DIFFERENTIAL EVOLUTION BASED POWER DISPATCH ALGORITHMS

By

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ABSTRACT

This research work presents the application of the Differential Evolution algorithm in the solution of the economic dispatch problem and the reactive power dispatch problem. To test the performance and capability of the algorithm, four case studies were designed all of which are extremely complex, highly nonlinear and in occasions discontinuous.

The case studies can be classified into four groups: economic dispatch using non-conventional cost functions, economic-environmental power dispatch, security constrained economic dispatch and reactive power dispatch. Each case study presents several variants based on typical systems used in other references that help validate the results obtained by Differential Evolution.

The main contribution of this research regards the application of evolutionary computation techniques, in particular Differential Evolution, in the solution of complex optimization problems where classical techniques may fail to obtain optimal solutions or may result inefficient to implement.

RESUMEN

Esta investigación presenta la aplicación de la técnica de optimización Evolución Diferencial en la solución de los problemas de Despacho Económico de Potencia y Despacho de Potencia Reactiva. Para evaluar el desempeño y capacidad del algoritmo, cuatro casos de estudio fueron desarrollados los cuales se caracterizan por ser extremadamente complejos, altamente no lineales y en muchos casos presentan un espacio de soluciones discontinuo lo que dificulta su solución mediante técnicas convencionales como las basadas en gradientes.

Los casos de estudios se resumen en despacho económico con curvas de costo no convencionales, despacho económico-ambiental de potencia, despacho económico con restricciones de seguridad y despacho de potencia reactiva. Varias modalidades de estos casos fueron evaluadas basadas en sistemas característicos utilizados en otras investigaciones que permiten validar los resultados obtenidos por el algoritmo.

La principal contribución de este trabajo, es la aplicación de técnicas no convencionales, específicamente Evolución Diferencial en la solución de problemas difíciles y complejos dentro del campo de sistemas de potencia, donde las técnicas clásicas fallan en obtener una solución óptima o pueden resultar ineficientes de implementar.

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$F_i\left(P_{G_i}\right)$	i^{th} generator cost function
P_{G_i}	i^{th} generator power output
N_G	Total number of online generators
P_D	Total system load
P_L	System losses
B_{ij}, B_{i0}, B_{00}	Loss coefficients or B-coefficients
$P_{G_i}^{\min}$	Lower power production limits of the i^{th} generator
$P_{G_i}^{\max}$	Upper power production limits of the i^{th} generator
a_i, b_i, c_i, d_i and e_i	Cost coefficients of unit i
$\underline{P}_{G,i}^{k}$	Lower bound of the k^{th} fuel type/prohibited zone of unit i
$\overline{P}_{G,i}^{k}$	Upper bound of the k^{th} fuel type/prohibited zone of unit i
$a_{i,k}, b_{i,k}, c_{i,k}$	k^{th} fuel cost coefficients of unit i
n_z	Number of prohibited zones of unit i
$\alpha_i, \beta_i, \gamma_i, \mu_i$ and λ_i	Emissions coefficients of unit i
$E_i\left(P_{G_i}\right)$	Emissions function for unit i
E_S	System/Area emission limit
E_{U_i}	i^{th} unit emission limit
Lf_i	Power flowing on branch i
$Lf_i^{\max}$	Maximum power transfer capability of branch i
N_L	Number of branches

$\boldsymbol{Lf}^0$	Original vector of line flows
$\boldsymbol{Lf}^1$	Updated vector of line flows
$\mathbf{A}_{GSF}$	Sensitivity shift factors matrix
$\boldsymbol{P}^0$	Original column vector of power outputs
$\boldsymbol{P}^1$	Updated column vector of power outputs
S_{R_i}	Spinning reserve capability of unit *i* at given output
S_R^{req}	System spinning reserve requirement
$S_{R_i}^{\max}$	Maximum spinning reserve capability of unit *i* in emergency conditions
$\underline{P}_{G_i}$	Lower real power generation limit due to ramp rate
$\overline{P}_{G_i}$	Upper real power generation limit due to ramp rate
$P_{G,i}^0$	Current i^{th} unit real power output
DR_i	i^{th} unit descending ramp
AR_i	i^{th} unit ascending ramp
g_{ij}	Transmission line *ij* conductance
$\lvert V_i - V_j \rvert$	Magnitude of the voltage drop across the branch between buses *i* and *j*
V_i	Complex voltage at bus *i*
N_B	Number of system buses
Q_{G_i}	Reactive power injected at bus *i*
P_{D_i}	Active power demanded at bus *i*
Q_{D_i}	Reactive power demanded at bus *i*
$\lvert Y_{ij} \rvert$	Admittance magnitude connecting between nodes *i* and *j*
θ_{ij}	Admittance angle connecting between nodes *i* and *j*

$\lvert V_i \rvert$	Voltage magnitude at bus *i*
δ_i	Voltage angle at bus *i*
$Q_G^{\min}$	Lower reactive power production limit
$Q_G^{\max}$	Upper reactive power production limit
$T_i^{\min}$	Lower adjustable tap ratio of the i^{th} transformer
$T_i^{\max}$	Upper adjustable tap ratio of the i^{th} transformer
N_T	Number of LTC transformers.
$Q_{C_i}^{\min}$	Lower limit of the i^{th} capacitor bank
$Q_{C_i}^{\max}$	Upper limit of the i^{th} capacitor bank
N_C	Number of adjustable capacitor banks
$S_{G_i}^{\max}$	Apparent power upper limit of the i^{th} generator
$\lvert V_i \rvert^{\min}$	Voltage magnitude lower bound
$\lvert V_i \rvert^{\max}$	Voltage magnitude upper bound

CHAPTER 3

N_P	Population Size
C_R	Crossover Constant
F	Scaling Factor
D	Parameter Vector Dimension
$\mathbf{G}$	Generation
$\mathbf{P}^{(\mathbf{G})}$	Population of generation **G**
$\mathbf{X}_i$	Individual *i*
$X_{D,i}$	*D* parameter of Individual *i*
$X_j^{\min}$	Lower bound of the j^{th} decision parameter

$X_j^{\max}$	Upper bound of the j^{th} decision parameter
η_j	Uniformly distributed random number within [0, 1]
$\mathbf{X}_i'$	Mutant Vector
$\mathbf{X}_i''$	Trial Vector
η_j'	Uniformly distributed random number within [0, 1]
$\mathbf{Y}$	Vector of continuous parameters
$\mathbf{Z}$	Vector of discrete parameters

CHAPTER 4

F'	Objective Function
G_i	i^{th} Equality Penalty Function
H_j	j^{th} Inequality Penalty Function
F''	Fitness Function
ω_i	Equality Penalty Weight
μ_i	Inequality Penalty Weight
$\boldsymbol{P}_G$	Vector of Real Power Outputs
$P_{G,i}$	i^{th} element of the vector $\boldsymbol{P}_G$
$\mathbf{X}$	Decision Parameter Vector
δ	Pareto Weight
κ_i	Emissions Conversion Factor

CHAPTER 1

INTRODUCTION

1.1 Introduction

Optimal generation dispatch represents one of the most important problems in power systems engineering, being a technique commonly used by operators in everyday system operation. Optimal generation dispatch seeks to allocate the real and reactive power throughout the power system obtaining an optimal operating state that reduces costs and improves overall system efficiency. This problem can be formulated and solved as two separate problems. One is the economic dispatch problem which reduces system cost by allocating the real power among the online generating units. Another problem is the reactive power dispatch which improves system voltage profile and reduces system losses by allocating the reactive power efficiently.

Modeling in the generation dispatch problem is critical to achieve optimal results. In the economic dispatch problem, the classical formulation presents deficiencies due to the simplicity of the models. Here, the power system is modeled through the power balance equation and generators are modeled with smooth quadratic cost functions and generator output side constraints. In the reactive power problem, a common approach is to model transformers and capacitor banks as continuous variables instead of the discrete variables.

To improve power systems studies, new models are continuously being developed that result in a more efficient system operation. Cost functions that consider valve point loadings [1-6], fuel switching [7-12] and prohibited operating zones [13-18] as well as constraints that provide a more accurate representation of the system such as: emissions [19-31], line flow limits [32-36], ramp rate limits [37], spinning reserve requirement [38, 39] and system voltage profile [40-55]. These improved models generally increase the level of complexity of the optimization problem due to the nonlinearity associated with them.

Many different traditional optimization methods have been used to solve the classical economic dispatch and reactive power dispatch problems including: Steepest Descent, Newton, Interior Point Methods, Linear Programming, Quadratic Programming and Dynamic Programming. Some of these techniques are not capable of solving efficiently optimization problems with a non-convex, non-continuous and highly nonlinear solution space. Other techniques become inefficient since they require too many computational resources to provide accurate results for large scale systems such as electric power systems.

Recent advances in computation and the search for better results of complex optimization problems have fomented the development of techniques known as Evolutionary Algorithms. Evolutionary Algorithms are stochastic based optimization techniques that search for the solution of problems using a simplified model of the evolutionary process. These algorithms provide an alternative for obtaining global optimal solutions, especially in the presence of non-continuous, non-convex, highly solution spaces. These algorithms are population based techniques which explore the solution space randomly by using several candidate solutions instead of the single solution estimate used by many classical techniques. The success of evolutionary algorithms lies in the capability of finding solutions with random exploration of the feasible region rather than exploring the complete region. This results in a faster optimization process with lesser computational resources while maintaining the capability of finding global optima.

Several techniques have been developed inside the Evolutionary Computation field being the most popular techniques: Genetic Algorithms (GA), Evolutionary Programming (EP) and Evolution Strategies (ES) all of which have been applied successfully to numerous engineering problems. The recent advances in parallel computation along with faster and more powerful processors have improved greatly the performance of these techniques, and have stimulated the development of new techniques such as Differential Evolution, Particle Swarm Optimization, Ant Colony Search, Scatter Search and Cultural Algorithms. References [56-58] provide a good review on evolutionary computation application and formulation.

One algorithm that has become increasingly popular in the field of evolutionary computation is Differential Evolution (DE). DE is very appealing due to the great convergence characteristics that it presents when compared to other algorithms from evolutionary computation. Also the few control parameters of DE require minimum tuning and remain fixed throughout the optimization process [59-61]. DE obtains solutions to optimization problems using three basic operations: Mutation, Crossover and

Selection. The mutation operator generates noisy replicas (mutant vectors) of the current population inserting new parameters in the optimization process. The crossover operator generates the trial vector by combining the parameters of the mutant vector with the parameters of a parent vector selected from the population. In the selection operator the trial vector competes against the parent vector and the one with better performance advances to the next generation. This process is repeated over several generations resulting in an evolution of the population to an optimal value.

1.2 Topic of the Thesis

The topic of this thesis is "Differential Evolution Based Power Dispatch Algorithms". This research covers four different generation dispatch problems and solves them using the novel evolutionary computation technique known as Differential Evolution.

1.3 Objectives and Contributions of the Thesis

The main purpose of this research work is to investigate the applicability of Differential Evolution to the economic dispatch problem and prove that this algorithm can be used to efficiently determine solutions to complex economic dispatch problems. Differential Evolution will be tested on several case studies that are extremely difficult or impossible to solve by standard techniques due to the non-convex, non-continuous and highly nonlinear solution space of the problem.

Specific objectives are:

1. To analyze and solve the optimal generation dispatch problem using different objective functions and constraints which present discontinuities and increase the degree of difficulty of the problem using the differential evolution algorithm.

2. To compare the results obtained with results from other evolutionary algorithms and/or other optimization algorithms used in the industry.

3. To test different economic dispatch problem formulations that may result in an improved optimization process in terms of type of solution (local or global minima), consistency of the solution, algorithm quickness and computational requirements.

4. Test the algorithm potential to obtain global minima solutions of complex optimization problems.

5. To evaluate the tradeoff associated with the algorithm control parameters variation.

6. To organize the systems used for testing and results of the cases studies to allow easy reproduction of the research, for future developments in the evolutionary optimization field or any other optimization algorithm.

7. To present recommendations regarding the implementation and control of the algorithm.

1.4 Thesis Outline

An introduction to the differential evolution based power dispatch algorithm was presented in Chapter 1 along with the research objectives and scope. Chapter 2 provides a review of the economic dispatch and the reactive power dispatch problem, problem formulation and available literature. Chapter 3 presents an overview of the differential evolution algorithm. In Chapter 4 the case studies and their implementation using the differential evolution algorithm are presented. Results and validation are provided and discussed for each case study in Chapter 5. Chapter 6 presents conclusions and recommendations for future work.

CHAPTER 2

POWER DISPATCH

2.1 Introduction

To operate power systems in an efficient and reliable way, several techniques have been developed to schedule power plants and determine their production level. Power dispatch is one of these techniques which adjusts some control variables and allocates the power throughout the system resulting in an optimal operation. Power dispatch has two approaches: Economic Dispatch Problem and the Reactive Power Dispatch Problem. Economic dispatch seeks to optimize the system operation by allocating the real power among the power system while reducing production costs. The reactive power dispatch minimizes the system losses improving the system efficiency and utilization of resources.

To improve the solution obtained from the power dispatch, system modeling is critical. Reduced models are often used, simplifying the problem solution at the expense of quality. The use of more precise and accurate models yield better solutions but also increases problem difficulty significantly. Common modeling efforts to improve the economic dispatch include cost functions with valve point loadings, prohibited operating zones and fuel switching; security constraints such as line flow limits, spinning reserve allocation and other constraints like emissions and voltage profile. This chapter reviews how the economic dispatch and reactive power dispatch problems are formulated, and the available literature related to these problems.

2.2 Classical Economic Dispatch Problem Formulation

The classical economic dispatch problem is an optimization problem that determines the power output of each online generator that will result in a least cost system operating state [1, 2]. The objective of the classical economic dispatch is to minimize the total system cost where the total system cost is a function composed by the sum of the cost functions of each online generator. This power allocation is done considering system balance between generation and loads, and feasible regions of operation for each generating unit.

2.2.1 Objective Function

The objective of the classical economic dispatch is to minimize the total system cost (2.1) by adjusting the power output of each of the generators connected to the grid. The total system cost is modeled as the sum of the cost function of each generator.

$$\min \sum_{i=1}^{N_G} F_i\left(P_{G_i}\right) \tag{2.1}$$

where $F_i\left(P_{G_i}\right)$ is the i^{th} generator cost function, P_{G_i} is the i^{th} generator real power output and N_G is the total number of generators connected to the power system.

Each generator cost function establishes the relationship between the power injected to the system by the generator and the incurred costs to load the machine to that capacity. Typically, generators are modeled by smooth quadratic functions such as (2.2) to simplify the optimization problem and facilitate the application of classical techniques.

$$F_i\left(P_{G_i}\right) = a_i + b_i P_{G_i} + c_i P_{G_i}^2 \tag{2.2}$$

where a_i, b_i, c_i are the cost coefficients of the i^{th} generator cost function.

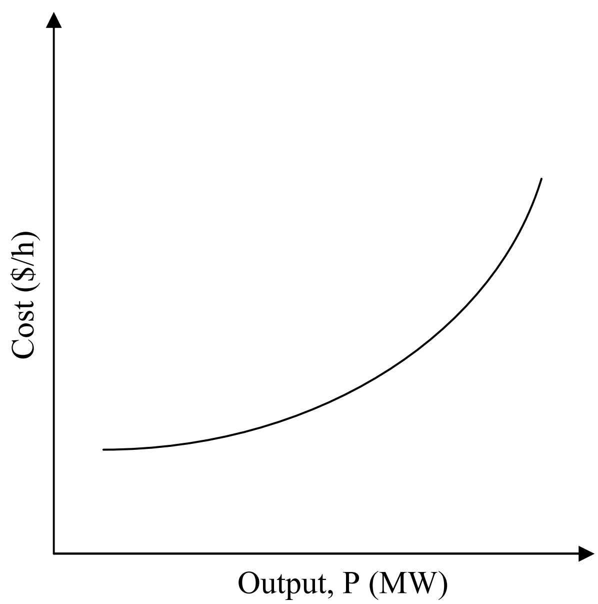

Fig. 1 Typical fuel cost function of a thermal generation unit

2.2.2 Equality Constraint

Power Balance Constraint: The power balance constraint is an equality constraint that reduces the power system to a basic principle of equilibrium between total system generation and total system loads. Equilibrium is only met when the total system generation $\left(\sum P_{G_i}\right)$ equals the total system load $\left(P_D\right)$ plus system losses $\left(P_L\right)$ as stated in (2.3).

$$\sum_{i=1}^{N_G} P_{G_i} = P_D + P_L \tag{2.3}$$

Systems losses can be determined exactly as a result of solving the power flow problem. One approach to estimate losses is by modeling them as a function of the system generators outputs using Kron's loss formula (2.4). Other ways to model losses are with the use of penalty factors or considering losses as constant.

$$P_L = \sum_{i=1}^{N_G}\sum_{j=1}^{N_G} P_{G_i} B_{ij} P_{G_i} + \sum_{i=1}^{N_G} P_{G_i} B_{i0} + B_{00} \tag{2.4}$$

where B_{ij}, B_{i0}, B_{00} are known as the loss or *B*-coefficients.

2.2.3 Inequality Constraint

<u>Real Power Generation limits</u>: Generating units have lower $\left(P_{G_i}^{\min}\right)$ and upper $\left(P_{G_i}^{\max}\right)$ production limits that are directly related to the machine design. These bounds can be defined as a pair of inequality constraints (2.5).

$$P_{G_i}^{\min} \le P_{G_i} \le P_{G_i}^{\max}, \quad i = 1,\ldots,N_G \tag{2.5}$$

2.3 Non-Conventional Fuel Cost Functions

Generators are commonly modeled using smooth quadratic functions (Fig.1) to relate power output to production cost. This type of cost function simplifies greatly the economic dispatch problem and increases the number of techniques that can be applied to solve it. For some cases, quadratic representations do not model properly generators, requiring more accurate models to provide better results in the solution of the economic dispatch problem. More accurate models usually result in higher nonlinear, non-smooth and non-convex functions. Valve point loadings, piecewise quadratic functions due to multiple fuels and prohibited regions of operation are examples of these types of cost functions.

2.3.1 Valve Point Loadings

Power plants commonly have multiple valves that are used to control the power output of the unit [1-6]. When steam admission valves in thermal units are first opened, a sudden increase in losses is registered which results in ripples in the cost function (Fig. 2). This effect is known as a valve point loading. This type of problem is extremely difficult to solve with conventional gradient based techniques due to the abrupt changes and discontinuities present in the incremental cost function.

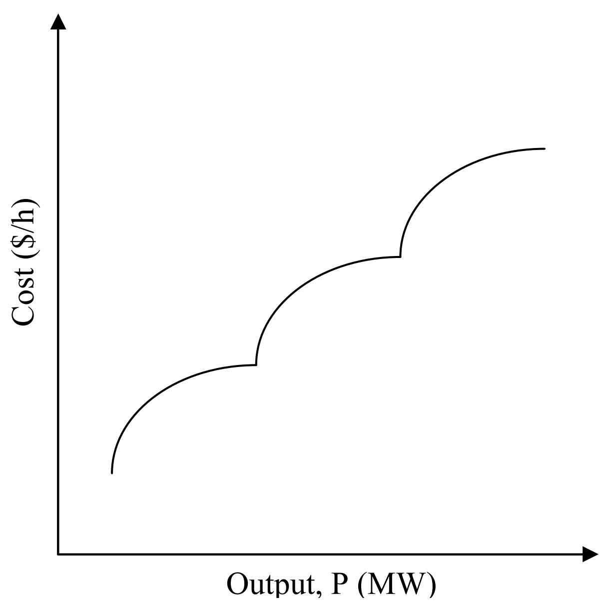

Fig. 2 Fuel cost function for a thermal generation unit with three admission valves

2.3.1.1 Economic Dispatch with Valve Point Loadings Formulation

Valve Point Loadings economic dispatch minimizes the system cost (2.1) based on the valve point loading cost function that considers valve transitions. Valve point loadings are usually modeled adding a sinusoidal term to the basic quadratic cost function (2.6).

$$F_i\left(P_{G_i}\right) = a_i + b_i P_{G_i} + c_i P_{G_i}^2 + \left| d_i \sin\left(e_i\left(P_{G_i}^{\min} - P_{G_i}\right)\right)\right| \tag{2.6}$$

where a_i, b_i, c_i, d_i and e_i are the cost coefficients of unit *i*.

The basic formulation of this problem is subject to the power balance constraint (2.3) and generation limits (2.5). Further constraints can be added depending on the modeling requirements.

The economic dispatch with valve point loadings has received attention from several researchers. Sheblé and Walters [3] used a genetic algorithm to solve the economic dispatch featuring units with valve point loadings. Also, K. Wong and Y. Wong [4] proposed a way of solving the economic dispatch problem with valve point loadings using genetic and genetic/simulated annealing techniques. K. Wong along with B. Lau and A. Fry [5] presented a neural network approach for economic dispatch featuring valve point loadings. Basic concepts of valve point loadings and their cost functions are presented in [1] and [2].

2.3.2 Piecewise Quadratic Functions

Some generating units are capable of operating under different types of fuels [7]. The use of multiple fuel types may result in multiple cost curves that are not necessarily parallel or continuous. The lower contour of the resulting cost curve determines which fuel cost is most economical to burn.

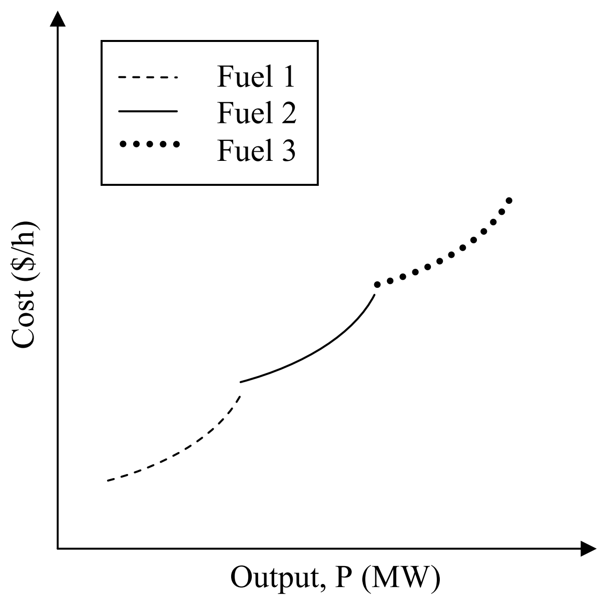

Fig. 3 Fuel cost function of a thermal generation unit supplied with multiple Fuels

This cost function can be represented by a piecewise curve (Fig. 3), and the segments are defined by the range in which each fuel is used (2.7). Piecewise quadratic curves are extremely difficult to solve by standard techniques. Piecewise quadratic functions have as many segments as fuel types.

$$F_i\left(P_{G_i}\right)=\begin{cases} a_{i,1}+b_{i,1}P_{G_i}+c_{i,1}P_{G_i}^2\,, & \underline{P}_{G_i}^1 < P_{G_i} < \overline{P}_{G_i}^1 \\ a_{i,2}+b_{i,2}P_{G_i}+c_{i,2}P_{G_i}^2, & \underline{P}_{G_i}^2 < P_{G_i} < \overline{P}_{G_i}^2 \\ \quad\vdots & \\ a_{i,k}+b_{i,k}P_{G_i}+c_{i,k}P_{G_i}^2, & \underline{P}_{G_i}^k < P_{G_i} < \overline{P}_{G_i}^k \end{cases} \tag{2.7}$$

where $\underline{P}_{G_i}^k$ and $\overline{P}_{G_i}^k$ are the lower and upper bound respectively of the k^{th} fuel of unit i and $a_{i,k}, b_{i,k}, c_{i,k}$ are the k^{th} fuel cost coefficients of unit i.

2.3.2.1 Piecewise Quadratic Functions Economic Dispatch Formulation

This economic dispatch minimizes the system cost (2.1) based on piecewise quadratic cost functions (2.7) subject to the power balance constraint (2.3) and the generation limits (2.5). Further constraints can be added depending on the modeling requirements.

One of the classical approaches for solving this problem was proposed by C. Lin and G. Viviani [7]. In this paper they used a Hierarchical method to solve the economic dispatch of a system with piecewise quadratic cost functions. Other approaches capable of solving the piecewise quadratic economic dispatch based on evolutionary algorithms have been proposed. El-Gallad et al. [8] used the Particle Swarm Optimization technique to solve the economic dispatch with piecewise quadratic cost functions. Also, hybrid approaches were proposed by Whei-Min Lin [9] and by J. H. Park et al. [10] to determine the solution to piecewise quadratic case. In reference [9] Lin solves the Economic Dispatch problem featuring piecewise quadratic functions using an algorithm that integrates evolutionary programming, tabu search, and quadratic programming while Park et al. in [10] used several Evolutionary Algorithms to solve single and piecewise quadratic cost functions. These algorithms were Genetic Algorithm (GA), Evolution Strategies (ES), Evolutionary Programming (EP), GA + ES and EP + ES.

Neural Networks also have been applied to solve this type of Economic Dispatch. Lee et al. [11] presented an Adaptive Hopfield Neural Networks approach for Economic Load Dispatch with piecewise quadratic cost functions and Park et al. [10] also solved piecewise quadratic problems using Hopfield neural networks.

2.3.3 Prohibited Operating Zones

Units may have certain regions [13-18] where operation is undesired due to physical limitations of the machine components or issues related to instability. These regions (Fig. 4) produce discontinuities in the cost curve since the unit must operate under or over certain specified limit. This type of functions results in non-convex sets of feasible solutions.

2.3.3.1 Prohibited Operating Zones Formulation Economic Dispatch

The basic economic dispatch with prohibited zones minimizes the system cost (2.1) based on smooth quadratic cost functions (2.2). This cost function present regions were operation is not allowed and this regions can be modeled as inequality constraints (2.8-2.10). The dispatch considers also the power balance constraint (2.3) and the generation limits constraint (2.5). Further constraints can be added depending on the requirements of the model.

$$P_{G_i}^{\min} \le P_{G_i} \le \underline{P}_{G_i}^{1} \tag{2.8}$$

$$\overline{P}_{G_i}^{k-1} \le P_{G_i} \le \underline{P}_{G_i}^{k} \quad , \quad k = 2, \ldots, n_z \tag{2.9}$$

$$\overline{P}_{G_i}^{n_z} \le P_{G_i} \le P_{G_i}^{\max} \tag{2.10}$$

where $\underline{P}_{G_i}^{k}$ and $\overline{P}_{G_i}^{k}$ are the lower and upper bound of the k^{th} prohibited zone of unit i and n_z the number of prohibited zones of unit *i*.

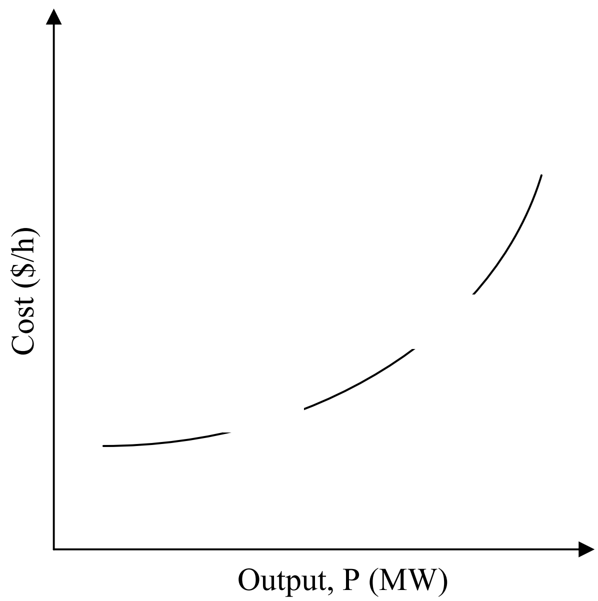

Fig. 4 Fuel cost function for a unit with two prohibited operating zones

Several techniques have been used to solve the economic dispatch problem considering prohibited operating zones. Lee and Breipohl [13] and Fan and McDonald [14] used techniques based on decision spaces to solve the economic dispatch with prohibited operating zones while Orero and Irving [15] used genetic algorithms. Chen et al. [16] presented a new genetic approach for solving the economic dispatch problem in large scale systems considering ramp rate limits and prohibited zones.

An evolutionary programming algorithm for prohibited zones economic dispatch was proposed by Jayabarthi, et al in [17]. Non convex economic dispatch by integrated artificial intelligence proposed by Whei-Min Lin, Fu-Sheng Cheng and Ming-Tong Tsay [9] solves prohibited zones using an algorithm that integrates EP, TS and QP. Su and Chiou [18] proposed a hopfield neural network approach considering prohibited zones.

2.4 Economic-Environmental Power Dispatch

After the 1990 Clean Air Act Amendments, environmental considerations have regained considerable attention in the power system industry due to the significant amount of emissions and other pollutants derived from fossil based power generation. The most important emissions considered in the power generation industry due to their effects on the environment are sulfur dioxide (SO_2) and nitrogen oxides (NO_X).

One of the techniques used to reduce emissions production in power systems is the Economic-Environmental Power Dispatch. This dispatch determines the power allocation that reduces system cost considering the level of emissions produced. To be able to carry out an Economic-Environmental Dispatch, these emissions must be modeled through functions that relate emissions with power production for each unit. Sulfur dioxide emissions are dependent on fuel consumption and they take the same form as the fuel cost functions used for economic dispatch [19-21]. NO_X emissions are more difficult to predict since they come from two different sources and their production is associated with several factors such as boiler temperature and air content [21].

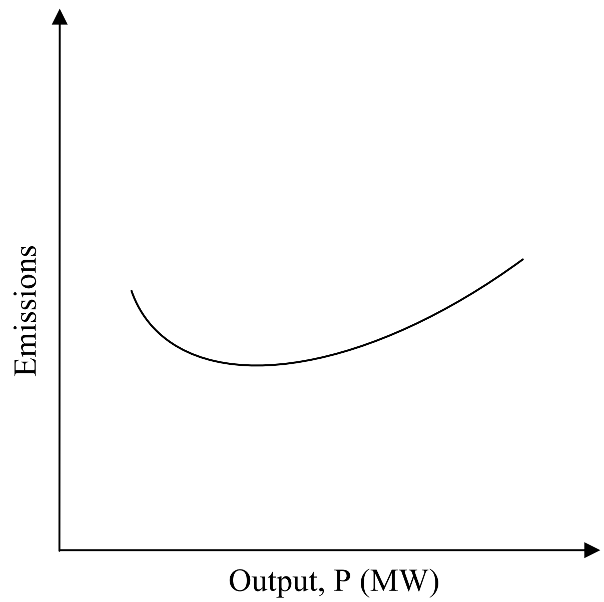

Fig. 5 Combined SO_2 and NO_X Emissions Function Example

One approach to represent SO_2 and NO_X emissions is to use a combination of polynomial and exponential terms (2.11). The parameters *α, β, γ, μ* and *λ* are determined by curve fitting techniques based on real test data [20]. Other approach is to model SO_2 emissions and NO_X emissions separately. The NO_X emission function is highly nonlinear and difficult to generalize. A NO_X emissions function example is shown on Fig. 6 [22].

$$E_i(P_{G_i}) = \alpha_i + \beta_i P_{G_i} + \gamma_i P_{G_i}^2 + \mu_i \exp(\lambda_i P_{G_i}) \tag{2.11}$$

where $\alpha_i, \beta_i, \gamma_i, \mu_i$ and λ_i are the emissions coefficients of unit *i*

EED has become an important topic of research due to the 1990 Clean Air Act that established emission control and reduction. Because of the nonlinear characteristics of emissions, several approaches using evolutionary algorithms and neural networks have been developed capable of solving the EED.

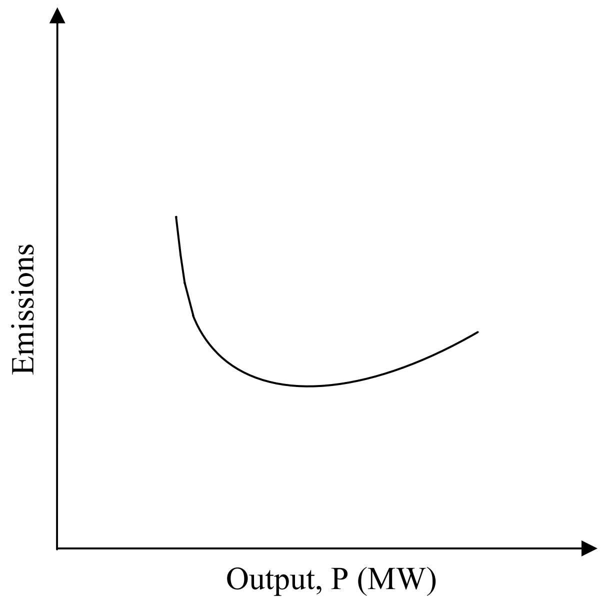

Fig. 6 NOx Emissions Function Example

Talaq et al. [20] and Lamont et al. [21] have presented comprehensive studies that feature emissions modeling, problem formulation and dispatching strategies. Wong and Yuryevich [23] developed an evolutionary programming based algorithm presenting emissions as constraints. Das and Patvardhan [24] proposed a multiobjective stochastic search technique (MOSST) based on real coded GA and SA using single criterion function optimization. Abido [25, 27] presents a Multiobjective Evolutionary Algorithm that determines the pareto optimal set simultaneously using the strength pareto evolutionary algorithm. Other implementations have been proposed to solve the economic/environmental dispatch such as the heuristic guided evolutionary algorithm, [27] genetic algorithm with generation compensation [28], neural networks and hierarchical approach [29, 30].

2.4.1 Multiobjective Economic/Environmental Dispatch Formulation

The nature of cost and emission production allows the economic/environmental power dispatch problem to be formulated and solved as a multiobjective optimization problem. In multiobjective optimization problems (MOP) two competing objectives are minimized simultaneously, subject to the imposed constraints. MOP's have infinite optimal solutions, and this set of possible solutions is referred to as the Pareto optimal set. Multiobjective optimization problems can be solved by different approaches. One approach converts the problem to a single function optimization problem using aggregating techniques such as weighted sum. Another approach is based on non-dominated ranking and selection to determine the Pareto-optimal set [62].

2.4.1.1 Objective Function

The objective of the economic/environmental power dispatch is to minimize simultaneously the cost function and the emissions function (2.12).

$$\min\left[\sum_{i=1}^{N_G} F_i\left(P_{G_i}\right), \sum_{i=1}^{N_G} E_i\left(P_{G_i}\right)\right] \tag{2.12}$$

where $F_i\left(P_{G_i}\right)$ is a cost function such as (2.2); $E_i\left(P_{G_i}\right)$ is an emissions function such as (2.11).

2.4.1.2 Constraints

This problem is subject to the basic system constraints such as the power balance equality constraint (2.3) and generation limits inequality constraint (2.5). Other constraints such as security or operational constraints can be considered depending on the study requirements.

2.4.2 Emissions Constrained Economic Dispatch Formulation

The purpose of an emissions constrained dispatch is to minimize the cost function (2.2) subject to the power balance constraint (2.3) and generation limits (2.5) while satisfying the desired emissions limits (2.13-2.14). Emissions can be expressed as a nonlinear function such as (2.11) or other expressions depending on the unit characteristics. Other constraints such as line flow constraints and/or voltage profile can also be considered to improve the security of the system.

Emission constraints are nonlinear inequality constraints that impose a limit on the emissions of certain generation units or system areas (2.13, 2.14).

$$\sum_{i=1}^{N_G} E_i\left(P_{G_i}\right) \leq E_S \tag{2.13}$$

$$E_i\left(P_{G_i}\right) \leq E_{U_i} \tag{2.14}$$

where E_S is the System/Area emission limit for the corresponding emission (SO_2 and/or NO_X) and E_{U_i} the i^{th} unit emission limit for the corresponding emission (SO_2 and/or NO_X).

2.5 Security Constrained Power Dispatch

To improve the results of the economic dispatch and maintain proper system operation, other constraints such as line flow limits [32-36], ramp rate limits [37] and spinning reserve [38, 39] can be considered in the economic dispatch. These constraints give a more realistic operating condition, and provide better solutions from an operating standpoint.

2.5.1 Security Constrained Power Dispatch Problem Formulation

The security constrained power dispatch seeks to minimize the system cost (2.1) based on smooth quadratic cost functions (2.2). This problem is subject to the power balance equality constraint (2.3) and the generation limits inequality constraint (2.5). To provide a power allocation that will yield a better system operating point, the basic economic dispatch is enhanced with constraints that model better the power system and help attain the desired system condition. Common concerns of the power systems are overloading of transmission lines, proper allocation of the spinning reserve to enhance system stability and ramp rate limits to consider proper unit loading.

2.5.1.1 Line Flow Constraint

In many occasions, the power allocation from the economic dispatch leads to congestions in the transmission grid. The line flow constraint seeks to avoid undesired line loadings due to power allocation. This constraint is formulated as an inequality constraint (2.15).

$$Lf_i \le Lf_i^{\max}, \quad i = 1, \ldots, N_L \tag{2.15}$$

where Lf_i is the power flowing on branch i; $Lf_i^{\max}$ is the maximum power transfer capability of branch i and N_L is the number of transmission branches.

Line Flows can be determined by several methods. The most common approach is to determine the flows after solving the power flow algorithm. Another approach is to estimate the flows as a linear function of the power outputs using the generation shift factors (2.16) [2, 39].

$$\boldsymbol{Lf}^{1} = \boldsymbol{Lf}^{0} + \mathbf{A}_{GSF} \times \left(\boldsymbol{P}^{1} - \boldsymbol{P}^{0} \right) \tag{2.16}$$

where $\boldsymbol{Lf}^{0}$, $\boldsymbol{Lf}^{1}$ are the original and updated vector of line flows; $\mathbf{A}_{GSF}$ is the sensitivity shift factors matrix and $\boldsymbol{P}^{0}$, $\boldsymbol{P}^{1}$ are the original and updated column vector of power outputs.

2.5.1.2 Spinning Reserve Constraint

Spinning reserve is the amount of synchronized generation that can be used to pickup source contingencies or load increase. System spinning reserve requirement can be determined by several criteria such as a percentage of the forecasted peak demand, the most heavily loaded unit or the probability of not having sufficient generation to meet the load [2]. Spinning reserve should be sufficient to absorb source contingencies and has to be allocated efficiently to provide adequate response and sufficient reserve across the system in the case it becomes electrically disconnected, avoiding limitations in transportation due to grid congestion.

Spinning reserve can be associated to system emergency conditions or regulating conditions. Since both conditions are related, several formulations of spinning reserve are available. One way to allocate power for reserve purposes is expressed in (2.17-2.19) [39]. The available system reserve should be at least equal to the system requirement to overcome contingencies (2.17). For emergency conditions, the unit reserve should not exceed the established unit pickup capability (2.18). For regulating purposes in normal conditions, the unit available reserve should not exceed the difference between the maximum power output established for dispatch purposes and the current point of operation (2.19).

$$\sum_{i=1}^{N_G} S_{R_i} \geq S_R^{\mathrm{req}} \tag{2.17}$$

$$S_{R_i} \leq S_{R_i}^{\max} \tag{2.18}$$

$$S_{R_i} \leq (P_{G_i}^{\max} - P_{G_i}) \tag{2.19}$$

where S_{R_i} is the spinning reserve capability of unit i at given output, S_R^{req} the system spinning reserve requirement, $S_{R_i}^{\max}$ the maximum spinning reserve capability of unit i in emergency conditions.

2.5.1.3 Ramp Rate Limit Constraint

Due to the high nonlinear solution space of the economic dispatch, especially in large scale systems, the best solution of the economic dispatch can be located distant from the current point of operation when adjustments to the power allocation are required. Due to physical limitations, generating units adjust their power output according to ascending and descending ramp rates [2].

The ramp rate limit constraint gives better generation control, avoiding unacceptable changes in the power production of certain machines. This constraint updates the lower and upper generation limit (2.5, 2.22) according to (2.20) and (2.21) when a system operating point along with the machine ramp rate will prevent the unit from increasing/decreasing the loading to the desired value.

$$\underline{P}_{G_i} = \max\left[P_{G_i}^{\min}, P_{G_i}^{0} - DR_i\right] \tag{2.20}$$

$$\overline{P}_{G_i} = \min\left[P_{G_i}^{\max}, P_{G_i}^{0} + AR_i\right] \tag{2.21}$$

$$\underline{P}_{G_i} \le P_{G_i} \le \overline{P}_{G_i} \tag{2.22}$$

where $\underline{P}_{G_i}$ is the lower real power generation limit due to ramp rate, $\overline{P}_{G_i}$ the upper real power generation limit due to ramp rate, $P_{G_i}^{0}$ the previous hour i^{th} unit real power output, DR_i the i^{th} unit descending ramp and AR_i the i^{th} unit ascending ramp.

Several papers have been published that address the power dispatch security issues such as line flows and spinning reserve allocation. J. Chen and S. Chen [32] presented a power dispatch with line flow constraints based on sensitivity factors to obtain line flows. Several economic dispatch approaches considering line flows were proposed by Fan and Zhang [33], Nanda et al. in [34] and [35] and Yalcinoz and Short [36]. These articles solve the line flow constrained economic dispatch using quadratic programming, genetic algorithms, neural networks and other classical techniques.

Ongsakul et al. [37] proposed a genetic algorithm based on simulated annealing to solve ramp rate constrained dynamic economic dispatch. G. Sheblé [38] and R. Lugtu [39] have conducted research work on spinning reserve requirement and allocation, respectively.

2.6 Reactive Power Dispatch

Reactive power dispatch is treated as an optimization problem that reduces grid congestion by minimizing the active power losses for a fixed economic power dispatch. The RPD requires solving the power flow problem and for this reason is usually known as optimal reactive power dispatch or as an optimal power flow problem. Reactive power dispatch (RPD) reduces power system losses and provides better system voltage control, resulting in an improved voltage profile, system security, power transfer capability and overall system operation [40].

2.6.1 Problem Formulation

The reactive power dispatch (RPD) problem consists of minimizing the active power losses of the system by adjusting the system reactive power control variables such as generator voltages, transformers taps, and capacitor banks for a fixed real power dispatch. The RPD is subject to control variables boundary constraints, as well as other system constraints such as system balance and bus voltage limits.

2.6.1.1 Objective Function

The objective of the reactive power dispatch is to minimize the active power losses of the system by adjusting the generator voltages, transformer taps and other sources of reactive power such as capacitor banks.

$$\min P_L \tag{2.23}$$

where

$$P_L = \sum_{i=1}^{N_B} \sum_{j=1}^{N_B} g_{ij} \times \left|V_i - V_j\right|^2 \tag{2.24}$$

and P_L is the power system losses, g_{ij} is the transmission line *ij* conductance, $\left|V_i - V_j\right|$ represents the magnitude of the voltage drop across the branch between buses *i* and *j* respectively and N_B is the number of system buses. V_i is the complex voltage at bus *i*.

2.6.1.2 Equality Constraints

<u>Real and Reactive Power Mismatch</u>: These equality constraints seek to find the set of voltages (magnitude and angle) that satisfy the proposed system conditions. These are the power expressions of the Kirchhoff laws that establish system equilibrium and energy conservation in electric circuits.

$$P_{G_i} - P_{D_i} - \sum_{j=1}^{N_B} \left|Y_{ij}\right|\left|V_i\right|\left|V_j\right| \cos\left(\theta_{ij} + \delta_j - \delta_i\right) = 0 \tag{2.24}$$

$$Q_{G_i} - Q_{D_i} + \sum_{j=1}^{N_B} \left|Y_{ij}\right|\left|V_i\right|\left|V_j\right| \sin\left(\theta_{ij} + \delta_j - \delta_i\right) = 0 \tag{2.25}$$

where P_{G_i} and Q_{G_i} are the active and reactive power injected at bus *i*; P_{D_i} and Q_{D_i} are the active and reactive power demanded at bus *i*; $|Y_{ij}|$ and θ_{ij} are the admittance magnitude and angle connecting nodes *i* and *j*, $|V_i|$ and δ_i the voltage magnitude and angle at bus *i* and $|V_j|$ and δ_j voltage magnitude and angle at bus *j*.

2.6.1.3 Inequality Constraints

Reactive Power Generation limits: Generating units have lower $\left(Q_G^{\min}\right)$ and upper $\left(Q_G^{\max}\right)$ reactive power production limits that are directly related to the machine design. These bounds can be defined as a pair of inequality constraints.

$$Q_{G_i}^{\min} \le Q_{G_i} \le Q_{G_i}^{\max}, \quad i = 1, \ldots, N_G \tag{2.26}$$

where Q_{G_i} is the reactive power production of the i^{th} generator.

Transformer taps limits: Many transformers are capable of providing small adjustments to the output voltage by changing their turn ratio or taps. Transformers that can perform this operation while energized are called load-tap-changing transformers (LTC). These taps can be changed inside a range usually of ±10%. As the reactive power generation limits, these bounds can also be defined as a pair of inequality constraints.

$$T_i^{\min} \le T_i \le T_i^{\max}, \quad i = 1, \ldots, N_T \tag{2.27}$$

where $T_i^{\min}$ and $T_i^{\max}$ are the lower and upper adjustable tap ratio of the i^{th} transformer and N_T the number of LTC transformers.

In addition transformer taps are discrete, having fixed increments (Δ_T) between consecutive values.

$$\Delta_T = T_{i,k+1} - T_{i,k} \tag{2.28}$$

where $T_{i,k}$ and $T_{i,k+1}$ are the k^{th} and k^{th} +1 tap positions.

Capacitor Bank limits: Some capacitor banks can adjust their capacity by connecting/disconnecting capacitors. These as well as generating units, have a region of operation with lower and upper limits.

$$Q_{C_i}^{\min} \le Q_{C_i} \le Q_{C_i}^{\max}, \quad i = 1, \ldots, N_C \tag{2.29}$$

where $Q_{C_i}^{\min}$ and $Q_{C_i}^{\max}$ are the lower and upper limit of the i^{th} capacitor bank and N_C the number of adjustable capacitor banks.

Capacitor banks have fixed increments between consecutive values that depend on the combination of capacitors in service, between stages. These increments are not necessarily equal throughout the range of operation.

$$\Delta_{Q_c} = Q_{C_{i,k+1}} - Q_{C_{i,k}} \tag{2.30}$$

where Δ_{Q_c} is the increment between consecutive values and $Q_{C_{i,k}}$ and $Q_{C_{i,k+1}}$ are the k^{th} and k^{th} +1 capacitor size.

Maximum Power Output limit: Generating units can not exceed their maximum apparent power output due to physical machine limitations.

$$S_{G_i} \le S_{G_i}^{\max}, \quad i = 1, \ldots, N_G \tag{2.31}$$

where $S_{G_i}^{\max}$ is the upper limit of apparent power production of the i^{th} generator.

Bus Voltage limits: Reactive power is capable of improving the system voltages. The purpose of this constraint is to keep buses operating between desired per unit voltage limits, and determine the reactive power production related to this profile. Bus voltages are state variables derived from the solution of the power flow problem. This constraint can be defined by (2.32).

$$|V_i|^{\min} \le |V_i| \le |V_i|^{\max}, \quad i = 1, \ldots, N_B \tag{2.32}$$

where $|V_i|^{\min}$ and $|V_i|^{\max}$ the upper and lower voltage magnitude bounds for the i^{th} bus.

Several optimization techniques have been applied in the RPD problem. Gradient based approach [41], Modified Newton [42], Quadratic Programming [43], Newton Based Primal-Dual Method [44] and Interior Point Methods [45, 46] are some of the classical techniques used to solve the reactive power dispatch problem. More recently, evolutionary computation techniques also have been used to solve the RPD problem. Genetic Algorithms [47], Evolutionary Programming [48] and Evolution Strategies [49] along with some hybrid approaches [50, 51] are examples of evolutionary algorithms which also have been used to solve the reactive power dispatch problem. Reference [52] provides a comprehensive review of the reactive power dispatch problem.

CHAPTER 3

DIFFERENTIAL EVOLUTION

3.1 Introduction

Evolutionary Algorithms are optimization techniques that solve problems using a simplified model of the evolution process. These algorithms are based on the concept of a population of individuals that evolve and improve their fitness through probabilistic operators like recombination and mutation. These individuals are evaluated and those that perform better are selected to compose the population in the next generation. After several generations these individuals should improve their fitness as they explore the solution space for the optimal value.

The field of evolutionary computation has experienced significant growth in the optimization area thanks to the recent advances in computation. These algorithms are capable of solving complex optimization problems such as those with a non-continuous, non-convex and highly nonlinear solution space. In addition, they can solve problems that feature discrete or binary variables, which are extremely difficult.

Several algorithms have been developed within the field of Evolutionary Computation being the most studied Genetic Algorithms, Evolutionary Programming and Evolution Strategies. These algorithms were first conceived in the 1960's when Evolutionary Computation started to get attention. Recently, the success achieved by Evolutionary Algorithms in the solution of complex problems and the improvements made in computation, such as parallel computation, have stimulated the development of new algorithms like Differential Evolution, Particle Swarm Optimization, Ant Colony Search and Scatter Search that present great convergence characteristics and capability of determining global optima. Evolutionary algorithms have been successfully applied to many optimization problems within the power systems area and to the economic dispatch problem in particular. References [56-57] provide excellent reviews on this subject.

3.2 Differential Evolution

One extremely powerful algorithm from Evolutionary Computation due to convergence characteristics and few control parameters is differential evolution. Differential Evolution is an optimization algorithm that solves real-valued problems based on the principles of natural evolution [59-61] using a population **P** of N_P floating point encoded individuals (3.1) that evolve over **G** generations to reach an optimal solution. Each individual, or candidate solution, is a vector that contains as many parameters (3.2) as the problem decision variables *D*. In Differential Evolution, the population size (N_P) remains constant throughout the optimization process.

$$\mathbf{P}^{(\mathbf{G})} = \left[\mathbf{X}_1^{(\mathbf{G})}, \ldots, \mathbf{X}_{N_P}^{(\mathbf{G})}\right] \tag{3.1}$$

$$\mathbf{X}_i^{(\mathbf{G})} = \left[X_{1,i}^{(\mathbf{G})}, \ldots, X_{D,i}^{(\mathbf{G})}\right]^{\mathbf{T}}, i = 1, \ldots, N_P \tag{3.2}$$

Differential Evolution creates new offsprings by generating a noisy replica of each individual of the population. The individual that performs better from the parent vector (target vector) and the replica (trial vector) advances to the next generation. This optimization process is carried out with three basic operations: Mutation, Crossover and Selection. First, the mutation operation creates mutant vectors by perturbing each target vector with the weighted difference of two other individuals selected randomly. Then, the crossover operation generates trial vectors by mixing the parameters of the mutant vectors with the target vectors, according to a selected probability distribution. Finally, the selection operator forms the next generation population by selecting between the trial vector and the corresponding target vector those that fit better the objective function.

3.3 DE Optimization Process

The first step in the DE optimization process is to create an initial population of candidate solutions by assigning random values to each decision parameter of each individual of the population. Such values must lie inside the feasible bounds of the decision variable, and can be generated by (3.3).

$$X_{j,i}^{(\mathbf{0})} = X_j^{\min} + \eta_j \left(X_j^{\max} - X_j^{\min} \right), \; i = 1, \ldots, N_P; \; j = 1, \ldots, D \tag{3.3}$$

where $X_j^{\min}$ and $X_j^{\max}$ are respectively, the lower and upper bound of the j^{th} decision parameter and η_j is a uniformly distributed random number within [0, 1] generated anew for each value of j.

After the population is initialized, this evolves through the operators of mutation, crossover and selection. The mutation operator is in charge of introducing new parameters into the population. To achieve this, the mutation operator creates mutant vectors by perturbing a randomly selected vector ($\mathbf{X}_a$) with the difference of two other randomly selected vectors ($\mathbf{X}_b$ and $\mathbf{X}_c$) according Eq. 2.37. All of these vectors must be different from each other, requiring the population to be of at least four individuals to satisfy this condition. To control the perturbation and improve convergence, the difference vector is scaled by a user defined constant in the range [0, 1.2]. This constant is commonly known as the scaling constant (F).

$$\mathbf{X}_i'^{(\mathbf{G})} = \mathbf{X}_a^{(\mathbf{G})} + F\left(\mathbf{X}_b^{(\mathbf{G})} - \mathbf{X}_c^{(\mathbf{G})}\right),\ i = 1, \ldots, N_P \tag{3.4}$$

where $\mathbf{X}_a, \mathbf{X}_b, \mathbf{X}_c,$ are randomly chosen vectors $\in \{1, \ldots, N_P\}$ and $a \neq b \neq c \neq i$. $\mathbf{X}_a, \mathbf{X}_b$ and $\mathbf{X}_c,$ are generated anew for each parent vector. F is the scaling constant.

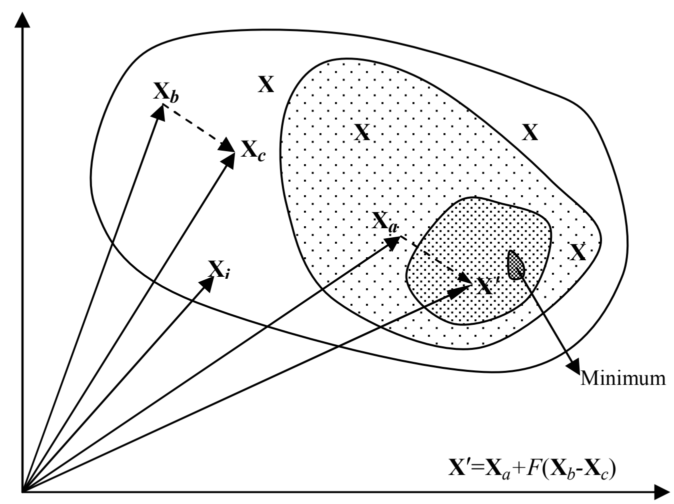

Fig. 7 Mutation Operator

The crossover operator creates the trial vectors, which are used in the selection process. A trial vector is a combination of a mutant vector and a parent (target) vector performed based on probability distributions. For each parameter, a random value based on binomial distribution (preferred approach) is generated in the range [0, 1] and compared against a user defined constant referred to as the crossover constant. If the value of the random number is less or equal than the value of the crossover constant the parameter will come from the mutant vector, otherwise the parameter comes from the parent vector (3.5). Fig. 8 shows how the crossover operation is performed.

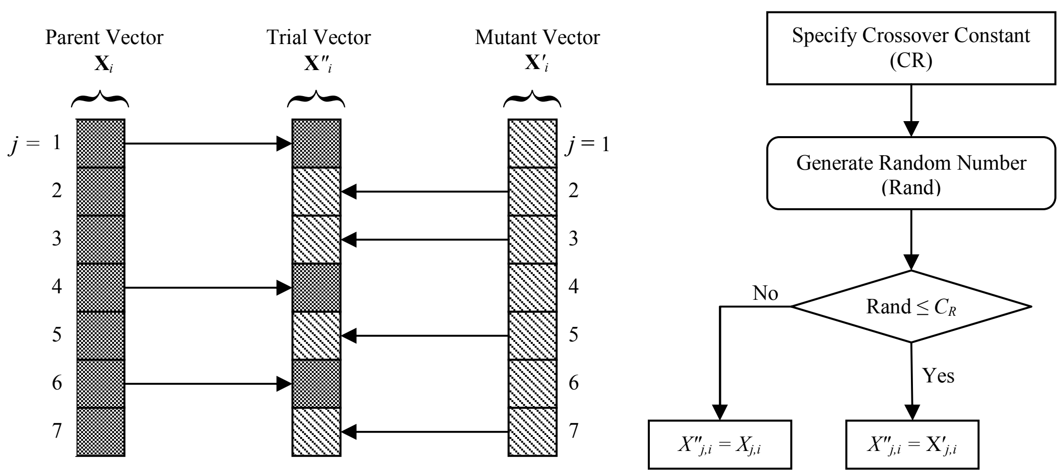

Fig. 8 Crossover Operator

The crossover operation maintains diversity in the population, preventing local minima convergence. The crossover constant (C_R) must be in the range of [0, 1]. A crossover constant of one means the trial vector will be composed entirely of mutant vector parameters. A crossover constant near zero results in more probability of having parameters from the target vector in the trial vector. A randomly chosen parameter from the mutant vector is always selected to ensure that the trial vector gets at least one parameter from the mutant vector even if the crossover constant is set to zero.

$$X''^{(\mathbf{G})}_{j,i} = \begin{cases} X'^{(\mathbf{G})}_{j,i} & \text{if} \quad \eta'_j \le C_R \quad \text{or} \quad j = q \\ X^{(\mathbf{G})}_{j,i} & \text{otherwise} \end{cases}, \quad i = 1,\ldots,N_p, \quad j = 1,\ldots,D \quad (3.5)$$

where q is a randomly chosen index $\in \{1,\ldots,D\}$ that guarantees that the trial vector gets at least one parameter from the mutant vector; η'_j is a uniformly distributed random number within [0, 1) generated anew for each value of j. $X^{(\mathbf{G})}_{j,i}$ is the parent (target) vector, $X'^{(\mathbf{G})}_{j,i}$ the mutant vector and $X''^{(\mathbf{G})}_{j,i}$ the trial vector.

The selection operator chooses the vectors that are going to compose the population in the next generation. This operator compares the fitness of the trial vector and the fitness of the corresponding target vector, and selects the one that performs better (3.6). The selection process is repeated for each pair of target/trial vector until the population for the next generation is complete.

$$\mathbf{X}^{(\mathbf{G+1})}_i = \begin{cases} \mathbf{X}''^{(\mathbf{G})}_i & \text{if} \quad f\left(\mathbf{X}''^{(\mathbf{G})}_i\right) \le f\left(\mathbf{X}^{(\mathbf{G})}_i\right) \\ \mathbf{X}^{(\mathbf{G})}_i & \text{otherwise} \end{cases}, \quad i = 1,\ldots,N_p \quad (3.6)$$

Canonical DE Algorithm

1. *Initialize population* (3.3)
2. *While convergence criteria are not satisfied*
3. *Create mutant vectors with the difference vector and the scaling constant* (3.4)
4. *Generate Trial vectors applying the selected crossover scheme* (3.5)
5. *Select next generation members according to competition performance* (3.6)

Several strategies may be used in differential evolution to generate new parameter vectors. These strategies, which differ on how the perturbation is performed, can be denoted as *DE/x/y/z* where x refers to the perturbation type, y the number of pair of vectors used in the perturbation process and z the crossover scheme used in the recombination process. The perturbation type x can be selected to generate new populations of candidate solutions by perturbing either a randomly selected vector from the population or the best candidate solution found so far. This perturbation can have either one or two pair of vectors (y) while the crossover used (z) can be based on binomial or exponential distributions.

From testing, the best DE strategy for global optimization is *DE/best/2/bin* which perturbs the best solution found so far with two difference vectors (3.7) based on a binomial distribution crossover scheme. The basic strategy is *DE/rand/1/bin* which is explained in equations (2.37-2.39) also is good for finding global optima, but presents a lower convergence rate.

$$\mathbf{X}_i'^{(\mathbf{G})} = \mathbf{X}_{best}^{(\mathbf{G})} + F\left(\mathbf{X}_a^{(\mathbf{G})} - \mathbf{X}_b^{(\mathbf{G})} + \mathbf{X}_c^{(\mathbf{G})} - \mathbf{X}_d^{(\mathbf{G})}\right),\ i = 1,\dots,N_P \tag{3.7}$$

where $\mathbf{X}_a, \mathbf{X}_b, \mathbf{X}_c$ and $\mathbf{X}_d$ are randomly chosen vectors $\in \{1,\dots,N_P\}$ and $a \neq b \neq c \neq d \neq i$. $\mathbf{X}_a, \mathbf{X}_b, \mathbf{X}_c$ and $\mathbf{X}_d$ are generated anew for each parent vector. $\mathbf{X}_{best}$ is the best solution found so far.

3.4 Constraint Handling Techniques

Most evolutionary algorithms such as differential evolution were originally conceived to solve unconstrained problems. Over the years, a different number of constraint handling techniques have been used in conjunction with evolutionary algorithms. Michalewicz et al. [63] presented a complete review of constrained optimization in evolutionary algorithms with a classification of the methods used to handle constraints. A four group classification was established: methods based on preserving feasibility of solutions, methods based on penalty functions, methods which make a clear distinction between feasible and infeasible solutions and other hybrid methods.

$$X_{j,i}^{(\mathbf{G})} = \begin{cases} X_{j,i}^{\min} & \text{if} \quad X_{j,i}^{(\mathbf{G})} < X_{j,i}^{\min} \\ X_{j,i}^{\max} & \text{if} \quad X_{j,i}^{(\mathbf{G})} > X_{j,i}^{\max}, \quad i = 1,\ldots,N_P, \quad j = 1,\ldots,D \\ X_{j,i}^{(\mathbf{G})} & \text{otherwise} \end{cases} \tag{3.8}$$

The two main groups are the methods that preserve feasibility of solutions and the methods based on penalty functions. Feasibility of solution can be achieved through the use of specialized operators or feasible region boundary search. One strategy used to explore only the feasible solution space is to generate and keep candidate solutions in the feasible region [64]. Values outside the boundary limits need to be adjusted to values inside the feasible space guaranteeing that only feasible solutions will be tested. This can be achieved by fixing the value to the nearest bound violated (3.8), or generating a new value within the feasible range [64].

Methods based on penalty functions [63, 65 and 66] modify the objective function providing information of the feasible/infeasible regions aiding the algorithm to find the desired optimal solution. Basically, the objective function $F(X)$ is substituted by a fitness function $F'(X)$ that penalizes the fitness whenever the solution contains parameters that violate the problem constraints (3.9). Penalty functions can be classified as exterior or interior penalty functions depending on whether they penalize infeasible solutions or feasible solutions respectively. Penalties can be implemented using static, dynamic, adaptive or annealing techniques.

$$F'(X) = F(X) + Penalty(X) \tag{3.9}$$

Slack techniques can also be used to handle equality constraints that depend entirely on control variables. This technique forces the equality constraint to be satisfied by specifying N-1 variables while the remaining variable (dependent variable) adjusts taking the necessary value to satisfy the constraint. The slack technique guarantees that the equality constraint will always be satisfied. On the downside, this technique requires the variables to be control variables. The use of state variables in slack techniques may lead to local optima results, especially in highly nonlinear systems. The power balance constraint is an example of an economic dispatch constraint that can be handled with a slack technique [67].

Lampinen [64] and Michalewicz et al. [63, 65] have performed research in constrained optimization and constraint handling techniques in differential evolution and evolutionary algorithms, respectively.

3.5 Discrete Variables Handling Techniques

Although the canonical form of differential evolution solves optimization problems over continuous spaces, minor adjustments to the code allow DE to solve mixed integer optimization problems [68]. This is achieved with the use of an operator that rounds the variable to the nearest integer value, when the value lies between two integer values. This operator (3.10) is included after the initialization (3.3) and mutation process (3.4).

$$\mathbf{X}_{1,\ldots,D} = \left[\mathbf{Y}_{1,\ldots,k},\ \mathrm{round}(\mathbf{Z}_{k+1,\ldots,D})\right]^{\mathrm{T}} \tag{3.10}$$

where **X** is the *D* dimensional parameter vector, **Y** the *k* dimensional vector of continuous parameters and **Z** the vector of ($D-k$) discrete parameters.

Mixed Discrete DE Algorithm	
1. *Initialize population*	(3.3)
2. *Apply rounding operator*	(3.10)
3. *While convergence criteria are not satisfied*	
4. *Create mutant vectors with the difference vector and the scaling constant*	(3.4)
5. *Apply rounding operator*	(3.10)
6. *Generate Trial vectors applying the selected crossover scheme*	(3.5)
7. *Select next generation members according to competition performance*	(3.6)

Discrete variables with fixed step sizes Δ between consecutive values can easily be converted from integer values to discrete values with (3.11).

$$Z_i = n \times \Delta + Z_i^{\min},\ i = 1, \ldots, (D-k) \tag{3.11}$$

where n is an integer in the range of $\left[0, \ldots, n^{\max}\right]$ such as $n = 0, 1, 2, \ldots, n^{\max}$

3.6 Literature Review

Differential Evolution is starting to get attention inside the field of evolutionary computation and computational intelligence thanks to the robustness and ability to find global optima of nonlinear and non-convex problems. Most of the initial research was conducted by the developers of Differential Evolution (Price and Storm) [59-61], with papers that describe the algorithm and explain how the optimization process is carried out. Constraint handling techniques for DE have been proposed by Lampinen [64] and along with Zelinka [69] presented the DE stagnation phenomena. Gamperle et al. [70] published a parameter study for differential evolution and Lopez et al. [71] developed strategies for selection of Differential Evolution control parameters for optimal control.

Several hybrid approaches of DE have been proposed. Chiou and Wang [72] developed a hybrid differential evolution method (HDE) which uses two additional operations, an acceleration phase and a migration phase that improve convergence speed while maintaining diversity in the population. Lin et al. [68] proposed a mixed integer hybrid differential evolution method (MIHDE), which modeled continuous and discrete variables through mixed coding while rounding integer variables. Also Lin et al. [73] proposed a hybrid DE with multiplier updating for constrained optimization with adaptive penalties. Magoulas et al. [74] combined Differential Evolution with Stochastic

Gradient Descent to improve the optimization process for on-line training while Xie and Zhang [75] used the mutation operator of differential evolution in combination with particle swarm optimization.

Also, Differential Evolution has been adjusted to solve mulitobjective optimization problems. Madavan [62] proposed a Pareto-based Differential Evolution algorithm based on non-dominated sorting and ranking selection. Abbass et al. [76] developed the Pareto-frontier Differential Evolution (PDE) which creates the pareto front by evolving non-dominated solutions. Chang et al. [77] also proposed a Pareto-based Differential Evolution algorithm, and applied it in the optimization of train movement and Xue et al. [78] used a multiobjective DE for enterprise planning.

Other combinations of Differential Evolution have been proposed such as a Fuzzy Differential Evolution that incorporates fuzzy logic controllers to adapt the search parameters for the mutation and crossover operators [79]. A differential evolution approach with minimal spanning distances was proposed by Rumpler and Moore [80] while a DE with decreasing-based mutations and self-adaptive mutations was proposed by Yang et al [81].

Differential Evolution has been applied to problems from several areas. Some power engineering problems have been solved with DE including: Distribution systems capacitor placement [82], harmonic voltage distortion reduction [83] and passive shunt harmonic filter planning [84]. DE has also been used in the design of filters [85, 86], neural network learning [87, 88], fuzzy logic applications [89], optimal control problems [71, 90], among others.

DIFFERENTIAL EVOLUTION EXAMPLE

Objective Function: $f(\mathbf{X}) = x_1 + x_2 + x_3 + x_4 + x_5 + x_6$

where **X** represents a candidate solution and x_1, x_2, x_3, x_4, x_5 and x_6 are the parameters of the individual.

1- Select Control Variables N_P (Population Size), F (Scaling Factor), C_R (Crossover Constant)

Decision Variables or Parameters (D)	6
Population size	5
Scaling Factor	0.7
Crossover Constant	0.6

2- Initialize Population with random values according to Eq. 24 (Current Population)

	Individual 1	**Individual 2**	**Individual 3**	**Individual 4**	**Individual 5**
Parameter 1 (x_1)	0.99	0.57	0.25	0.28	0.27
Parameter 2 (x_2)	0.52	0.12	0.17	0.43	0.71
Parameter 3 (x_3)	0.88	0.19	0.47	0.18	0.85
Parameter 4 (x_4)	0.85	0.21	0.50	0.82	0.64
Parameter 5 (x_5)	0.45	0.73	0.43	0.08	0.86
Parameter 6 (x_6)	0.96	0.90	0.71	0.70	0.10
Fitness $f(X)$	**4.66**	**2.72**	**2.52**	**2.50**	**3.43**

3- Select Target Vector from current population

$\mathbf{X}_i$	1

4- Select Random Indices a, b and c from current population. These indices must be chosen so that $a \neq b \neq c \neq i$.

a	5
b	2
c	3

5- Create Mutant Vector X' according to Eq. 25

	X_a	X_b	X_c	X_b-X_c	F*(X_b-X_c)	X_a+F*(X_b-X_c)
Parameter 1	0.27	0.57	0.25	0.32	0.22	0.50
Parameter 2	0.71	0.12	0.17	-0.05	-0.04	0.67
Parameter 3	0.85	0.19	0.47	-0.28	-0.19	0.66
Parameter 4	0.64	0.21	0.50	-0.29	-0.20	0.44
Parameter 5	0.86	0.73	0.43	0.31	0.22	1.07
Parameter 6	0.10	0.90	0.71	0.19	0.13	0.23
Fitness	**3.43**	**2.72**	**2.52**	-	-	**3.56**

6- Create Trial Vectors X" according to Eq. 26

	Target Vector	Mutant Vector	Trial Vector	Random #
Parameter 1	0.99	0.50	0.50	0.37
Parameter 2	0.52	0.67	0.67	0.41
Parameter 3	0.88	0.66	0.66	0.32
Parameter 4	0.85	0.44	0.85	0.86
Parameter 5	0.45	1.07	0.45	0.96
Parameter 6	0.96	0.23	0.23	0.06
Fitness	**4.66**	**3.56**	**3.36**	-

7- Select the vector that will advance to the next generation to Eq. 27

	Trial Vector Selected Individual 1	Individual 2	Individual 3	Individual 4	Individual 5
Parameter 1	0.50				
Parameter 2	0.67				
Parameter 3	0.66				
Parameter 4	0.85				
Parameter 5	0.45				
Parameter 6	0.23				
Fitness	**3.36**				

8- Return to step 3 and repeat until the next generation population is filled using a different target vector each time

9- Return to step 3 and repeat for several generations iterations until convergence criteria are satisfied

CHAPTER 4

METHOD

4.1 Introduction

Power dispatch is an optimization problem from power systems which determines the optimal settings of a few control variables to operate the system properly. From the optimal generation dispatch problem, four case studies were designed based to test the Differential Evolution algorithm: Economic Dispatch with Non-Conventional Cost Functions, Economic/Environmental Power Dispatch, Security Constrained Economic Power Dispatch and Reactive Power Dispatch.

This classification tests differential evolution against highly nonlinear and discontinuous objective functions, multiobjective optimization problems, nonlinear constraints and discrete variables and evaluate the performance, effectiveness and applicability of the algorithm in power systems and similar large scale optimization problems.

TABLE 4.1
CASE STUDIES SUMMARY

Case Study		Characteristics
1	Non Conventional Cost Functions	Highly nonlinear and discontinuous solution space
2	Economic/Environmental Dispatch	Multiobjective optimization problem
3	Security Constrained Dispatch	Linear and highly nonlinear constraints
4	Reactive Power Dispatch	Discrete variables, highly nonlinear constraints

4.2 Differential Evolution based Power Dispatch Algorithm

The purpose of DE is to find an individual $\mathbf{X}_k$ that optimizes the fitness function, where the fitness function is a combination of the objective function and weighted equality and inequality constraints. The vector $\mathbf{X}_k$ is evolved over several generations with mutation and crossover operations and tested according to its fitness with other members of the population.

Control Variable Classification: In the case of mixed optimization problems such as the reactive power dispatch, the control variables are classified and grouped as continuous variables or discrete variables (4.1).

$$\mathbf{X}_{1,\ldots,D} = \left[\mathbf{Y}_{1,\ldots,k}, \mathbf{Z}_{k+1,\ldots,D}\right]^{\mathbf{T}} \tag{4.1}$$

where $\mathbf{X}$ is the D dimensional parameter vector, $\mathbf{Y}$ the k dimensional vector of continuous parameters and $\mathbf{Z}$ the vector of (D-k) discrete parameters.

Initialization: The population $\mathbf{P}$ is composed by N_P individuals of D parameters. Each parameter represents a control variable, and is initialized by assigning to each parameter of each individual a value inside the feasible region of the variable (4.2). In the event the problem contains discrete variables such as the case of tap settings and capacitor banks, these are adjusted to the nearest discrete value when they are initialized with unfeasible values.

$$\mathbf{X}_{1,\ldots,D} = \left[\mathbf{Y}_{1,\ldots,k}, \text{round}(\mathbf{Z}_{k+1,\ldots,D})\right]^{\mathbf{T}} \tag{4.2}$$

Optimization Process: New system settings (or individuals) are generated with the mutation and crossover operators and tested using the fitness function. The settings that perform better against the fitness function are selected to compose the next population according to (3.6). This process is repeated for several iterations until the best system setting of decision parameters is determined. The mutation strategy mostly used is (3.7) due to its improved performance over the basic strategy. DE basic strategy (3.4) was used in selected cases for comparison purposes.

Fitness Function: The fitness function is a combination of the objective function and the penalty functions used to model equality and inequality constraints (4.3). This function is used to measure the performance of candidate solutions in the selection operator.

$$F''(\mathbf{X}) = F'(\mathbf{X}) + \sum_{i=1}^{m} G_i(\mathbf{X}) + \sum_{j=1}^{n} H_j(\mathbf{X}) \tag{4.3}$$

where $F''(\mathbf{X})$ is the fitness function and $F'(\mathbf{X})$, $G_i(\mathbf{X})$ and $H_j(\mathbf{X})$ the objective function, i^{th} equality constraint penalty function and j^{th} inequality constraint penalty function, respectively. **X** is the vector of decision variables or parameter vector.

4.3 Case Study I: Non-conventional Cost Functions ED

Differential Evolution algorithm can be adjusted to solve the economic dispatch with non-conventional cost functions. This case study is known for being highly nonlinear with a non-continuous solution space. Solution to this problem is very difficult due to the non-differentiable functions present and the complexity associated prevents conventional gradient techniques from solving them.

4.3.1 Cost Functions with Valve Point Loadings

Objective Function: Minimize the sum of the cost functions of all the online generators.

$$F'\left(\boldsymbol{P}_G\right) = \sum_{i=1}^{N_G} F_i\left(P_{G_i}\right) \tag{4.4}$$

where

$$F_i\left(P_{G_i}\right) = a_i + b_i P_{G_i} + c_i P_{G_i}^2 + d_i \sin\left(e_i\left(P_{G_i}^{\min} - P_{G_i}\right)\right) \tag{4.5}$$

Equality Penalty Functions: The power balance constraint can be modeled through penalty functions as (4.6).

$$G_1\left(\boldsymbol{P}_G\right) = \omega_1 \left| P_D - \sum_{i=1}^{N_G} P_{G_i} \right| \tag{4.6}$$

Inequality Penalty Functions: No inequality penalty functions were used in the valve point loadings study.

Fitness Function: The fitness function used for the valve point loadings case study was (4.7).

$$F''\left(\boldsymbol{P}_G\right) = F'\left(\boldsymbol{P}_G\right) + G_1\left(\boldsymbol{P}_G\right) \tag{4.7}$$

Non-Penalty Function Inequality Constraints: Power generation limits where handled with non-penalty function inequality constraints. If during any generation of the evolution process, any of these settings become unfeasible, they are adjusted to the bound violated according to (4.8).

$$X_i = \begin{cases} X_i^{\min} & \text{if} \quad X_i < X_i^{\min} \\ X_i^{\max} & \text{if} \quad X_i > X_i^{\max}, \quad i = 1,\ldots,D \\ X_i & \text{otherwise} \end{cases} \tag{4.8}$$

Test System: To test this problem a three generator system was selected from [3]. The generators on this system are modeled with cost functions that consider valve point loadings. The system data is available on Table 4.2.

TABLE 4.2
VALVE POINT LOADINGS SYSTEM DATA

	$\mathbf{G_1}$	$\mathbf{G_2}$	$\mathbf{G_3}$
a	561	310	78
b	7.92	7.85	7.97
c	0.001562	0.00194	0.00482
d	300	200	150
e	0.0315	0.042	0.063
$P^{\max}$	600	400	200
$P^{\min}$	100	100	50

4.3.2 Piecewise Quadratic Cost Functions

Objective Function: Minimize the sum of the cost functions of all the online generators.

$$F'(\boldsymbol{P_G}) = \sum_{i=1}^{N_G} F_i\left(P_{G_i}\right) \tag{4.9}$$

where

$$F_i\left(P_{G_i}\right)=\begin{cases} a_{i,1}+b_{i,1}P_{G_i}+c_{i,1}P_{G_i}^2\ , & \underline{P}_{G_i}^1 < P_{G_i} < \overline{P}_{G_i}^1 \\ a_{i,2}+b_{i,2}P_{G_i}+c_{i,2}P_{G_i}^2, & \underline{P}_{G_i}^2 < P_{G_i} < \overline{P}_{G_i}^2 \\ \vdots & \\ a_{i,k}+b_{i,k}P_{G_i}+c_{i,k}P_{G_i}^2, & \underline{P}_{G_i}^k < P_{G_i} < \overline{P}_{G_i}^k \end{cases} \tag{4.10}$$

Equality Penalty Functions: The power balance constraint can be modeled through penalty functions as (4.11). In this case, no losses were considered.

$$G_1\left(\boldsymbol{P}_G\right)=\omega_1\left|P_D-\sum_{i=1}^{N_G}P_{G_i}\right| \tag{4.11}$$

Inequality Penalty Functions: No inequality penalty functions were used in the valve point loadings study.

Fitness Function: The fitness function used for the piecewise quadratic cost functions case study was (4.12).

$$F''\left(\boldsymbol{P}_G\right)=F'\left(\boldsymbol{P}_G\right)+G_1\left(\boldsymbol{P}_G\right) \tag{4.12}$$

Non-Penalty Function Inequality Constraints: Power generation limits where handled with non-penalty function inequality constraints. If during any generation of the evolution process, any of these settings become unfeasible, they are adjusted to the bound violated according to (4.8).

Test System: This problem was tested based on a 10 generator system selected from [7, 8]. The generators are operated with multiple fuels and their cost functions are piecewise quadratic. The system data is available on Table 4.3. No losses were considered for this approach.

TABLE 4.3
PIECEWISE QUADRATIC SYSTEM DATA

	Fuel	a	b	c	$P^{\min}$	$P^{\max}$
G$_1$	1	26.97	-0.3975	2.176E-03	100	196
	2	21.13	-0.3059	1.861E-03	196	250
G$_2$	1	118.40	-1.2690	4.194E-03	157	230
	2	1.87	-0.0399	1.138E-03	50	114
	3	13.65	-0.1980	1.620E-03	114	157
G$_3$	1	39.79	-0.3116	1.457E-03	200	332
	2	-59.14	0.4864	1.176E-05	388	500
	3	-2.88	0.0339	8.035E-04	332	388
G$_4$	1	1.98	-0.0311	1.049E-03	99	138
	2	52.85	-0.6348	2.758E-03	138	200
	3	266.80	-2.3380	5.935E-03	200	265
G$_5$	1	13.92	-0.0873	1.066E-03	190	338
	2	99.76	-0.5206	1.597E-03	338	407
	3	-53.99	0.4462	1.498E-04	407	490
G$_6$	1	52.85	-0.6348	2.758E-03	138	200
	2	1.98	-0.0311	1.049E-03	85	138
	3	266.80	-2.3380	5.935E-03	200	205
G$_7$	1	18.93	-0.1325	1.107E-03	200	331
	2	43.77	-0.2267	1.165E-03	331	391
	3	-43.35	0.3559	2.454E-04	391	500
G$_8$	1	1.98	-0.0311	1.049E-03	99	138
	2	52.85	-0.6348	2.758E-03	138	200
	3	266.80	-2.3380	5.935E-03	200	265
G$_9$	1	88.53	-0.5675	1.554E-03	213	370
	3	14.23	-0.0182	6.121E-04	130	213
	3	14.23	-0.0182	6.121E-04	370	440
G$_{10}$	1	13.97	-0.0994	1.102E-03	200	362
	2	-61.13	0.5084	4.164E-05	407	490
	3	46.71	-0.2024	1.137E-03	362	407

4.3.3 Cost Functions with Prohibited Operating Zones

Objective Function: Minimize the sum of the cost functions of all the online generators.

$$F'(\boldsymbol{P_G}) = \sum_{i=1}^{N_G} F_i\left(P_{G_i}\right) \tag{4.13}$$

where

$$F_i\left(P_{G_i}\right) = a_i + b_i P_{G_i} + c_i P_{G_i}^2 \tag{4.14}$$

<u>Equality Penalty Functions</u>: The power balance constraint can be modeled through penalty functions as (4.15).

$$G_1\left(\boldsymbol{P}_G\right) = \omega_1 \left| P_D - \sum_{i=1}^{N_G} P_{G_i} \right| \tag{4.15}$$

<u>Inequality Penalty Functions</u>: The prohibited zones were modeled through penalty functions with the best design tested being (4.16).

$$H_1\left(\boldsymbol{P}_G\right) = \sum_{j \in G^{pz}} \mu_j \sin\left(\frac{\pi}{2} \times h_j\left(P_{G_j}\right)\right) \tag{4.16}$$

where

$$h_j\left(P_{G_j}\right) = \begin{cases} \dfrac{\min\left(P_{G_j} - PZ_{j,k}^{\min}, PZ_{j,k}^{\max} - P_{G_j}\right)}{\left(PZ_{j,k}^{\max} - PZ_{j,k}^{\min}\right)/2}, \text{ if } PZ_{j,k}^{\min} < P_{G_j} < PZ_{j,k}^{\max}, k = 1, \ldots, n_z \\ 0, \text{ otherwise} \end{cases}$$

and $G^{pz} = \left\{G_1^{pz}, G_2^{pz}, \ldots, G_n^{pz}\right\}$ is the set of n generators with prohibited zones, j is the j^{th} element of the set of generators with prohibited zones; k is the k^{th} prohibited zone of generator j and $PZ_{j,k}^{\min}$ and $PZ_{j,k}^{\max}$ are the lower and upper bounds of the k^{th} prohibited zone of generator j.

<u>Fitness Function</u>: The fitness function used for the cost functions with prohibited zones case study was (4.17).

$$F''\left(\boldsymbol{P}_G\right) = F'\left(\boldsymbol{P}_G\right) + G_1\left(\boldsymbol{P}_G\right) + H_1\left(\boldsymbol{P}_G\right) \tag{4.17}$$

Non-Penalty Function Inequality Constraints: Power generation limits where handled with non-penalty function inequality constraints. If during any generation of the evolution process, any of these settings become unfeasible, they are adjusted to the bound violated according to (4.8).

Test System: A 15 generator system was used to test the algorithm against cost functions with prohibited operating zones. This test system contains 4 generators with multiple prohibited zones of operation. The system data is available on Tables 4.4 and 4.5 and reference [15]. No losses were considered in this approach.

TABLE 4.4
PROHIBITED OPERATING ZONES SYSTEM DATA

	a	b	c	P^{min}	P^{max}
$\mathbf{G}_1$	671.03	10.07	0.000299	150	455
$\mathbf{G}_2$	574.54	10.22	0.000183	150	455
$\mathbf{G}_3$	374.59	8.8	0.001126	20	130
$\mathbf{G}_4$	374.59	8.8	0.001126	20	130
$\mathbf{G}_5$	461.37	10.4	0.000205	105	470
$\mathbf{G}_6$	630.14	10.1	0.000301	135	460
$\mathbf{G}_7$	548.2	9.87	0.000364	135	465
$\mathbf{G}_8$	227.09	11.21	0.000338	60	300
$\mathbf{G}_9$	173.72	11.21	0.000807	25	162
$\mathbf{G}_{10}$	175.95	10.72	0.001203	20	160
$\mathbf{G}_{11}$	186.86	10.21	0.003586	20	80
$\mathbf{G}_{12}$	230.27	9.9	0.005513	20	80
$\mathbf{G}_{13}$	225.28	13.12	0.000371	25	85
$\mathbf{G}_{14}$	309.03	12.12	0.001929	15	55
$\mathbf{G}_{15}$	323.79	12.41	0.004447	15	55

TABLE 4.5
PROHIBITED REGIONS

	Zone 1	Zone 2	Zone 3
$\mathbf{G}_2$	[185 225]	[305 335]	[420 450]
$\mathbf{G}_5$	[180 200]	[260 335]	[390 420]
$\mathbf{G}_6$	[230 255]	[365 395]	[430 455]
$\mathbf{G}_{12}$	[30 55]	[65 75]	

4.4 Case Study II: Economic/Environmental Power Dispatch

The Economic/Environmental Power dispatch is known for being a highly nonlinear optimization problem due to the functions used to model SO_2 and NO_X emissions properly. This problem can be formulated either as an emissions constrained economic dispatch or as a multiobjective optimization problem.

4.4.1 Emissions Constrained Economic Dispatch

Objective Function: Minimize the sum of the cost functions of all the online generators.

$$F'\left(\boldsymbol{P_G}\right)=\sum_{i=1}^{N_G}F_i\left(P_{G_i}\right) \tag{4.18}$$

where

$$F_i\left(P_{G_i}\right)=a_i+b_iP_{G_i}+c_iP_{G_i}^2 \tag{4.19}$$

Equality Penalty Functions: The power balance constraint can be modeled through penalty functions as (4.20). System losses were estimated in this case using the *B* coefficients.

$$G_1\left(\boldsymbol{P}_G\right)=\omega_1\left|P_D+P_L-\sum_{i=1}^{N_G}P_{G_i}\right| \tag{4.20}$$

Inequality Penalty Functions: The emission constraint was modeled through penalty functions with (4.21).

$$H_1\left(\boldsymbol{P}_G\right) = \mu_1 \max\left[0, \sum_{i=1}^{N_G} E_i\left(P_{G_i}\right) - E_S\right] \tag{4.21}$$

Fitness Function: The fitness function used for the emission constrained economic dispatch case study was (4.22).

$$F''\left(\boldsymbol{P}_G\right) = F'\left(\boldsymbol{P}_G\right) + G_1\left(\boldsymbol{P}_G\right) + H_1\left(\boldsymbol{P}_G\right) \tag{4.22}$$

Non-Penalty Function Inequality Constraints: Power generation limits where handled with non-penalty function inequality constraints. If during any generation of the evolution process, any of these settings become unfeasible, they are adjusted to the bound violated according to (4.8).

4.4.2 Multiobjective Economic/Environmental Dispatch

Objective Function: Minimize the weighted sum of the cost functions and the emissions functions of all the online generators. Here δ is a constant in the range of [0 1] used to determine the pareto optimal set.

$$F'\left(\boldsymbol{P}_G\right) = \delta \sum_{i=1}^{N_G} F_i\left(P_{G_i}\right) + \left(1-\delta\right) \times \kappa_i \sum_{i=1}^{N_G} E_i\left(P_{G_i}\right), \ \delta = [0 \quad 1] \tag{4.23}$$

where

$$F_i\left(P_{G_i}\right) = a_i + b_i P_{G_i} + c_i P_{G_i}^2 \tag{4.24}$$

$$E_i\left(P_{G_i}\right) = \alpha_i + \beta_i P_{G_i} + \gamma_i P_{G_i}^2 + \mu_i \exp\left(\lambda_i P_{G_i}\right) \tag{4.25}$$

Equality Penalty Functions: The power balance constraint can be modeled through penalty functions as (4.26). System losses were estimated in this case using the B coefficients.

$$G_1\left(\boldsymbol{P}_G\right)=\omega_1\left|P_D+P_L-\sum_{i=1}^{N_G}P_{G_i}\right| \tag{4.26}$$

Inequality Penalty Functions: No inequality penalty functions were used in the multiobjective economic-environmental power dispatch study.

Fitness Function: The fitness function used for the multiobjective economic-environmental power dispatch case study was (4.27).

$$F''\left(\boldsymbol{P}_G\right)=F'\left(\boldsymbol{P}_G\right)+G_1\left(\boldsymbol{P}_G\right) \tag{4.27}$$

Non-Penalty Function Inequality Constraints: Power generation limits where handled with non-penalty function inequality constraints. If during any generation of the evolution process, any of these settings become unfeasible, they are adjusted to the bound violated according to (4.8).

Test Systems: The economic/environmental power dispatch algorithm was tested using the IEEE 6 generator/30 bus test system and a 14 generator/118 test system. A reduction was applied to these systems by modeling losses as a function of the generators output through Kron's loss coefficients instead of obtaining losses via the power flow solution. The 6 generator system data is available on Table 4.6 and can be found on [25, 26] and the 14 generator system data is presented on Table 4.7 and [31].

TABLE 4.6
ECONOMIC/ENVIRONMENTAL 6 GENERATORS SYSTEM DATA

	G_1	G_2	G_3	G_4	G_5	G_6
a	10	10	20	10	20	10
b	200	150	180	100	180	150
c	100	120	40	60	40	100
α	4.091	2.543	4.258	5.426	4.258	6.131
β	-5.554	-6.047	-5.094	-3.550	-5.094	-5.555
γ	6.490	5.638	4.586	3.380	4.586	5.151
μ	2.0E-4	5.0E-4	1.0E-6	2.0E-3	1.0E-6	1.0E-5
λ	2.857	3.333	8.000	2.000	8.000	6.667
$P^{\min}$	.05	.05	.05	.05	.05	.05
$P^{\max}$	1.5	1.5	1.5	1.5	1.5	1.5

B COEFFICIENTS OF THE 6 GENERATOR STUDY

$$B = \begin{bmatrix} 0.1382 & -0.0299 & 0.0044 & -0.0022 & -0.0010 & -0.0008 & -0.0535 \\ -0.0299 & 0.0487 & -0.0025 & 0.0004 & 0.0016 & 0.0041 & 0.0030 \\ 0.0044 & -0.0025 & 0.0182 & -0.0070 & -0.0066 & -0.0066 & -0.0085 \\ -0.0022 & 0.0004 & -0.0070 & 0.0137 & 0.0050 & 0.0033 & 0.0004 \\ -0.0010 & 0.0016 & -0.0066 & 0.0050 & 0.0109 & 0.0005 & 0.0001 \\ -0.0008 & 0.0041 & -0.0066 & 0.0033 & 0.0005 & 0.0244 & 0.0015 \\ -0.0535 & 0.0030 & -0.0085 & 0.0004 & 0.0001 & 0.0015 & 0.000986 \end{bmatrix}$$

where

$$B = \left[\begin{array}{c|c} B_{ij} & B_{i0}/2 \\ \hline B_{i0}/2 & B_{00} \end{array}\right]$$

TABLE 4.7
Economic/Environmental 118 Bus and 14 Generators System Data

	a	b	c	α	β	γ	$P^{\min}$	$P^{\max}$
$\mathbf{G}_1$	150	1.89	0.0050	0.016	-1.500	23.333	50	1000
$\mathbf{G}_2$	115	2.00	0.0055	0.031	-1.820	21.022	50	1000
$\mathbf{G}_3$	40	3.50	0.0060	0.013	-1.249	22.050	50	1000
$\mathbf{G}_4$	122	3.15	0.0050	0.012	-1.355	22.983	50	1000
$\mathbf{G}_5$	125	3.05	0.0050	0.020	-1.900	21.313	50	1000
$\mathbf{G}_6$	70	2.75	0.0070	0.007	0.805	21.900	50	1000
$\mathbf{G}_7$	70	3.45	0.0070	0.015	-1.401	23.001	50	1000
$\mathbf{G}_8$	70	3.45	0.0070	0.018	-1.800	24.003	50	1000
$\mathbf{G}_9$	130	2.45	0.0050	0.019	-2.000	25.121	50	1000
$\mathbf{G}_{10}$	130	2.45	0.0050	0.012	-1.360	22.990	50	1000
$\mathbf{G}_{11}$	135	2.35	0.0055	0.033	-2.100	27.010	50	1000
$\mathbf{G}_{12}$	200	1.30	0.0045	0.018	-1.800	25.101	50	1000
$\mathbf{G}_{13}$	70	3.45	0.0070	0.018	-1.810	24.313	50	1000
$\mathbf{G}_{14}$	45	3.89	0.0060	0.030	-1.921	27.119	50	1000

B COEFFICIENTS OF THE 14 GENERATOR STUDY

$$B_{11} = \begin{bmatrix} 0.042741 & 0.030108 & 0.019242 & 0.021506 & -0.00288 & -0.00400 & -0.00447 \\ 0.030108 & 0.037946 & 0.020710 & 0.020912 & -0.00363 & -0.00525 & -0.00448 \\ 0.019242 & 0.02071 & 0.026780 & 0.024696 & -0.00247 & -0.00378 & -0.00298 \\ 0.021506 & 0.020912 & 0.024696 & 0.024393 & -0.00232 & -0.00352 & -0.00309 \\ -0.00288 & -0.00363 & -0.00247 & -0.00232 & 0.009543 & 0.003659 & 0.002951 \\ -0.00400 & -0.00525 & -0.00378 & -0.00352 & 0.003659 & 0.010678 & 0.005763 \\ -0.00447 & -0.00448 & -0.00298 & -0.00309 & 0.002951 & 0.005763 & 0.008092 \end{bmatrix}$$

$$B_{12} = \begin{bmatrix} -0.00272 & -0.00323 & -0.00694 & -0.00745 & -0.01952 & -0.01217 & -0.01718 \\ -0.00366 & -0.00359 & -0.00695 & -0.01018 & -0.02004 & -0.01844 & -0.02057 \\ -0.00239 & -0.00231 & -0.00467 & -0.00786 & -0.01583 & -0.01529 & -0.01668 \\ -0.00223 & -0.0023 & -0.00475 & -0.00715 & -0.016 & -0.01346 & -0.01588 \\ 0.003116 & 0.004207 & 0.002066 & 0.000366 & -0.00365 & -0.00381 & -0.00424 \\ 0.003740 & 0.003341 & 0.002486 & 0.001192 & -0.00279 & -0.00288 & -0.00331 \\ 0.003370 & 0.003566 & 0.003054 & 0.001293 & -0.00252 & -0.00192 & -0.00272 \end{bmatrix}$$

$$B_{21} = \begin{bmatrix} -0.00272 & -0.00366 & -0.00239 & -0.00223 & 0.003116 & 0.00374 & 0.00337 \\ -0.00323 & -0.00359 & -0.00231 & -0.0023 & 0.004207 & 0.003341 & 0.003566 \\ -0.00694 & -0.00695 & -0.00467 & -0.00475 & 0.002066 & 0.002486 & 0.003054 \\ -0.00745 & -0.01018 & -0.00786 & -0.00715 & 0.000366 & 0.001192 & 0.001293 \\ -0.01952 & -0.02004 & -0.01583 & -0.01600 & -0.00365 & -0.00279 & -0.00252 \\ -0.01217 & -0.01844 & -0.01529 & -0.01346 & -0.00381 & -0.00288 & -0.00192 \\ -0.01718 & -0.02057 & -0.01668 & -0.01588 & -0.00424 & -0.00331 & -0.00272 \end{bmatrix}$$

$$B_{22} = \begin{bmatrix} 0.003876 & 0.003746 & 0.002934 & 0.002063 & -0.00152 & -0.00142 & -0.00188 \\ 0.003746 & 0.005404 & 0.002869 & 0.001477 & -0.00225 & -0.00189 & -0.00254 \\ 0.002934 & 0.002869 & 0.006738 & 0.003054 & 0.001212 & 0.001331 & 0.000955 \\ 0.002063 & 0.001477 & 0.003054 & 0.008576 & 0.006171 & 0.008179 & 0.007260 \\ -0.00152 & -0.00225 & 0.001212 & 0.006171 & 0.036153 & 0.018390 & 0.020017 \\ -0.00142 & -0.00189 & 0.001331 & 0.008179 & 0.018390 & 0.033117 & 0.029414 \\ -0.00188 & -0.00254 & 0.000955 & 0.007260 & 0.020017 & 0.029414 & 0.041297 \end{bmatrix}$$

$$B_{10} = \begin{bmatrix} -0.538520 & -0.283225 & -0.1929400 & -0.26424 & 0.017755 & 0.021917 & 0.040508 \end{bmatrix}$$

$$B_{20} = \begin{bmatrix} 0.012216 & 0.014007 & 0.0044072 & 0.032732 & 0.217820 & 0.032560 & 0.155630 \end{bmatrix}$$

$$B_{00} = 2.8378 \times 10^{2}$$

where

$$B_{ij} = \begin{bmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{bmatrix} \text{ and } B_{i0} = \begin{bmatrix} B_{10} \, B_{20} \end{bmatrix}$$

4.5 Case Study III: Security Constrained Power Dispatch

The security constrained power dispatch determines the optimal solution of an optimization problem that features multiple inequality constraints. This case study is highly nonlinear and multimodal favoring the application of global optimization techniques. Two basic security constraints were modeled: maximum line flow and spinning reserve. Line flows can be estimated either by solving the power flow problem or by estimating the flows through a linear approximation with generation shift factors. Both approaches were explored in this paper.

4.5.1 Security Constrained Economic Dispatch

Objective Function: Minimize the sum of the cost functions of all the online generators.

$$F'\left(\boldsymbol{P_G}\right)=\sum_{i=1}^{N_G} F_i\left(P_{G_i}\right) \tag{4.28}$$

where

$$\sum_{i=1}^{N_G} F_i\left(P_{G_i}\right)=\sum_{i=1}^{N_G} a_i + b_i P_{G_i} + c_i P_{G_i}^2 \tag{4.29}$$

Equality Penalty Functions: The power balance constraint can be modeled through penalty functions as (4.30). System losses were estimated by solving the power flow algorithm for the IEEE 30 bus case study. For the 8 generator – 6 lines study no losses were considered.

$$G_1\left(\boldsymbol{P}_G\right)=\omega_1\left|P_D+P_L-\sum_{i=1}^{N_G} P_{G_i}\right| \tag{4.30}$$

Inequality Penalty Functions: Line flow constraints and spinning reserve constraint were modeled through penalty functions with (4.31), (4.32) respectively.

$$H_1\left(\boldsymbol{P}_G\right)=\mu_1\sum_{i=1}^{N_L}\max\left[0,\, S_{f_i}-S_{f_i}^{\max}\right] \tag{4.31}$$

$$H_2\left(\boldsymbol{P}_G\right)=\mu_2\max\left[0,\, S_R^{\text{req}}-\sum_{i=1}^{N_G} S_{R_i}\right] \tag{4.32}$$

Fitness Function: The fitness function used for the security constrained economic dispatch case study was (4.33). When either the line flow constraint or the spinning reserve constraint was not considered, the corresponding penalty was eliminated from the fitness function.

$$F''(\boldsymbol{P}_G) = F'(\boldsymbol{P}_G) + G_1(\boldsymbol{P}_G) + H_1(\boldsymbol{P}_G) + H_2(\boldsymbol{P}_G) \tag{4.33}$$

Non-Penalty Function Inequality Constraints: Power generation limits where handled with non-penalty function inequality constraints. If during any generation of the evolution process, any of these settings become unfeasible, they are adjusted to the bound violated according to (4.8).

Test System: The security constrained power dispatch algorithm was tested with an 8 generator and 6 monitored lines system from reference [39]. Also the IEEE 6 generator/30 bust test systems was modified and adjusted to provide a second case study for the security constrained dispatch. The basic difference between both studies is how line flows are determined. The first case uses a linear approximation based on generation shift factors and dispatches for a constant load without considering losses. The second case uses the power flow to determine losses and system line flows. The spinning reserve criteria used was the same for both approaches. The system data of the first case is presented on Table 4.8 and Table 4.9. The data for the IEEE 6 generator 30 bus test system can be found on Tables 4.10, 4.11 and 4.12.

TABLE 4.8
8 GENERATORS – 6 LINES SYSTEM DATA

Bus	G_1	G_2	G_3	G_4	G_5	G_6	G_7	G_8
a	0	0	0	0	0	0	0	0
b	23.074	23.343	18.094	20.687	16.201	18.094	20.000	19.000
c	0.022	0.023	0.009	0.010	0.015	0.010	0.015	0.009
$P^{\min}$	20	20	20	20	20	20	20	20
$P^{\max}$	400	550	350	200	250	200	100	350
$S_R^{\max}$	40	60	35	20	25	20	10	35

TABLE 4.9
8 GENERATORS – 6 LINES GENERATION SHIFT FACTORS

Line No.	Line Limit	G_1	G_2	G_3	G_4	G_5	G_6	G_7	G_8
L_1	300	1.0000	0.0000	0.0000	0.00000	0.00000	0.0000	0.0000	0.0000
L_2	500	0.06235	0.06235	-0.79483	-0.09577	-0.06639	-0.11252	0.17575	-0.08823
L_3	500	0.01226	0.01226	0.05927	-0.021280	-0.00211	-0.00138	0.01429	-0.02690
L_4	300	0.03225	0.03225	0.09574	-0.02078	-0.02201	-0.04738	-0.21399	-0.02970
L_5	200	0.00190	0.00190	0.00211	0.0090	-0.00390	0.00288	0.00229	0.00486
L_6	200	-0.01334	-0.01334	-0.01174	0.04137	-0.00869	-0.02256	-0.016433	-0.01728

TABLE 4.10
SECURITY CONSTRAINED IEEE 30 BUS GENERATORS SYSTEM DATA

Bus	G_1	G_2	G_3	G_4	G_5	G_6
a	0	0	0	0	0	0
b	2.00	1.75	1.00	3.25	3.00	3.00
c	0.00375	0.01750	0.06250	0.00834	0.02500	0.02500
$P^{\min}$	50	20	15	10	10	12
$P^{\max}$	200	80	50	35	30	40
$S_R^{\max}$	20	10	5	5	5	5

TABLE 4.11
SECURITY CONSTRAINED IEEE 30 BUS LOAD DATA

Bus	Type	MW	MVAR	Bus	Type	MW	MVAR
1	Slack	0	0	16	PQ	4.2	2.16
2	PV	21.7	12.7	17	PQ	10.8	6.96
3	PQ	2.88	1.44	18	PQ	3.84	1.08
4	PQ	9.12	1.92	19	PQ	11.4	4.08
5	PV	94.2	19	20	PQ	2.64	0.84
6	PQ	0	0	21	PQ	21	13.44
7	PQ	27.36	13.08	22	PQ	0	0
8	PV	30	30	23	PQ	3.84	1.92
9	PQ	0	0	24	PQ	13.05	10.05
10	PQ	40.6	14	25	PQ	0	0
11	PV	0	0	26	PQ	4.2	2.76
12	PQ	22.4	15	27	PQ	0	0
13	PV	0	0	28	PQ	0	0
14	PQ	7.44	1.92	29	PQ	2.88	1.08
15	PQ	12.3	3.75	30	PQ	12.72	2.28

TABLE 4.12
IEEE 30 BUS SYSTEM DATA

From Bus	To Bus	R	X	B	From Bus	To Bus	R	X	B
1	2	0.0192	0.0575	0.0264	15	18	0.1070	0.2185	0.0000
1	3	0.0452	0.1852	0.0204	18	19	0.0639	0.1292	0.0000
2	4	0.0570	0.1737	0.0184	19	20	0.0340	0.0680	0.0000
3	4	0.0132	0.0379	0.0042	10	20	0.0936	0.2090	0.0000
2	5	0.0472	0.1983	0.0209	10	17	0.0324	0.0845	0.0000
2	6	0.0581	0.1763	0.0187	10	21	0.0348	0.0749	0.0000
4	6	0.0119	0.0414	0.0045	10	22	0.0727	0.1499	0.0000
5	7	0.0460	0.1160	0.0102	21	22	0.0116	0.0236	0.0000
6	7	0.0267	0.0820	0.0085	15	23	0.1000	0.2020	0.0000
6	8	0.0120	0.0420	0.0045	22	24	0.1150	0.1790	0.0000
6	9	0.0000	0.2080	0.0000	23	24	0.1320	0.2700	0.0000
6	10	0.0000	0.5560	0.0000	24	25	0.1885	0.3292	0.0000
9	11	0.0000	0.2080	0.0000	25	26	0.2544	0.3800	0.0000
9	10	0.0000	0.1100	0.0000	25	27	0.1093	0.2087	0.0000
4	12	0.0000	0.2560	0.0000	28	27	0.0000	0.3960	0.0000
12	13	0.0000	0.1400	0.0000	27	29	0.2198	0.4153	0.0000
12	14	0.1231	0.2559	0.0000	27	30	0.3202	0.6027	0.0000
12	15	0.0662	0.1304	0.0000	29	30	0.2399	0.4533	0.0000
12	16	0.0945	0.1987	0.0000	8	28	0.0636	0.2000	0.0214
14	15	0.2210	0.1997	0.0000	6	28	0.0169	0.0599	0.0065
16	17	0.0824	0.1932	0.0000					

4.6 Case Study IV: Reactive Power Dispatch

The reactive power dispatch enhances system operation by optimizing the allocation of the reactive power. This case study is inherently a mixed discrete optimization problem since many of the sources of reactive power are non-continuous. The mixed discrete approach results in an extremely complex optimization problem with multiple nonlinear constraints.

Objective Function: Minimize the system active power losses.

$$F'(\mathbf{X}) = \sum_{i=1}^{N_B} \sum_{j=1}^{N_B} g_{ij} \times \left| V_i - V_j \right|^2 \tag{4.34}$$

Equality Penalty Functions: Since the equality constraints (4.35) and (4.36) are met when the power flow subroutine used to determine the system state variables converges, no equality penalty functions were used in the fitness function.

$$P_{G_i} - P_{D_i} - \sum_{j=1}^{N_B} \left| Y_{ij} \right| \left| V_i \right| \left| V_j \right| \cos\left(\theta_{ij} + \delta_j - \delta_i \right) = 0 \tag{4.35}$$

$$Q_{G_i} - Q_{D_i} + \sum_{j=1}^{N_B} \left| Y_{ij} \right| \left| V_i \right| \left| V_j \right| \sin\left(\theta_{ij} + \delta_j - \delta_i \right) = 0 \tag{4.36}$$

Inequality Penalty Functions: Maximum Apparent Power, Generator Reactive Power Limits and Bus Voltages Limits were modeled through penalty functions with (4.37), (4.38), and (4.39), respectively.

$$H_1(\mathbf{X}) = \mu_1 \sum_{i=1}^{N_G} \max\left[0,\ S_{G_i} - S_{G_i}^{\max} \right] \tag{4.37}$$

$$H_2\left(\mathbf{X}\right)=\mu_2\sum_{i=1}^{N_G}\max\left[0,\,Q_{G_i}-Q_{G_i}^{\max},Q_{G_i}^{\min}-Q_{G_i}\right] \tag{4.38}$$

$$H_3\left(\mathbf{X}\right)=\mu_3\sum_{i=1}^{N_B}\max\left[0,\,\left|V_i\right|-\left|V_i\right|^{\max},\left|V_i\right|^{\min}-\left|V_i\right|\right] \tag{4.39}$$

Fitness Function: The fitness function used for the reactive power dispatch case study was (4.40).

$$F''\left(\mathbf{X}\right)=F'\left(\mathbf{X}\right)+H_1\left(\mathbf{X}\right)+H_2\left(\mathbf{X}\right)+H_3\left(\mathbf{X}\right) \tag{4.40}$$

Non-Penalty Function Inequality Constraints: Generator voltage settings, Transformer Taps and Capacitor Banks lower and upper limits were handled with (4.8). If during the evolution process, any of these settings become unfeasible, they are adjusted to the bound violated.

Test System: The reactive power dispatch algorithm was tested with the IEEE 6 generator/30 bust test system found on reference [41]. Two base studies were developed from here by incorporating 9 capacitor banks to the system to the base case study with 6 generators and 4 load tap changing transformers. Tables 4.12, 4.13, 4.14 and 4.15 present the system data of the IEEE 30 bus test system.

TABLE 4.13
IEEE 30 BUS LOAD DATA

Bus	Type	MW	MVAR	Bus	Type	MW	MVAR
1	Slack	0	0	16	PQ	3.5	1.8
2	PV	21.7	12.7	17	PQ	9	5.8
3	PQ	2.4	1.2	18	PQ	3.2	0.9
4	PQ	7.6	1.6	19	PQ	9.5	3.4
5	PV	94.2	19	20	PQ	2.2	0.7
6	PQ	0	0	21	PQ	17.5	11.2
7	PQ	22.8	10.9	22	PQ	0	0
8	PV	30	30	23	PQ	3.2	1.6
9	PQ	0	0	24	PQ	8.7	6.7
10	PQ	5.8	2	25	PQ	0	0
11	PV	0	0	26	PQ	3.5	2.3
12	PQ	11.2	7.5	27	PQ	0	0
13	PV	0	0	28	PQ	0	0
14	PQ	6.2	1.6	29	PQ	2.4	0.9
15	PQ	8.2	2.5	30	PQ	10.6	1.9

TABLE 4.14
IEEE 30 BUS TRANSFORMER DATA

Transformer	From Bus	To Bus	Minimum Tap	Maximum Tap
$T_{6\text{-}9}$	6	9	0.9	1.1
$T_{6\text{-}10}$	6	10	0.9	1.1
$T_{4\text{-}12}$	4	12	0.9	1.1
$T_{28\text{-}27}$	28	27	0.9	1.1

TABLE 4.15
IEEE 30 BUS CAPACITOR BANK DATA

Transformer	At Bus	Minimum Size (MVAR)	Maximum Size (MVAR)
Qc_{10}	10	0	5
Qc_{12}	12	0	5
Qc_{15}	15	0	5
Qc_{17}	17	0	5
Qc_{20}	20	0	5
Qc_{21}	21	0	5
Qc_{23}	23	0	5
Qc_{24}	24	0	5
Qc_{29}	29	0	5

CHAPTER 5

RESULTS AND DISCUSSIONS

5.1 Introduction

This chapter presents the results obtained on the four case studies selected to test the differential evolution algorithm. Each case study has several variants that help validate the results obtained and the algorithm capability. All case studies were solved using Matlab 6.5 on a 1.8 GHz Pentium 4 processor with 256 MB of RAM.

Case Study 1 is composed of three variants which test the algorithm with non-smooth and non-continuous objective functions. These variants are Cost Functions with Valve Point Loadings, Piecewise Quadratic Cost Functions and Cost Functions with Prohibited Zones. Case Study 2 solves the highly nonlinear Economic-Environmental Power Dispatch using two approaches: a Multiobjective approach and the Emission constrained approach. Each approach was tested on two systems, a 6 generators system based on the IEEE 30 bus system and a 14 generators system based on the IEEE 118 bus.

Case study 3 solves the economic dispatch adding two security constraints: Line flow constraints and spinning reserve constraints. This case study was tested using an 8 generator – 6 lines system and a modified 30 bus test system. Case Study 4 solves the Reactive Power Dispatch problem using the IEEE 30 bus test system. Two variants were studied: a Reactive Power Dispatch modeling transformer taps as continuous and

Discrete Variables and a second study that included Capacitor Banks and modeled them as Continuous and Discrete Variables.

5.2 Case Study I: Non-conventional cost functions ED

Economic dispatch with Valve Point Loadings, Prohibited Operating Zones and Piecewise quadratic cost functions problems were solved using the differential evolution algorithm. For each case 100 independent runs were made using the best suited control parameters determined with parameter tuning (scaling constant and crossover) shown in Table 5.1.

TABLE 5.1
NON-CONVENTIONAL COST FUNCTIONS CONTROL PARAMETERS AND WEIGHTS

Control Parameters	Valve Point Loadings	Piecewise Quadratic	Prohibited Operating Zones
F	1	0.9	0.51
C_R	.99	0.99	0.96
N_P	45	20	150
ω_1	1×10^3	1×10^3	1×10^3
μ_1	-	-	2
μ_2	-	-	5
μ_3	-	-	2
μ_4	-	-	2

5.2.1 Valve Point Loadings

DE is capable of solving efficiently problems featuring valve point loadings. DE offers improvement in the cost function when being compared to the Genetic Algorithm approach performed in [3] while providing consistent results throughout the simulation runs as can be seen on Table 5.2. The strategy DE/best/2/bin performed better than DE/rand/1/bin in terms of consistency of solution as shown in Table 5.3.

TABLE 5.2
COMPARISON OF VALVE POINT LOADING RESULTS

	DE	**GA** [3]
$\mathbf{G}_1$ (MW)	300.3	300
$\mathbf{G}_2$ (MW)	400.0	400
$\mathbf{G}_3$ (MW)	149.7	150
Cost $/h	8234.1	8237.6

TABLE 5.3
VALVE POINT LOADINGS TEST RESULTS

Strategy	**DE/rand/1/bin**	**DE/best/2/bin**
N_P	45	45
Max. Gen.	2000	2000
$\mathbf{G}_1$ (MW)	300.3	300.3
$\mathbf{G}_2$ (MW)	400.0	400.0
$\mathbf{G}_3$ (MW)	149.7	149.7
BSF $/h	8234.1	8234.1
WSF $/h	8400.2	8241.6
Median $/h	8234.1	8234.1
Mode $/h	8234.1	8234.1
Standard Deviation	16.6	1.2
Variance	276.4	1.5

5.2.2 Piecewise Quadratic

DE can solve economic dispatch featuring piecewise quadratic functions as shown on Table 5.4. DE converged to almost identical results for the 100 runs, in all four cases as can be seen by the standard deviation index on Table 5.4. The strategy DE/best/2/bin finds global optima on a more consistent basis than DE/rand/1/bin. Compared to techniques such as the Hierarchical approach [7] and Adaptive Hopfield Neural Networks [8] Differential Evolution delivered successful results, as shown on Table 5.5.

TABLE 5.4
PIECEWISE QUADRATIC ECONOMIC DISPATCH DE TEST RESULTS

Load (MW)	**2400**	**2500**	**2600**	**2700**
N_P	45	45	45	45
Max. Gen.	2000	2000	2000	2000
$\mathbf{G}_1$ (MW)	189.7	206.5	216.5	218.2
$\mathbf{G}_2$ (MW)	202.4	206.5	210.9	211.7
$\mathbf{G}_3$ (MW)	253.9	265.7	278.5	280.7
$\mathbf{G}_4$ (MW)	233.1	236.0	239.1	239.6
$\mathbf{G}_5$ (MW)	241.8	258.0	275.5	278.7
$\mathbf{G}_6$ (MW)	233.0	236.0	239.1	239.6
$\mathbf{G}_7$ (MW)	253.3	268.9	285.7	288.6
$\mathbf{G}_8$ (MW)	233.1	236.0	239.1	239.6
$\mathbf{G}_9$ (MW)	320.4	331.5	343.5	428.4
$\mathbf{G}_{10}$ (MW)	239.4	255.1	272.0	274.8
BSF \$/h	481.7	526.2	574.4	623.8
WSF \$/h	481.7	526.2	574.7	623.8
Median \$/h	481.7	526.2	574.4	623.8
Mode \$/h	481.7	526.2	574.4	623.8
Standard Deviation	0.0	0.0	0.1	0.0
Variance	0.0	0.0	0.0	0.0

TABLE 5.5
COMPARISON OF PIECEWISE QUADRATIC RESULTS

Cost $/h	**DE**	**Hopfield** [8]	**Hierarchical** [7]
2400 MW	481.7	481.7	488.5*
2500 MW	526.2	526.2	526.7*
2600 MW	574.4	574.4	574.0*
2700 MW	623.8	626.2	625.2*

*Power Balance constraint not satisfied.

5.2.3 Prohibited Operating Zones

DE is capable of solving economic dispatch featuring prohibited zones. These types of problems are extremely difficult to solve due to the large discontinuities in the feasible region. Strategy DE/best/2/bin is very consistent throughout the 100 trials presenting a standard deviation and variance of 1.43 and 2.05 respectively. The penalty factors were set to 2 for each of the zones of generators 2, 6 and 12; and to 5 for the zones of generator 5.

TABLE 5.6
PROHIBITED OPERATING ZONES TEST RESULTS AND COMPARISON

MW	**DE**	**ETQ** [10]	**Deterministic Crowding GA** [13]	**Dynamic Programming** [13]
$\mathbf{G}_1$	455	450	406.1	455
$\mathbf{G}_2$	455	450	453.8	455
$\mathbf{G}_3$	130	130	130	130
$\mathbf{G}_4$	130	130	130	130
$\mathbf{G}_5$	260	335	355	260
$\mathbf{G}_6$	460	455	456.8	460
$\mathbf{G}_7$	465	465	459.8	465
$\mathbf{G}_8$	60	60	60	60
$\mathbf{G}_9$	25	25	26.6	25
$\mathbf{G}_{10}$	20	20	21.6	20
$\mathbf{G}_{11}$	60	20	36.2	60
$\mathbf{G}_{12}$	75	55	59	75
$\mathbf{G}_{13}$	25	25	25	25
$\mathbf{G}_{14}$	15	15	15	15
$\mathbf{G}_{15}$	15	15	15	15
BSF $	32506.14	32507.5	32515	32506.14

In comparison, DE was capable of reaching $32,506.14 which is the best solution found so far for this particular problem. As shown on Table 5.7, 61 runs reached the top three local minima with 21 of those reaching the global minimum value. Compared against other techniques (Table 5.6), DE proves to be a suitable technique for global optimization, by determining the global optima solution.

TABLE 5.7
PROHIBITED ZONES DIFFERENTIAL EVOLUTION PERFORMANCE

Cost Function	Results Distribution	Cost Function	Results Distribution
32506.14	21%	32508.15	9%
32506.18	20%	32508.28	5%
32507.57	20%	32512.07	3%
32507.76	21%	32515.31	1%

5.3 Case Study II: Economic-Environmental Power Dispatch

Emissions Constrained Economic Dispatch (ECED) and Multiobjective Economic Environmental Dispatch (MEED) were solved using differential evolution algorithm. For every study, 10 independent runs for each of the 20 pareto points were made using the best suited control parameters determined via parameter tuning (scaling constant and crossover) shown on Table 5.8. Both ECED and MEED were solved with and without losses. Losses were determined using the Kron's Loss Formula (4).

The economic dispatch with emissions was simulated using the 30 bus and 6 Generator IEEE Test system described in [26] and the 118 Bus and 14 generators system described in [31]. Each system was solved formulated as a multiobjective approach and as an emissions constrained economic dispatch. Since MEED determines optimal values for cost and emission, the emission results obtained in this approach were used as constraints in ECED. This will allow better comparison of both approaches in terms of solution obtained.

TABLE 5.8
ECONOMIC/ENVIRONMENTAL DISPATCH CONTROL PARAMETERS

Control Parameters	30 Bus System	118 Bus System
F	0.55	0.5
C_R	0.95	0.95
N_P	40	100
ω_1	1×10^3	1×10^3
μ_1	1×10^8	1×10^8
κ_1	3.0738×10^3	0.0665

5.3.1 IEEE 30 bus - Six Generator Test System

The parameters used for the 30 bus system are presented as follows: Scaling factor (F) was set to .55 and the crossover constant (C_R) to 0.95, strategy to DE/best/2/bin and a population size (N_P) of 40. The load was set to 2.834 p.u. on a 100 MVA base. Figures 9 and 10 show the tradeoff curves of cost/emissions without losses and with losses, respectively. Implementation of the MEED or ECED with DE provides almost identical results with slight variations. Table 5.9 and 5.10, show the result for both approaches when losses are not considered, and compare them to other results available in the literature. Table 5.11 shows the tradeoff values for the pareto front.

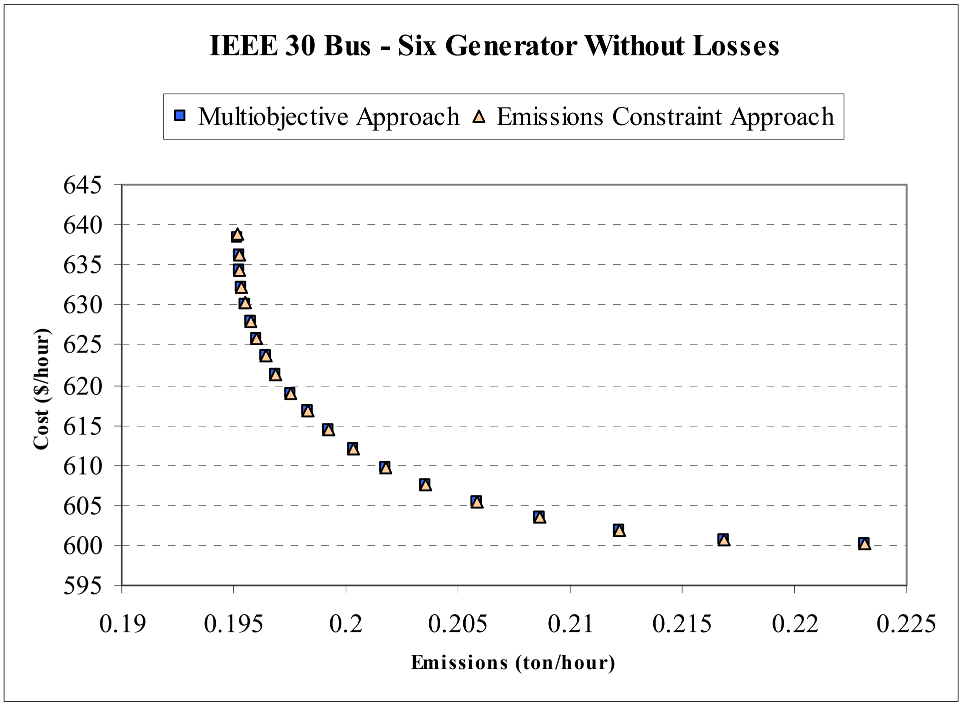

Fig. 9 Emission-Cost Tradeoff Curve for MEED and ECED

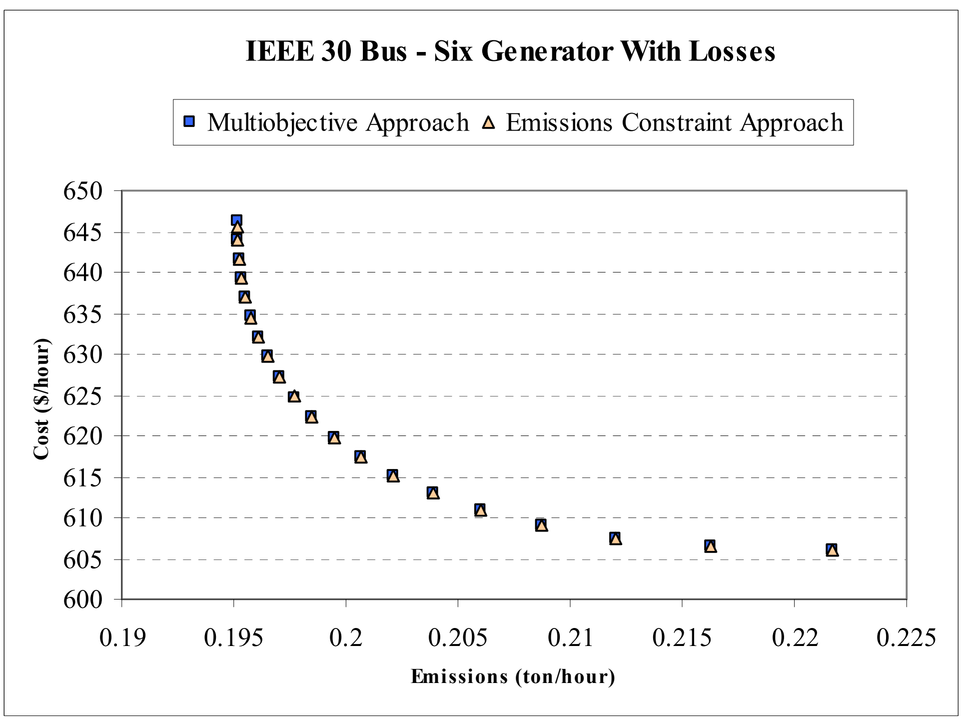

Fig. 10 Emission-Cost Tradeoff Curve for MEED and ECED

As seen from figures 9 and 10, Differential Evolution provides very accurate solutions to the IEEE 30 Bus System. The use of Kron's Loss formula, resulted in an increased computational time but results continued to be accurate. Data dispersion is low, with a maximum standard deviation of 0.03 without losses and 0.19 with losses.

TABLE 5.9
BEST COST RESULTS COMPARISON WITHOUT LOSSES
Best Cost

	DE ECED	DE MEED	SPEA [26]	LP [26]	MOSST [26]
$\mathbf{G_1}$	0.110	0.110	0.110	0.150	0.113
$\mathbf{G_2}$	0.300	0.300	0.300	0.300	0.302
$\mathbf{G_3}$	0.524	0.524	0.524	0.550	0.531
$\mathbf{G_4}$	1.016	1.016	1.016	1.050	1.021
$\mathbf{G_5}$	0.524	0.524	0.525	0.460	0.531
$\mathbf{G_6}$	0.360	0.360	0.360	0.350	0.363
$/hr	600.110	600.110	600.114	606.310	605.890
ton-hr	0.2231	0.2231	0.2221	0.223	0.222

TABLE 5.10
BEST EMISSIONS RESULTS COMPARISON WITHOUT LOSSES
Best Emissions

	DE ECED	DE MEED	SPEA [26]	LP [26]	MOSST [26]
$\mathbf{G_1}$	0.406	0.406	0.412	0.400	0.410
$\mathbf{G_2}$	0.459	0.459	0.453	0.450	0.463
$\mathbf{G_3}$	0.539	0.538	0.533	0.550	0.543
$\mathbf{G_4}$	0.384	0.383	0.383	0.400	0.388
$\mathbf{G_5}$	0.539	0.538	0.538	0.550	0.543
$\mathbf{G_6}$	0.510	0.510	0.515	0.500	0.514
$/hr	638.860	638.270	638.510	639.600	644.110
ton-hr	0.1952	0.1952	0.1942	0.1942	0.1942

TABLE 5.11

TRADEOFF VALUES FOR IEEE 30 BUS – 6 GENERATOR SYSTEM

Emission-Cost Tradeoff Values

Without Losses			**With Losses**		
	MEED	ECED		MEED	ECED
Best Emission	Best Cost	Best Cost	Best Emission	Best Cost	Best Cost
0.1952	638.27	638.86	0.19518	646.2	645.6
0.19522	636.33	636.34	0.1952	644.0	643.9
0.19528	634.33	634.23	0.19526	641.7	641.7
0.19538	632.28	632.24	0.19538	639.3	639.3
0.19553	630.18	630.21	0.19555	637.0	637.0
0.19575	628.04	628.03	0.1958	634.6	634.5
0.19604	625.84	625.85	0.19612	632.1	632.1
0.19642	623.61	623.6	0.19653	629.7	629.7
0.1969	621.34	621.35	0.19706	627.2	627.2
0.19751	619.03	619.03	0.1977	624.8	624.8
0.19827	616.71	616.7	0.1985	622.3	622.3
0.19921	614.37	614.37	0.19948	619.9	619.9
0.20037	612.05	612.05	0.20067	617.5	617.5
0.20181	609.75	609.75	0.20212	615.2	615.2
0.2036	607.52	607.52	0.20389	613.0	613.0
0.20582	605.41	605.41	0.20605	610.9	610.9
0.20862	603.47	603.48	0.20872	609.1	609.1
0.2122	601.82	601.82	0.21203	607.5	607.5
0.21686	600.61	600.61	0.21624	606.4	606.4
0.22314	600.11	600.11	0.22173	606.0	606.0

5.3.2 IEEE 118 bus - 14 Generator Test System

The parameters used for the 118 bus system are presented as follows: scaling factor (*F*) was set to .5 and the crossover constant (C_R) to 0.95, strategy to DE/best/2/bin and a population size (N_P) of 100. The load condition was 4,242 MW.

Figure 11 and Figure 12 show the tradeoff curve of cost/emissions for the IEEE 118 Bus System. Implementation of the EED or ECED continued to be successful for this higher scale system. The system dimension resulted in a more nonlinear surface, which increased when losses were considered. Nevertheless, DE obtained solutions with very good variance and standard deviation, being almost identical for most of the runs. When the objective was only minimizing the cost function, ECED provided a better value than the multiobjective approach. Again, this value is an improvement of less than 0.1% over the multiobjective approach which shows the robustness of DE for obtaining solutions.

Table 5.12, shows the tradeoff values for both approaches (MEED and ECED) with and without losses. The use of the Kron's Loss formula, also resulted in more time to solve the problem, but results continued to be accurate. Data dispersion continues to be low for the 20 runs used to create the pareto front with a max standard deviation of 9.3 for a median of 21,378. One advantage of the ECED is that it offers better control of the emissions than MEED. It does not require weight selection and conversion factor to obtain the well distributed pareto front as the multiobjective approach requires.

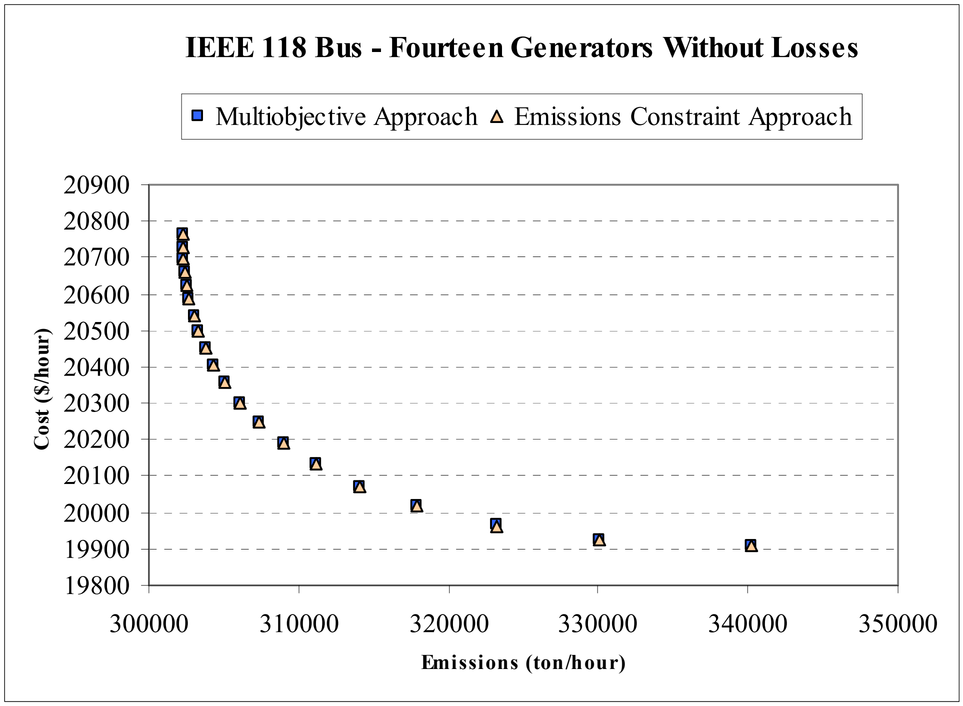

Fig. 11 Emission-Cost Tradeoff Curve for MEED and ECED

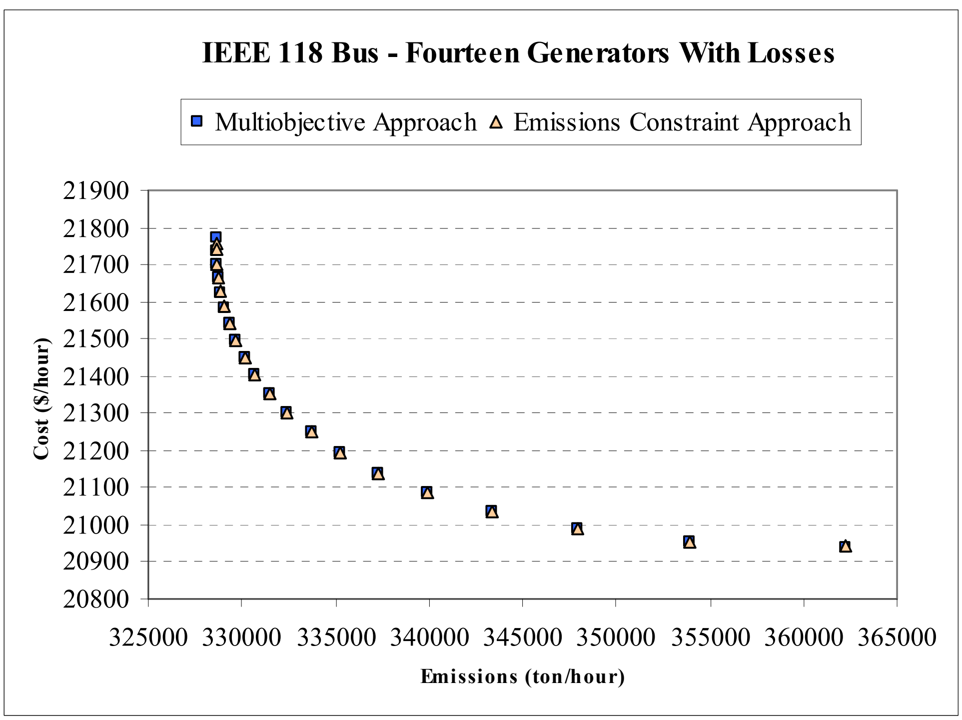

Fig. 12 Emission-Cost Tradeoff Curve for MEED and ECED

TABLE 5.12

TRADEOFF VALUES FOR IEEE 118 BUS – 14 GENERATOR SYSTEM

Emission-Cost Tradeoff Values

Without Losses			**With Losses**		
	EED	ECED		EED	ECED
Best Emission	Best Cost	Best Cost	Best Emission	Best Cost	Best Cost
302270	20762	20762	328610	21771	21756
302290	20730	20728	328620	21737	21739
302330	20697	20698	328670	21702	21700
302410	20662	20662	328750	21664	21665
302540	20624	20624	328880	21626	21627
302720	20585	20585	329070	21585	21586
302990	20542	20542	329330	21543	21543
303320	20500	20500	329680	21498	21498
303770	20454	20454	330140	21452	21452
304360	20406	20406	330730	21404	21403
305100	20357	20357	331480	21353	21354
306110	20302	20302	332450	21301	21302
307380	20247	20247	333690	21248	21248
309040	20190	20190	335270	21193	21194
311200	20132	20132	337310	21138	21138
314050	20073	20073	339940	21084	21084
317850	20017	20017	343370	21033	21036
323260	19968	19963	347910	20988	20988
330110	19926	19926	353970	20954	20954
340230	-	19908	362230	-	20942
340240	19908	-	362260	20939	-

5.4 Case Study III: Security Constrained Dispatch

Differential evolution algorithm was used to solve the security constrained power dispatch problem using two systems: an 8 generator with 6 monitored lines test system [39] and a modified 30 bus and 6 Generator IEEE Test system based in the one described in [41]. Each system has four case studies that show how the system reliability improves by adding some security constraints such as maximum line flows and a criterion for spinning reserve. The four case studies are: classical economic dispatch (case 1), economic dispatch with line flows (case 2), economic dispatch with spinning reserve (case 3) and economic dispatch with line flows and spinning reserve constraints (case 4).

TABLE 5.13
CASE STUDIES CONTROL PARAMETERS

Control Parameters	8 Generators	Modified IEEE 30 Bus - 6 Generators
F	0.6	0.6
C_R	0.9	0.93
N_P	15	15
ω_1	3000	100
μ_1	500	50
μ_2	100	300

The 8 generators/6 lines study differs from the 6 generator/30 bus on how the line flows are determined. The first study dispatches without considering losses and uses a linear approximation based on generation shift factors to determine the power flowing in each line. The second study solves the power flow problem and then obtains the power losses and power flowing in each line. The same spinning reserve criterion was used for both studies. The powerflow algorithm used was the Full Newton-Raphson from Matpower 2.0 [91].

5.4.1 8 Generators – 6 Lines system

For each study 100 independent runs were made using the best suited control parameters. These control parameters (scaling constant, crossover and population size) were determined via parameter tuning and are given in Table 5.13.

DE was successful, obtaining the best solution with consistency for all cases and returning a more economical operation when compared to the previous technique. In addition, DE satisfies the constraints by limiting the power flowing on line L_2 to 500 MW and by allocating the spinning reserve adequately according to the criterion used in this research.

TABLE 5.14
SECURITY CONSTRAINED DISPATCH TEST RESULTS

	Case 1	**Case 2**	**Case 3**	**Case 4**
$\mathbf{G}_1$	158.36	206.75	183.92	213.07
$\mathbf{G}_2$	145.63	191.92	170.08	197.96
$\mathbf{G}_3$	350	255.33	349.82	257.96
$\mathbf{G}_4$	200	200	185.18	200
$\mathbf{G}_5$	250	250	250	250
$\mathbf{G}_6$	200	200	200	200
$\mathbf{G}_7$	100	100	100	100
$\mathbf{G}_8$	350	350	315	335
Reserve	100	135	150	150
BSF $	38974.94	39691.16	39262.70	39773.05
L_1	279.64	231.25	254.08	224.93
L_2	581.15	500.00	573.38	500.00
L_3	398.15	402.60	396.29	401.89
L_4	152.13	158.14	149.19	157.04
L_5	54.472	54.45	54.26	54.41
L_6	48.598	48.75	49.27	48.69

TABLE 5.15
SECURITY CONSTRAINED DISPATCH COMPARISON

	Ref. [39]	**DE**
Case 1	38975.50	38974.94
Case 2	39688.71	39687.93
Case 3	39246.30	39243.92
Case 4	39781.64	39773.05

For proper comparison, since two case studies from [39] did not satisfy completely the power balance constraint, DE was dispatched according to the sum of the generators outputs of [39]. Also, the objective function was recalculated as the sum of the generator costs for the power outputs of [39]. These results are shown on Table 5.15.

TABLE 5.16
STATISTICAL RESULTS BASED ON 100 INDEPENDENT RUNS

	Case 1	Case 2	Case 3	Case 4
Median	38974.94	39691.16	39262.70	39773.05
Standard Deviation	703.51	296.68	347.38	152.65
Mode	38974.94	39691.16	39263.00	39773.05
BSF	38974.94	39691.16	39263.00	39773.05
WSF	44755.64	41326.00	41339.00	41299.71
SR	98%	96%	93%	95%

5.4.2 Modified Load IEEE 30 Bus – 6 Generator System

For each study 100 independent runs were made using the best suited control parameters. These control parameters (scaling constant, crossover and population size) were determined via parameter tuning and are given in Table 5.13. This system is a modification of the basic IEEE 30 bus test system with an increased load condition that results in violation of the line flow limits in several lines.

For the modified IEEE 30 bus system DE returned successful results by minimizing the cost function and satisfying the imposed constraints. The best solution was found with consistency for all cases with very low data dispersion (maximum standard deviation of 0.28). Table 5.17 and 5.18 show the results for this case study.

TABLE 5.17
MODIFIED IEEE 30 BUS TEST SYSTEM SECURITY DISPATCH TEST RESULTS

MW	Case 1	Case 2	Case 3	Case 4
G_1	200.00	198.38	186.49	185
G_2	63.32	70.86	70	70
G_3	25.97	27.83	27.95	39.33
G_4	35.00	35	33.51	35
G_5	24.35	20.45	25	20.48
G_6	22.36	18.81	27.08	19.32
Reserve	25	25.76	40	40
BSF $	1094.12	1096.60	1100.97	1112.76

TABLE 5.18
STATISTICAL RESULTS BASED ON 100 INDEPENDENT RUNS

	Case 1	Case 2	Case 3	Case 4
Median	1094.12	1096.58	1100.97	1112.76
Standard Deviation	0.00	0.00	0.28	0.00
Mode	1094.12	1096.58	1100.97	1112.76
BSF	1094.12	1096.58	1100.97	1112.76
WSF	1094.12	1096.60	1103.75	1112.76
SR	100%	99%	99%	100%

5.5 Case Study IV: Reactive Power Dispatch

Differential evolution algorithm was used to solve the reactive power dispatch problem using the 30 bus and 6 Generator IEEE Test system described in [41]. Two different case studies were designed based on this test system. The first case study adjusts the generator output voltages and the transformer taps of the system to improve the reactive power allocation. In this case, the transformer taps were modeled as both continuous (case 1A) and discrete variables (case 1B). The second study includes 9 dynamic capacitor banks distributed over the network to improve the system reactive power flow. This study, models the capacitor banks as continuous variables (case 2A) and as discrete variables (case 2B) and the transformer taps only as discrete variables for both approaches. Both of these case studies test the capability of the algorithm for solving mixed discrete optimization problems.

When transformer taps were modeled as discrete variables, the tap step was set to 0.00625 pu with 16 steps over and 16 steps under 1.0 pu. Capacitor banks steps were chosen to be of 0.050 MVAR from 0 to 5 MVAR. Capacitor banks were included as part of the system admittance matrix, considering the sensitivity of capacitor banks to voltage variations. The powerflow algorithm used was the Full Newton-Raphson from Matpower 2.0 [91]. For proper comparison, power loss and bus voltages for initial conditions were recalculated with Matpower based on the settings given in [41].

TABLE 5.19
CASE STUDIES CONTROL PARAMETERS

Control Parameters	Case 1A	Case 1B	Case 2A	Case 2B
F	0.6	0.6	0.6	0.6
C_R	0.7	0.7	0.85	0.85
N_P	20	20	35	35
μ_1	500	500	500	500
μ_2	500	500	500	500
μ_3	500	500	500	500

5.5.1 IEEE 30 Bus – 6 Generators System

For each approach (continuous and discrete transformer taps) 60 independent runs were made using the best suited control parameters. These control parameters (scaling constant, crossover and population size) were determined via parameter tuning and are given in Table 5.19. The fixed real power dispatch is given on Table 5.21. System conditions can be found on reference [41]. This case study included the capacitor banks at bus 10 and at bus 24 of .1901 MVAR and .04 MVAR.

TABLE 5.20
STATISTICAL RESULTS BASED ON 60 INDEPENDENT RUNS

	Continuous Xfmr	**Discrete Xfmr**
Median	5.0485	5.0486
Std. Deviation	9.8E-07	9.9E-05
BSF	5.0485	5.0486
WSF	5.0485	5.0493
SR	100%	98%

TABLE 5.21
IEEE 30 BUS – 6 GENERATOR RESULTS

	Initial Condition [41]	**Continuous Approach**	**Discrete Approach**
E_{G1} (p.u.)	1.05	1.0718	1.0718
E_{G2} (p.u.)	1.04	1.0626	1.0626
E_{G5} (p.u.)	1.01	1.0400	1.0400
E_{G8} (p.u.)	1.01	1.0406	1.0405
E_{G11} (p.u.)	1.05	1.1000	1.1000
E_{G13} (p.u.)	1.05	1.0810	1.0812
P_{G1} (MW)	99.23	98.448	98.449
P_{G2} (MW)	80	80	80
P_{G5} (MW)	50	50	50
P_{G8} (MW)	20	20	20
P_{G11} (MW)	20	20	20
P_{G13} (MW)	20	20	20
Q_{G1} (MVAR)	1.89	-0.022	-0.0385
Q_{G2} (MVAR)	21.67	18.059	18.005
Q_{G5} (MVAR)	18.95	25.673	25.647
Q_{G8} (MVAR)	18.21	39.597	39.451
Q_{G11} (MVAR)	38.25	26.962	27.098
Q_{G13} (MVAR)	39.91	24.180	24.344
$T_{6\text{-}9}$ (p.u.)	1.078	1.0242	1.0250
$T_{6\text{-}10}$ (p.u.)	1.069	0.9000	0.9000
$T_{4\text{-}12}$ (p.u.)	1.032	1.0059	1.0063
$T_{28\text{-}27}$ (p.u.)	1.068	0.95785	0.95625
Q_{C10} (MVAR)	0.1901	0.1901	0.1901
Q_{C24} (MVAR)	0.04	0.04	0.04
Ploss (MW)	5.829	5.0485	5.0486

TABLE 5.22
VOLTAGE IMPROVEMENT CASE STUDY 1

	Initial Condition	Continuous Taps	Discrete Taps
V19	0.942	1.0217	1.0216
V20	0.945	1.0262	1.0261
V21	0.940	1.0303	1.0302
V22	0.941	1.0307	1.0307
V23	0.946	1.0223	1.0224
V24	0.927	1.0182	1.0184
V25	0.920	1.0288	1.0296
V26	0.900	1.0113	1.0121
V27	0.925	1.0440	1.0451
V29	0.902	1.0246	1.0257
V30	0.890	1.0134	1.0145

5.5.2 IEEE 30 Bus – 6 Generators System with Dynamic Capacitor Banks

For each approach (continuous and discrete capacitor banks) 60 independent runs were made using the best suited control parameters. These control parameters (scaling constant, crossover and population size) were determined via parameter tuning and are given in Table 5.19. The fixed real power dispatch is given on Table 5.23.

DE solved the highly nonlinear RPD considering capacitor banks as continuous and as discrete variables. Losses were reduced by .469 MW for both approaches. This problem is more complex due to the number of possible combinations of capacitor banks that provide almost the same system power loss. The best solution found was 10.133056 MW for the continuous approach while the discrete approach best solution was 10.133088 MW. Algorithm convergence was good reducing losses to 10.1334 MW within 450 iterations and 10.13316 within 1050 iterations. Improving the objective function to 10.13306 (in the continuous approach) required an additional 1000 iterations from 10.13316 which represents a significant drop in the convergence rate. Both approaches improved the voltage profile of the case study by eliminating 5 voltage violations as seen on Table 5.25.

TABLE 5.23
IEEE 30 BUS – 6 GENERATOR WITH DYNAMIC CAPACITOR BANKS RESULTS

		Case Study 2	
	Initial Condition [41]	**Continuous Banks**	**Discrete Banks**
E_{G1} (p.u.)	1.10	1.0877	1.0876
E_{G2} (p.u.)	1.08	1.0674	1.0673
E_{G5} (p.u.)	1.03	1.0340	1.0341
E_{G8} (p.u.)	1.04	1.0370	1.0371
E_{G11} (p.u.)	1.08	1.1000	1.0999
E_{G13} (p.u.)	1.08	1.0446	1.0410
P_{G1} (MW)	187.34	186.867	186.867
P_{G2} (MW)	53.781	53.781	53.781
P_{G5} (MW)	16.955	16.955	16.955
P_{G8} (MW)	11.288	11.288	11.288
P_{G11} (MW)	11.287	11.287	11.287
P_{G13} (MW)	13.355	13.355	13.355
Q_{G1} (MVAR)	6.90	7.73	7.76
Q_{G2} (MVAR)	39.39	27.95	27.73
Q_{G5} (MVAR)	13.52	28.63	28.68
Q_{G8} (MVAR)	15.46	29.60	29.72
Q_{G11} (MVAR)	37.26	29.43	29.37
Q_{G13} (MVAR)	38.81	-3.93	-6.59
$T_{6\text{-}9}$ (p.u.)	1.072	1.0500	1.0500
$T_{6\text{-}10}$ (p.u.)	1.070	0.94375	0.94375
$T_{4\text{-}12}$ (p.u.)	1.032	0.9625	0.9625
$T_{28\text{-}27}$ (p.u.)	1.068	0.9750	0.9750
Q_{C10} (MVAR)	0.692	1.45	1.55
Q_{C12} (MVAR)	0.046	0.02	2.40
Q_{C15} (MVAR)	0.285	4.19	4.30
Q_{C17} (MVAR)	0.287	5.00	5.00
Q_{C20} (MVAR)	0.208	3.96	3.90
Q_{C21} (MVAR)	0.000	5.00	5.00
Q_{C23} (MVAR)	0.330	2.91	2.85
Q_{C24} (MVAR)	0.938	5.00	5.00
Q_{C29} (MVAR)	0.269	2.50	2.55
Ploss (MW)	10.602	10.133056	10.133088

TABLE 5.24
CASE STUDY 2 STATISTICAL RESULTS BASED ON 60 INDEPENDENT RUNS

	Continuous Banks	**Discrete Banks**
Median	10.1331487	10.1331259
Standard Deviation	6.617E-05	9.899E-05
BSF	10.1330556	10.1330599
WSF	10.1332903	10.1333099
SR	43%	63%

Both case studies were successfully optimized providing better results than the previous gradient based optimization technique [41]. Optimization problems with discrete variables were easy to handle with DE since the technique only required minor adjustments to the canonical form. Also, the results obtained proved that the technique is suitable for solving highly nonlinear mixed discrete optimization problems.

TABLE 5.25
VOLTAGE IMPROVEMENT CASE STUDY 2

	Initial Condition [41]	**Continuous Banks**	**Discrete Banks**
V3	1.063	1.050	1.050
V4	1.055	1.042	1.041
V26	0.936	1.018	1.018
V29	0.939	1.034	1.034
V30	0.926	1.020	1.020

CHAPTER 6

CONCLUSIONS AND FUTURE WORK

6.1 Conclusions

This research has presented a novel technique for the solution of power systems optimization problems in particular the economic dispatch problem and reactive power dispatch problem. The algorithm was successful in finding global optima solutions while providing a good convergence rate. Four base case studies were designed to test the algorithm: Non-Conventional Cost Functions, Economic-Environmental Power Dispatch, Security Constrained Economic Dispatch and Reactive Power Dispatch. These case studies were solved and compared with existing literature, proving the capability of the algorithm to solve these problems.

DE, as well as other evolutionary algorithms, is based on stochastic methods to determine the solution and therefore do not guarantee an optimal solution at all times. Nonetheless, an adequate perturbation strategy along with a correct set of control parameters such as the scaling factor, crossover constant and sufficient members may lead to very successful results, in reasonable computational time.

The two strategies that performed better were DE/best/2/bin and DE/rand/1/bin. The first one creates generations perturbing the best solution found with 2 difference vectors. DE/rand/1/bin instead creates generations by perturbing one randomly selected vector with the difference vector. Both strategies use binomial distribution in the recombination process. DE/best/2/bin performed better in terms of convergence, consistency and type of minimum obtained. Since the strategy DE/best/2/bin perturbs the best solution found, it may be difficult to escape from local minima as the population diversity diminishes. Since DE/rand/1/bin, perturbs randomly selected vectors over the solution space, it offers the advantage of perturbing more candidate solutions and escaping from local minima more easily.

The scaling constant controls the perturbation applied to the individuals. This value can be selected from [0 1.2+] but a more suitable range should be [0.5 1.0] depending on the case study. DE/best/2/bin performed better from [0.5 0.65] for almost all cases. When the system is converging in local minima an increase in the scaling factor is recommended. Higher scaling factors will slow down convergence rate since the perturbation will be relatively high to explore efficiently the neighborhood, until diversity reduces in such a way that the difference vector will also reduce.

Crossover constants (C_R) control the diversity of the population. A constant near 1.0 provide faster results but with more probabilities of converging in local minima. A smaller constant increases the diversity of the population and also increases simulation time, since it will require more generations to bring together the complete population. From all the experiments a suitable range for the crossover constant (strategy DE/best/2/bin) was [0.70 1.00]. Values lower than 0.7 offered too much diversity and increased significantly generations without a big improvement in the population. A more strict range of operation could be [0.80 0.95] since within this range the algorithm provided the best performance.

Population size plays an important role in the algorithm success. Large populations give the algorithm more opportunities to find the desired solution since it can evaluate more thoroughly the feasible space at the expense of computational time. Small populations tend to converge to a solution faster than large populations, but more susceptible to local minima. Initially a recommended population should be near three times the problem dimension providing the algorithm enough members according to the problem to find the optimal solution and increased or reduced depending on the problem requirements. From experimentation it was noted that very large populations have such great diversity that affect the search and the converge rate. Very large populations do not guarantee that it will locate the global optimal solution. Also, when the power flow subroutine was incorporated, larger populations increased dramatically simulation time becoming more suitable a reduction in the crossover constant to improve diversity instead of an increase in population size.

Penalty strategy selection for constraint evaluation is very important for the success and performance of DE. Different penalty strategies may lead to different results in solution type, accuracy or algorithm performance. The use of static or constant penalties is not suitable for all constraints, but improves simulations since they require less floating point operations than dynamic penalties. Dynamic penalties give the algorithm a better understanding of the solution space but increase the number of floating point operations required by the algorithm and consequently increases computational time.

In the prohibited zones case, prohibited regions were modeled better with penalty functions than by assigning the value of the nearest bound violated and preventing the algorithm from exploring combinations near the prohibited zones. Several penalty functions were tested being noticeable that abrupt slopes and high penalties did not provide the best results. The best the one was based on a half cycle sinusoidal function which provided a smooth exploration and success of individuals near the prohibited zones. A penalty factor was used to assure that the constraint would be satisfied.

Selection of penalty factors was done considering the order of the objective function. Normally, the algorithm performs well with several penalty factors determining successfully global optimal solutions with consistency. The penalty factor with best performance was the least one possible that satisfied the constraint, but tuning of this factor will lead to multiple runs for a negligible increase in the algorithm success. The most critical penalty factor selection was the prohibited zones case. Higher penalty factors make the prohibited zones harder to explore, and solutions near the limit of the prohibited zone harder to find. For this reason, several simulations were required to find the proper set of penalty factors that improved the most the algorithm success.

6.2 Future Work

The work previously presented provides an understanding of new optimization techniques capable of solving complex power systems engineering problems. The economic dispatch problem was covered and the results demonstrate the capability of the algorithm to obtain the desired value and the applicability to large scale optimization problems. Several questions should be addressed in the future concerning the applicability of new optimization techniques such as DE to further optimization problems in power systems. Some lines of future work should be:

- Application of DE to other power systems optimization problems such as unit commitment, powerflow and power system planning techniques.
- Penalty function design and testing that improves algorithm performance and reduces or avoids penalty factor selection.
- Implementation of a pareto-based differential evolution algorithm for multiobjective optimization.
- Enhancements to the algorithm code that improve performance and reduce simulation times (OPF parallel implementation).

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