$$OC = \sum_{i=1}^{NG} a_i + b_i P_i + c_i P_i^2 + \left| e_i \sin(f_i(P_i^{min} - P_i)) \right|$$

Subject to,

$$P_D + P_{Loss} - \sum_{i=1}^{NG} P_i = 0,$$

$$P_i^{min} \le P_i \le P_i^{max}$$

$$\max\left(P_i^{min}, P_i^0 - DR_i\right) \le P_i \le \min(P_i^{max}, P_i^0 + UR_i) \tag{5.3}$$

$$\begin{aligned} &P_i^{min} \le P_i \le P_i^{l_1} \\ &P_i^{u_{j-1}} \le P_i \le P_i^{l_j}, \qquad j = 1, .., N_{POZ} \\ &P_i^{u_j} \le P_i \le P_i^{max} \end{aligned}$$

$$where\ P_{Loss} = \sum_{i=1}^{NG} \sum_{j=1}^{NG} P_i B_{ij} P_j + \sum_{i=1}^{NG} B_{i0} P_i + B_{00}$$

5.3 GAAPI for constrained optimization

In the previous chapter the GAAPI algorithm was introduced and validated as a viable solution for a class of complex unconstrained optimization problems. In this chapter, this algorithm will be applied to the constrained optimization of economic dispatch of generation in power systems. Therefore, limited number of adaptations/transformations of the algorithm is needed in order to cope with the constraints of this optimization problem. These adaptations are discussed in the following two subsections.

5.3.1 Handling constraints

One of the major issues to deal within constrained optimization problems is how to cope with the infeasible individuals throughout the search process. There are two major possible approaches to handle infeasible individuals. One approach is to completely disregard them and continue the search with feasible individuals only. This option might have a drawback for probabilistic search approaches, such as Gas, because some information contained in infeasible solutions could be utilized. Thus, if the search space is discontinuous, then the algorithm may be trapped in local minima. The other approach to handle constraints is to use a penalty fitness function (optimization function) that aggregates the objective function with the constraint functions penalized [46, 65, 80]. The simplicity of penalty functions has made them the most commonly used methods for solving constrained optimization problems. In penalty functions, infeasible individuals will be penalized for violation of constraints by adding a penalty value to their original fitness (determined only by the objective function evaluation). Adding a penalty value will decrease the probability of an infeasible individual being selected for recombination. The penalty functions have the following general form:

$$F(x) = f(x) + \sum_{i=1}^{m} pf_i \cdot h_i(x) \tag{5.4}$$

where, $F(x)$ is the aggregated fitness function (fitness plus constraints); $f(x)$ is the objective function; pf_i is the i-th penalty coefficient; h_i is the i-th constraint function (counting for both equality and inequality constraints), which takes the value of zero if there is no violation and greater than zero if there is a violation; and m is the number of constraints of the constrained optimization function.

Two main approaches regarding the use of penalty functions can be identified in the literature: (a) the simplest and the earliest approach is using static penalty functions (or constant penalty coefficients) during the whole search procedure, and (b) the adaptive approach using dynamic adjustments of the penalty coefficients during the evolution of the search. In the first case, the penalty coefficients must be carefully chosen to distinguish between feasible and infeasible solutions. Sometimes this parameter training is a difficult task even when the problem is well known.

In this work, a hybrid approach is used to cope with the constraints. The algorithm mainly works with feasible solutions. However, from time to time, as the search progresses, infeasible solutions are allowed throughout the search process. This happens because the objective function the algorithm tries to optimize is the aggregated penalty function $F(x)$ as defined in (5.4).

Our approach in handling constraints is called "*the feasible solution generator"* and reads as follows. First, an initial solution, $x = P = (P_1, P_2, \ldots, P_i, \ldots, P_{NG})$ is generated respecting generation and ramp rate limits, according to,

$$P_i = P_i^{min} + rand() \cdot (P_i^{max} - P_i^{min}) \tag{5.5}$$

where, *rand*() is a uniform random number between 0 and 1. Then, the balance constraint with losses is checked. While the balance constraint considering losses is not satisfied (the first constraint in any of the models (5.1), (5.2) and (5.3)), a random generator is chosen as slack from the pool of *NG* generators, and its output is set to meet the balance. If its limits are exceeded, then another random slack generator is chosen from the (*NG*-1) pool. If all the generators are checked and no one can cover the difference to meet the balance, then two generators will be chosen as slack and share the difference, and so on. When a generator is in a prohibited zone, then its output is set to the closest feasible bound.

The RCGA, which is the part of the GAAPI does not follow this handling constraint rule, but only pays attention to the bounding limits of the solution space. So, the process of handling the constraints is relaxed from the point of view of the feasible solution space. However, if these solutions are highly infeasible (they are far from the feasible region), then they will be ultimately discharged due to the high penalty assigned to the optimization function.

5.3.2 Adaptation of GAAPI for the solution of economic dispatch

The first step of the proposed GAAPI algorithm is to find a starting point for the search (referred from here on as the *initialization process*). This starting point is given by the solution of the Lagrange multipliers (LM) method applied to the simplified model of the problem (5.1). The reason for this choice is provided below.

If one uses a quadratic cost function or a generation function with valve point effects (see Figure 5.3) and ignores transmission losses and all other constraints (except the balance constraint), an approximate area containing the optimal solution may be identified. Taking the particular case presented in Figure 5.3, the balance constraint is a straight line crossing the cost function at the point where the generation output equals the load demand (the geometrical view for one generator). With more constraints taken into account, this geometrical delimitation is more difficult to draw. Therefore, if at time t_0 the losses are computed using an approximate solution given for the economic dispatch problem for this time frame (t_0) and set as a constant value in the balance constraint equation, then this equation becomes linear. Then, using the quadratic approximation of the generation function, a good starting point for the next, more accurate search can be determined. This starting point is the optimal solution of the optimization system described by an extension of the simplified model, as described in (5.1), with transmission constraints taken into consideration.

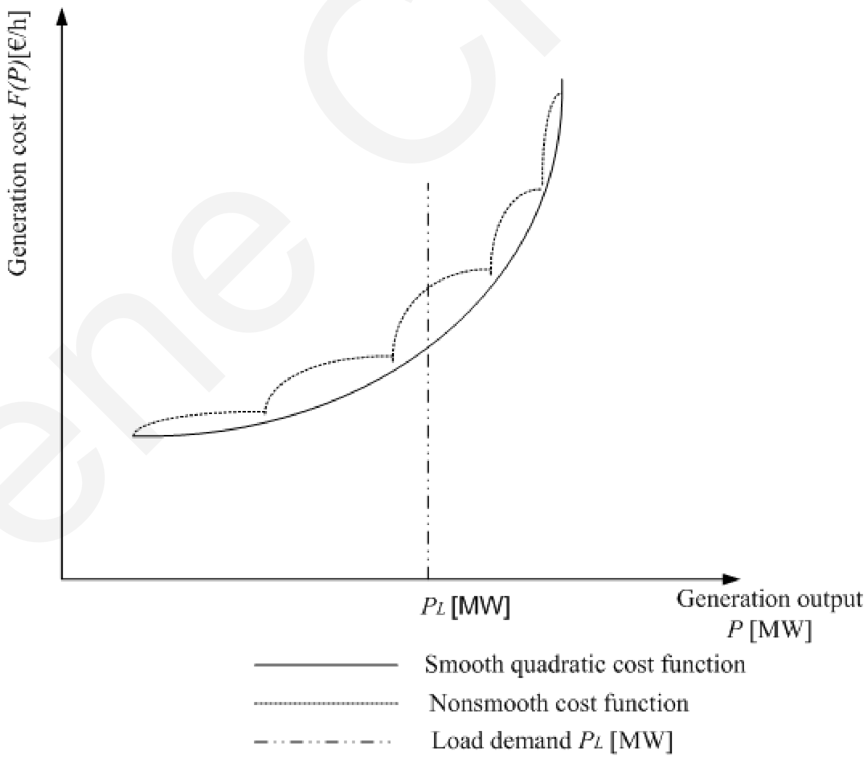

Figure 5.3 Determining the first approximation of the ED solution

Note that after the initialization process (when the nest is first placed at a point of the search space), each ant of the nest takes a different position according to their "experience" (e.g., some ants search/take positions closer to the nest if they are less experienced, while some others search in larger areas around the nest, up to the entire search space). The amplitude coefficient differs from one ant to another, and thus resulting in a heterogeneous population of ants according to their specialization or their age. The implication of this is that the ants that are more experienced are allowed to search in a wider area and also recruit followers, as the search progresses (Figure 5.4).

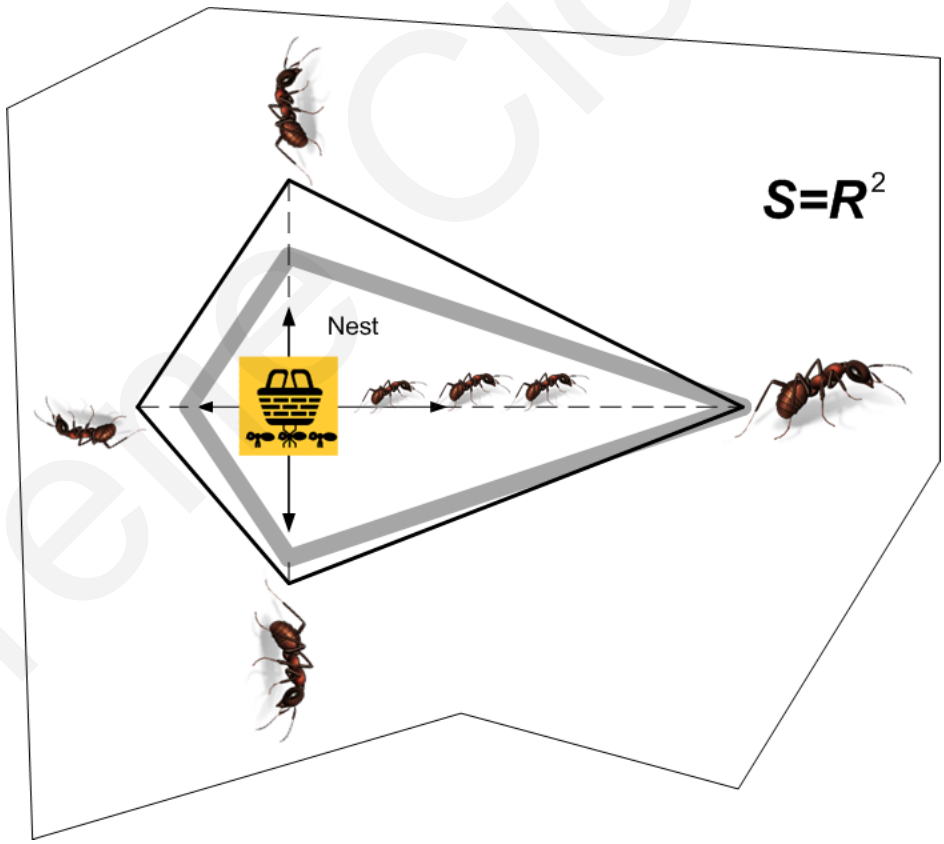

Figure 5.4 Heterogenous population of ants: recruitment mechanism

The main steps of the GAAPI for economic dispatch are described below.

Table 5.2 Constrained GAAPI for the ED problem

1. **Read** the power system data
2. **Assign** as first best solution of RCGA a high dummy value (this is useful for the first time comparison between the best solutions given by API and RCGA at step 7.2).
3. **Run LM method** for the simplified model of the data system
4. **Assign** the solution from step 2 to the **initial position of the nest**
5. **Generate** the position of the **ants** around the nest using *the feasible solution generator*
6. **IF** the number of nest movements OR the number of consecutive failures in solution improvement reached?
   6.1. **THEN** go to step 10.
   6.2. **ELSE**, apply API search always using the feasible solution generator for exploring new points in the search domain
7. **IF** there are any sites to be "forgotten" at the end of one API call
   7.1. **THEN** add these sites to the current initial population of the RCGA
      7.1.1. Perform RCGA search (note that here, infeasible solutions may appear due to the genetic transformations of the solutions)
      7.1.2. Recruit ant/sites for information sharing
      7.1.3. Check for feasibility and transform infeasible recruited individuals into feasible ones and go to (6.2.)
   7.2. **ELSE**, choose the best solution between API and RCGA outputs from steps (6) and (7), respectively.
      - Note that the comparison is based on the aggregated penalty objective function.
      - Thus, infeasible solutions are less likely to be chosen as the next position of the nest.
8. **Move the nest** in the next best point found at step (7.2)
9. **Reset the memory** of all ants and go to step (6).
10. **Print** the best solution

5.4 Validation of GAAPI as a solution for economic dispatch

5.4.1 Benchmark Power Systems

In the literature, besides the formulations of the economic dispatch of generation in power systems there are different generic or real test systems used for validating different solution methodologies. A summary of the most common IEEE power test systems used in the literature to test ED algorithms is given in Chapter 3, Table 3.1. From this large set of benchmarks, four test power systems have been selected, on the basis of their characteristics and constraints as explained in this subsection. These test systems allow a full testing of the GAAPI algorithm under development. The description and characteristics of these test systems are presented below.

The first test system is a 3-unit system with a valve point effect cost of generation and only the balance constraint considered. The data for this system was taken from [114] and [40]. The minimum cost of generation found for this system is 8234.07 $/h [46].

The second test system is a 6-unit power system (obtained from the IEEE 30 bus test system) and having a demand of 1263 MW [35]. The cost of generation for this system is chosen to be a smooth (quadratic) function and the nonconvexity is given by the prohibited operating zones and ramp rate limits. The reason for choosing these generator characteristics is to compare the results with other similar metaheuristic methods described in [46] and [65]. Then, the complexity of the problem is increased by using the cost of generation with valve point effect included, as in (2). The comparison for this second case covers implementations of a binary GA and a simple RCGA and compared to the best cost obtained with the GAAPI method. The data of this test system can be found in [68].

The third test system is a 15-unit system with smooth (quadratic) cost of generation (but discontinuous due to prohibited operating zones and ramp rate limits) and having a demand of 2630 MW. The system data were taken from [171] and [45]. The minimum generation cost reported so far for this system is 32751.39 $/h [36].

The fourth test system is a larger system with 40 units, a nonconvex generation function with valve point effect, and considering power losses. The load demand for this system is 10500 MW [65, 66]. It seems that this system has not been tested by other researchers using constraints such as transmission losses. This system was chosen to demonstrate the applicability of the proposed algorithm in relatively large and complex systems. The B-loss coefficients used to compute the transmission losses of this system were derived from the B-loss coefficients of the 6-generator test system [68], by multiplication on rows and columns up to 40 units. All the characteristics of the test power systems are presented in detail in the Appendix (section A3).

5.4.2 Parameter settings

a. Parameters of API

The number of ants to perform the search is directly proportional to the dimension of the system (number of generating units). For all the test systems, the number of ants is ten times the number of generating units. Therefore, for a 3-generator test system, the number of search agents in API is 3x10 = 30 ants. The number of hunting sites which each ant can memorize is five (*TotalAnts*=5) as suggested in [136]. The number of consecutive search failures of each site in the memory of ants is also five (*PF*=5). The maximum number of site exploitations (searches) is directly proportional to the dimension of the system (five times the number of generating units, e.g., for a 3-generator test system this number is 3x5=15).

b. Parameters of RCGA

The population size is set dynamically as the minimum between the number of ants from API and a maximum of 1000 ants. The population size is a function of the number of the forgotten sites appearing during each movement of the nest. Having a variable population size of RCGA aids in increasing the probability of the generated solution being different than the API-generated solution, thus triggering the search in a region less explored (in the case of large RCGA population). In case that the API search improves the solution in an adequate pace, the role of RCGA is limited by its small population size (less diversity). The probability of crossover (*Pc*) is 0.3 and the probability of mutation (*Pm*) is 0.35; the factor α of the blend crossover operator is 0.366. All the parameter settings were chosen either according to the directions of other authors (based on their experience in working with API or the RCGA adopted in GAAPI), or based on our personal experience in performing different searches with GAAPI.

5.4.3 Convergence Tests

In the power systems literature, the convergence tests in the field of economic dispatch are mainly related to the number of iterations or generations (e.g., in the case of GAs and PSO) until the solution falls below a certain threshold, and/or related to the CPU time per iteration/generation [36, 46, 65, 70, 111]. However, the CPU time is subject to the computer infrastructure available and therefore, it is a parameter that is difficult to be used as an evaluation criterion. Thus, the measure of the speed of convergence adopted in this work is the mean number of (objective) function evaluations (denoted as *M_num_fun*) until the algorithm stops [166]. This measure was introduced and explained in Chapter 4.

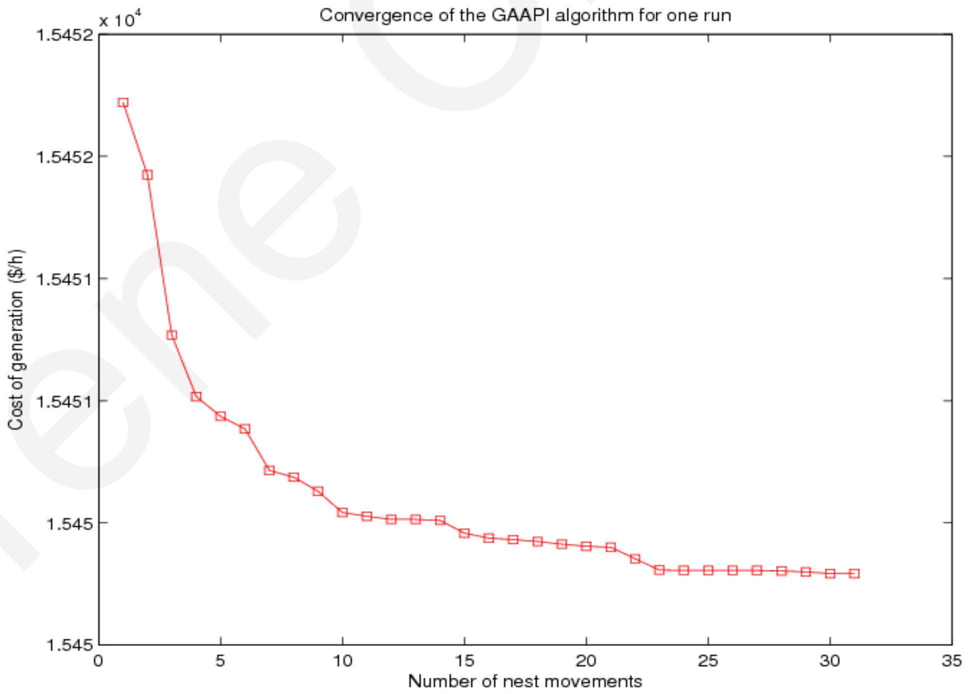

Figure 5.5 Convergence characteristics of the GAAPI for a 6-generator test system with smooth cost of generation

The convergence behavior of the GAAPI algorithm was tested in order to determine how fast the proposed algorithm drops under the best average cost of generation reported so far and to prove that the algorithm convergence is not steep, therefore avoiding local minima trapping. Figure 5.5 and 5.6 show the convergence behavior of the GAAPI algorithm for the test system with 6 generators and 40-generators, respectively, both having nonconvex fuel cost optimization functions. It can be noticed that the solution drops quickly (only after 10 iterations) under the average best solution reported so far and smoothly decreases in time trying to gather better solutions, as near as possible to the global.

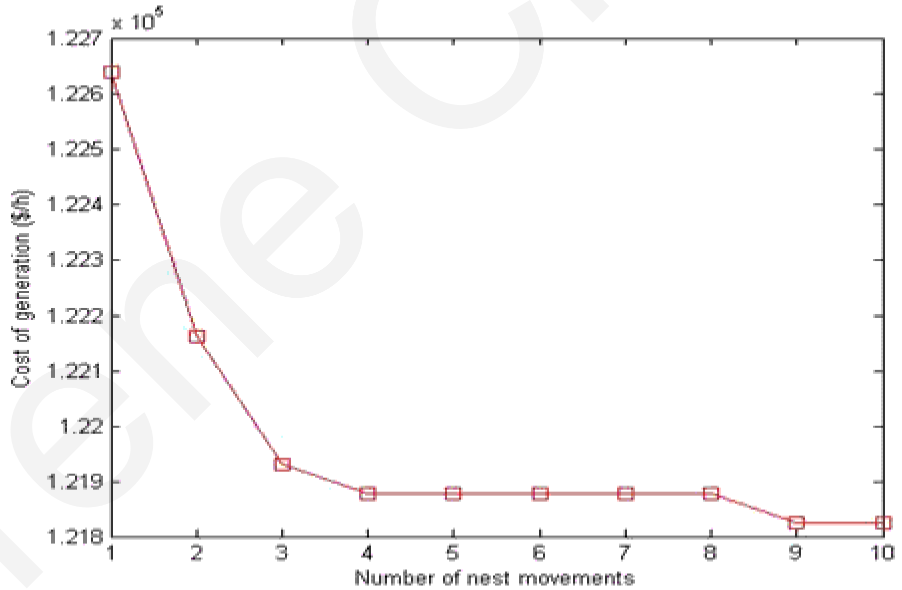

Figure 5.6 Convergence characteristics of the GAAPI algorithm (40-generator test system)

5.4.4 Robustness tests

Due to the random process that heuristic algorithms involve, the robustness tests of the algorithms imply the need to perform several independent trials/runs of the algorithms. In this work, *robustness tests* refer to the analysis of consistency in results over a number of independent runs of the algorithms. The measure used to emphasize the robustness in this case is the ***average*** value gathered during fifty independent runs of the algorithms. The standard deviation is not presented in the comparison tables, since other authors who solved the same problem using other powerful stochastic methods, have not represented this metric. Two other measures are also presented in the comparison tables below, and they refer to the ***maximum*** and the ***minimum*** values obtained over the fifty independent runs.

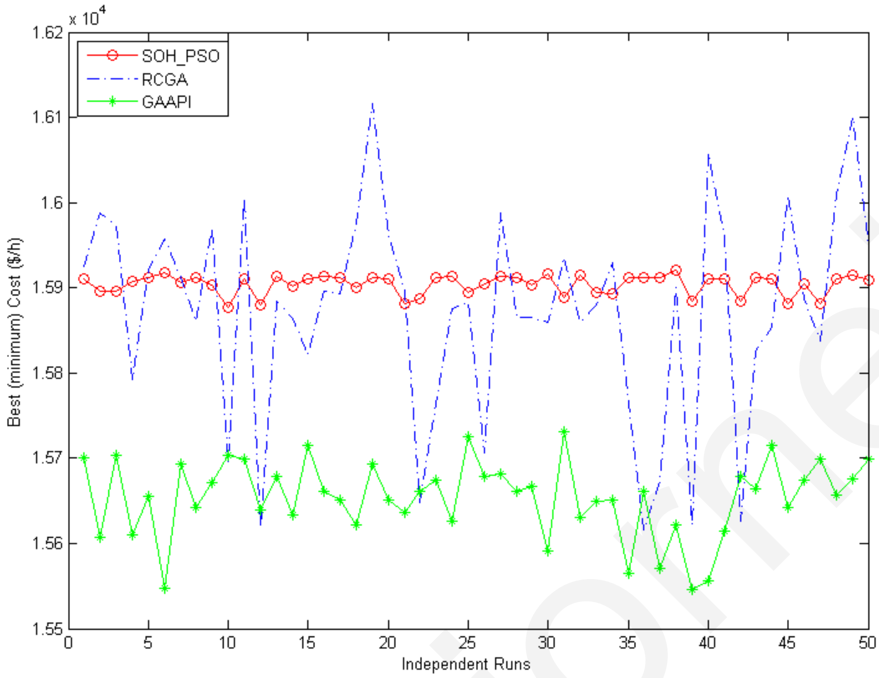

Figure 5.7 Comparison on consistency of results over fifty independent runs: 6-generator test system with nonconvex cost of generation

A plot of the distribution of the best cost (minimum cost) found by GAAPI for the 6-generator test system with nonconvex cost of generation is provided in Figure 5.7. In the same graph, the optimum cost of two other recent evolutionary based algorithms (the author's implementation of SOH-PSO [65] and RCGA [125]) is plotted for the same number of independent runs. It can be observed that GAAPI outperforms the other two functions in terms of the minimum cost of generation (in average and at the end of each independent run). Further, it is consistently giving almost the same result over the independent runs, clearly outperforming in consistency the RCGA. SOH-PSO appears to be slightly more consistent than GAAPI, however with a highest cost.

For the smooth 6-generator test system (Table 5.3), it can be noticed that GAAPI gives comparable results with the NPSO-LRS and SOHPSO methods in terms of the minimum best solution, and better average than all other methods used in the comparison table. *GA binary* refers to the GA optimization package from MATLAB. The results used for comparison in the case of GA, NPSO-LRS and SOHPSO were obtained from [39, 65].

Table 5.3 Comparison on robustness for a 6-generator test system with smooth cost of generation

Method	Max ($/h)	Min ($/h)	Average ($/h)
GA binary	15519.87	15451.66	15469.21
GA	15524.00	15459.00	15469.00
NPSO-LRS	15455.00	15450.0	15454.00
SOHPSO	15609.64	15446.02*	15497.35
GAAPI	15449.85	15449.78	15449.81

(*) The loss value computed with the B-Loss formula (12.95 MW) is higher than the one given by the author (12.55 MW) [65] which can lead to a higher minimum value of the cost of generation than the one reported in [65].

Table 5.4 Comparison on robustness for a 15-generator test system

Method	Max ($/h)	Min ($/h)	Average ($/h)
GA	33337.00	33113.00	33228.00
SOHPSO	32945.00	32751.00	32878.00
GAAPI	32756.01	32732.95	32735.06

For the 15-generator test system (Table 5.4), it can be noticed that GAAPI gives the best results compared to the GA and SOHPSO [65] methods in terms of both minimum value and average value found in fifty independent runs. Figure 5.8 gives an insight to the robustness characteristics of the proposed algorithm when applying it to the 15-

generator test system. The picture presents an evaluation of the performance over one hundred independent runs.

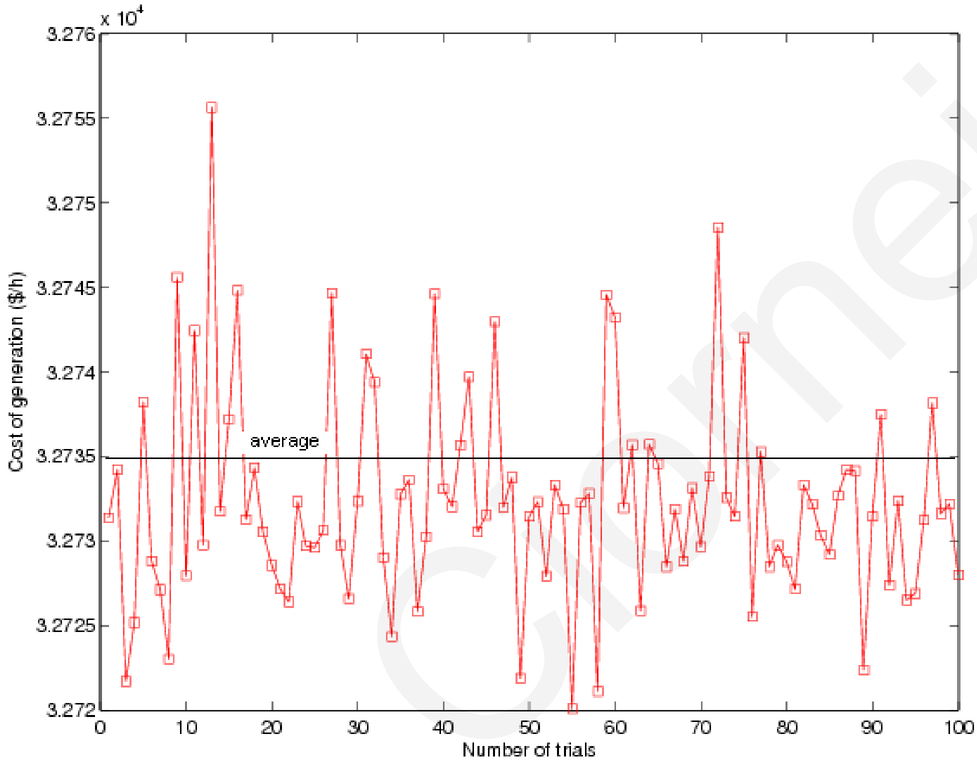

Figure 5.8 GAAPI performance analysis for the 15-generator test system

5.4.5 Comparison with respect to the quality of the solution

For all the power test systems used in this work, the best solutions obtained in a predefined number of independent runs (in this work this number is fifty) are compared to the corresponding values reported in the literature, when available (Tables 5.5 to 5.9). The fourth test power system, including constraints, seems to have not been used in the literature. The best solution determined using the GAAPI algorithm (in fifty independent runs) for this last test system is provided in Table 5.9.

The first test system (3-generator), being a small test system, has a known global solution [46]. Table 5.5 presents a comparison of the best results obtained with GAAPI for this test system with different powerful optimization methods. It can be noticed that GAAPI performed as good as other recent and powerful methods such as EP and MPSO, and little better than GA and IEP algorithms.

Table 5.5 Best solution for a 3-generator test with nonconvex cost of generation

Unit output (MW)	GA	IEP	EP	MPSO	GAAPI
P_1	300.00	300.23	300.26	300.27	300.25
P_2	400.00	400.00	400.00	400.00	399.98
P_3	150.00	149.77	149.74	149.73	149.77
Total output	850.00	850.00	850.00	850.00	850.00
Generation cost ($/h)	8237.60	8234.09	8234.07	8234.07	8234.07

For the 6-generator test system with smooth-convex and nonconvex cost of generation, the best results reported so far are summarized in Tables 5.6 and 5.7, respectively. It was shown that in terms of the best cost of generation in the case of the system with smooth-convex cost of generation, the GAAPI method and all variations of PSO and LM method, all have comparable results and better than the GA binary of real coded algorithms. However, for the nonconvex generation cost function, GAAPI proved its superiority against SOH-PSO and the RCGA algorithms (for both, binary and real coded GAs).

Table 5.6 Best solution for a 6-generator test system with a smooth cost of generation

Unit output (MW)	LM	GA binary	RCGA	NPSO-LRS	SOH-PSO	GAAPI
P_1	447.00	456.46	474.81	446.96	447.49	447.12
P_2	173.50	168.26	178.64	173.39	173.32	173.41
P_3	264.00	258.68	262.21	262.34	263.47	264.11
P_4	138.50	132.66	134.28	139.51	139.06	138.31
P_5	166.04	170.97	151.90	164.70	165.47	166.02
P_6	87.00	89.10	74.18	89.01	87.13	87.00
Losses	13.00	13.13	13.02	12.93	12.55*	12.98
Total output	1276.00	1276.13	1276.03	1275.94	1275.55	1275.97
Generation cost ($/h)	15450.00	15451.66	15459.00	15450.0	15446.02	15449.7

(*) The loss value computed with the B-Loss formula (12.95 MW) is higher than the one given by the authors (12.55 MW) in [65].

Table 5.7 Best solution for a 6-generator test system with a nonconvex cost of generation

Unit output (MW)	SOH-PSO	RCGA	GAAPI
P_1	419.64	495.09	499.98
P_2	188.16	150.45	199.89
P_3	198.15	223.11	225.75
P_4	150.00	149.40	124.95
P_5	200.00	147.94	150.19
P_6	120.00	109.72	74.97
Losses	12.95	12.07	13.13
Total power output	1275.95	1275.70	1276.13
Total generation cost ($/h)	15896.73	15634.70	15607.47

A comparison of the best solutions obtained with different heuristic methods for the third power test system examined (the 15-genarator test system), is given in Table 5.8. It can be observed that the proposed GAAPI gives the best solution over fifty independent trials, when compared to two other recent, recognized powerful heuristic methods such as classical PSO and SOH-PSO.

Table 5.8 Best solution for a 15-generator test system with a discontinuous cost of generation

Unit output (MW)	PSO	SOH-PSO	GAAPI
P_1	455.00	455.00	454.70
P_2	380.00	380.00	380.00
P_3	130.00	130.00	130.00
P_4	129.28	130.00	129.53
P_5	164.77	170.00	170.00
P_6	460.00	459.96	460.00
P_7	424.52	430.00	429.71
P_8	60.00	117.53	75.35
P_9	25.00	77.90	34.96
P_{10}	160.00	119.54	160.00
P_{11}	80.00	54.50	79.75
P_{12}	72.62	80.00	80.00
P_{13}	25.00	25.00	34.21
P_{14}	44.83	17.86	21.14
P_{15}	49.42	15.00	21.02
Losses	30.49	32.28	30.36
Total power output	2660.44	2662.29	2660.36
Total generation cost ($/h)	32798.69	32751.39	32732.95

The best solution determined using the GAAPI algorithm (in fifty independent runs) for the 40-generator test system is provided in Table 5.9. For this test system, transmission constraints were considered and because no such approach was taken into account up to now in the literature for this system, no comparison is available.

Table 5.9 Best solution for a 40-generator test system with a nonconvex cost of generation

Unit output (MW)	GAAPI	Unit output (MW)	GAAPI
P_1	114.00	P_{21}	550.00
P_2	114.00	P_{22}	550.00
P_3	120.00	P_{23}	550.00
P_4	190.00	P_{24}	550.00
P_5	97.00	P_{25}	550.00
P_6	140.00	P_{26}	550.00
P_7	300.00	P_{27}	11.44
P_8	300.00	P_{28}	11.56
P_9	300.00	P_{29}	11.42
P_{10}	205.25	P_{30}	97.00
P_{11}	226.30	P_{31}	190.00
P_{12}	204.72	P_{32}	190.00
P_{13}	346.48	P_{33}	190.00
P_{14}	434.32	P_{34}	200.00
P_{15}	431.34	P_{35}	200.00
P_{16}	440.22	P_{36}	200.00
P_{17}	500.00	P_{37}	110.00
P_{18}	500.00	P_{38}	110.00
P_{19}	550.00	P_{39}	110.00
P_{20}	550.00	P_{40}	550.00
Losses		10.4506	
Total power output		11545.06	
Total generation cost ($/h)		139864.96	

5.5 Chapter summary

This chapter proposed the application of the GAAPI algorithm to solve the nonconvex economic load dispatch problem. The proposed algorithm was redesigned in such a way that the various power system constraints may be modelled and respected. It is also shown that starting from the solution obtained for the quadratic cost function (Lagrange multipliers method), the search space is reduced, and implicitly the computational effort is reduced. The strategy for handling the constraints is to always generate feasible solutions and work only with these feasible solutions during the search process of API, while the RCGA algorithm may allow infeasible solutions which are further controlled by an aggregated penalty objective function. This constraint handling method is therefore a hybrid one.

The proposed algorithm is proven to always find comparable or better solutions in a number of independent trials, as compared to other methods available in the power systems literature. GAAPI has provided near global solutions, while always satisfying the constraints. Further, through the test cases presented, its superiority in robustness is evident: it has a high probability to reach the global or quasi-global solution, especially in nonconvex formulations. GAAPI converges smoothly to the global optimum, avoiding fast convergence that may lead to local optima.

Chapter 6

Challenges and solutions for economic dispatch in isolated power systems with stochastic generation

6.1 Introduction

This chapter deals with the economic dispatch problem of power systems with stochastic generation such as electricity generation from wind parks. In this work it is assumed that the power system under consideration is an isolated one and that it does not have access to an electricity market. The chapter is divided into two parts: i) the first part deals with the technical and economic challenges of a system with high share of variable generation may face and it is a real case study for the power system of Cyprus; ii) the second part deals with economic dispatch decision solutions in order to overcome part of the challenges emphasized in the first part of this chapter.

6.2 Challenges in operating isolated power systems with wind power

6.2.1 Brief overview of wind integration studies

In the last decade there has been an increased interest in renewable energy solutions for replacing large scale power thermal plants which burn high pollutant fuels such as coal, and heavy oil. Some examples of renewable energy sources are wind, solar photovoltaic, solar thermal, biomass, and hydro. These sources have the advantage that they do not emit any greenhouse gas emissions. Further, some of these technologies, such as hydro and wind have competitive capital and generation costs compared to conventional generation technologies. Nevertheless, with the exeption of biomass and hydro, these technologies have a number of technical and economic drawbacks due to their partially predictable generation and almost no dispatch capabilities (in the classical sense). Wind energy is the most emerging renewable technology accommodated by the power system industry in recent years [172], and therefore several studies have been performed concerning the integration of the wind farms in power systems. The focus of these studies is mainly on economic (cost of integration) and technical issues (reliability, robustness, control). It should be noted that the majority of the literature in the field of wind integration mainly deals with the unit commitment problem, while the economic dispatch problem has not been addressed as much.

A bibliographical list of wind impact studies in different countries in Europe, USA and Canada with more than 250 references is given in [173]. From these studies, a significant contribution was added by Scandinavian countries, Germany, Spain, and

USA [174, 175] [176-179]. These countries are among the leaders in the amount of electricity generation shared from wind sources. The results of these studies are not easy to compare due to a number of factors, such as the models used for wind farms (e.g., negative load, or thermal generator with effective load carrying capability), the conventional generation mix of the power system under analysis, the size of the balancing area and the size of interconnections, differences in methodology, tools and data used, and representation and terminology of results. However, some common conclusions related to wind integration measures are:

- Increase in power system reserve is necessary as the penetration level of wind generation increases;
- The variability of wind power is reduced when referring to a large interconnected power system with different sources of generation and having a dispersed wind power production;
- For some systems, there may be a need for increased transmission and larger control areas as the penetration level of wind generation increases;
- Interconnections with other systems allow increasing the share of wind power in the power system.

6.2.2 Methodologies and assumptions

In order to address the technical feasibility and the relative costs and benefits associated with the installation and operation of a significant amount of wind power farms, this study is carried out using a public version of the WILMAR Planning Tool (from here on referred in short as WILMAR), which is a rolling stochastic linear programming tool. Further, in order to estimate the needed amount of increase in reserve due to the increased stochasticity in the system caused by the variable generation, a very recent reliability method [22] is adopted.

a. WILMAR Model

WILMAR is an hour-per-hour stochastic, rolling planning optimization model. It was initially designed as a stochastic optimization model for the electricity systems in Denmark, Finland, Germany, Norway and Sweden. The tool has been used successfully in several studies related to wind integration into the main power grid, studies performed for many TSOs in Europe [180] and, recently, in the USA [181]. The model optimizes the unit commitment and economic dispatch taking into account the trading activities of the different actors on three different types of energy markets: a *day-ahead market* (for physical delivery of electricity), *an intra-day market* (for handling deviations between expected production and consumption agreed upon on the day-ahead market and the realized values of production and consumption in the actual operation hour), and *a day-ahead market for automatically activated reserve* (frequency activated or power-flow activated).

WILMAR consists of a number of sub-models and databases as shown in Figure 6.1. However, the main functionality of this planning tool is embedded in the two main components: i) a Scenario Tree Tool (STT) which in essence is a program that creates the probabilistic forecasts of wind and load, as well as demands for stochastic reserve; and, ii) a Scheduling Model (SM), which is a stochastic mixed-integer optimization model (rolling planning procedure) that uses the outputs of the STT as inputs along with other generation and transmission data to minimize the expected production cost.

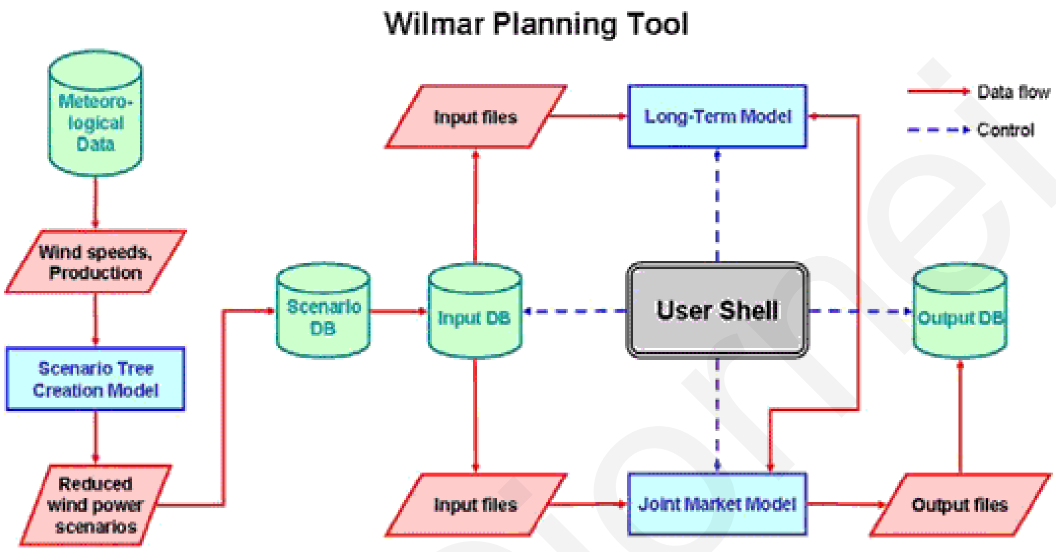

Figure 6.1 Operation schemata of the WILMAR planning tool [182]

The rectangle boxes are models, cylinders are databases, and parallelograms are exchanges of data between models and between models and databases. The User Shell controls the selection of cases and execution of the models. The arrows indicate data exchange, and the dash arrows indicate the flow of commands from the User shell to the models.

b. Sensitivity analysis for operating reserve relative to wind power stochasticity

The reliability of the system is an objective measure to determine the effect of increasing wind power penetration. The actual variability of the load and wind power itself do not directly impact the system reserve levels. However, the accuracy of the load and wind power forecasts have a significant effect on the system reserve levels as they introduce greater uncertainty in the system. In order to quantify the effects of increased uncertainty due to wind generation, the methodology developed by Doherty and O'Malley [22], which is based on the reliability criterion explained below.

The reliability criterion is defined either as being the number of load shedding incidents (LSI), or the loss of load expectation (LOLE) tolerated per year. A load shedding incident is defined as an incident when there is not enough reserve to meet a generation shortfall. Both the LSI and LOLE reliability criteria quantify the likelihood of failure but do not quantify the magnitude of load shedding. Doherty linked these criteria to the cumulative uncertainty in load and wind forecast and determined the probability of LSI in one hour, as a function of the probability of having an incident during normal operation hours and after a full or partial outage of one generating unit. The full outage probability (*FOP*) of a unit is the probability that the unit will stop providing all of its current output in a period of one hour. Similarly, the partial outage probability (*POP*) is the probability of an instantaneous loss of a portion of the generation.

c. Assumptions of the study

The power system of Cyprus was chosen as a case study in order to determine the technical and economic challenges in isolated power systems with high share of stochastic generation. The reference historical year chosen for this study is the year of

2008, while the reference forecasted year is the year of 2011. All data that follows are related to these reference years, unless mentioned otherwise.

The power system of Cyprus is a small, isolated power system with an installed capacity of 1288MW. There is no hydro energy generation and no heat energy production. The thermal generation mix is ensured from three power plants owned by the Electricity Authority of Cyprus and from a small power plant owned by one independent power producer. The maximum power demand in Cyprus appears in the summer due to the influence of tourism, when the population of the island almost doubles, and due to the air conditioning devices that work at their full load. Hence, the power demand difference between summer and winter is large, reaching a coefficient of variance of 0.246. In short, the seasonality of load demand can be summarized in Table 6.1.

Table 6.1 Power system seasonality in Cyprus as per reference year 2008

Period	Date	Time	P (MW)	Q (MVAr)	S (MVA)	pf
Winter Peak	30/1/2008	18:15	908.08	278.00	949,68	0,956
Spring Off-Peak	26/3/2008	4:00	282.45	-81.00	293,83	0,961
Summer Peak	28/8/2008	14:00	1024.48	466.13	1125,54	0,933
Autumn Off-Peak	24/11/2008	3:45	290.60	-93.00	305,12	0,952

The expected wind generation capacity to be installed in Cyprus by the end of 2011 was around 455 MW, according to CERA's approval plan [183]. From the set of all wind farms approved to operate around the island there were formed three clustered sites as shown in Figure 6.2 (the figure was adapted from [183]). The clusters of wind farms (WF) were set up as follows: one wind farm for the Pafos–Limassol (PL) region and having a total installed capacity of 118 MW, and two wind farm clusters for Larnaca-Lefkosia (LL) region having total installed capacities 311 MW and 26.5 MW, respectively.

According to the distance between the wind farm clusters, a correlation coefficient for the wind speed forecasting error between individual farms can be calculated using Figure 6.3 which was adopted from [180].

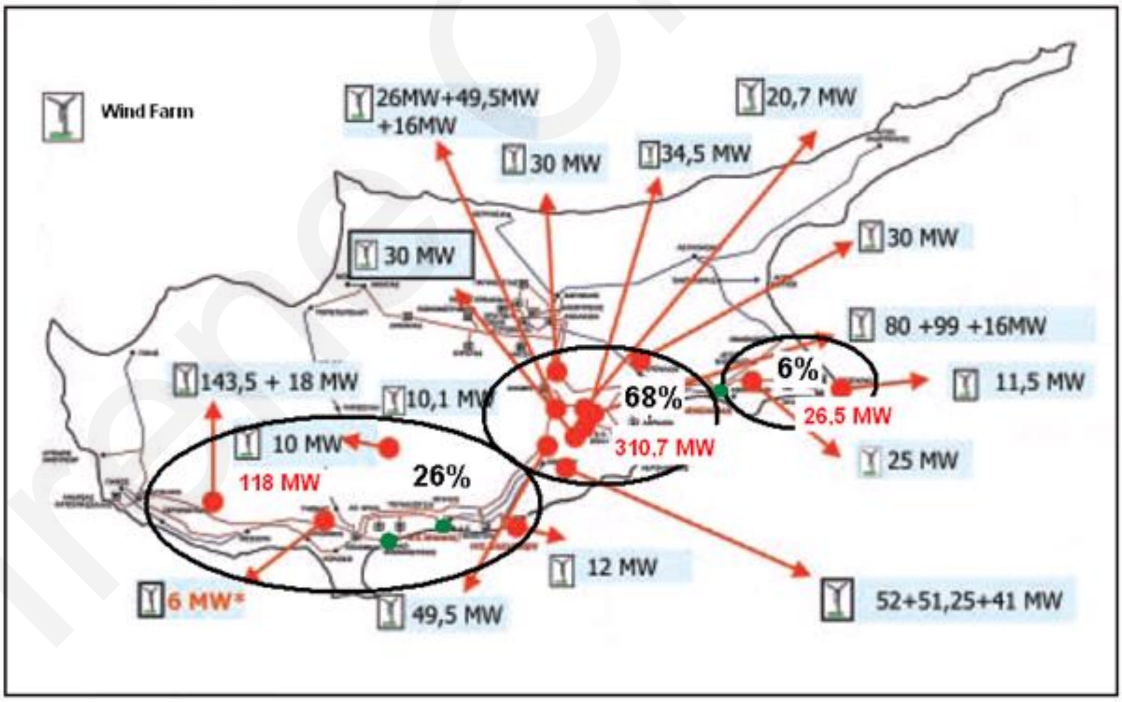

Figure 6.2 Clusters of wind farms used for WILMAR planning tool simulations

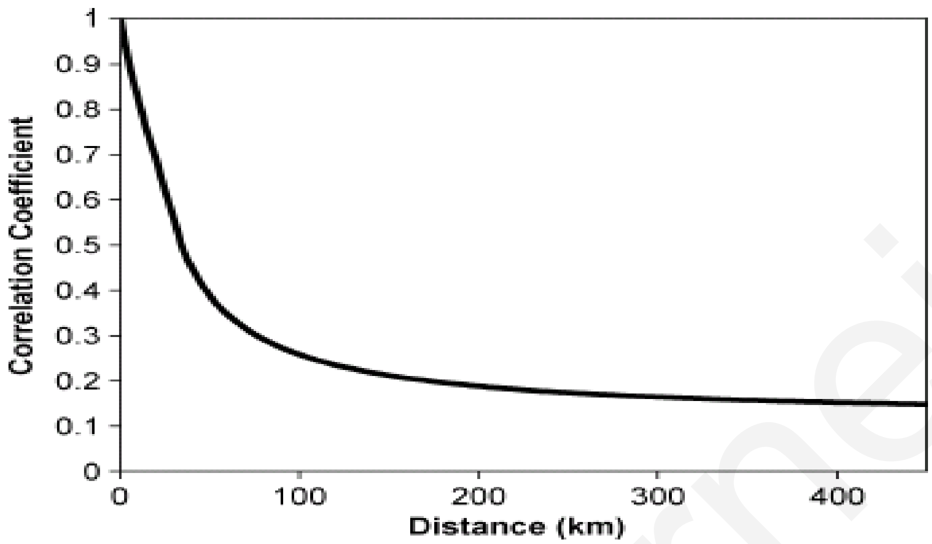

Figure 6.3 Correlation coefficient of wind speed forecast errors as a function of distance between individual wind farms

The estimated power output (PWF_k) of a cluster k of WFs was obtained applying the power curve given in Figure 6.4 and multiplied with the number of turbines available on that specific site. Note that this is a rough approximation which may significantly differ from the real generation from one wind farm to another, depending on the terrain and consequently the dynamics of the air flow hitting each wind turbine of the wind farm. The power curve in Figure 6.4 was obtained using real measurement data from an onshore Bonus 2 MW wind turbine in Finland. For simplification, in this study it is assumed that all the WFs around the island have only Bonus-type wind turbines of a rating of 2 MW.

$$PWF_k = \sum_{k=1}^{NWF} WP_{i,k} \tag{6.1}$$

where, k is the index of wind farm clusters (with k=1:3); NWF is the number of wind turbines of the wind farm cluster k, and $WP_{i,k}$ is the power output of the wind turbine i of the wind farm cluster k.

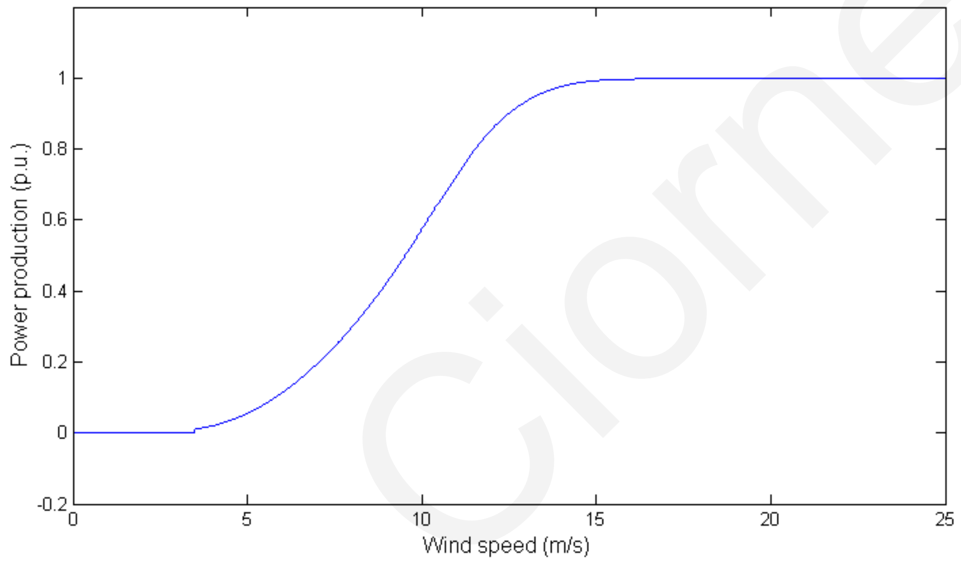

Figure 6.4 Wind power curve for a generic Bonus 2 MW wind turbine

The standard deviation of load forecast error (σ_{load}) was determined based on historical data and it has a value of 25 MW. The standard deviation of the wind forecast error for the three clusters of wind farms was determined from [22] and has the following vector values according to the established three wind farm clusters:

σ_{wind} = [10.3, 26.35, 2.21] MW

Due to the roughness of the terrain, the real distances between wind farms were assumed to be 100 km more than the real distance between the wind farm clusters.

Therefore, the correlation coefficients were determined from Figure 6.3 and based on the increased distance. The standard deviation of the wind forecast error was observed to increase with the prediction time horizon [22, 184].

The probability of full and partial outage of the generating units was calculated from historical operation data of the units owned by the Electricity Authority of Cyprus (EAC). The most reliable unit has an unplanned full outage probability of 0.6% from the total number of hours of operation during one year, and the least reliable unit a value of 4.4%. The partial outage probabilities are in the range of 0 to 2.1%. As the amount of electricity generated by the independent power producers (IPP) is negligible compared to the EAC production, their reliability data were ignored. For the clearance of a generator outage, it is assumed that two hours pass until the reliability of the system is restored (same assumption as proposed in [22]).

Table 6.2 Full and partial non-availability of the generating units of the power system of Cyprus (2008 data)

Power Plant	Installed Capacity	Full Non-availability (hours)			Non-availability (partial)		
		Planned	Un-planned	Total	Planned	Un-planned	Total
Gas turbine	5x37.5MW	0.0%	0.6%	0.6%	0.0%	0.0%	0.0%
Steam turbine Moni	5x25 MW	17.5%	4.4%	21.9%	0.0%	0.3%	0.3%
Steam turbine Dekelia	6x60 MW	14.2%	1.5%	15.7%	0.0%	0.1%	0.1%
Steam turbine Vasilikos	3x128 MW	11.4%	1.9%	13.3%	0.0%	2.1%	2.1%

Table 6.2 summarizes the data for full and partial non-availability of the generating units of the power system of Cyprus as per the reference year 2008. It is assumed that the same data are valid for the reference forecasted year of 2011. No data were available related to the CC unit, so it was assumed that the unit will be fully available in the forecasted year 2011.

6.2.3 Dispatch challenges arising from the study

The study was carried out adapting the WILMAR Planning Tool to the power system of Cyprus, together with the estimation of the increase in power reserve using the reliability method described above. Two main generation regions were considered: PL region - with one generic large wind farm and LL region - with two generic wind farms. There is full interconnection between them, which reads as there are no bottlenecks on the transmission lines between the two regions. Two cases were analysed in this study: 1) the case when the system is operated only with conventional sources of energy (*noWind*); and 2) the case when the wind generation will be part of the electricity generation mix in Cyprus (*withWind*).

Real wind measurements for the representative months were scaled to determine the estimated power production according to the assumptions given at the beginning of this chapter. The same is true for the estimated load demand for the representative year 2011.

Figure 6.5 and 6.6 present the estimated thermal generation mix for the case *noWind* in the regions PL and LL respectively, for one week of the winter peak load. The gas turbines (GT) and steam turbines (ST) run with fuel oil, and the CC unit of Vasilikos is considered to operate with liquefied gas (it is assumed that the liquefied gas has the same parameters as the natural gas). The Pafos-Limassol (PL) region has generation from the Moni power plant, only, while the Larnaca-Lefkosia region has two power plants under its jurisdiction (Vasilikos and Dekelia).

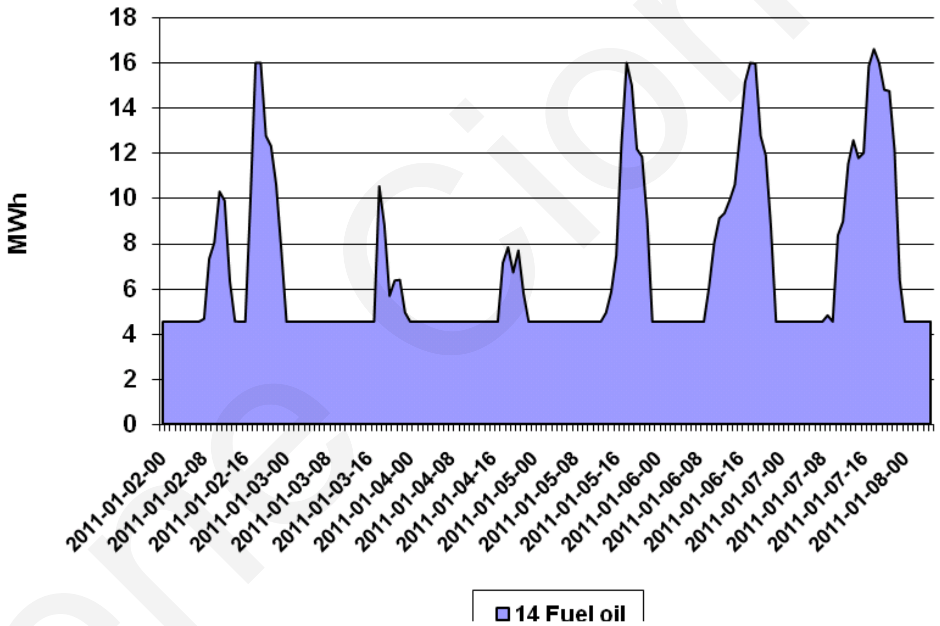

Figure 6.5 Generation mix in PL region: *noWind* case

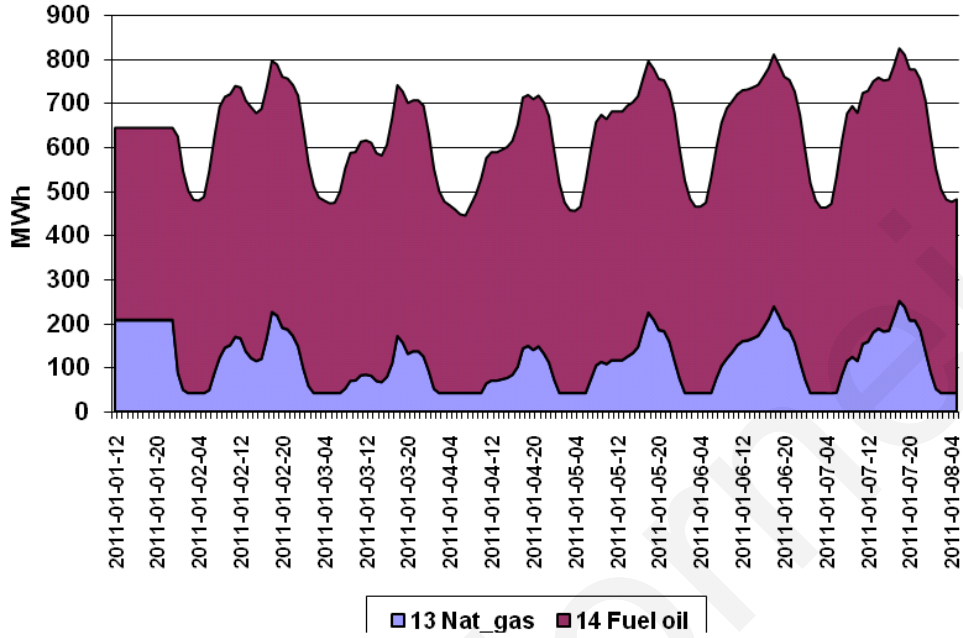

Figure 6.6 Generation mix in LL region: *noWind* case

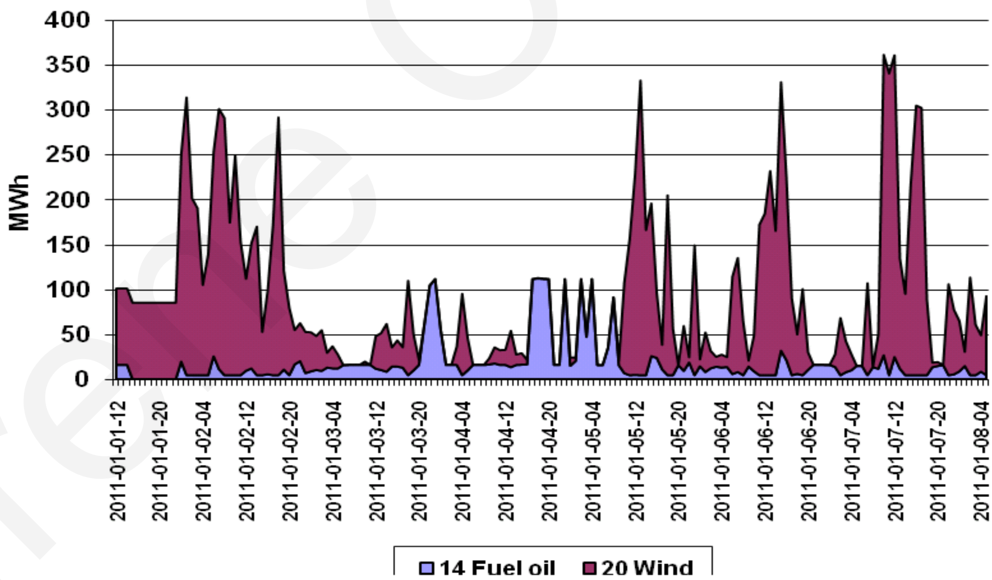

Figure 6.7 Generation mix in PL region: *withWind* case

The generation mix in the case *withWind*, for the same peak load period is presented in Figure 6.7 and 6.8, respectively. It can be noted that the wind generation is not following the daily load curve as smooth as the thermal units do in the case *noWind*, thus forcing also the thermal units to ramp up or down their generation more often in order to meet the load curve shape continuously. The importance of the ramping effect of the conventional generation will be emphasized later in Section 6.2.

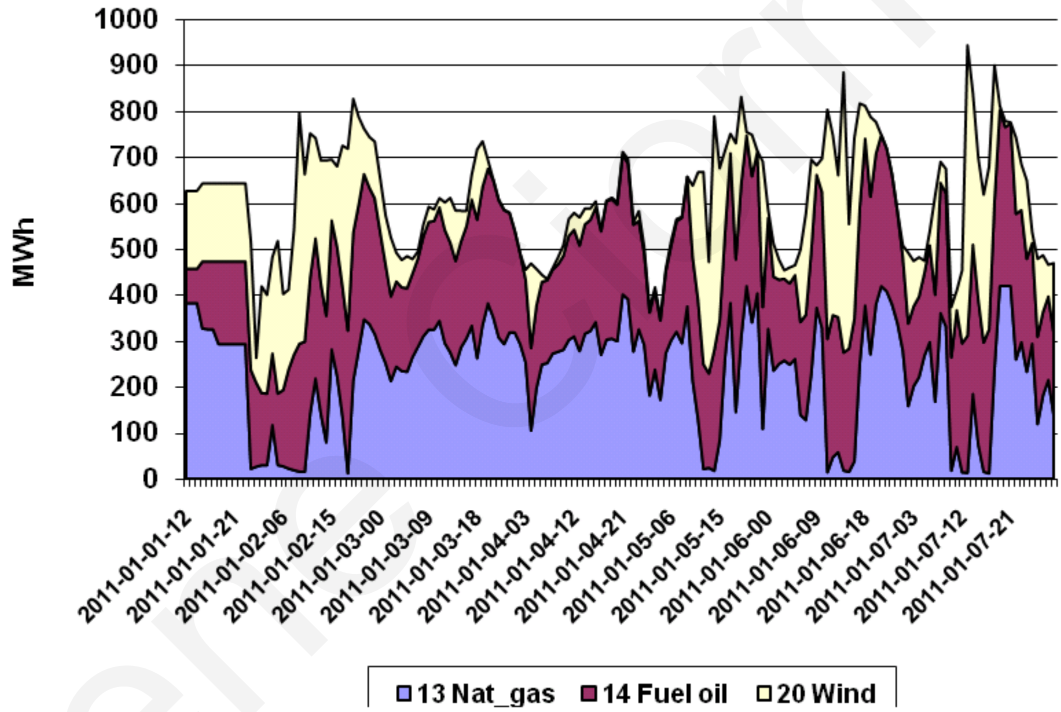

Figure 6.8 Generation mix in LL region: *withWind* case

The variation of load demand and power production, as well as the power flow in terms of the export/import of energy between the two regions such that to meet the demand, for the same peak load period, are provided in Figure 6.9 and 6.10, respectively. The negative values of the *Net_Export* (export of energy from one region to another) in the PL region, has the meaning that the generation mix in this region cannot cover its demand. It therefore imports energy from the LL region. In other words, the flux of energy goes from the LL region (which has positive values of *Net_Export*) to PL such that at all times the balance between generation and demand are respected. *CapOnline_conv* denotes the available online capacity from conventional sources (fuel based units). The real production from conventional sources is denoted as *Prod_Conv* in these figures. *Realized_Wind* denotes the estimated wind energy production.

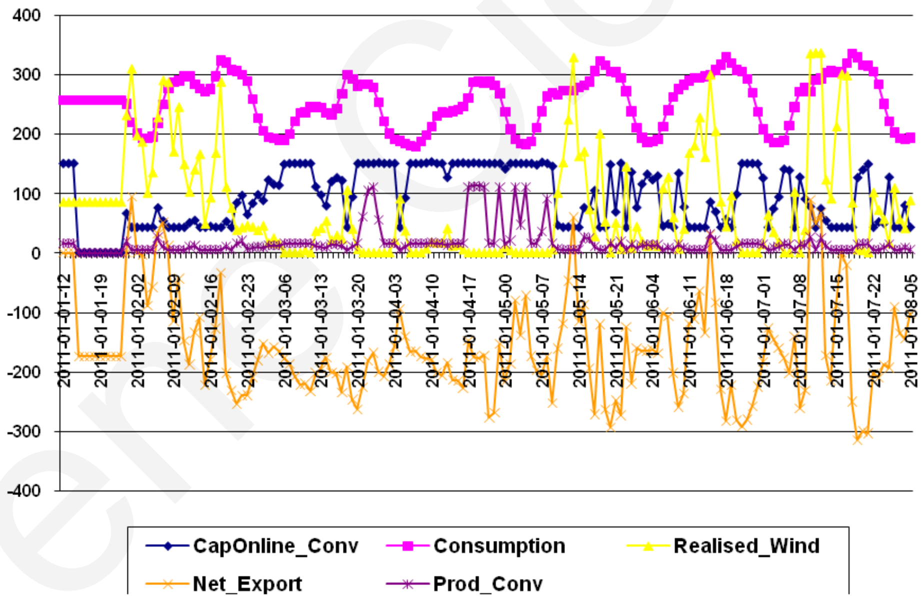

Figure 6.9 Detailed load demand and realised power for the PL region: *withWind* case

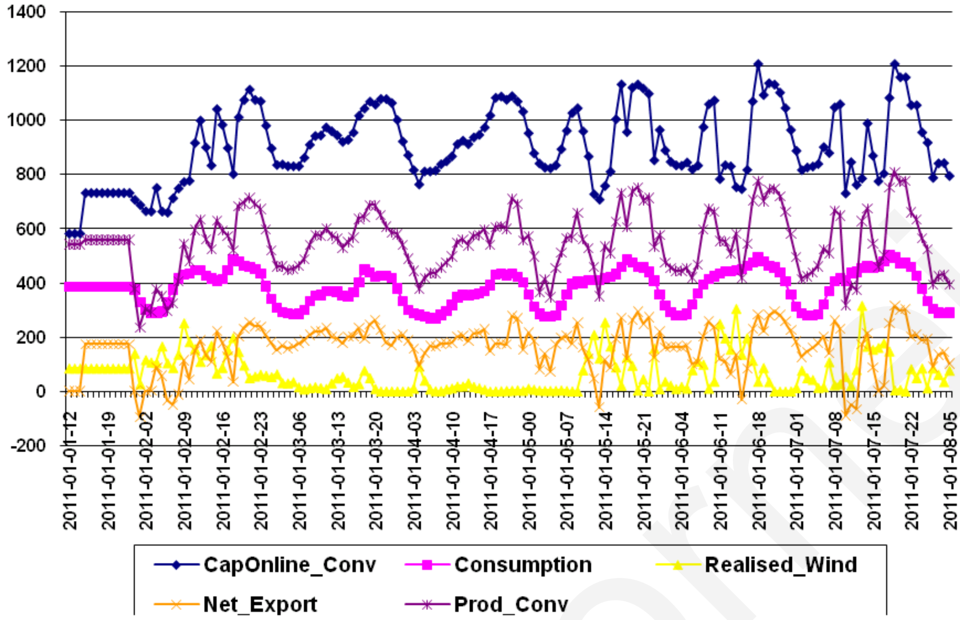

Figure 6.10 Detailed load demand and realised power for the LL region: *withWind* case

WILMAR has the ability to simulate the error in forecasting (the difference between the simulated wind power production and the simulated forecast of the wind power). The simulation of this forecasting error from the valley-load case *withWind* for the PL and LL region is presented in Figure 6.11 and 6.12, respectively. In the legend of the figures, the simulated signal of wind power forecast is denoted by *Wind_Forecast*, and the simulated power production from wind is denoted as *Realized_Wind*, while *Wind_Shed* denotes the amount of wind power which can cause stability problems in the operation of the power system. The TSO is therefore advised to shed this amount of power.

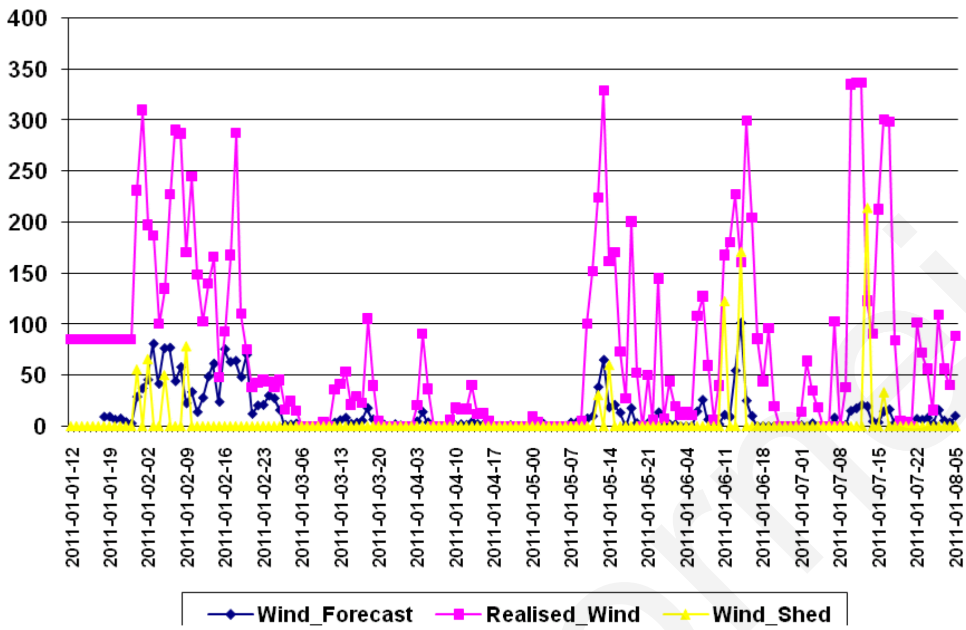

Figure 6.11 Wind curtailments in the period of valley-load for the PL region: *withWind* case

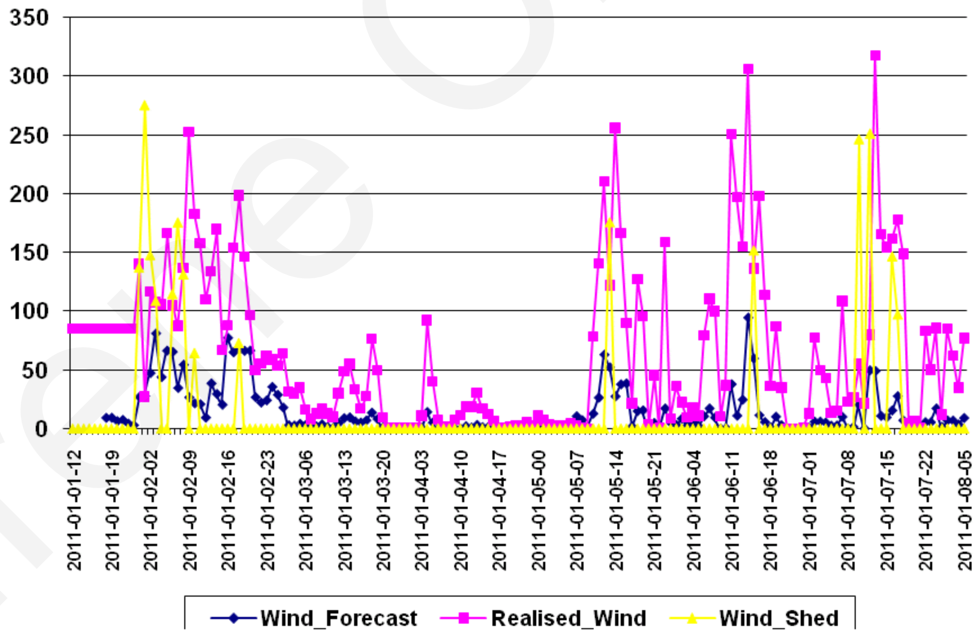

Figure 6.12 Wind curtailments in the period of valley-load in the LL region: *withWind* case

Besides the need for wind curtailment/shedding, it was observed that an increase in the frequency of change in loading was needed especially for the fast units (i.e., GTs). This effect can be observed by comparing Figure 6.13 with Figure 6.14. Following engineering logic, if there is an increase in the frequency of ramping, then there must be an increase in the stress of the unit, and consequently a decrease in the maintenance period. Therefore, an increase in the cost of operation may occur in long term running of the system. However, this study was not intended to estimate this final cost. Future research may go in this direction.

In Figure 6.13 and 6.14, the following notations were used: *vgonline* denotes the online available capacity of the thermal unit (e.g., one GT from Moni power station); *vgelec* is the electricity production (MWh) sold in the Day-Ahead market for the thermal unit; *vgelec_dpos* is the up regulation needed in the Intra-Day market, and *vgelec_dneg* is the down regulation needed in the Intra-Day market, respectively; while *Prod_rea* is the realized production.

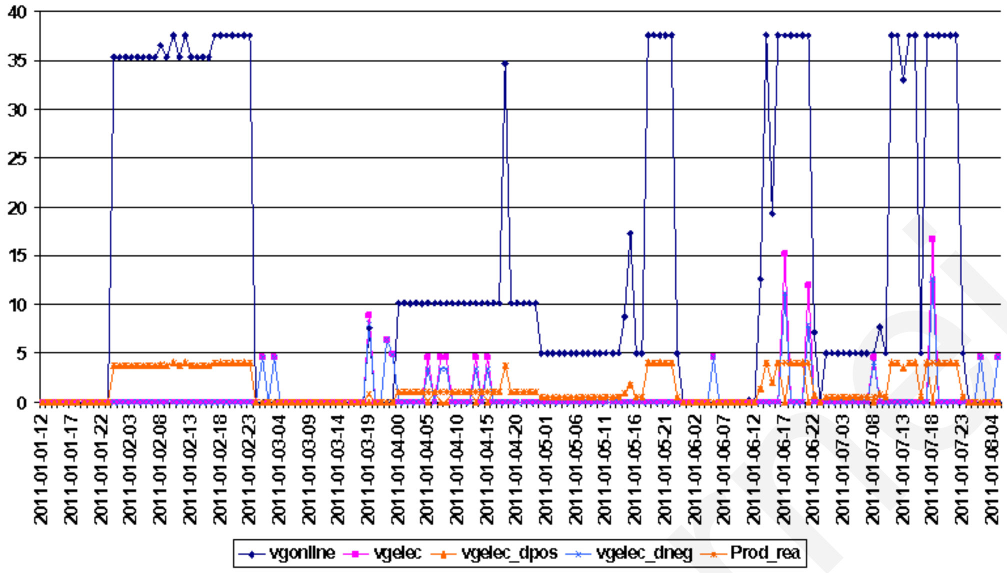

Figure 6.13 Production from one generic GT at Moni power plant: *noWind* case

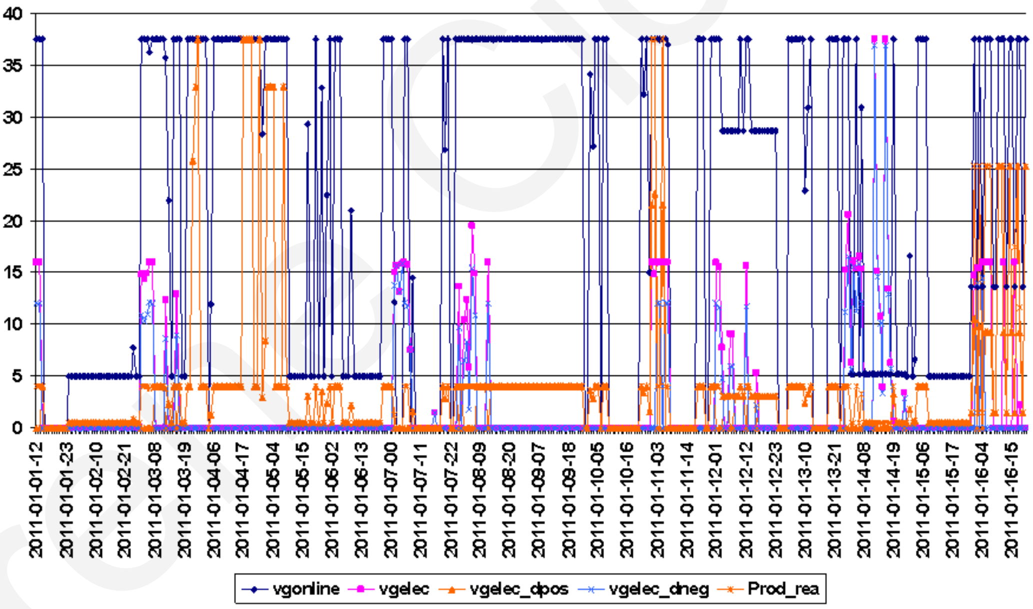

Figure 6.14 Production from one generic GT at Moni power plant: *withWind* case

Applying the reliability method of Doherty, and limiting the number of shedding incidents per year (LSI) up to four, the result shows a need for increase in reserve, as follows: during peak load periods a 10% increase in reserve margins is necessary, while up to 20% increase in reserve is required for the valley-load periods in the study case *withWind*.

6.3 Solutions for better integrating wind power into the main grid

With the variable and unpredictable nature of many renewable sources of energy such as wind and solar energy, many new technical and economic challenges arise when operating a power system with a significant infusion of such energy sources. The first part of this chapter presented specific technical and economic challenges which may appear, especially in isolated power systems, due to variable, unpredictable energy generation. In this Section, two solutions are proposed which may help the system operator to better integrate wind power into the dispatch process (both economically and securely). The first solution refers to a reformulation of the dispatch problem as a multi-objective (bi-objective) optimization, where both the operation cost and the security of the system are to be optimized simultaneously. The second solution refers to the integration of the wind forecast module and the ramping constraint into the dispatch process. It is shown that these solutions can help the dispatcher to avoid suboptimal or even infeasible dispatch solutions as well as to better use the available reserve. Suboptimal solutions means higher costs of generation, while infeasible solutions may lead to higher levels of reserve needed to operate the system, which also translates to higher generation costs.

6.3.1 Multi-objective model for economic dispatch with wind

A fuzzy model to encounter the penetration level of wind generation acceptable for a power system dispatcher at each dispatch time was proposed in [11]. The interpretation of this model is as follows: after an a priori stability analysis of the power system with variable RES generation, the dispatcher can set thresholds which define the stability status of the power system. For example, the dispatcher may state that for a specific load demand covered by classical controllable thermal generation and wind with a penetration level less than a Π^{min} value, the operation of the power system is stable; and if the penetration level of wind is higher than a Π^{max}, the system is unstable. The interesting part comes when analyzing cases between these two thresholds, because the dispatcher may have the flexibility to decide on the safe level of wind power to accept at one determined moment of dispatch. In this work, the quadratic fuzzy model of dispatcher attitude towards wind integration (the multi-objective model) is used (Figure 6.15).

The mathematical formulation of the economic dispatch model including the dispatcher attitude towards high level of variable RES integration into the main grid is given in (6.2), below, where μ is the function that defines the system security level, and can be expressed as amount in MW or a cost (μC) expressed in € /h; W represents the actual wind power generation (MW) integrated at the current moment into the generation mix (dispatched generation); W_{av} is the total available wind power of the wind parks; and C_w is the penalty cost for not using all the available wind power. μ and μC are defined in (6.3) and (6.4), respectively.

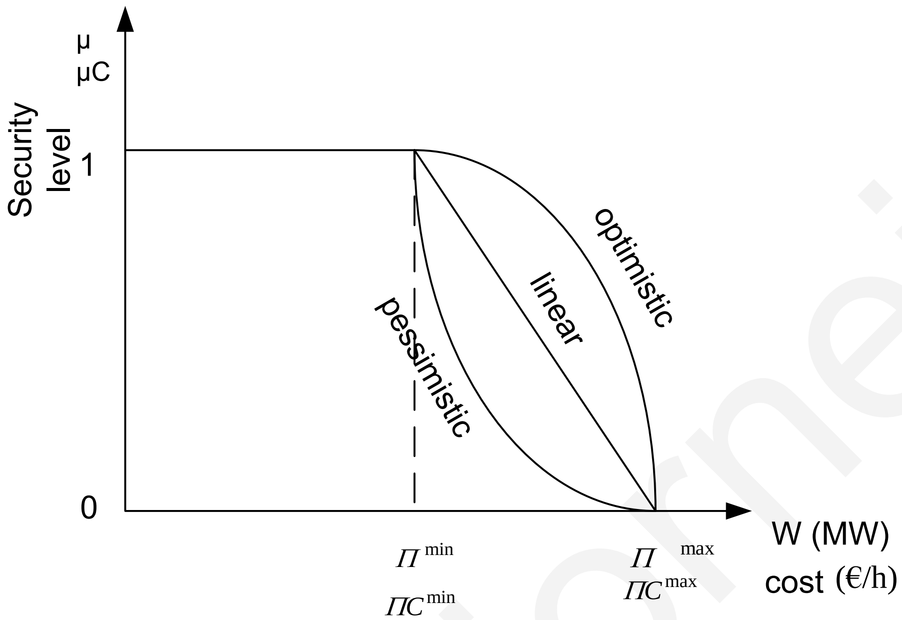

Figure 6.15 Fuzzy quadratic representation of the security level in terms of wind power penetration and cost

$$\text{minimize } OC = \sum_i F_i(P_i) + C_w(W_{av} - W) \;\; and \text{ maximize } \mu$$

subject to

$$\sum_i^{NG} P_i + W + P_{Loss} = P_D$$

$$P_{Loss} = \sum_i^{NG} \sum_j^{NG} P_i B_{ij} P_j + \sum_i^{NG} B_{i0} P_i + B_{00} \tag{6.2}$$

$$P_i^{min} \le P_i \le P_i^{max}$$

$$0 \le W \le W_{av}$$

$$\mu = \begin{cases} 1 & for \quad W \le \Pi^{\min} \\ a_w W^2 + b_w W + c_w & for \quad \Pi^{\min} \le \mathrm{W} \le \Pi^{\max} \\ 0 & for \quad W \ge \Pi^{\max} \end{cases} \tag{6.3}$$

$$\mu C = \begin{cases} 1 & for \quad CW \leq \Pi C^{\min} \\ a_w CW^2 + b_w CW + c_w & for \quad \Pi C^{\min} \leq CW \leq \Pi C^{\max} \\ 0 & for \quad CW \geq \Pi C^{\max} \end{cases} \tag{6.4}$$

CW refers to the cost associated with the security level, and a_w, b_w, c_w are the coefficients of the quadratic fuzzy membership function that defines the security level of the system in terms of wind power penetration, and they are determined based on experts' experience.

We assume that the relationship between the function which defines the level of security in terms of power (μ) and its associated cost (CW) is linear. Therefore the coefficients remain the same for both functions. A value of one, for the security level, states that the system is secure, and a value equal to zero states that the system is insecure. The parameters Π^{min} (or ΠC^{min}) and Π^{max} (or ΠC^{max}) depend on the total demand of the power system at the specified dispatch time. If the coefficient a_w is null, then the security level function is linear (Figure 6.15). If a_w, b_w, c_w are chosen such that a concave curve is formed above the linear security level, then it is said that the dispatcher has an "optimistic attitude", while if they are chosen such that a convex curve is formed below the linear security level, it is said that the dispatcher has a "pessimistic attitude" towards the amount of wind power to be accepted in the grid.

The cost of generation OC was chosen to have a nonconvex representation (as described in Chapter 2, (2.11)), so as to encounter more realistically modern generators, which may form the committed set of generation units.

a. Overview of multi-objective optimization

Most of the real world optimization problems (in any domain) do not concern only one objective. Generally, multiple objectives or parameters have to be optimized or met, each representing one criterion to be taken into account [112]. In such cases, typically there is no single solution that simultaneously optimizes each objective to its fullest. Often, an improvement in one objective is gained at the cost of deterioration in other objectives, therefore trade-offs are necessary. In short, multi-objective optimization refers to the optimization of $\boldsymbol{F}$ sets of N objective functions f_i, each of them representing one criterion to be optimized.

$$\boldsymbol{F} = \{f_i : X \rightarrow Y_i \;/\; i = 1, .., n, and\ Y_i \subset \boldsymbol{R}\} \tag{6.5}$$

There are two main ways to treat multi-objective optimization problems. The simplest way, but not always the best, to determine what is optimal in a multi-objective optimization problem is to reduce the problem to a single objective optimization problem, which implies the creation of a composite objective function. This composite function (also known as *the aggregation function*) is a linear weighted sum $F(x)$ of all the functions $f_i(x)$ from $\boldsymbol{F}$. Each objective f_i is multiplied with a weight w_i representing its importance. Using signed weights is also possible to minimize one objective while maximizing another. Thus, the aggregation function which represents the single new objective function is of the form,

$$F(x) = \sum_{i=1}^{N} w_i f_i(x), \forall f_i \in \boldsymbol{F}\ and\ \forall x \in R^n \tag{6.6}$$

The above approach will always lead to a single solution according to the vector of weights (*w*) chosen. It is evident that the decision maker may make a better (informed) decision if a trade-off surface (*Pareto front*) between conflicting objectives can be inspected before any choice is made. Thus, the second way to treat multi-objective (sometimes conflicting) optimization problems is to look for a solution for which each objective has been optimized to such an extent/limit that if going any further will lead to the deterioration of other objective(s). This limit is called *pareto-optimal set* or *pareto front*, and it will be presented in detail below.

A practical approach to multi-objective optimization is to investigate a set of solutions (*the best-known Pareto set*) that represents the Pareto optimal set as closely as possible [185]. A multi-objective optimization approach should achieve the following three conflicting goals [186]:

i. *The best-known Pareto front* should be as close as possible to the true Pareto front. Ideally, *the best-known Pareto set* should be a subset of the Pareto optimal set.

ii. Solutions in *the best-known Pareto set* should be uniformly distributed and diverse over of the Pareto front in order to provide the decision-maker with a true picture of trade-offs.

iii. The *best-known Pareto front* should capture the whole spectrum of the Pareto front. This requires investigating solutions at the extreme ends of the objective function space.

For a given computational time limit, the first goal is best served by focusing (intensifying) the search on a particular region of the Pareto front. On the contrary, the second goal demands the search effort to be uniformly distributed over the Pareto front. The third goal aims at extending the Pareto front at both ends, exploring new extreme solutions.

More specifically, in multi-objective optimization problems we seek to simultaneously reach N objectives: $y_i = f_i(x)$, where $i = 1,\ldots, N$, and where each objective depends upon a vector x of K parameters or decision variables. The parameters may also be subject to the J constraints: $h_j(x) \geq 0$ for $j = 1,\ldots, J$.

Without loss of generality, it is assumed that these objectives are to be minimized; the problem can therefore be stated as:

$$\begin{gathered} minimize\ f(x) \equiv \big(f_1(x), f_2(x), \ldots, f_N(x)\big) \\ \text{Subject to} \\ h(x) \equiv (h_1(x), h_2(x), \ldots, h_J(x)) \geq 0 \end{gathered} \tag{6.7}$$

A decision vector u is said to strictly dominate another decision vector v (denoted $u < v$) if $f_i(u) \leq f_i(v)$ for any $i = 1, . ., D$, and $f_i(u) < f_i(v)$ for some i; less stringently u weakly dominates v (denoted u - v) if $f_i(u) \leq f_i(v)$ for all i. A set of decision vectors is said to be a non-dominated set if no member of the set is dominated by any other member. The true *Pareto front*, ***PF***, is the non-dominated set of solutions which are not dominated by any feasible solution.

As a summary, the Pareto dominance concept defines that a solution x dominates another solution y if no objective of x is worse than the corresponding one of y and at least one objective of x is better than y. Based on this concept, the Pareto optimal front is defined as the set of all non-dominated solutions, and this set is what we want to find to solve the multi-objective optimization problem. By searching for the Pareto optimal front, this kind of approach relieves the burdens of the decision makers since they only need to pick the desired solution from the obtained (approximate) Pareto front, whose size is much smaller than the original solution space. This is one reason for the rapid growth of research work on solving multi-objective optimization problems by achieving (or approximating) the Pareto optimal front.

b. Modified Pareto-Differential Evolution Algorithm (MPDEA) for the multi-objective economic dispatch

Evolutionary algorithms are a kind of global optimization techniques that use selection and recombination as their primary operators to tackle optimization problems. The *Pareto-Differential Evolution algorithm* (PDE) was first proposed in [187]. The PDE is an adaptation for multi-objective optimization derived from *Differential Evolution* (DE), a branch of evolutionary algorithms developed by Storn and Price [188] for optimization problems over continuous domains. In DE, each variable is represented in the chromosome by a real number. The description of the algorithm is provided below.

Table 6.3 Pseudo-code of the Pareto-Differential Evolution Algorithm

1. **Create a random initial population** of potential solutions. Each variable is assigned a random value according to a Gaussian distribution between its specific *LB* and *UB*
2. **Repeat**
   - 2.1. **Evaluate** the individuals in the population and label those that are non–dominated.
   - 2.2. **Repeat**

     Find a non–dominated solution among those that are not labeled

     Label the solution as non–dominated

     Until the number of non–dominated individuals in the population is greater than or equal to three
   - 2.3. **If** the number of non–dominated individuals in the population is greater than the allowed maximum

     Then

     Repeat apply the *neighborhood distance function*

     Until the number of non–dominated individuals in the population is less than the allowed maximum
   - 2.4. **Delete** all dominated solutions from the population
   - 2.5. **Repeat**
     - 2.5.1. **Select** at random an individual as the main parent *p1*, and two individuals, *p2*; *p3* as supporting parents.
     - 2.5.2. **Select** at random a variable *j*.
     - 2.5.3. **For** each variable *i*

       With some probability *Uniform*(0; 1)

       If $i = j$

       Then $\boldsymbol{x_i^{child}} = \boldsymbol{x_i^{p1}} + \boldsymbol{rand} \cdot (\boldsymbol{x_i^{p2}} - \boldsymbol{x_i^{p3}})$

       Else $\boldsymbol{x_i^{child}} = \boldsymbol{x_i^{p1}}$
     - 2.5.4. **If** the child dominates the main parent

       Then place it into the population

     Until the population size reaches its maximum.

   Until termination conditions are satisfied

LB and *UB* are the lower and the upper bounds, respectively, of the solution vector *x*. The solution vector *x* is classified into other two main categories, such as *children* (e.g. x^{child}) and *parents* (x^p). A solution may be a *parent* in generation *i+1* and a *child* in generation *i*. In order to create a child solution for the next generation, each variable *i* in the main parent, x_i^{p1}, is perturbed by adding to it a ratio *rand*=*Gaussian*(0; 1) of the difference between the i^{th} variables of the two supporting parents x_i^{p2} and x_i^{p3}, respectively, if a random generated number *j* is bigger or equal than a predefined threshold (probability). At least one variable must be changed. The *neighborhood distance function* determines the individuals that are concentrated in a search area, and it is based on Euclidean distance as the distance metric.

One of the main difficulties in applying any multi-objective optimization commercial or open source tool is dealing with the constraints, as the majority of the algorithms designed to solve this type of problems were built for unconstrained optimization problems, or with linear constraints, only. Therefore, the approach followed in this work was to first design a random function that creates the initial population only with feasible individuals. A summary of the modifications needed for the applicability of PDE algorithm to the multi-objective economic dispatch model is given bellow.

At *step 1 (Create a random initial population)* from the PDE algorithm described above, instead of using the Gaussian distribution between low (*LB*) and upper (*UB*) bounds, a *Feasible Generation function* is used to create a random population only with feasible individuals according to (6.2). This is the same approach described in the

GAAPI algorithm for the economic dispatch problem.

The *neighborhood distance function* from point 2.3 is not applied, as the maximum number of Pareto-Optimal solutions is set to be the same as the population size. At point 2.5.3, the children are checked if they are feasible or not. If they are not, the process to create a feasible child is repeated (select other main parent and supporting parents from point 2.5.1) until a feasible solution is found or until a number of trials is reached. If the exit from the above mentioned loop is done with the maximum number of trials, then the child is created at random with the feasible generation function.

In order to validate the proposed solution, the algorithm was run for all three cases (*optimistic*, *pessimistic* and *linear*) of the dispatcher attitude towards wind energy integration into the power system as presented in Figure 6.15. A modified IEEE 30-bus test system was used to test the proposed algorithm. This test system comprises six thermal generators with nonconvex cost of generation and one wind farm. The Pareto-Optimal sets for these three scenarios are shown in Figure 6.16. Unlike single-objective optimization, in multi-objective optimization the decision maker can choose a suitable solution based on his/her goals at a certain point in time, from a pool of non-dominated solutions. It can be also appreciated that for the same risk level, calculated from different membership functions, the optimistic design has the lowest operational cost since it includes the largest amount of wind power among all of the three designs. It should be noted that the Pareto-Optimal sets are Nonconvex, since the cost of generation for all six thermal generating units is also nonconvex.

An illustrative non-dominated solution derived in different design scenarios is given in Table 6.4. The table gives different Pareto-Optimal dispatch solutions for the three scenarios under analysis. The data depicted in the table include the output of thermal generating units ($P_1,\ldots, P_6$) and the output of the wind farm (W), the transmission system losses (calculated only for the thermal generating units), the amount of total generation, the total generation cost and the risk level. It can be noticed that for a low cost of generation a higher risk must be assumed (the linear case from the table), and vice-versa (the optimistic case from the table).

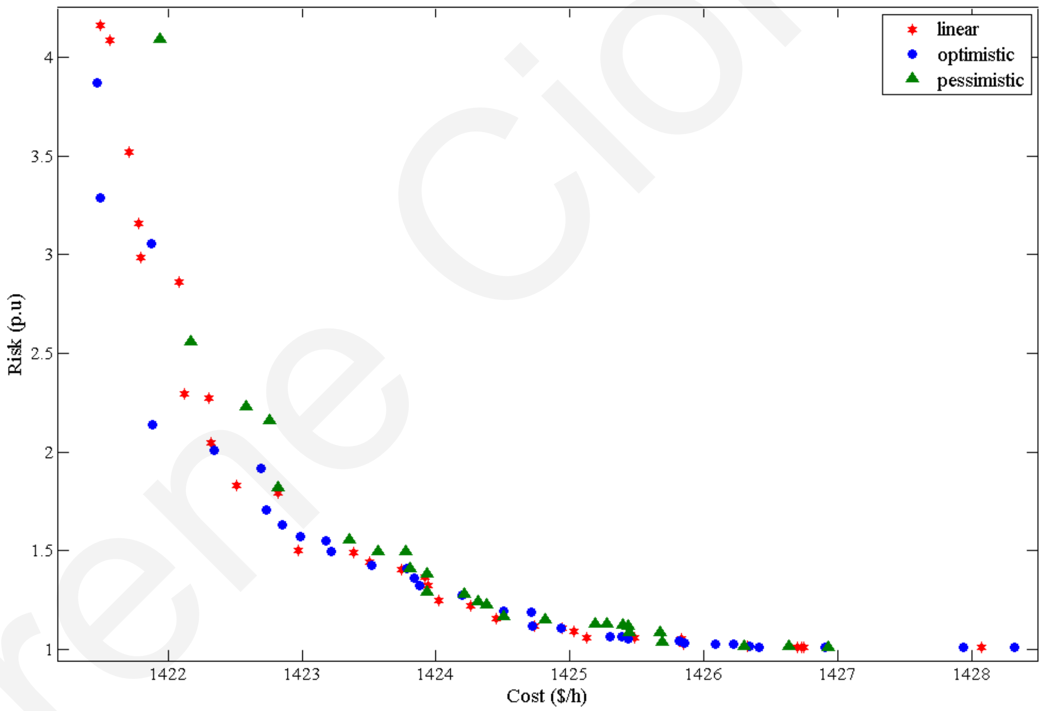

Figure 6.16 Pareto-optimal sets for different attitudes of the dispatcher

The data presented in Table 6.4 is a snapshot of the Pareto-Optimal solutions plotted in Figure 6.16. The data were collected randomly from the solution vectors of the three scenarios (*pessimistic*, *optimistic*, and *linear*). Due to the random process of the algorithm it is almost impossible to have the solutions in all three cases for the same risk level, or for the same cost of generation.

Table 6.4 Solution for different dispatcher attitudes with respect to the level of wind power penetration

Power output [p.u.]	Dispatcher attitude		
	Pessimistic 10-20%	Linear 10-20%	Optimistic 10-20%
P1	5.0000	5.0000	5.0000
P2	1.6826	0.9027	1.6129
P3	2.1048	2.5713	2.6031
P4	1.1232	1.4084	1.0727
P5	1.7843	1.2760	1.0486
P6	0.5392	1.0066	1.0439
W	0.5237	0.5724	0.3765
Losses	0.1278	0.1274	0.1277
Total generation	12.8856	12.8648	12.8854
Generation cost ($/h)	1425.3	1423.3	1427.0
Risk level	1.2942	1.9056	1.0318

6.3.2 Stochastic economic dispatch with secondary reserve regulation

The second solution which may lead to a better integration of wind power into the grid refers to the integration of a wind forecasting module and the reserve constraint into the economic dispatch solution. A stochastic economic load dispatch (SED) formulation is proposed to incorporate the impact of the variability of wind generation on the ramp rate limits constraints. The purpose of this method is to limit the probability of generation plus reserve not meeting the load due to the aggregated variability of the wind generation and the load demand. To better represent the conditions in real power systems, the cost of modern thermal units with multiple valves is considered. The problem is nonconvex and complex; therefore, the hybrid heuristic GAAPI algorithm is used to generate the dispatch solution. Numerical results based on a modified IEEE 30-bus test system are presented to validate the proposed solution.

a. Secondary Reserve Regulation

The secondary reserve correction actions are taken to balance the net load and wind deviations from their predicted values. In Figure 6.17 it is shown that the scheduled up and down secondary reserves (*UR* and *DR*, respectively), which are identical to the total ramping available from the committed units, may be insufficient to balance the power for certain time intervals. In the figure, $\Delta(W\text{-}P_D)$ is the estimated mean variation of aggregated wind power and load values over the dispatch interval; η_t is the deviation from the estimated mean. If the mean variation is not zero, the system frequency may temporarily deviate from its acceptable limits.

If the calculation of the reserve for unit commitment planning is performed using a deterministic approach, then such frequency violations may not be tolerated. However, if a probabilistic approach is used, some power imbalance is acceptable, if it occurs with a sufficiently low probability. In [189], it is shown that instead of using a stochastic program with recurrence, where different net load realizations are modeled by scenarios carrying a certain probability of occurrence ([174], [190]), a better and less computationally intensive solution is to incorporate the stochasticity of wind generation and load demand as a constraint in the ED model.

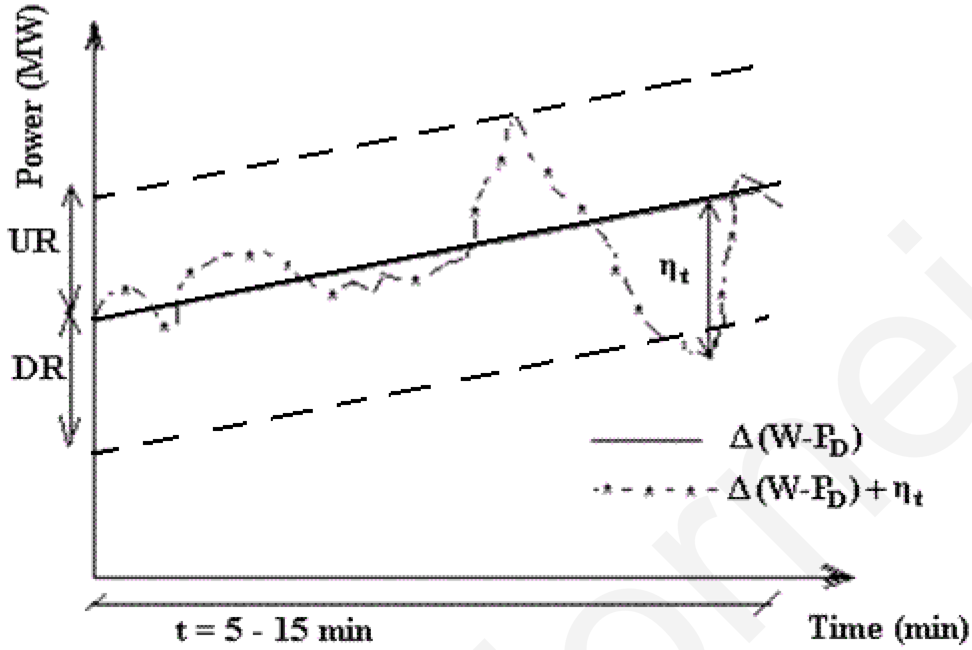

Figure 6.17 Automatic secondary regulation

When the stochastic wind and load variability are to be considered in the ED model, an additional constraint has to be added to the nonconvex economic dispatch model (5.3). It should be noted that in this model the wind generation is treated as negative load and that the variability of the wind and of the load is aggregated. The additional constraint states that the probability of the generation plus reserve not meeting the load is bounded by the maximum number of load shedding incidents per year relative to the economic dispatch time interval and it is summarized as,

$$\sum_i UR_i \geq UR$$

$$\sum_i DR_i \geq DR \qquad (6.8)$$

$$UR = CDF^{-1}(1 - \epsilon)$$

$$DR = CDF^{-1}(\epsilon)$$

UR and *DR* are the total upper and lower ramp rate available, respectively; *CDF* is the *Cumulative Distribution Function* that defines the uncertainty in load and wind prediction (Figure 6.18), and ε is the user specified probability bound which can be easily determined from a LOLE (loss of load expectation) calculation [22].

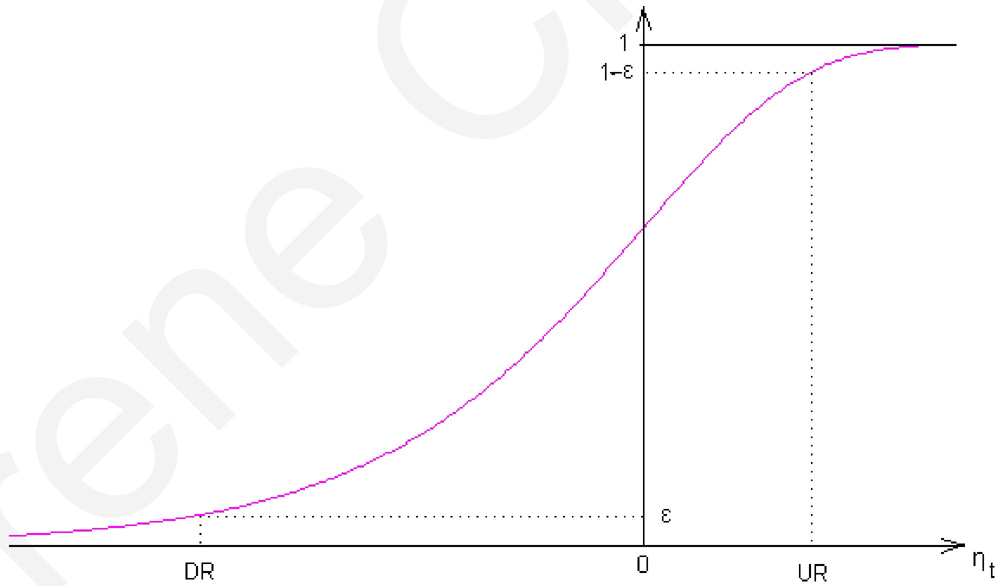

Figure 6.18 Normal cumulative density function of the deviation from the estimated mean *(η_t)*

b. Case study

The test system under analysis is a modified IEEE 30 bus test system which consists of six generators having nonconvex cost of generation and to which one big wind farm was added. In order to have a more realistic data, a scatter of 5 minutes of real measured data from an offshore wind farm in Denmark is used [191]. Figure 6.19, which was adapted from [191], shows the measurements obtained during one hour with high weather turbulences.

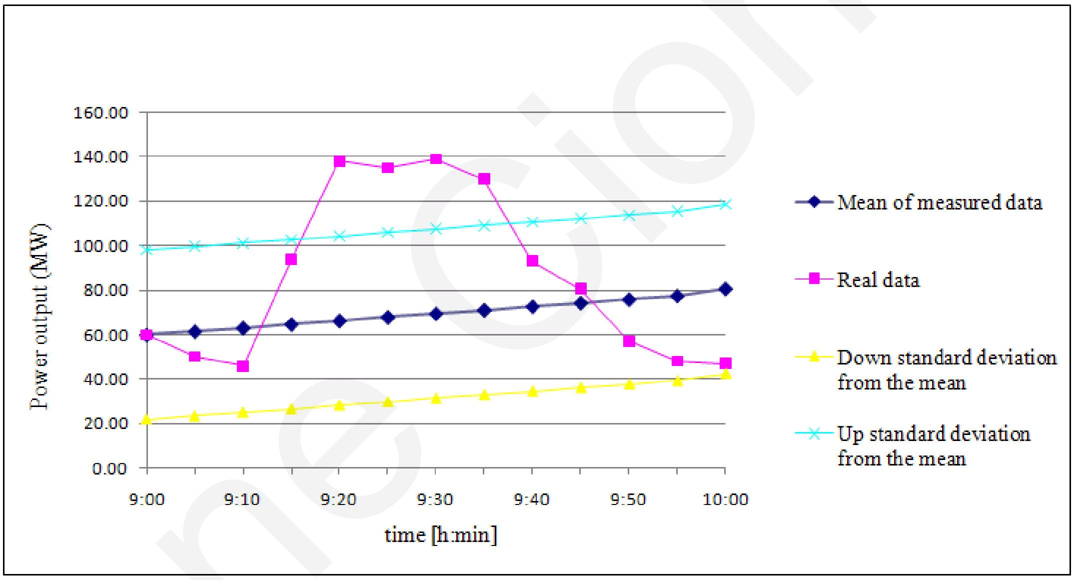

Figure 6.19 Power generation of Horns Rev offshore wind farm on January 18, 2005

c. Analysis of results

The analysis is carried out for four intra-hour secure economic dispatch (SED) runs, using both mean forecasted values of load minus wind generation (and when the forecasted wind power is estimated only one day ahead), and intra-hour forecasted values (supposing that the system is assisted online by a wind forecasting algorithm). An assumption made for the calculations in this work is that the active power losses associated with the power generated from the wind farm are negligible compared to the active power losses due to the contributions of the thermal generators of the power system. Therefore, the losses of the system are considered to be the same as when the wind farm generates zero power. The assumption is not far from reality as the maximum share of wind generation for this particular example is less than 10% of the total thermal power share, while the losses are about 1.2% of the total generated power, meaning that the contribution of the wind farm to the total system losses is expected to be less than 0.12%. The system data are available in Tables A3, A4 and A5. The load demand for four fifteen-minute time intervals are given in Table 6.5, where the following notations are used: *load* shall be read as the difference between real power load demand and wind generation; *Mean load* is the estimated average *load* as determined by a day-ahead forecast for each hour of the day; and the *Real load* is determined based on the value received from a wind forecasting module, which always runs before the ED algorithm (this can be seen as a real time forecasting).

Table 6.5 Intrahour load demand

Time [h:min]	Real load [MW]	Mean Load [MW]
9:15	1153	1182
9:30	1108	1177
9:45	1166.5	1172.8
10:00	1200	1166

For a fair comparison, the effect of ramp rate constraint on the SED formulation is emphasized, due to the increased variability that may occur in the intra-hour SED runs. Tables 6.6 to 6.9 present the ED solutions for 15 minute intervals during one hour. For each 15 minute interval, four cases are examined: using *real* load values (with and without ramp rate limits) and *mean* load values (with and without ramp rate limits, denoted in the tables as *WithRamp* and *NoRamp*, respectively).

Table 6.6 ED solution for hour 9:15

Power (MW)	Real		Mean	
	NoRamp	WithRamp	NoRamp	WithRamp
P_1	432.39	434.46	435.10	435.17
P_2	149.06	147.53	147.73	172.58
P_3	200.03	199.44	200.14	175.15
P_4	127.50	127.51	129.01	128.90
P_5	167.52	167.56	169.27	193.31
P_6	87.50	87.50	112.39	88.83
Total Generation	1164.03	1164.04	1193.67	1193.97
Losses	11.034	11.04	11.67	11.97
Generation Cost ($/h)	1378.89	1378.84	1384.82	1385.41
P_{LOAD}	1153		1182	

Table 6.7 ED solution for hour 9:30

Power (MW)	Real		Mean	
	NoRamp	WithRamp	NoRamp	WithRamp
P_1	411.58	410.43	435.21	434.93
P_2	147.53	148.26	149.14	173.78
P_3	175.05	176.61	196.85	176.67
P_4	129.04	127.63	127.67	127.50
P_5	167.51	167.69	192.50	193.37
P_6	87.50	87.59	87.51	82.63
Total Generation	1118.23	1118.24	1188.90	1188.90
Losses	10.22	10.24	11.89	11.90
Generation Cost ($/h)	1371.22	1371.22	1383.86	1385.16
P_{LOAD}	1108		1177	

The economic load dispatch solutions indicate a difference in the results depending on the case considered. This is expected, since on one hand the load data are *real* or *mean*, and on the other hand the ramping constraints are or are not considered. For the *real load* data scenario with ramping considered, the total generation cost is always smaller or equal than when ramping is not taken into account. For the *mean load* data scenario, the opposite happens, but this is only due to the fact that some units exceed their ramping limit, and therefore the solution is also suboptimal in terms of constraint violation (e.g., the third unit in Table 6.6).

Table 6.8 ED solution for hour 9:45

Power (MW)	Real		Mean	
	NoRamp	WithRamp	NoRamp	WithRamp
P1	438.55	430.01	434.70	427.71
P2	168.48	159.98	147.50	175.19
P3	177.40	188.33	175.05	171.60
P4	134.87	137.34	129.09	135.27
P5	168.18	173.07	192.46	186.77
P6	90.17	88.95	105.88	87.816
Total Generation	1177.66	1177.69	1184.70	1184.37
Losses	11.16	11.19	11.90	11.57
Generation Cost ($/h)	1381.96	1381.96	1383.78	1384.38
P_{LOAD}	1166.5		1172.8	

Table 6.9 ED solution for hour 10:00

Power (MW)	Real		Mean	
	NoRamp	WithRamp	NoRamp	WithRamp
P_1	439.38	430.43	436.33	410.95
P_2	174.37	160.76	153.90	173.20
P_3	202.07	192.86	187.18	177.43
P_4	128.35	140.13	128.72	130.09
P_5	180.27	180.19	179.29	198.45
P_6	87.56	100.09	92.00	87.61
Total Generation	1212.04	1204.49	1177.44	1177.76
Losses	12.04	11.76	11.44	11.76
Generation Cost ($/h)	1388.05	1387.19	1381.81	1382.93
P_{LOAD}	1200		1166	

When comparing the *real load* data scenario to *the mean load* data scenario, it is obvious that the ED solution depends heavily on the accuracy of load prediction. Therefore, as long as the forecasting procedure is called as near as possible to the ED run, a more accurate solution will be obtained. On the other hand, when less accurate data are used (e.g., the *mean load* data scenario), more energy from expensive generators will be used as an effect of the regulation action (for automatic control regulation units) to keep the system generation and load in balance.

6.4 Summary of the chapter

This chapter presented a real case study for economic and technical challenges in dispatching isolated power systems with stochastic generation such as electricity generation from wind parks and limited flexibility. The power system of Cyprus was used as a case study. Some of the main conclusions/challenges resulting from the study are: (i) there may be an increase in reserve demand (which can go up to 20% increase) especially in the valley load periods which coincide with high instant penetration of wind power; (ii) an increase in frequency of ramping in the case of fast units which can be translated into shortening the maintenance period intervals, leading to higher maintenance costs per year and therefore increasing the failure risk of those units; (iii) wind power curtailment may be advised by the system operator when a large error between predicted and realized wind occur. Two solutions are proposed to overcome some of the above mentioned challenges. The first solution refers to the reformulation of the ED problem as a multi/bi-objective optimization, where the cost of generation and the security level of the system are optimized simultaneously. The second solution addresses the importance of the ramp rate limits in the formulation of the ED problem, especially when more variability due to wind power generation is experienced during intra-hour dispatch. The second solution refers to a stochastic ED formulation where the ramping constraints are depicted as linear stochastic functions. Moreover, when a forecasting program is run before each ED run, better integration of wind energy is expected, as suboptimal solutions and eventually wind curtailment may be avoided.

Chapter 7

Conclusions

7.1 Concluding remarks

The economic dispatch is one of the most important, and still challenging and highly complex optimization problems in power systems operations. The economic dispatch problem, in its primary form, provides an answer to the question "what is the optimal sharing of generation between generators such that the total fuel cost is minimized?" However, other questions that are important in the operation of power systems may also be related to economic dispatch, such as "what savings are possible with economic dispatch and how these savings can be estimated?" or "are there any environmental advantages of economic dispatch?"

This work concentrated on novel optimization solutions for the economic dispatch problem in power systems using more accurate models than the majority of methods applied in practice. The models used reflect better the practices of power system planning and operation, the integration of renewable generation and the approach of handling greenhouse gas emissions, while a secure and reliable operation is ensured.

One of the major contributions of the present work is the development of a novel heuristic optimization algorithm, entitled GAAPI. The hybrid meta-heuristic algorithm proposed in this work came into life by linking two other powerful algorithms (RCGA and API). The proposed algorithm is relatively simple to implement and manage, and is proven to always find comparable or even better solutions compared to other optimization methods. The GAAPI algorithm was successfully tested on twenty benchmark functions proposed in 2005 at the "IEEE Congress on Evolutionary Computation" as test-bed systems for global optimization methods and proved its superiority in the quality of the solution, consistency of results on a number of independent runs, and computational efficiency in comparison to various efficient heuristic algorithms. It was proven that for most of these functions (15 out of 20 benchmark functions) GAAPI provided satisfactory or optimum solutions, with very little computational effort. The algorithm best performed especially for large, complex problems with a dimensionality greater than 30. For seven benchmark functions GAAPI gave the best solution reported so far in the literature, with a smaller number of function evaluations (10 to 50 times less than other powerful methods). For eight other test functions with high dimensionality (n = 30), GAAPI gave near global solutions with much less computational effort. However, for a small class of functions (five benchmark functions), having mainly small dimensionality (n = 2, n = 4, or n = 6), GAAPI failed to find the global optimum solution. The main reasons for this failure is the small dimensionality of the problem and the flatness of the objective function around the global minimum.

As a first conclusion, GAAPI is proposed to be used as a robust solution to a large class of continuous global optimization problems such as engineering complex optimization problems, especially with large dimensionality, where analytical or other heuristic methods fail to give satisfactory results in a reasonable computational time.

Another major contribution of this work, is the adaptation and application of the proposed GAAPI algorithm on the economic dispatch problem in power systems. Several formulations of this problem were targeted, having a quadratic cost of generation or a nonconvex cost function (with valve point loading effect). The algorithm was tested successfully on several IEEE test power systems. Accurate power system models were used in order to gain a more realistic view of the problem, as well as to improve the current economic dispatch procedures. Comparison with other powerful evolutionary computation methods proved the effectiveness and superiority of the proposed method and its applicability to real time processing in power systems operation. GAAPI has provided the global solution, always satisfying the constraints, and proved its superiority in robustness by its high probability to reach the global or quasi-global solution, especially in nonconvex formulations. GAAPI converges smoothly to the global, avoiding fast convergence that may lead to local optima. Moreover, it was proven that starting from the solution obtained for the quadratic form of the generation cost function (Lagrange multipliers method), the search space can be reduced, and implicitly the computational effort can be reduced. The strategy for handling the constraints proposed in this dissertation is to always generate feasible solutions and work only with these feasible solutions during the search process. Compared to the penalty factors method, this strategy has the advantage of not dealing with other parameter settings that complicate the use of the method.

The dissertation also contributes with a study which identified and analysed challenges in isolated power system operation, as well as with solutions to be undertaken to solve this coming problem. The study performed in this dissertation discussed both the advantages and the challenges an isolated power system may face when variable sources of energy, such as wind energy, are part of the generation mix. This is a very hot topic as more and more renewables are to be connected to regional power grids. The power system of Cyprus was used as a case study, and the analysis was carried out using an open source tool called WILMAR and a reliability based method to estimate the spinning reserve needed for a safe operation of the system.

The results emphasized some advantages wind energy can bring to the economy of system operation: CO_2 emission reductions due to the partial replacement of thermal units' usage in load coverage, increase in self sustainability and decrease in the dependency on fuel imports for the power system of Cyprus. Note that currently Cyprus is 100% dependent on fuel import. There is no need for additional conventional capacity. However, in terms of TSO concerns, a number of technical and economic challenges may occur due to the wider variation of load at balancing units (reduction in maintenance period and increase of operation cost). Another challenge, when large amounts of wind energy penetrate the network, refers to an increase in spinning reserve allocation for isolated power systems. In terms of wind farm owners, they may face curtailments due to technical infeasibilities such as unacceptable high costs, generation greater than load, and system security concerns, especially during valley-load periods. Therefore, a reduction in their revenue may occur. The issue of wind curtailment in Cyprus is another serious problem, as there is already an executive decision to accommodate all wind generation. Further studies need to be performed to address this issue.

Two solutions are proposed to overcome part of the above mentioned challenges. One refers to the reformulation of the economic dispatch problem as a multi/bi-objective optimization where the cost of generation and the security level of the system are optimized simultaneously. Therefore, another contribution of the current dissertation refers to an improved Pareto-Differential Evolution algorithm (MPDEA) which was proposed to solve the multi-objective economic dispatch problem, when risk assessment due to the partial predictability of the wind and economic operation are both taken into account. To perform the economic dispatch of a hybrid power system (classical thermal, dispatchable units and RES units with variable generation), the dispatcher must ensure the security of the system while the generation cost is minimized. An analysis of a dual-objective economic dispatch problem considering wind power generation was performed. Economic and security impacts as conflicting objectives were modeled in the proposed optimization problem. A quadratic fuzzy membership function was used to reflect the dispatcher's attitude toward the wind penetration and the wind power cost. In order to validate the model and its applicability, the proposed MPDEA method was tested on a modified IEEE bus test system. The Pareto-Optimal set of solutions obtained can be interpreted as a map based on which the dispatcher (decision maker) can decide which solution serves better his/her interest at a specific decision moment. The results of the simulations also proved that the algorithm is capable of determining the nearest Pareto Optimal set of the generation dispatch with wind power integration, while preserving the diversity in the solution space.

The other solution to the dispatch challenges of power systems with variable generation addresses the importance of the ramp rate limits in the formulation of the economic dispatch problem, especially when several deviations from the predicted load/generation are experienced during intra-hour dispatch. The dissertation proposes a stochastic economic dispatch formulation where the ramping constraints are depicted as linear stochastic functions. A comparison between the model without ramping constraints and the model which takes them into account was performed. It was shown that the former model can lead to infeasible solutions due to sudden, large deviations from the predictions in the case of wind power generation (especially centralized generation), which may exceed the ramping capability of the units. Moreover, it was shown that when a forecasting program is run before each economic dispatch call, better integration of wind energy is expected, as suboptimal solutions and eventually wind curtailment are avoided.

The dissertation also contributes with a number of implementations of well known algorithms such as lambda iteration method for the simplified quadratic economic dispatch model, binary and real coded genetic algorithms and particle swarm optimization methods used in different stages of the work, mainly for comparison reasons.

7.2 Future steps

This dissertation contributed with a novel optimization solution, entitled GAAPI, with potential applicability to a large class of global continuous complex and unconstrained optimization problems. Therefore, future steps need to be directed towards identifying real world problems which can be solved using GAAPI, while further improvement in algorithm performance can emerge from these applications. One possible improvement of the improvement may result from the investigation of an optimal adaptive setting of some of algorithm parameters and by investigating the optimal time of switching between the two algorithms (API and the RCGA). Further, a more general approach towards the application of GAAPI to constrained global optimization can be conducted. Developments in this direction can be guided by identification of other engineering complex optimization problems (besides its application to the economic dispatch problem in power systems), where GAAPI may be applied.

The proposed GAAPI was adapted for application to the dispatch of generation in power systems, where IEEE test systems were used to validate the algorithm performance. Adaptation of GAAPI for multi-objective optimization and application to the environmental and secure economic dispatch formulation may also be conducted. Furthermore, an interest from various industry members was expressed in the possibility of using the GAAPI solution to the generation dispatch of real power systems, such as the power system of Cyprus. This possibility is being investigated.

The GAAPI algorithm may be extended to address the more general problem of unit commitment. Further, as the solution is finally intended to be extended as an economic dispatch tool for the power industry, further work needs to be directed towards the development of a GUI with a user friendly interface for the power system engineers. The GUI application is intended to be offered to a number of electric utilities (for user acceptance tests), thus receiving constructive criticism on the performance of the tool, which may lead to further enhancements of its features.

This dissertation has also addressed the economic and technical challenges in dispatching the generation from a mixed power portfolio where renewable and partially predictable generation in significant amounts is part of the generation mix. Some of the challenges raised from the study are difficult to quantify, such as the increase in cost of operating the system. A study to quantify the increase in maintenance cost of fast generating units that cope with the partial predictability of wind energy generation accommodated in large amounts may give one indication, while the amount of reserve needed for secure operation and how this translates into cost is another potential indicator.

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Appendix

A1. Global optimization benchmark test functions

$F_1 = \sum_{i=1}^{n} -x_i \sin\left(\sqrt{|x_i|}\right)$

$F_2 = \sum_{i=1}^{n}(x_i^2 - 10\cos(2\pi i) + 10)$

$F_3 = -20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right) - exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi i)\right) + 20 + \exp(1)$

$F_4 = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n}\cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$

$F_5 = \frac{\pi}{n}\{10\sin^2(\pi y_1) + \sum_{i=1}^{n-1}(y_i - 1)^2[1 + 10\sin(\pi y_{i+1})] + (y_n - 1)^2\} + \sum_{i=1}^{n} u(x_i, 10, 100, 4)$

where,

$y_i = 1 + \frac{1}{4}(x_i + 1)$

and

$$u(x_i, a, k, m) = \begin{cases} k(x_i - a)^m & , \quad x_i > a \\ 0 & , \quad -a \leq x_i \leq a \\ k(-x_i - a)^m & , \quad x_i < -a \end{cases}$$

$F_6 = \frac{1}{10}\{\sin^2(3\pi x_1) + \sum_{i=1}^{n-1}(x_i - 1)^2[1 + \sin^2(3\pi x_{i+1})] + (x_n - 1)^2[1 + \sin^2(2\pi x_n)]\} + \sum_{i=1}^{n} u(x_i, 5, 100, 4)$

$F_7 = -\sum_{i=1}^{n}\sin(x_i)\sin^{20}\left(\frac{ix^2}{\pi}\right)$

$F_8 = \sum_{i=1}^{n}\left(\sum_{j}^{n} \chi_{ij} \sin \omega_j + \psi_{ij} \cos\ \omega_j\ - \sum_{j=1}^{n}\left(\chi_{ij} \sin x_j + \psi_{ij} \cos x_j\right)\right)^2$

where, χ_{ij} and ψ_{ij} are random numbers in [-100, 100], and ω_i is a random number in [-π, π].

$F_9 = \frac{1}{n}\sum_{i=1}^{n}(x_i^4 - 16x_i^2 + 5x_i)$

$F_{10} = \sum_{i=1}^{n}[100(x_i^2 + x_{i+1})^2 + (x_i - 1)^2]$

$F_{11} = \sum_{i=1}^{n} x_i^2$

$F_{12} \sum_{i=1}^{n} -ix_i^4 + rand[0,1)$

$F_{13} = \sum_{i=1}^{n}|x_i| + \prod_{i=1}^{n}|x_i|$

$F_{14} = \sum_{i=1}^{n}\left(\sum_{j=1}^{i} x_j\right)$

$F_{15} = \max\{|x_i|,\ i = 1, 2, \dots, n\}$

$F_{16} = 4x_i^2 - 2.1x_1^4 + \frac{1}{3}x_1^6 + x_1x_2 - 4x_2^2 + 4x_2^4$

$F_{17} = \left(x_2 - \frac{5.1}{4\pi^2}x_1^2 + \frac{5}{\pi}x_1 - 6\right)^2 + 10\left(1 - \frac{1}{8\pi}\right)\cos x_1 + 10$

$F_{18} = [1 + (x_1 + x_2 + 1)^2(19 - 14x_1 + 3x_1^2 - 14x_2 + 6x_1x_2 + 3x_2^2)][30 + (2x_1 - 3x_2)^2(18 - 32x_1 + 12x_1^2 + 42x_2 - 36x_1x_2 + 27x_2^2)]$

$$F_{19} = \sum_{i=1}^{11}\left[a_i - \frac{x_1(b_i^2 + b_ix_2)}{b_i^2 + b_ix_3 + x_4}\right]$$

where,

[$a_1,\dots, a_{11}$] = [0.1957 0.1947 0.1735 0.16 0.0844 0.0627 0.0456 0.0342 0.0323 0.0235 0.0246];

[$b_1,\dots, b_{11}$] = [4 2 1 0.5 1/4 1/6 1/8 1/10 1/12 1/14 1/16].

$F_{20} = -\sum_{i=1}^{4} c_i \exp\left[-\sum_{j=1}^{6} a_{ij}\left(x_j - p_{ij}\right)^2\right]$

where,

$[c_1 \ldots c_4] = [1\ 1.2\ \ 3\ \ 3.2]$;

$$[a_{ij}]_{4x6} = \begin{bmatrix} 10 & 3 & 17 & 3.5 & 1.7 & 8 \\ 0.05 & 10 & 17 & 0.1 & 8 & 14 \\ 3 & 3.5 & 17 & 10 & 17 & 8 \\ 17 & 8 & 0.05 & 10 & 0.1 & 14 \end{bmatrix}$$

$$[p_{ij}]_{4x6} = \begin{bmatrix} 0.1312 & 0.1696 & 0.5569 & 0.0124 & 0.8283 & 0.5886 \\ 0.2329 & 0.4135 & 0.8307 & 0.3736 & 0.1004 & 0.9991 \\ 0.2348 & 0.1415 & 0.3522 & 0.2883 & 0.3047 & 0.6650 \\ 0.4047 & 0.8828 & 0.8732 & 0.5743 & 0.1091 & 0.0381 \end{bmatrix}$$

A2. Plots of the most common global optimization benchmark functions

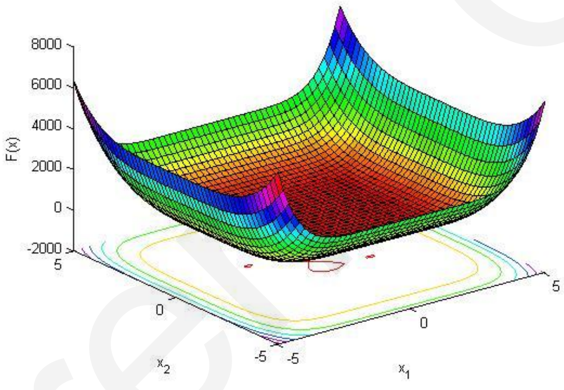

Figure A.1 Test function F16

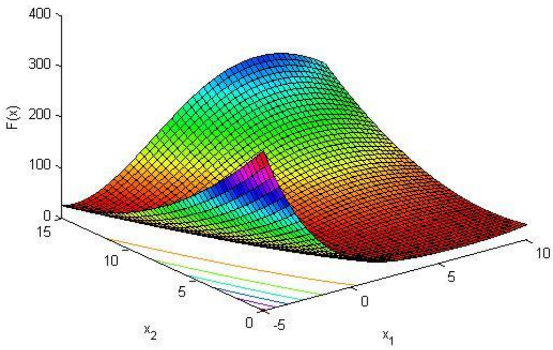

Figure A.2 Test function F17

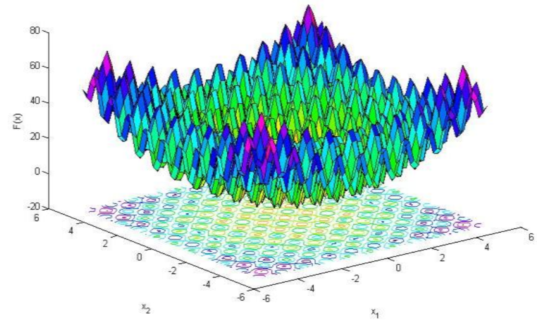

Figure A.3 Rastrigin's function

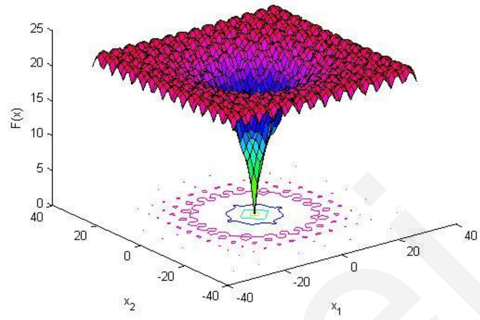

Figure A.4 Akley's function

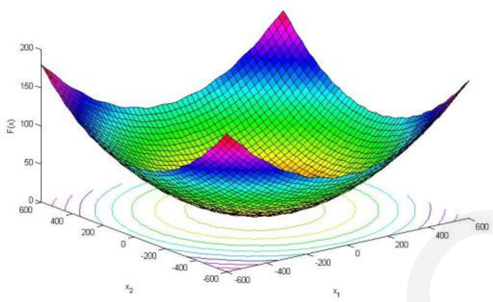

Figure A.5 Grienwangk's function

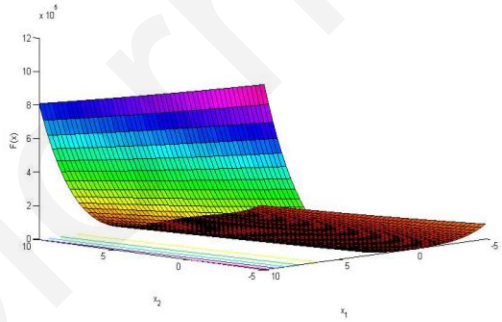

Figure A.6 Rosenbrock's function

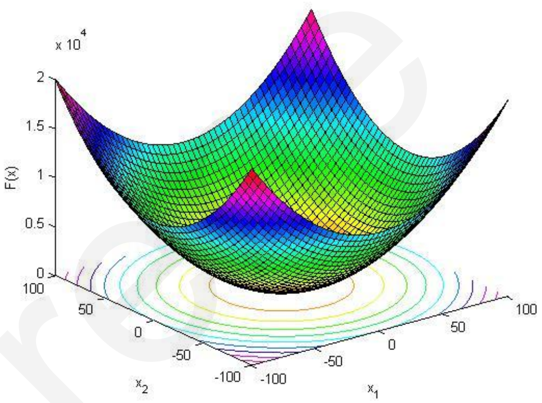

Figure A.7 Sphere function

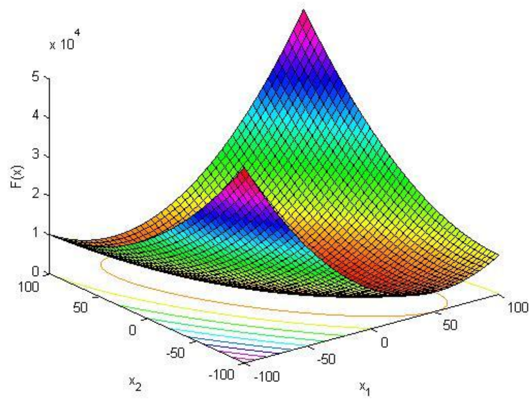

Figure A.8 Quadratic function

A3. Characteristics of the IEEE test power systems

Table A.1 Capacity and cost coefficients: 3-unit test system (P_D=850 MW)

Generator	P_{min}	P_{max}	A	b	c	e	f
1	150	600	561	7.92	0.001562	300	0.0315
2	100	400	310	7.85	0.001940	200	0.0420
3	50	200	78	7.97	0.004820	150	0.0630

Table A.2 B-loss coefficients: 3-unit test system

$$B = \begin{bmatrix} 0.00670 & 0.00953 & -0.00507 \\ 0.00953 & 0.05210 & 0.00901 \\ -0.00507 & 0.00901 & 0.29400 \end{bmatrix}$$

$$B_0 = [-0.07660 \quad -0.00342 \quad 0.01890] \times 10^{-3}$$

B_{00} = 0.040357

Table A.3 Capacity and cost coefficients: 6-unit test system (P_D=1263 MW)

Generator	P_{min}	P_{max}	A	b	C	E	F
1	100	500	240	7.0	0.0070	300	0.0315
2	50	200	200	10.0	0.0095	150	0.063
3	80	300	220	8.5	0.0090	200	0.042
4	50	150	200	11.0	0.0090	100	0.084
5	50	200	220	10.5	0.0080	150	0.063
6	50	120	190	12.0	0.0075	100	0.084

Table A.4 B-loss coefficients: 6-unit test system

$$B = \begin{bmatrix} 0.0017 & 0.0012 & 0.0007 & -0.0001 & -0.0005 & -0.0002 \\ 0.0012 & 0.0014 & 0.0009 & 0.0001 & -0.0006 & -0.0001 \\ 0.0007 & 0.0009 & 0.0031 & 0 & -0.0010 & -0.0006 \\ -0.0001 & 0.0001 & 0.0000 & 0.0024 & -0.0006 & -0.0008 \\ -0.0005 & -0.0006 & -0.0010 & -0.0006 & 0.0129 & -0.0002 \\ -0.0002 & -0.0001 & -0.0006 & -0.0008 & -0.0002 & 0.0150 \end{bmatrix}$$

$$B_0 = [-0.3908 \quad -0.197 \quad 0.7047 \quad 0.0591 \quad 0.2161 \quad -0.6635] \times 10^{-3}$$

$$B_{00} = 0.0056$$

Table A.5 Ramp rate limits and prohibited operating zones: 6-unit test system

Generator	P^0 (MW)	UR (MW/h)	DR (MW/h)	Prohibited zones (MW)
1	440	80	120	[210 240]; [350 380]
2	170	50	90	[90 110]; [140 160]
3	200	65	100	[150 170]; [210 240]
4	150	50	90	[80 90]; [110 120]
5	190	50	90	[90 110]; [140 150]
6	110	50	90	[75 85]; [100 105]

Table A.6 Capacity and cost coefficients: 15-unit test system (P_D=2630 MW)

Generator	Pmin	Pmax	a	b	C
1	150	455	671	10.1	0.000299
2	150	455	574	10.2	0.000183
3	20	130	374	8.8	0.001126
4	20	130	374	8.8	0.001126
5	150	470	461	10.4	0.000205
6	135	460	630	10.1	0.000301
7	135	465	548	9.8	0.000364
8	60	300	227	11.2	0.000338
9	25	162	173	11.2	0.000807
10	25	160	175	10.7	0.001203
11	20	80	186	10.2	0.003586
12	20	80	230	9.9	0.005513
13	25	85	225	13.1	0.000371
14	15	55	309	12.1	0.001929
15	15	55	323	12.4	0.004447

Table A.7 Ramp rate limits and prohibited operating zones: 15-unit test system

Generator	P^0 (MW)	UR (MW/h)	DR (MW/h)	Prohibited zones (MW)
1	400	80	120	-
2	300	80	120	[185 225]; [305 335]; [420 450]
3	105	130	130	-
4	100	130	130	-
5	90	80	120	[180 200]; [305 335]; [390 420]
6	400	80	120	[230 255]; [365 395]; [430 455]
7	350	80	120	-
8	95	65	100	-
9	105	60	100	-
10	110	60	100	-
11	60	80	80	-
12	40	80	80	[30 40]; [55 65]
13	30	80	80	-
14	20	55	55	-
15	20	55	55	-

Table A.8 Capacity and cost coefficients: 40-unit test system (P_D=10500 MW)

Generator	P_{min}	P_{max}	a	b	c	e	f
1	36	114	94.705	6.73	0.0069	100	0.084
2	36	114	94.705	6.73	0.0069	100	0.084
3	60	120	309.54	7.07	0.02028	100	0.084
4	80	190	369.03	8.18	0.00942	150	0.063
5	47	97	148.89	5.35	0.0114	120	0.077
6	68	140	222.33	8.05	0.01142	100	0.084
7	110	300	287.71	8.03	0.00357	200	0.042
8	135	300	391.98	6.99	0.00492	200	0.042
9	135	300	455.76	6.6	0.00573	200	0.042
10	130	300	722.82	12.9	0.00605	200	0.042
11	94	375	635.2	12.9	0.00515	200	0.042
12	94	375	654.69	12.8	0.00569	200	0.042
13	125	500	913.4	12.5	0.00421	300	0.035
14	125	500	1760.4	8.84	0.00752	300	0.035
15	125	500	1728.3	9.15	0.00708	300	0.035

Generator	P_{min}	P_{max}	a	b	c	e	f
16	125	500	1728.3	9.15	0.00708	300	0.035
17	220	500	647.85	7.97	0.00313	300	0.035
18	220	500	649.69	7.95	0.00313	300	0.035
19	242	550	647.83	7.97	0.00313	300	0.035
20	242	550	647.81	7.97	0.00313	300	0.035
21	254	550	785.96	6.63	0.00298	300	0.035
22	254	550	785.96	6.63	0.00298	300	0.035
23	254	550	794.53	6.66	0.00284	300	0.035
24	254	550	794.53	6.66	0.00284	300	0.035
25	254	550	801.32	7.1	0.00277	300	0.035
26	254	550	801.32	7.1	0.00277	300	0.035
27	10	150	1055.1	3.33	0.52124	120	0.077
28	10	150	1055.1	3.33	0.52124	120	0.077
29	10	150	1055.1	3.33	0.52124	120	0.077
30	47	97	148.89	5.35	0.0114	120	0.077
31	60	190	222.92	6.43	0.0016	150	0.063
32	60	190	222.92	6.43	0.0016	150	0.063
33	60	190	222.92	6.43	0.0016	150	0.063
34	90	200	107.87	8.95	0.0001	200	0.042
35	90	200	116.58	8.62	0.0001	200	0.042
36	90	200	116.58	8.62	0.0001	200	0.042
37	25	110	307.45	5.88	0.0161	80	0.098
38	25	110	307.45	5.88	0.0161	80	0.098
39	25	110	307.45	5.88	0.0161	80	0.098
40	242	550	647.83	7.97	0.00313	300	0.035