APPLICATIONS OF THE EVOLUTIONARY PROGRAMMING OPTIMIZATION TECHNIQUE IN POWER SYSTEMS PLANNING AND OPERATION

By

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ABSTRACT

This thesis presents the application of the Evolutionary Programming optimization technique in various Power Systems Engineering problems. In particular, two areas are addressed:

- Power System Operation, in which the following two problems are studied: Branch Outage Simulation for power system contingency studies and Power System State Estimation.
- Power System Planning, in which the following two problems are studied: Profit-Based Unit Commitment and Unit Commitment with Network Flows Constraints.

The above problems were properly formulated as optimization problems subject to the applicable constraints. In order to show the flexibility and applicability of the models developed to solve the addressed problems, these models were tested with systems whose solution had been previously obtained by means of classical approaches available in the literature reviewed.

The main contribution of this thesis is the incorporation in the heuristic research field, of novel optimization models based in Evolutionary Programming with capacity to solve the mentioned power systems optimization problems. Thus, the available power system optimization tools are enhanced with these new models which in some cases surpass the existing optimization resources.

RESUMEN

Esta tesis presenta la aplicación de la técnica de optimización de Programación Evolutiva en varios problemas de Ingeniería en Sistemas de Potencia. En particular, dos áreas son tratadas:

- Operación de Sistemas de Potencia, en la cual los siguientes dos problemas son estudiados: Simulación de Interrupción de Líneas/Transformadores para ser usado en estudios de contingencias de sistemas de potencia y Estimación de Estado de Sistemas de Potencia.
- Planificación de Sistemas de Potencia, en la cual los siguientes dos problemas son estudiados: Programación Horaria Basada en Beneficio, de Unidades Generatrices y Programación Horaria de Unidades Generatrices tomando en consideración las Restricciones de Flujos en la Red.

Los problemas antes señalados fueron apropiadamente formulados como problemas de optimización sujetos a las restricciones aplicables a los mismos. Con el objetivo de mostrar la flexibilidad y capacidad de los modelos desarrollados para resolver los problemas a ser tratados, dichos modelos fueron probados con sistemas de prueba cuyas soluciones habían sido previamente obtenidas por medio de técnicas clásicas que se encontraban disponibles en la literatura revisada.

La contribución principal de esta tesis es la incorporación al campo de la investigación de métodos heurísticos, de novedosos modelos de optimización basados en

Programación Evolutiva, con capacidad de resolver los problemas de optimización de sistemas de potencia antes mencionados. Por lo tanto, las herramientas de optimización de sistemas de potencia disponibles son enriquecidas con estos nuevos modelos los cuales, en algunos casos, superan los recursos de optimización existentes.

Dedicated to my family, especially to my father.

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CHAPTER 2:

$\mathbf{x}^i$	is the vector of trial solutions corresponding to the i^{th} individual
$\boldsymbol{\eta}^i$	is the vector of strategies parameters corresponding to the i^{th} individual
μ	is the number of individuals in the population
x_j^i	is the j^{th} element of i^{th} vector of trial solutions
η_j^i	is the j^{th} element of i^{th} vector of strategies parameters
$x_j^{\max}$	is the maximum value that can acquire the j^{th} element of i^{th} vector of trial solutions
$x_j^{\min}$	is the minimum value that can acquire the j^{th} element of i^{th} vector of trial solutions
υ_j^i	is a random number uniformly distributed in the interval $(0,1)$ generated for each j^{th} element of i^{th} individual
τ	is a scaling factor used in the mutation process
τ'	is a scaling factor used in the mutation process
ν_j^i	is a random number normally distributed with mean zero and standard deviation one generated for each j^{th} element of i^{th} individual
f^i	is the fitness function of i^{th} individual
q	is the number of individuals that will be compared against each individual in the population during the selection process

w_s is the score obtained for an individual when is compared with one of its opponents

w_r is the sum of scores of an individual during the comparison stage

N_g is the generation tolerance used in the stop criterion checking

ε is the error tolerance

L_j^i is a random number from Lévy distribution generated for each j^{th} element of i^{th} individual

σ_z is the standard deviation of value z

α is the factor which controls the shape of the Lévy distribution

$\Phi(\mathbf{x})$ is the augmented fitness function

p_0 is a fixed penalty parameter

$\Phi_u(\mathbf{x})$ is the penalty function

$g_i^+(\mathbf{x})$ is the magnitude of the violation of the i^{th} inequality constraint in the penalty function

CHAPTER 3:

δ_n is the pre-outage bus voltage phase angle at bus n

$\overline{\delta}_n$ is the post-outage bus voltage phase angle at bus n

P_r is the original active power through branch r before it was opened

x_r is the reactance of branch r

$\mathbf{B}'$ is the matrix which relates the P-δ quantities in fast decouple load flow method

$\Delta\mathbf{V}$ is the load bus voltage magnitude increment vector

$\Delta\mathbf{Q}$ is the net reactive power change vector

$\mathbf{B}''$ is the matrix which relates Q-V quantities in fast decouple load flow method

N_{PQ} is the number of load buses in the system

$\mathbf{V}$ is the pre-outage load bus voltage magnitude vector

$\bar{\mathbf{V}}$ is the post-outage load bus voltage magnitude vector

$\overline{Q}_i$ is the post-outage net reactive power at bus i

Q_{schi} is the schedule bus reactive power at bus i

N is the number of buses in the system

G_{ik} is the real part of the ik^{th} element of the admittance matrix

B_{ik} is the imaginary part of the ik^{th} element of the admittance matrix

S represents the set of values of load bus voltage magnitude to study

NLF is the Newton-Rapshon Power Flow method

PEP is the proposed method for branch outage simulation

CHAPTER 4:

$J(\mathbf{x})$ is the state estimation function to minimize

$\mathbf{x}$ is the vector of unknowns values to be estimated

N_m is the number of independent measurements

σ_j^2 is the variance of the j^{th} measurement value

z_j is the j^{th} measurement value

$h_j(\mathbf{x})$ is the function that is used to calculate the value being measured by the j^{th} measurement

$\mathbf{r}$ is the residual vector

σ_j is the standard deviation of the j^{th} measurement value

P_i is the real power injection at bus i

P_{ik} is the real power flow from bus i to bus k

Q_i is the reactive power injection at bus i

Q_{ik} is the reactive power flow from bus i to bus k

M_b is the number of voltage measurements

$M_{P_{\text{inj}}}$ is the number of real power injection measurements

$M_{P_{\text{flow}}}$ is the number of real power flow measurements

σ_{V_i} is the standard deviation of the voltage meter installed at bus i

V_j^{meas} is the j^{th} voltage measurement

V_j^{est} is the j^{th} voltage estimation

WLS is the Weighted Least Square formulation

WLAV is the Weighted Least Absolute Value formulation

EPSE	is the proposed EP model for state estimation
GNSE	is the classical method for solving state estimation
MSE	is the Mean Square Error analysis
u	is the number of values
E_u	is the u^{th} estimated value
T_u	is the u^{th} true value

CHAPTER 5:

TC	is total production cost
N	is the number of generator units
T	is the number of hours
F_i	is fuel cost function of generator i
P_{it}	is real power output of generator i at hour t
ST_i	is startup cost of generator i
SD_i	is shutdown cost of generator i
X_{it}	is the on/off status of generator i at hour t
D_t	is load demand at hour t
SR_t	is spinning reserve at hour t
$P_{i\min}$	is minimum generation limit of generator i

$P_{i\max}$	is maximum generation limit of generator i
T_i^{on}	is the minimum time which the generator i have been continuously On
T_i^{off}	is the minimum time which the generator i have been continuously Off
T_{iup}	is the minimum up time of generator i
T_{idown}	is the minimum down time of generator i
UR_i	is the maximum ramp-up rate limit of generator i
DR_i	is the maximum ramp-down rate limit of generator i
PF	is the total profit of Generation Company
RV	is the total revenue of Generation Company
R_{it}	is reserve generation of generator i at time t
D'_t	is forecasted demand at hour t
SR'_t	is forecasted reserve at hour t
SP_t	is the forecasted spot price at hour t
RP_t	is the forecasted reserve price at hour t
r	is the probability that the reserve power is called and generated
$\mathbf{X}$	is the matrix of binary variables to optimized
p	is the number of hours in each set of status
λ_t	is the system marginal cost at hour t

α_i is the constant term in the quadratic cost curve of the unit i

β_i is the linear term in the quadratic cost curve of the unit i

γ_i is the quadratic term in the quadratic cost curve of the unit i

ζ is the dispatch factor which help account the type of reserve market by modifying the initial energy offer

PF_1^k is the k^{th} trial profit of GENCO in problem 1

RV_1^k is the k^{th} trial revenue in problem 1

C_F^k is the k^{th} trial total fuel cost of units in problem 1

C_T^k is the k^{th} trial total transition cost of units in problem1

R is the matrix of reserve powers whose elements are the variables to be optimized

EPUCM is the EP model for profit-based unit commitment

TUC is the traditional unit commitment

EPLR is the classical method to solving profit-based unit commitment

UCFC is the EP model for unit commitment with network flow constraints

L_t is the system power loss at hour t

BCUC is the classical method used to solve unit commitment with network flow constraints

OPF is the optimal power flow routine

ED is the economic dispatch routine

CHAPTER 1
INTRODUCTION

There are many problems within the power system engineering field that have been solved by means of numerical optimization techniques. Some of the most popular applications include: network planning, maintenance scheduling, unit commitment, economic dispatch, optimal power flow and reactive power dispatch. Optimization methods like Linear Programming, Interior Point Method, Quadratic Programming, Newton Method and Dynamic Programming have a long history of success solving these kinds of problems.

Over the years, the formulations of these problems have grown in both dimensionality and complexity. In some cases, the solution of these complex multidimensional problems by means of classical optimization techniques is extremely difficult and/or computationally expensive.

Recent advances in computation, and the search for better results for complex optimization problems, have stimulated the development of a family of techniques known as Evolutionary Algorithms (EA). EA are stochastic based optimization techniques that search for the solution of problems using mathematical models that simulate the biological evolution process. These algorithms provide an alternative for obtaining global or near global optimal solutions, particularly in the presence of non-continuous, non-convex and wide solution spaces.

Specifically, these algorithms are population based techniques, which explore the solution space randomly by using a population of candidate solutions instead of the single solution estimate used by most classical techniques. The success of EA lies in the capability of finding solutions with random exploration of the solution space rather than performing exhaustive exploration. This results in a faster optimization process with less computational resources while maintaining the capability of finding global or near global solutions.

Several Evolutionary Computation (EC) techniques have been developed, which have become very popular for solving numerous engineering problems: Genetic Algorithms (GA), Evolutionary Programming (EP) and Evolution Strategies (ES) were the first EC techniques developed. Other techniques such as Differential Evolution (DE), Particle Swarm Optimization (PSO) and Ant Colony Search (ACS) have been developed recently, partly due to the recent advances in parallel computation as well as the utilization of faster and more powerful processors. Further information about EA, as well as their applications in power systems engineering, can be found in [1]-[3].

One of the most commonly used evolutionary algorithms is EP. This technique was originally conceived by Dr. Fogel in 1960 [2]. Its mathematical model places emphasis on the biological linkage between parents and their offspring. EP obtains solutions to optimization problems using two basic operators: mutation operator, in which offspring are generated by adding noise to the original structure of their corresponding parents; and selection operator, in which each parent and offspring is compared with a number of opponents selected at random in order to pick the individuals that will be chosen as parents for the next generation. This procedure is repeated for several generations, resulting in an evolutionary process that converges toward an optimal value.

1.1 Topic of the Thesis

The topic of this thesis is "Applications of Evolutionary Programming Optimization Technique in Power Systems Planning and Operation". This research work covers two main areas: Power System Operation and Power System Planning. Each area includes two different problems to be solved by means of Evolutionary Programming. Tables 1.1.1-1.1.2 summarize the problems covered in this thesis and include the main classical solving approach traditionally used to solve them.

Table 1.1.1: Power System Operation Problems to be solved by means of EP.

Power System Operation			
Problem	Control Variables Type	Description of the Problem	Main Classical Solving Method
Branch Outage Simulation	Continuous	Find a pair of fictitious source values at both end of the branch, which will create the effect of the branch outage	No classical approaches developed
Power System State Estimation	Continuous	Perform a reliable estimation of the current operating state of the system	WLS or WLAV method using Gradient and Newton methods

Table 1.1.2: Power System Planning Problems to be solved by means of EP.

Power System Planning			
Problem	Control Variables Type	Description of the Problem	Main Classical Solving Method
Profit Based Unit Commitment	Binary and Continuous	Find a schedule which maximizes the profits of the Generation Company while the system demand and units constraints are satisfied	Lagrangian Relaxation and Dynamic Programming
Unit Commitment with Network Flows Constraints	Binary	Find a day ahead schedule for the available generating units which minimizes the overall operating costs observing the network flows constraints.	Bender Decomposition with Lagrangian Relaxation or Dynamic programming using OPF

1.2 Objectives and Contributions of the Thesis

At the end of this research work, the following specific objectives must have been fulfilled:

1. The use of MATLAB® for the development of solution methodologies based in EP technique for solving the problems to be addressed in this thesis.
2. The comparison of the results obtained using EP with those obtained by means of other techniques.
3. The evaluation of the tradeoff associated with the EP control variables variations.
4. The organization of the test systems data used and the results obtained in order to facilitate future research from this work.
5. The presentation of recommendations regarding the performance and control of this algorithm.

These specific objectives will help to achieve the main objective of this research work, which consists in investigating the applicability and efficacy of EP for determining solutions to the power system problems to be addressed. The main contribution of this thesis is the incorporation of novel EP models in the Evolutionary Algorithms field with capacity to solve the complex power system problems addressed here.

1.3 Thesis Outline

The rest of this work is organized as follows. Chapter 2 describes the optimization method to be used along in this thesis (i.e. Evolutionary Programming), as well as its implementation for the solution of different problems. Chapters 3-5 are dedicated to show the general description of the problems to be solved and their general formulation, the EP model used to solve them, the results of different case studies, and their discussions. Finally, Chapter 6 presents general conclusions and recommendations for future work.

CHAPTER 2
EVOLUTIONARY PROGRAMMING

2.1 Introduction

More than 40 years ago, several researchers from US and Europe independently came up with the idea of mimicking the mechanism of biological evolution in order to develop powerful algorithms for problems of adaptation and optimization. It is known that optimization is the process that allows the maximization or minimization of an objective function. So as it is affirmed in [4], a typical optimization problem can be stated as a pair (M, f), where $M \subseteq \mathbb{R}^n$ is a bounded set on $\mathbb{R}^n$ and $f : M \to \mathbb{R}$ is an *n*-dimensional real value function. The problem is to find a vector $\vec{\mathbf{x}}^* \in M$ such that $f(\vec{\mathbf{x}}^*)$ is a global optimum in M, that is:

$$\forall \vec{\mathbf{x}} \in M : \begin{cases} f(\vec{\mathbf{x}}^*) \leq f(\vec{\mathbf{x}}) & \text{for minimization problems} \\ f(\vec{\mathbf{x}}^*) \geq f(\vec{\mathbf{x}}) & \text{for maximization problems} \end{cases} \tag{2.1.1}$$

where f must be bounded. Characteristics such as large dimensionality of the problem, strong nonlinearity, non-differentiability, noisy, and time varying objective function values require the search for robust global optimization methods that are still applicable and yield useful results when the traditional methods fail. Moreover, for many complex optimization problems, the identification of an improvement over the best solution found so far is considered a good accomplishment. In many cases, EA provides an effective method to achieve this.

EA rely on the concept of a population of individuals that represent potential solutions to a given optimization problem, these individuals undergo probabilistic operators such as mutation, selection, and crossover to evolve towards individuals with better fitness values. The function to be optimized acquires a value when it is evaluated with the elements of an individual; this value is known as the fitness of this individual. The mutation operator introduces innovation into the population by generating variations of individuals and the crossover operator performs an information exchange between different individuals from a population. The selection operator imposes a driving force on the process of evolution by preferring better individuals to survive and reproduce when the members of the next generation are selected.

2.2 Features of EP

One of the most popular EA is Evolutionary Programming (EP). This technique originally conceived by Dr. Fogel in 1960, has as goal to achieve intelligence behavior through simulated evolution. Dr. Fogel tried to clarify how simulated evolution could be used to achieve intelligence behavior when he said "Intelligence is the capability of a system to adapt its behavior to meet its goal in a range of environments." [4].

According to [5], the optimization process by means of EP is based in the following two major steps:

1. Mutate all the solutions in the current population
2. Select the next generation from the mutated and the current solutions.

These two steps can be regarded as a population-based version of the classical *"generate and test method"*, where mutation is used to generate new solutions (offspring) and selection is used to test which of the current and new generated solutions should survive for the next generation. The version for EP of generate and test indicates that mutation is a key search operator which generates new solutions from the current ones [6].

2.3 Function Optimization by EP

The first step in EP optimization process is to generate an initial population of μ individuals. Each individual represents a candidate solution, which is formed by a pair of real value vectors, $\left(\mathbf{x}^i, \boldsymbol{\eta}^i\right)$, $\forall i \in \{1,...,\mu\}$, where $\mathbf{x}^i$'s are the vectors whose components must be optimized and $\boldsymbol{\eta}^i$'s are known as the vectors of strategy parameters whose components are used in the mutation process. Each $\mathbf{x}^i$ and $\boldsymbol{\eta}^i$ has n independent components:

$$\mathbf{x}^i = \left\{x_1^i, x_2^i, ..., x_j^i, ..., x_n^i\right\} \tag{2.3.1}$$

$$\boldsymbol{\eta}^i = \left\{\eta_1^i, \eta_2^i, ..., \eta_j^i, ..., \eta_n^i\right\} \tag{2.3.2}$$

The initial components of each $\mathbf{x}^i$ $\forall i \in \{1,...,\mu\}$ are selected in accordance with a uniform distribution ranging over a presumed solution space, this is:

$$x_j^i\left[0\right] = x_j^{\min} + \upsilon_j^i\left(x_j^{\max} - x_j^{\min}\right) \tag{2.3.3}$$

$\forall j \in \{1,...,n\}$, here υ_j^i is a uniformly distributed random number in the interval $(0,1)$ generated anew for each value of j. The values of $\boldsymbol{\eta}^i$ $\forall i \in \{1,...,\mu\}$ are initially set as a constant value.

The second step is to create an offspring from each parent $(\mathbf{x}^i, \boldsymbol{\eta}^i)$, according to:

$$\eta_j^i[t] = \eta_j^i[t-1]\exp\left(\tau' \cdot \nu^i + \tau \cdot \nu_j^i\right) \tag{2.3.4}$$

$$x_j^i[t] = x_j^i[t-1] + \eta_j^i[t] \cdot \nu_j^i \tag{2.3.5}$$

$\forall i \in \{1,...,\mu\}$, $\forall j \in \{1,...,n\}$, where $x_j^i[t]$ denotes the j^{th} component in the i^{th} individual among μ individuals of the population at the t^{th} generation. ν^i is a normally distributed random number with mean zero and standard deviation one. ν_j^i indicates that the random number is sampled anew for each value of j. The factors τ and τ' are defined as [7]:

$$\tau = \frac{1}{\sqrt{2\sqrt{\mu}}} \quad \text{and} \quad \tau' = \frac{1}{\sqrt{2\mu}} \tag{2.3.6}$$

The third step is to calculate the fitness f^r, $\forall r \in \{1,...,2\mu\}$ of the μ parents and their μ offspring.

The fourth step is to initialize the selection process defining a winning function w_r in which each of the 2μ fitness is compared with q fitness selected at random with the same probability, where $q \subseteq 2\mu$. Thus, for a minimization problem:

$$w_r = \sum_{s=1}^{q} w_s \tag{2.3.7}$$

and

$$w_s = \begin{cases} 1 & \text{if} \quad f^r < f^m \\ 0 & \text{otherwise} \end{cases} \tag{2.3.8}$$

$\forall r \in \{1,...,2\mu\}$, $\forall m \in \{1,...,q\}$ and $r \neq m$. Here, w_s is the winning score obtained by the r^{th} individual when its fitness is compared with the fitness of the m^{th} individual. The μ individuals that have the largest w_r are selected to be parents for the next generation.

Finally, the algorithm proceeds to the second step unless the best individual does not change for a predefined interval of generations, specifically:

$$\left| \frac{f^{\text{best}}[t] - f^{\text{best}}[t-1]}{f^{\text{best}}[t]} \right| \leq \varepsilon \tag{2.3.9}$$

for N_g successive generations, here ε is a sufficiently small positive value.

2.4 Enhanced EP for Continuous Variables

Some continuous highly dimensional optimization problems create stagnations or slow convergences toward a good near optimum when EP is used to solve them. In order to fix this problem, [5]-[7] have shown methods based in the replacement of the Gaussian mutation operator for Cauchy or Lévy mutation operators, which create offspring further away from its parent and to provide a higher probability of escaping from local optimum solutions. In this work, only the Lévy mutation operator is explained, since Cauchy mutation operator is a special case of the first one [7].

2.4.1 EP with Lévy Mutation Operator

The function optimization by EP, based on the Lévy mutation operator, differs from that shown in (2.3.5) as follows:

$$x_j^i[t] = x_j^i[t-1] + \eta_j^i[t] \cdot L_j^i \tag{2.4.1}$$

$\forall i \in \{1,...,\mu\}$, $\forall j \in \{1,...,n\}$, where L_j^i is a random number from the Lévy distribution generated anew for each j^{th} component in the i^{th} individual. The generator of random numbers from the Lévy distribution is shown below:

$$L_j^i = \psi\left\{1 + \left[k(\alpha) - 1\right]\exp\left(-\frac{|\psi|}{C(\alpha)}\right)\right\} \tag{2.4.2}$$

where:

$$\psi = \frac{z_j}{\sqrt[\alpha]{|y_j|}} \tag{2.4.3}$$

here, y and z are two random numbers normally distributed with mean zero and standard deviation σ_y and σ_z respectively, where $\sigma_y = 1$. These random numbers can be obtained as follows:

$$z = \nu \cdot \sigma_z \tag{2.4.4}$$

In this chapter, α controls the shape of the Lévy distribution requiring $0 < \alpha < 2$, the parameters σ_z, $k(\alpha)$ and $C(\alpha)$ are calculated in [8] and shown in Table 2.4.1.

Table 2.4.1: Parameters to Generate Lévy Random Numbers

α	$\sigma_z(\alpha)$	$k(\alpha)$	$C(\alpha)$	α	$\sigma_z(\alpha)$	$k(\alpha)$	$C(\alpha)$
0.10	9.922440	0.000032		1.20	0.878829	1.205190	2.9410
0.20	3.138200	0.021243		1.30	0.819837	1.318360	2.9005
0.30	2.104110	0.124698		1.40	0.759679	1.446470	2.8315
0.40	1.700470	0.273510		1.50	0.696575	1.599220	2.7370
0.50	1.479340	0.423607		1.60	0.628231	1.793610	2.6125
0.60	1.333910	0.560589		1.70	0.551126	2.064480	2.4465
0.70	1.226370	0.683435		1.80	0.458638	2.501470	2.2060
0.80	1.139990	0.795112	2.4830	1.90	0.333819	3.461500	1.7915
0.90	1.066180	0.899389	2.7675	1.95	0.241176	4.806630	1.3925
1.00	1.000000	1.000000		1.99	0.110693	10.498000	0.6089
1.10	0.938291	1.100630	2.9450				

2.4.2 EP with Adaptive Lévy Mutation Operator

Reference [7] proved that different values of α lead to different final results for EP, therefore no single α value is optimum for all different problems. Moreover, it is desirable to have different α values for different evolutionary search stages for a single problem. Gaussian mutation ($\alpha = 2.0$) works better for searching a small local neighborhood, whereas Cauchy mutation ($\alpha = 1.0$) is more effective exploring a large area of the search space. Reference [7] proposes an adaptive mutation which determines α by evolution. The adaptive mutation consists in generating four candidate offspring with α=1.0, 1.3, 1.7, 2.0 from each parent and select the best one as the surviving offspring.

2.5 Constraints Handling Method in EP

EP, as well as other EA, was originally conceived to solve unconstrained problems. Several constraint handling techniques have been applied to EA over the years. Reference [9] presents a comprehensive review of constrained optimization in evolutionary algorithms with classification of the methods used to handle constraints. The two main classifications 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 proposed by [9] to explore only the feasible solution space is to generate and keep candidate solutions in the feasible region, thus, 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 or generating a new value within the feasible range.

Methods based on penalty functions [9]-[12] modify the objective function providing information of the feasibility or infeasibility of the current search space, aiding the algorithm to find the desired optimal solution. Basically, the original objective function $f(\mathbf{x})$ is substituted by an augmented function $\Phi(\mathbf{x})$ which will be used to evaluate the fitness of the solutions candidates. For instance, a general constrained optimization problem can be defined as:

$$\begin{aligned} & \min \ f(\mathbf{x}) \\ & \text{s.t.} \quad h_j(\mathbf{x}) = 0 \quad \forall j \in \{1,\dots,m\} \\ & \qquad g_i(\mathbf{x}) \le 0 \quad \forall i \in \{1,\dots,r\} \end{aligned} \tag{2.5.1}$$

Then, the augmented function is defined as follow:

$$\Phi(\mathbf{x}) = f(\mathbf{x}) + p\Phi_u(\mathbf{x}) \tag{2.5.2}$$

where

$$\Phi_u(\mathbf{x}) = \sum_{j=1}^{m} \left[h_i(\mathbf{x}) \right]^2 + \sum_{i=1}^{r} \left[g_i^+(\mathbf{x}) \right]^2. \tag{2.5.3}$$

Here, $f(\mathbf{x})$ represents the objective function which to evaluate the feasible solutions, $\Phi_u(\mathbf{x})$ is the constraint violation measure for the $m+r$ constraints, p is a penalty parameter which can either be fixed or monotonically increasing with time. One possible way of stating this parameter is as follows:

$$p[t] = p_0 + \log(t+1). \tag{2.5.4}$$

Finally, $g_i^+(\mathbf{x})$ is the magnitude of the violation of the i^{th} inequality constraint, which can be expressed as:

$$g_i^+(\mathbf{x}) = \max\{0,\ g_i(\mathbf{x})\}. \tag{2.5.5}$$

2.6 EP Model for Binary Variables

Many problems are set in a space featuring discrete variables, moreover, by binary variables in which the control variables will only assume the values 0 or 1. Few publications are focused in the development of a general EP model for binary variables;

in contrast, they are focused in specific problems. Reference [13] shows a mixed-integer EP model for solving mechanical design optimization problem which contains integer, discrete, binary and continuous variables. In the specific case of binary variables problems, the initial population of individuals is generated at random according to:

$$x_j^i[0] = \text{round}\left(\upsilon_j^i\right) \tag{2.6.1}$$

$\forall i \in \{1,...,\mu\}$, $\forall j \in \{1,...,n\}$, after from each parent is generated an offspring according to:

$$x_j^i[t] = \begin{cases} 1 \text{ if } x_j^i[t-1] = 0 \text{ and } \upsilon_1 \leq 0.5 \\ 0 \text{ if } x_j^i[t-1] = 0 \text{ and } \upsilon_1 > 0.5 \\ 0 \text{ if } x_j^i[t-1] = 1 \text{ and } \upsilon_1 \leq 0.5 \\ 1 \text{ if } x_j^i[t-1] = 1 \text{ and } \upsilon_1 > 0.5 \end{cases} \tag{2.6.2}$$

where υ_1 is a random number uniformly distributed in the interval $(0,1)$ generated once. Unfortunately, the above method is unsuccessful in power system problems like unit commitment, in which the binary numbers represents the operation status of the units. This status must obey physical and operational constraints, which must abide to certain combinations of binary numbers. The method proposed in this thesis to satisfy these constraints will be explained in detail in Chapter 5.

CHAPTER 3
BRANCH OUTAGE SIMULATION FOR CONTINGENCY STUDIES

3.1 Introduction

One of the principal objectives in the operation of a power system is to maintain system security [14]. Since the specific times at which initiating events that cause components to fail are unpredictable, the system must be operated at all times in such a way that the system will not be left in a dangerous condition should any plausible initiating event occur. Since power system equipment is designed to be operated within certain limits, most pieces of equipment are protected by automatic devices that can cause equipment to be switched out of the system if these limits are violated. If any event occurs on a system that leaves it operating with limits violated, the event may be followed by a series of further actions that switch other equipment out of service. If this process of cascading failures continues, the entire system or large parts of it may completely collapse.

The ability of a power system to withstand single or multiple contingencies (i.e., component outages) without service interruption is known as system security. One of the major functions that are carried out in an Energy Control Center in order to keep system security is Contingency Analysis (Security Assessment). The results of this type of analysis allow systems to be operated in a defensive mode. Many of the problems that occur on a power system can cause serious trouble within such a short time period that the operator could not take action fast enough. This is often the case with cascading failures. Because of this aspect of systems operation, modern computers at Energy Control Centers (ECC) are equipped with contingency analysis programs that model possible system troubles before they arise. These programs are based on a model of the power system and are used to study outage events and alarm the operators of any potential overloads and/or out of limit voltages.

The exact steady state post-contingency conditions can be obtained by means of a full AC power flow study. However, this approach results impractical for real-time applications, due to the large number of contingencies that may need to be evaluated in a realistic power system. On the other hand, it is well known that there is a trade-off between the accuracy of the methodology used to obtain the results and the calculation speed. Hence, fast and reasonably accurate methods are required in order to reduce the computational burden and still obtain sufficiently accurate results for the post-outage conditions.

In references [15]-[17], the authors have developed several distribution factors for branch outages studies. Distribution factors are very useful tools in contingency studies, which are used to identify the critical scenarios resulting in branch overloads or bus voltage magnitude violations. Unfortunately, these approaches are not effective when the network under consideration is operating in a stressed state. These deficiencies are mainly due to the fact that distribution factors typically give satisfactory results for MW flows, but they may produce inaccurate results for MVAR flows. Due to the well known coupling between bus voltage magnitudes and reactive power flows, a small error in calculated bus voltage magnitudes may result in fairly inaccurate reactive power flows.

According to the previous discussion, it would be highly desirable to develop more accurate approaches for calculating post-outage MVAR-bus voltage magnitude quantities. References [18]-[21] have developed techniques to calculate these quantities based on two reactive models, one for lines and other for transformers. The problem is formulated as a bounded network optimization problem, and it is then solved using Genetic Algorithm [18]-[19] or some other optimization technique [20], [22].

3.2 Simulation of Branch Outage

The outage of a branch r between buses i and j can either be simulated by setting its admittance y_{ij} to zero ($y_{ij} = 0$), or by injecting fictitious power sources at both ends of the line. This last method will be used in this analysis to preserve the original base case bus admittance matrix and save computational requirements.

Figure 3.2.1a shows the pre-outage condition of line r, its circuit breakers are closed and a flow S_{ij} goes through them. Figure 3.2.1b shows the post-outage condition of line r, its circuit breakers are opened and the line is completely isolated from the rest of the network. Now observe Figure 3.2.1c which shows the simulated post-outage condition of line r, note that its circuit breakers are still closed but injections S_i and S_j have been added at both ends of the line. If these fictitious power sources are determined so that the injected power flows only through the line r, then no impact will be reported on the rest of the system. This means that as far as the remainder of the network is concerned, the line is disconnected.

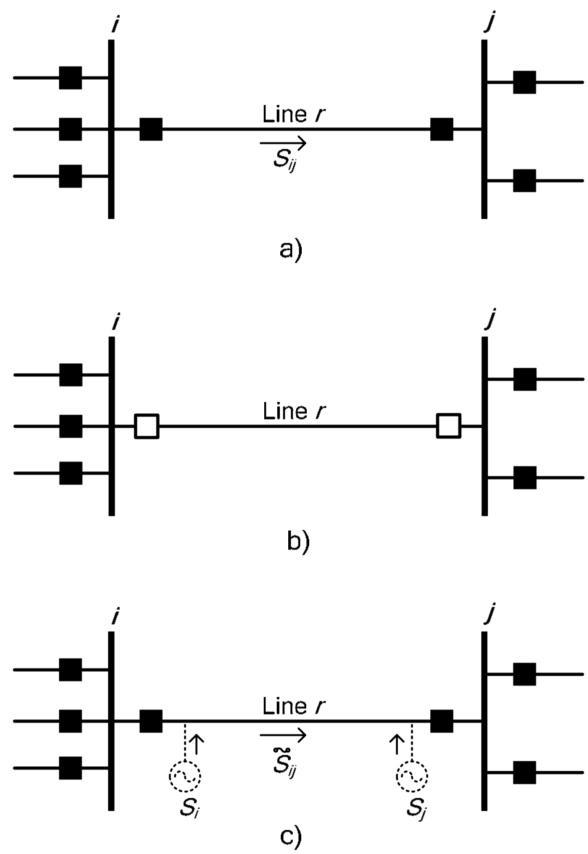

Figure 3.2.1: Line Outage Modeling Using Fictitious Injections. a) Pre-outage Condition. b) Post-outage Condition. c) Simulated Post-outage Condition.

Taking advantage of the decoupling principle between active power-bus voltage phase angle and reactive power-bus voltage magnitude [22], the procedure for obtaining the values of these hypothetical power sources can be separated into two sub-problems. In the first one, the post-outage bus voltage phase angles and active power flows can be obtained by using the straight DC sensitivity factors technique [14]. It should be pointed out that the nonlinearity and high sensitivity of bus voltage magnitudes and the associated reactive power flows prohibits these quantities from being updated in a similar style. Hence, in the second one, the MVAR-bus voltage magnitude quantities should be obtained by solving a numerical optimization problem based on a branch outage model for reactive power flows.

Figure 3.2.2 presents the branch outage model for reactive power flows. The variables in this figure are defined as follows:

Q_{ij} is the reactive power leaving bus *i*

Q_{ij}^T is the reactive power transferred through the line

Q_{Li} is the reactive power (loss) allocated at bus *i*

Q_{Si} is the fictitious reactive power injection at bus *i*

b_{ij} is the line susceptance

b_{i_0} is the half of shunt susceptance allocated at bus *i*

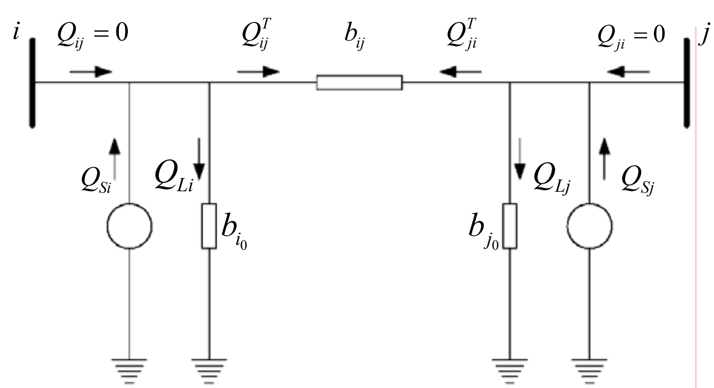

Figure 3.2.2: Simulated Post-Outage for Reactive Power.

Note that this figure shows the post-outage line condition. That means the fictitious power injections are being consumed by the line. The level of power injections that produces this post-outage condition is obtained by an iterative process. Several considerations need to be evaluated during this process. These considerations are sequentially explained as follows:

1. The variables corresponding to the system base case (i.e. pre-outage) must be previously known, for this reason before initiating the process, a full AC load flow is used to determine these base case values. Once determined the base case quantities, the post-outage bus voltage phase angles can be calculated by using the DC sensitivity factors technique [14] so as is showing below:

$$\overline{\delta}_n = \delta_n + \Delta\delta_n \tag{3.2.1}$$

where:

$$\Delta\delta_n = \frac{P_r\left[x_r\left(X_{ni} - X_{nj}\right)\right]}{x_r - \left(X_{ii} + X_{jj} - 2X_{ij}\right)} \tag{3.2.2}$$

$\forall n \neq$ to the slack bus. Here, δ_n and $\overline{\delta}_n$ are the base case and the post-outage bus voltage phase angle at bus n respectively. x_r is the reactance of outage branch r and X_{ni} represents the ni^{th} element of the matrix obtained by inverting the matrix $\mathbf{B}'$ whose elements are calculated according to:

$$B'_{ik} = \begin{cases} -\dfrac{1}{x_{ik}} & \text{assuming a branch from } i \text{ to } k \\ 0 & \text{otherwise} \end{cases} \tag{3.2.3}$$

$$B'_{ii} = \sum_{k=1}^{N} \frac{1}{x_{ik}} \tag{3.2.4}$$

Finally, P_r is the original active power through branch r before it was opened.

2. At the beginning of the process, when the reactive power injections are applied at both end of the line under study, the net reactive power at buses i and j will change with respect to their base case values. This change will produce an increment in the load bus voltage magnitudes which in turn, will produce new load bus voltage magnitudes. The following expressions are the mathematical formulations of the above facts:

$$\Delta\mathbf{V} = \left(\mathbf{B}''\right)^{-1} \Delta\mathbf{Q} \tag{3.2.5}$$

and
$$\bar{\mathbf{V}} = \mathbf{V} + \Delta\mathbf{V} \tag{3.2.6}$$

where $\Delta\mathbf{V}$ is the load bus voltage magnitude increment vector produced by the change in the net reactive power at buses i and j, $\Delta\mathbf{Q}$ is the net reactive power change vector produce by the injection of fictitious reactive sources at buses i and j. Obviously, this vector will have only two nonzero elements, i.e. those corresponding to the buses i and j. Therefore, the elements of $\Delta\mathbf{Q}$ can be stated as follows:

$$\Delta Q_p = \begin{cases} \Delta Q_i & \text{for} \quad p = i \\ \Delta Q_j & \text{for} \quad p = j \\ 0 & \text{otherwise} \end{cases} \tag{3.2.7}$$

On the other hand, $\mathbf{B}''$ is the matrix which relates $\Delta\mathbf{V}$ and $\Delta\mathbf{Q}$ in the fast decouple load flow method [22]. The elements of $\mathbf{B}''$ can be calculated as follows:

$$B''_{ii} = \sum_{k=1}^{N_{\mathrm{PQ}}} B''_{ik}; \quad B''_{ik} = -B_{ik} \tag{3.2.8}$$

where:

B_{ik} is the imaginary part of the ik^{th} element of the admittance matrix $\mathbf{Y}_{\mathrm{bus}}$

N_{PQ} is the number of load buses in the system.

Finally, $\mathbf{V}$ and $\overline{\mathbf{V}}$ are the base case and the new load bus voltage vector respectively.

3. The new load bus voltage vector obtained in the above step would be equivalent to the post-outage load bus voltage vector. However, this is not happening due to the change in the net reactive power at buses i and j also causes that the nodal power balance equation in these buses is not satisfied. Therefore, the optimization cycle consists in finding a pair of fictitious injections that minimize the mentioned violation. A possible mathematic formulation for this problem is stated as follows:

$$\min_{\Delta\mathbf{Q}} \quad \left|\overline{Q}_i - Q_{schi}\right| + \left|\overline{Q}_j - Q_{schj}\right| \tag{3.2.9}$$

here, Q_{schi} is the scheduled bus reactive power at bus i, $\overline{Q}_i$ is the new net reactive power at bus i which can be obtained as follows:

$$\overline{Q}_i = \sum_{k=1}^{N} \overline{V}_i \, \overline{V}_k \left(G_{ik} \sin \overline{\delta}_{ik} - B_{ik} \cos \overline{\delta}_{ik} \right) \tag{3.2.10}$$

where:

N is the number of buses in the system

G_{ik} is the real part of the ik^{th} element of the admittance matrix $\mathbf{Y}_{\text{bus}}$

$\overline{\delta}_{ik} = \overline{\delta}_i - \overline{\delta}_k$

Note that the above formulation is applicable as long as all PV buses remain within their reactive limits. For the cases where reactive power limits violations exist, the PV buses must be treated as PQ buses. These cases are not covered in this thesis.

3.3 EP Model for Branch Outage Simulation

The proposed method relies on a single branch outage model for $Q-V$ quantities which are used for both line and transformer outages instead of two different models. The original configuration of EP is applied and only the structure of the individuals and the fitness function to evaluate them are shown below. Thus, the post-outage bus voltage magnitudes when a branch r between buses i and j is opened can be simulated as explained next.

3.3.1 Statements

Each individual (parents and offspring) is structured as a pair of vectors $\left(\Delta\mathbf{Q}^k, \boldsymbol{\eta}^k\right)$, $\forall k \in \{1,...,\mu\}$ of dimensions N_{PQ} x 1. Here, $\boldsymbol{\eta}$ and μ are the same as defined in Chapter 2. $\Delta\mathbf{Q}$ is the vector of variables to be optimized, its elements correspond to the reactive power increments produced by the injection of fictitious reactive sources at buses i and j. Therefore, the two nonzero elements ΔQ_i and ΔQ_j will be the variables to optimize. Equation 3.3.1 shows the structure of $\Delta\mathbf{Q}$.

$$\Delta\mathbf{Q} = \left[0, 0, \cdots, \Delta Q_i, \cdots \Delta Q_j, \cdots 0\right]^T \tag{3.3.1}$$

The fitness function, by which each parents and offspring will be evaluated, is stated as follows:

$$\Phi\left(\Delta\mathbf{Q}^k\right) = \left(\overline{Q}_i^k - Q_{schi}\right)^2 + \left(\overline{Q}_j^k - Q_{schj}\right)^2 + p_0 \sum_{n=1}^{N_{\mathrm{PQ}}} \left[g_n^+\left(\mathbf{Q}^k\right)\right]^2 \tag{3.3.2}$$

where p_0 is a fixed penalty parameter and $g^+\left(\mathbf{Q}^k\right)$ is a penalty function added to the objective to enforce the algorithm to obtain a set of final post-outage bus voltage magnitudes within desires range of monitoring. This penalty function is evaluated according to:

$$g_n^+\left(\mathbf{Q}^k\right) = \max\left\{\left(\overline{V}_n^k - S_{\max}\right), \left(S_{\min} - \overline{V}_n^k\right), 0\right\} \tag{3.3.3}$$

$\forall n \in N_{\mathrm{PQ}}$, here, $S_{\min}$ and $S_{\max}$ are the lower and upper values of the set of bus voltage magnitude value which is desired to supervise.

3.4 Case Study

The effectiveness of the proposed algorithm has been tested with a modified IEEE 30-bus test system (Fig. 3.4.1). Post-outage bus voltage magnitudes are calculated both with the conventional Newton-Rapshon load flow (NLF) and with the proposed EP-based method (PEP). The results of the two solutions are compared with each other. The outage study by NLF was conducted using the MATPOWER 2.0 Toolbox [23].

The system data are given in [24]. Few modifications in base case control variables for the studied system have been adopted from Table 3 of [21]. Tables 3.4.1 and 3.4.2 summarize the system data. The system base is 100 MVA.

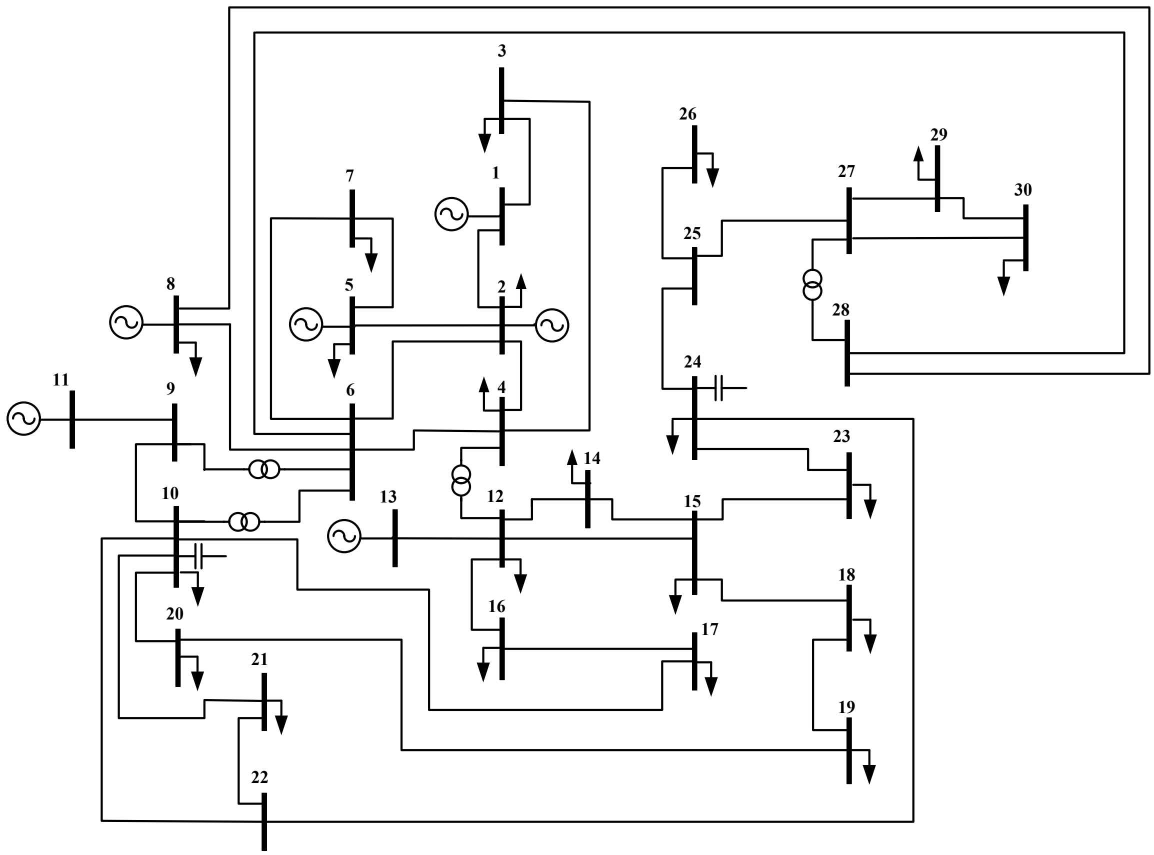

Figure 3.4.1: Modified IEEE 30 Bus Test System

Table 3.4.3 shows the EP control variables used for this study. Figures 3.4.2-3.4.6 illustrate the system post-outage bus voltage magnitudes profiles for the most severe outages. The permissible upper and lower bus voltage magnitude limits for this study have been set to 1.05 and 0.95 respectively. Finally, Table 3.4.4 shows the values of violating post-outage bus voltage magnitude.

Table 3.4.1: Network Data

Branch		R (pu)	X (pu)	B (pu)	Rating (MVA)	Branch		R (pu)	X (pu)	B (pu)	Rating (MVA)
From Bus	To Bus					From Bus	To Bus				
1	2	0.0192	0.0575	0.0264	130	15	18	0.1073	0.2185	0.0000	16
1	3	0.0452	0.1852	0.0204	130	18	19	0.0639	0.1292	0.0000	16
2	4	0.0570	0.1737	0.0184	65	19	20	0.0340	0.0680	0.0000	32
3	4	0.0132	0.0379	0.0042	130	10	20	0.0936	0.2090	0.0000	32
2	5	0.0472	0.1983	0.0209	130	10	17	0.0324	0.0845	0.0000	32
2	6	0.0581	0.1763	0.0187	65	10	21	0.0348	0.0749	0.0000	32
4	6	0.0119	0.0414	0.0045	90	10	22	0.0727	0.1499	0.0000	32
5	7	0.0460	0.1160	0.0102	70	21	22	0.0116	0.0236	0.0000	32
6	7	0.0267	0.0820	0.0085	130	15	23	0.1000	0.2020	0.0000	16
6	8	0.0120	0.0420	0.0045	32	22	24	0.1150	0.1790	0.0000	16
6	9	0.0000	0.2080	0.0000	65	23	24	0.1320	0.2700	0.0000	16
6	10	0.0000	0.5560	0.0000	32	24	25	0.1885	0.3292	0.0000	16
9	11	0.0000	0.2080	0.0000	65	25	26	0.2544	0.3800	0.0000	16
9	10	0.0000	0.1100	0.0000	65	25	27	0.1093	0.2087	0.0000	16
4	12	0.0000	0.2560	0.0000	65	28	27	0.0000	0.3960	0.0000	65
12	13	0.0000	0.1400	0.0000	65	27	29	0.2198	0.4153	0.0000	16
12	14	0.1231	0.2559	0.0000	32	27	30	0.3202	0.6027	0.0000	16
12	15	0.0662	0.1304	0.0000	32	29	30	0.2399	0.4533	0.0000	16
12	16	0.0945	0.1987	0.0000	32	8	28	0.0636	0.2000	0.0214	32
14	15	0.2210	0.1997	0.0000	16	6	28	0.0169	0.0599	0.0065	32
16	17	0.0824	0.1923	0.0000	16						

Branch		Off nominal transformer tap ratio	Branch		Off nominal transformer tap ratio
From Bus	To Bus		From Bus	To Bus	
4	12	0.932	6	10	0.969
6	9	0.978	28	27	0.968

Table 3.4.2: Bus Data

No.	Voltage		Power Demand		Power Generation	Power Limits (MVAR)		Shunt Susceptance	No.	Voltage		Power Demand		Power Generation	Power Limits (MVAR)		Shunt Susceptance
	|V|	δ	MW	MVAR	MW	Min	Max	MVAR		|V|	δ	MW	MVAR	MW	Min	Max	MVAR
1	1.05	0.00	0.00	0.00	-	-20	200	0.0	16	-	-	3.50	1.80	-	-	-	0.0
2	1.05	-	21.70	12.70	80	-20	80	0.0	17	-	-	9.00	5.80	-	-	-	0.0
3	-	-	2.40	1.20	-	-	-	0.0	18	-	-	3.20	0.90	-	-	-	0.0
4	-	-	7.60	1.60	-	-	-	0.0	19	-	-	9.50	3.40	-	-	-	0.0
5	1.05	-	94.20	19.00	15	-15	50	0.0	20	-	-	2.20	0.70	-	-	-	0.0
6	-	-	0.00	0.00	-	-	-	0.0	21	-	-	17.50	11.20	-	-	-	0.0
7	-	-	22.80	10.90	-	-	-	0.0	22	-	-	0.00	0.00	-	-	-	0.0
8	1.05	-	30.00	30.00	10	-15	35	0.0	23	-	-	3.20	1.60	-	-	-	0.0
9	-	-	0.00	0.00	-	-	-	0.0	24	-	-	8.70	6.70	-	-	-	4.3
10	-	-	5.80	2.00	-	-	-	19.0	25	-	-	0.00	0.00	-	-	-	0.0
11	1.05	-	0.00	0.00	10	-10	30	0.0	26	-	-	3.50	2.30	-	-	-	0.0
12	-	-	11.20	7.50	-	-	-	0.0	27	-	-	0.00	0.00	-	-	-	0.0
13	1.05	-	0.00	0.00	12	-15	40	0.0	28	-	-	0.00	0.00	-	-	-	0.0
14	-	-	6.20	1.60	-	-	-	0.0	29	-	-	2.40	0.90	-	-	-	0.0
15	-	-	8.20	2.50	-	-	-	0.0	30	-	-	10.60	1.90	-	-	-	0.0

Table 3.4.3: Control Parameters for the Proposed Algorithm

Control Variable	Value	Description
μ	40	Number of individuals
η	5	Initial perturbation
q	10	Number of opponents in stochastic ranking
ε	$1\text{x}10^{-4}$	Error tolerance
N_g	50	Generation tolerance
p_0	100	Penalty parameter
$S_{\min}$	0.75	Lower value of the range of bus voltage magnitude to analyze
$S_{\max}$	1.10	Upper value of the range of bus voltage magnitude to analyze

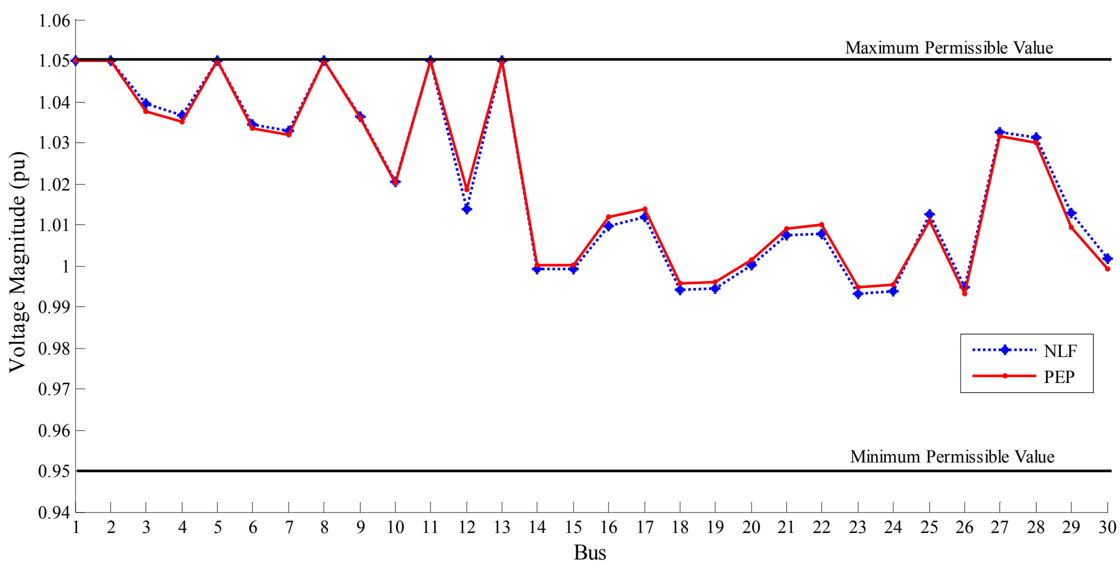

Figure 3.4.2: Post-outage Bus Voltage Magnitude Profile. Outage in Transf. 4-12.

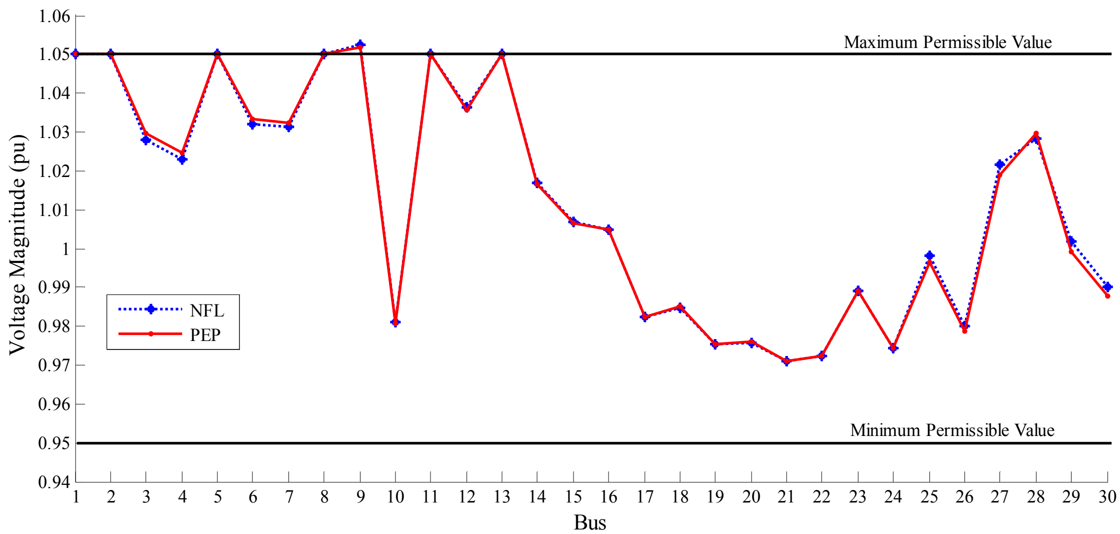

Figure 3.4.3: Post-outage Bus Voltage Magnitude Profile. Outage in Line 9-10

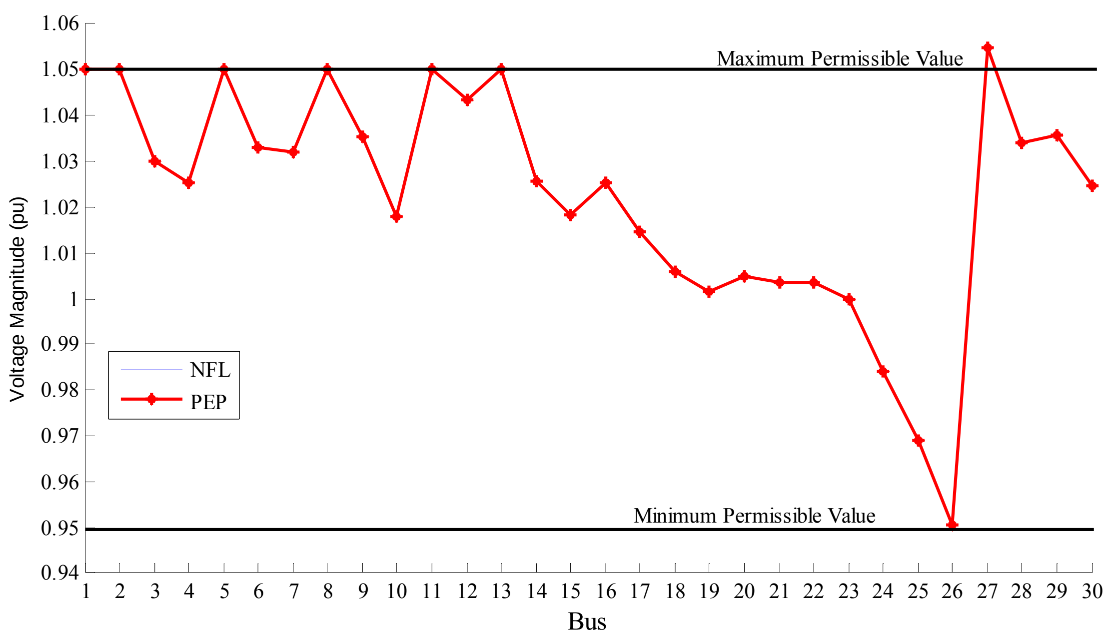

Figure 3.4.4: Post-outage Bus Voltage Magnitude Profile. Outage in Line 25-27

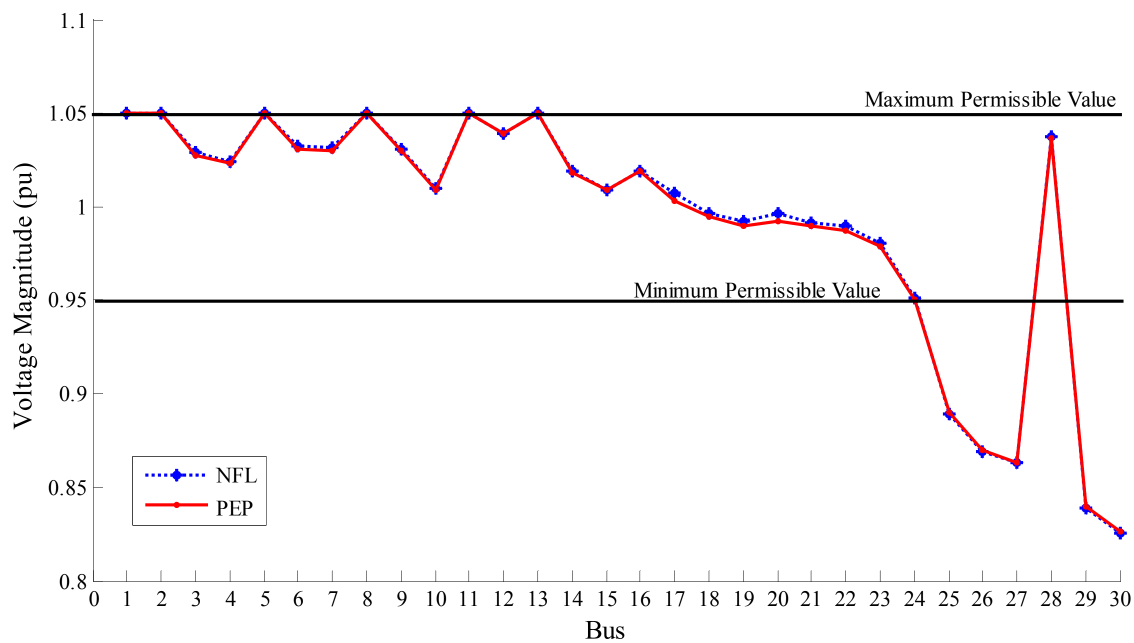

Figure 3.4.5: Post-outage Bus Voltage Magnitude Profile. Outage in Line 27-28

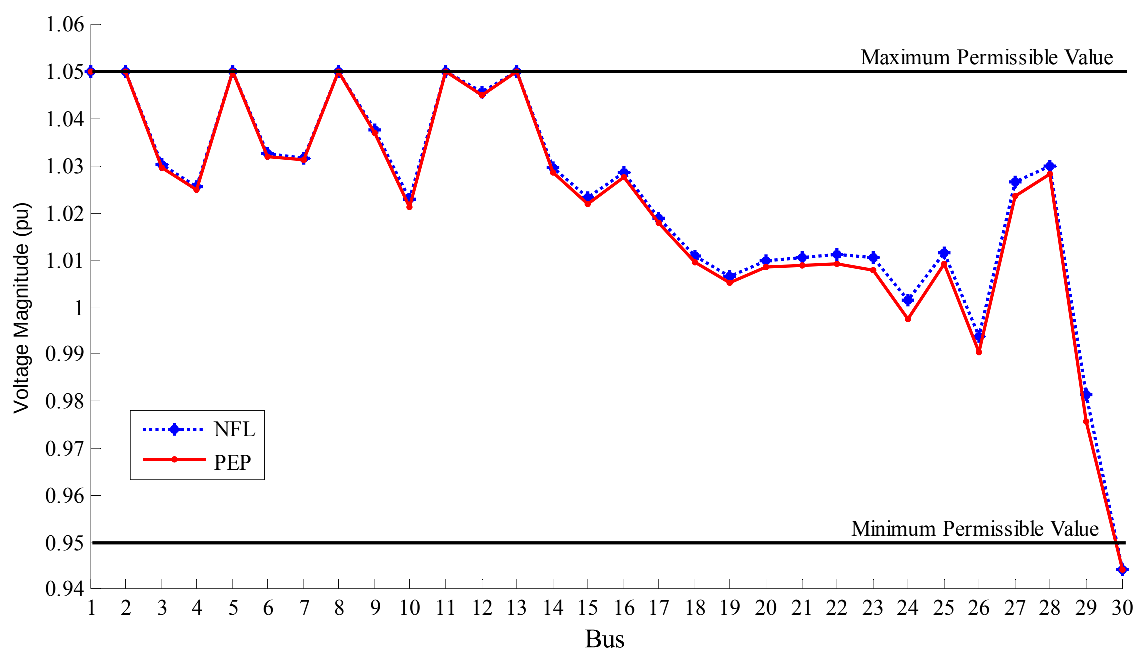

Figure 3.4.6: Post-outage Bus Voltage Magnitude Profile. Outage in Line 27-30

Table 3.4.4: Values of Violating Post-outage Bus Voltage Magnitude

Bus No.	Branch Outage							
	9-10		25-27		27-28		27-30	
	NLF	PEP	NLF	PEP	NLF	PEP	NLF	PLF
9	1.0524	1.0517	-	-	-	-	-	-
25	-	-	-	-	0.8894	0.8900	-	-
26	-	-	-	-	0.8690	0.8699	-	-
27	-	-	1.0548	1.0548	0.8633	0.8631	-	-
29	-	-	-	-	0.8393	0.8401	-	-
30	-	-	-	-	0.8254	0.8261	0.9441	0.9441
Violations	1	1	1	1	5	5	1	1

According with the results shown above, the proposed method is not only able to identify post outage bus voltage magnitude violations effectively, but also to find the post-outage bus voltage magnitude values with satisfactory accuracy. Due to the use of a full AC base-case load flow and the DC distribution factors, only the decoupled reactive power flow quantities are introduced in the simulation. Therefore, the computational effort is not significant, allowing the proposed method to be applicable for the purpose of Contingency Studies.

CHAPTER 4
POWER SYSTEM STATE ESTIMATION

4.1 Introduction

One of the major tasks at Energy Control Centers (ECC) is to maintain the power system security. In order to achieve this objective, utilities rely extensively on the Supervisory Control and Data Acquisition system (SCADA) and the Energy Management System (EMS). The SCADA system consists of two subsystems: the supervisory control system and the telemetry system.

The supervisory control system allows system operators the supervision and control of circuit breakers and switches status, transformers tap positions and capacitor/reactor bank values remotely. In the telemetry system critical quantities in the system are measured and the values of these measurements are transmitted to the ECC. These measurements are mainly branch power flows, bus voltage and branch current magnitudes, injected and demanded power.

Powerful computers installed at the ECC receive the incoming measurements and check them against pre-stored limits and alarm the operators in the event of a component overload or an out of limit bus voltage magnitude. Since the measurements are imperfect values of the measured quantities, and these measurements are not always available, methods like the AC Power Flow routine are not effective to determine the system state variables.

For the above reasons, it is desirable to use a method with capacity to find a good estimate of the system variables even with imperfections and in some cases, unavailability of the measurements. State estimation is known as the process that combines the measurements obtained from the telemetry system with a power system model in order to obtain the best estimate of the current power system conditions. Here, the best system estimate is described in a statistical sense, because state estimation is supported in a statistical criterion that estimates the true value of the state variables based on redundant and imperfect tele-metered system measurements. The state variables in a power system are always assigned to the complex bus voltages, since given these quantities, all other system quantities can be calculated. The redundant telemetry is used in state estimation in order to preserve the ability of the method to obtain good estimated values even with the loss of one or several measurements. In general it is necessary to have more available measurements than state variables to estimate. The imperfections in the measurements are caused by errors in the transducers and meters as well as the addition of noise in the communication to the ECC.

4.2 State Estimation Problem Formulation

Several criteria can be selected in order to estimate the state variables. This thesis is focused in two of these criteria which are described in sections below:

4.2.1 Weighed Least Square (WLS) State Estimation

In this state estimation method, the criterion used is to minimize the sum of squares of the differences between the measured value and the expected value of the measurements, with each squared difference weighted by the variance of their corresponding meter error [14], [25]-[32]. Mathematically this can be expressed as:

$$\min_{\mathbf{x}} \; J(\mathbf{x}) = \sum_{j=1}^{N_m} \frac{1}{\sigma_j^2} \left[z_j - h_j(\mathbf{x}) \right]^2 \tag{4.2.1}$$

where,

$\mathbf{x}$ is the vector of unknowns values to be estimated

N_m is the number of independent measurements,

σ_j^2 is the variance of the j^{th} measurement value,

z_j is the j^{th} measurement value,

$h_j(\mathbf{x})$ is the function that is used to calculate the value being measured by the j^{th} measurement.

To weight the squared differences in the objective function with σ^2 provides a mathematical way to discriminate the accuracy of the meters. To be exact, the standard deviation σ of a meter is a statistical value that tells us how tightly the measurements taken are clustered around the true value. For instance, if the standard deviation is large, the measurement is relatively inaccurate, while a small standard deviation value indicates a small error range.

4.2.2 Weighed Least Absolute Value (WLAV) State Estimation

In this state estimation method, the criterion used is to minimize the weighed sum of the absolute deviations of the components of the residual vector $\mathbf{r}$ [32]-[38]. Mathematically this can be expressed as:

$$\begin{aligned} &\min_{\mathbf{x}} \;\; J(\mathbf{x}) = \sum_{j=1}^{N_m} \frac{|r_j|}{\sigma_j} \\ &\text{s.t.} \quad r_j = z_j - h_j(\mathbf{x}), \qquad \forall j \in \{1,\ldots,N_m\} \end{aligned} \tag{4.2.2}$$

4.2.3 The Measurement Function

The measured quantities are represented by the vector $\mathbf{z}$, and as it was discussed before, $h(\mathbf{x})$ represents functions dependable of estimated values. With exception of the bus voltage magnitudes, these functions are nonlinear and are used to calculate the estimated values corresponding to measured values $\mathbf{z}$. For this study, only the bus voltage magnitude, the injected/demanded real and reactive power as well as the real and reactive power flows will be measured. The expressions of $h(\mathbf{x})$ for the calculated quantities are stated below:

Real and reactive power injection/demand at bus i:

$$P_i = \sum_{k=1}^{N} V_i V_k \left(G_{ik} \cos\delta_{ik} + B_{ik} \sin\delta_{ik} \right) \tag{4.2.3}$$

$$Q_i = \sum_{k=1}^{N} V_i V_k \left(G_{ik} \sin\delta_{ik} - B_{ik} \cos\delta_{ik} \right) \tag{4.2.4}$$

Real and reactive power flow from bus i to bus k:

$$P_{ik} = V_i^2 \left(g_{ik}^{\mathrm{sh}} + g_{ik} \right) - V_i V_k \left(g_{ik} \cos \delta_{ik} + b_{ik} \sin \delta_{ik} \right) \tag{4.2.5}$$

$$Q_{ik} = -V_i^2 \left(b_{ik}^{\mathrm{sh}} + b_{ik} \right) - V_i V_k \left(g_{ik} \sin \delta_{ik} - b_{ik} \cos \delta_{ik} \right) \tag{4.2.6}$$

where:

$V_i \sphericalangle \delta_i$ is the complex voltage at bus i

$\delta_{ik} = \delta_i - \delta_k$

$G_{ik} + jB_{ik}$ is the ik^{th} element of the complex bus admittance matrix

$g_{ik} + jb_{ik}$ is the series admittance of the branch connecting bus i and k

$g_{ik}^{\mathrm{sh}} + jb_{ik}^{\mathrm{sh}}$ is the shunt admittance of the branch connected to bus i

N is the number of buses in the system.

4.3 EP Model for Power System State Estimation

The original configuration of EP is applied as it was explained in Chapter 2, and only the structure of the individuals and the fitness function to evaluate them are shown below.

4.3.1 Statements

Each individual (parents and offspring) are structured as a pair of vector $\left(\mathbf{x}^k, \boldsymbol{\eta}^k \right)$, $\forall k \in \{1, ..., \mu\}$ with dimensions $(2N-1)\mathrm{x}1$. Here, $\boldsymbol{\eta}$ and μ are the same as defined in Chapter 2. $\mathbf{x}$ is the vector of variables to optimized, its corresponding elements are the bus voltage magnitudes and the bus voltage phase angles. Here the bus voltage phase angle of the slack bus is not included because its value is known (i.e., zero). Equation (4.3.1) shows the structure of an trial solution vector $\mathbf{x}$, assuming bus 1 as reference.

$$\mathbf{x} = [V_1 \; V_2 \; \cdots \; V_N \; \delta_2 \; \delta_3 \; \cdots \; \delta_N]^T \tag{4.3.1}$$

Each trial solution vector $\mathbf{x}$ represents a possible set of estimated values for the complex bus voltage. These estimated values are used to calculate the other estimated values by means of (4.2.3)-(4.2.6).

The fitness function by which each parents and offspring will be evaluated is stated as follows:

For WLS State Estimation:

$$\min J\left(\mathbf{V}\measuredangle\boldsymbol{\delta}\right) = \begin{cases} \displaystyle\sum_{j=1}^{M_b} \frac{\left(V_j^{\text{meas}} - V_j^{\text{est}}\right)^2}{\sigma_{V_j}^2} + \sum_{j=1}^{M_{P_{\text{inj}}}} \frac{\left(P_j^{\text{meas}} - P_j^{\text{est}}\right)^2}{\sigma_{P_j}^2} + \sum_{j=1}^{M_{Q_{\text{inj}}}} \frac{\left(Q_j^{\text{meas}} - Q_j^{\text{est}}\right)^2}{\sigma_{Q_j}^2} \\ \displaystyle + \sum_{j=1}^{M_{P_{\text{flow}}}} \frac{\left(P_{\text{flow}_j}^{\text{meas}} - P_{\text{flow}_j}^{\text{est}}\right)^2}{\sigma_{P_{\text{flow}_j}}^2} + \sum_{j=1}^{M_{Q_{\text{flow}}}} \frac{\left(Q_{\text{flow}_j}^{\text{meas}} - Q_{\text{flow}_j}^{\text{est}}\right)^2}{\sigma_{Q_{\text{flow}_j}}^2} \end{cases} \tag{4.3.2}$$

For WLAV State Estimation:

$$\min J\left(\mathbf{V}\measuredangle\boldsymbol{\delta}\right) = \begin{cases} \displaystyle\sum_{j=1}^{M_b} \frac{\left|V_j^{\text{meas}} - V_j^{\text{est}}\right|}{\sigma_{V_j}} + \sum_{j=1}^{M_{P_{\text{inj}}}} \frac{\left|P_j^{\text{meas}} - P_j^{\text{est}}\right|}{\sigma_{P_j}} + \sum_{j=1}^{M_{Q_{\text{inj}}}} \frac{\left|Q_j^{\text{meas}} - Q_j^{\text{est}}\right|}{\sigma_{Q_j}} \\ \displaystyle + \sum_{j=1}^{M_{P_{\text{flow}}}} \frac{\left|P_{\text{flow}_j}^{\text{meas}} - P_{\text{flow}_j}^{\text{est}}\right|}{\sigma_{P_{\text{flow}_j}}} + \sum_{j=1}^{M_{Q_{\text{flow}}}} \frac{\left|Q_{\text{flow}_j}^{\text{meas}} - Q_{\text{flow}_j}^{\text{est}}\right|}{\sigma_{Q_{\text{flow}_j}}} \end{cases} \tag{4.3.3}$$

where the variables are defined as follows:

M_b is the number of voltage measurements

$M_{P_{\text{inj}}}$ is the number of real power injection measurements

$M_{P_{\text{flow}}}$ is the number of real power flow measurements

σ_{V_i} is the standard deviation of the voltage meter installed at bus i

V_j^{meas} is the j^{th} voltage measurement

V_j^{est} is the j^{th} voltage estimation

4.4 Case Studies

In order to test its effectiveness, the proposed method (EPSE) was used in the two case studies described below.

4.4.1 6 Bus Test System

This case study has the intention of comparing the results obtained when solving the WLS state estimation by the proposed method as well as by the Gradient-Newton method (GNSE). The six bus test system is shown in Figure 4.4.1 [14]. The network data are given in Table 4.4.1. Table 4.4.2 shows measurements data for this system.

Table 4.4.3 shows the control variables used in the proposed method. Table 4.4.4 presents a comparison of the estimated values found using the proposed method and by the Gradient-Newton method used in [14].

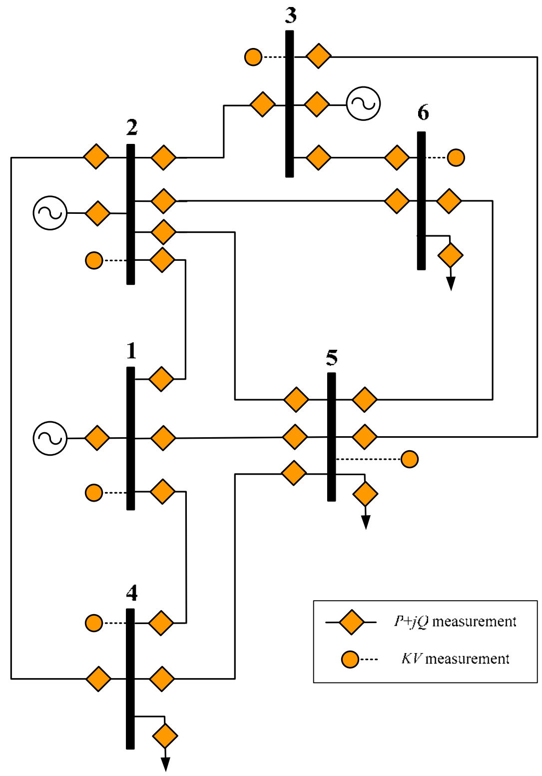

Figure 4.4.1: Six Bus Test System with Measurement Locations

Table 4.4.1: Network Data

Branch		R (pu)	X (pu)	½ B (pu)
From Bus	To Bus			
1	2	0.10	0.20	0.020
1	4	0.05	0.20	0.020
1	5	0.08	0.30	0.030
2	3	0.05	0.25	0.030
2	4	0.05	0.10	0.010
2	5	0.10	0.30	0.020
2	6	0.07	0.20	0.025
3	5	0.12	0.26	0.025
3	6	0.02	0.10	0.010
4	5	0.20	0.40	0.040
5	6	0.10	0.30	0.030

Table 4.4.2: Measurements Data

Voltage and Power Injection Measurements							
Bus No.	KV	MW	MVAR	Bus No.	KV	MW	MVAR
1	238.4	113.1	20.2	4	225.7	-71.8	-71.9
2	237.8	48.4	71.9	5	225.2	-72.0	-67.7
3	250.7	55.1	90.6	6	228.9	-72.3	-60.9
Power Flow Measurements							
Line		MW	MVAR	Line		MW	MVAR
From Bus	To Bus			From Bus	To Bus		
1	2	31.5	-13.2	4	1	-40.1	-14.3
1	4	38.9	21.2	4	2	-29.8	-44.3
1	5	35.7	9.4	4	5	0.7	-17.4
2	1	-34.9	9.7	5	1	-36.6	-17.5
2	3	8.6	-11.9	5	2	-11.7	-22.2
2	4	32.8	38.3	5	3	-25.1	-29.9
2	5	17.4	22.0	5	4	-2.1	-1.5
2	6	22.3	15.0	5	6	-2.1	-0.8
3	2	-2.1	10.2	6	2	-19.6	-22.3
3	5	17.7	23.9	6	3	-46.8	-51.1
3	6	43.3	58.3	6	5	1.0	2.9

Meter Precisions	
Measurement	Variance (σ^2)
Voltage Magnitude, V	3.83 KV
Real Power, P	5 MW
Reactive Power, Q	5 MVAR

Table 4.4.3: Control Parameters of the Proposed Algorithm

Control Variable	Value	Description
μ	40	Number of individuals
η_0	5	Initial Perturbation
x_{min}	0.95	Minimun Bus voltage Magnitude (pu)
	-0.50	Minimun Bus voltage Phase angle (radians)
x_{max}	1.10	Maximum Bus voltage Magnitude (pu)
	0.50	Maximum Bus voltage Phase angle (radians)
q	5	Number of opponents in stochastic ranking
ε	$1x10^{-8}$	Error tolerance
N_g	100	Generation tolerance

Table 4.4.4: Comparison of Estimated Values

Estimation of Voltages and Power Injections

Bus No.	KV		MW		MVAR		Bus No.	KV		MW		MVAR	
	GNSE	EPSE	GNSE	EPSE	GNSE	EPSE		GNSE	EPSE	GNSE	EPSE	GNSE	EPSE
1	240.6	241.4	111.9	110.2	18.7	17.8	4	226.1	226.9	-70.2	-70.6	-70.2	-70.3
2	239.9	240.6	47.5	48.9	70.3	69.6	5	225.3	226.3	-71.8	-71.3	-69.4	-68.3
3	244.7	245.4	59.5	60.4	87.4	87.2	6	230.1	230.8	-68.9	-71.5	-65.8	-65.1

Estimation of Power Flows

Line		MW		MVAR		Line		MW		MVAR	
From Bus	To Bus	GNSE	EPSE	GNSE	EPSE	From Bus	To Bus	GNSE	EPSE	GNSE	EPSE
1	2	30.4	30.2	-14.4	-14.6	4	1	-43.6	-44.4	-20.7	-20.5
1	4	44.8	44.6	21.2	21.1	4	2	-30.9	-30.6	-44.4	-44.4
1	5	36.8	37.0	11.8	11.4	4	5	4.3	4.4	-5.1	-5.4
2	1	-29.4	-28.8	11.9	12.3	5	1	-35.6	-36.3	-13.6	-13.2
2	3	3.0	3.7	-12.6	-12.8	5	2	-15.1	-15.2	-17.4	-17.1
2	4	32.4	32.5	45.3	45.2	5	3	-18.1	-17.7	-25.8	-25.7
2	5	15.6	15.7	14.8	14.4	5	4	-4.2	-4.3	-2.5	-2.3
2	6	25.9	26.6	10.8	10.4	5	6	1.3	2.3	-10.1	-10.1
3	2	-3.0	-3.7	6.2	6.3	6	2	-25.4	-27.0	-14.5	-14.3
3	5	19.2	18.7	22.9	22.7	6	3	-42.3	-44.3	-55.7	-56.4
3	6	43.3	45.3	58.3	58.2	6	5	-1.2	-2.2	4.4	4.3

Note that the results obtained with the proposed method have much similarity with those reached by GNSE which demonstrates its effectiveness. However, it is necessary to verify which of the two solutions is the closest to the true values. Therefore, a mean square error analysis (*MSE*) was carried out. *MSE* is defined as follows [39]:

$$MSE = \frac{1}{u}\sum_{i=1}^{u}\left(E_u - T_u\right)^2 \tag{4.4.1}$$

where:

u is the number of values

E_u is the u^{th} estimated value

T_u is the u^{th} true value

The true values correspond to the system base case values shown in Table 4.4.5. *MSE* provides an average error for all estimated values such that smaller values of *MSE* indicate a more accurate estimation method. Table 4.4.6 summarizes the mean square error analysis results.

Table 4.4.5: Base Case Values

Voltage and Power Injection							
Bus No.	KV	MW	MVAR	Bus No.	KV	MW	MVAR
1	241.5	107.9	16.0	4	227.6	-70.0	-70.0
2	241.5	50.0	74.4	5	226.7	-70.0	-70.0
3	246.1	60.0	89.6	6	231.0	-70.0	-70.0
Power Flow							
Line		MW	MVAR	Line		MW	MVAR
From Bus	To Bus			From Bus	To Bus		
1	2	28.7	-15.4	4	1	-42.5	-19.9
1	4	43.2	20.1	4	2	-31.6	-45.1
1	5	35.6	11.3	4	5	4.1	-4.9
2	1	-27.8	12.8	5	1	-34.5	-13.5
2	3	2.9	-12.3	5	2	-15.0	-18.0
2	4	33.1	46.1	5	3	-18.0	-26.1
2	5	15.5	15.4	5	4	-4.0	-2.8
2	6	26.2	12.4	5	6	1.6	-9.7
3	2	-2.9	5.7	6	2	-25.7	-16.0
3	5	19.1	23.2	6	3	-42.8	-57.9
3	6	43.8	60.7	6	5	-1.6	3.9

Table 4.4.6: Mean Square Error Results

MSE			
		GNSE	EPSE
Voltage		1.7250	0.3333
Real Power	Injection	4.4983	1.8278
	Flow	0.6327	1.0859
Reactive Power	Injection	7.8300	9.9557
	Flow	1.0109	1.0238
All Values		**1.9432**	**1.9212**

These results establish that the proposed method is in general more accurate than the GNSE method, only in the specific case of reactive power injection and the real and reactive power flow, the proposed method was less accurate than the GNSE method.

4.4.2 30 Bus Test System

The system state of the IEEE 30 bus system was estimated with WLS and WLAV formulations in order to prove the flexibility of the proposed method. Figure 4.4.2 shows the mentioned system. The system data are obtained from [40] and are shown in Tables 4.4.7-4.4.8. The quantity, type and location of these measurements were taken from [41]. The measurement values were obtained as follows:

$$M_i = T_i + \left(\nu_i \cdot \sigma_i\right) \tag{4.4.2}$$

$\forall i \in \{1,...,N_m\}$, here the variables are defined as follows:

M_i is the i^{th} measured value

T_i is the i^{th} true value

σ_i is the standard deviation corresponding to the i^{th} measured value

ν_i is a random number normally distributed with mean zero and standard deviation one generated anew for each value of i

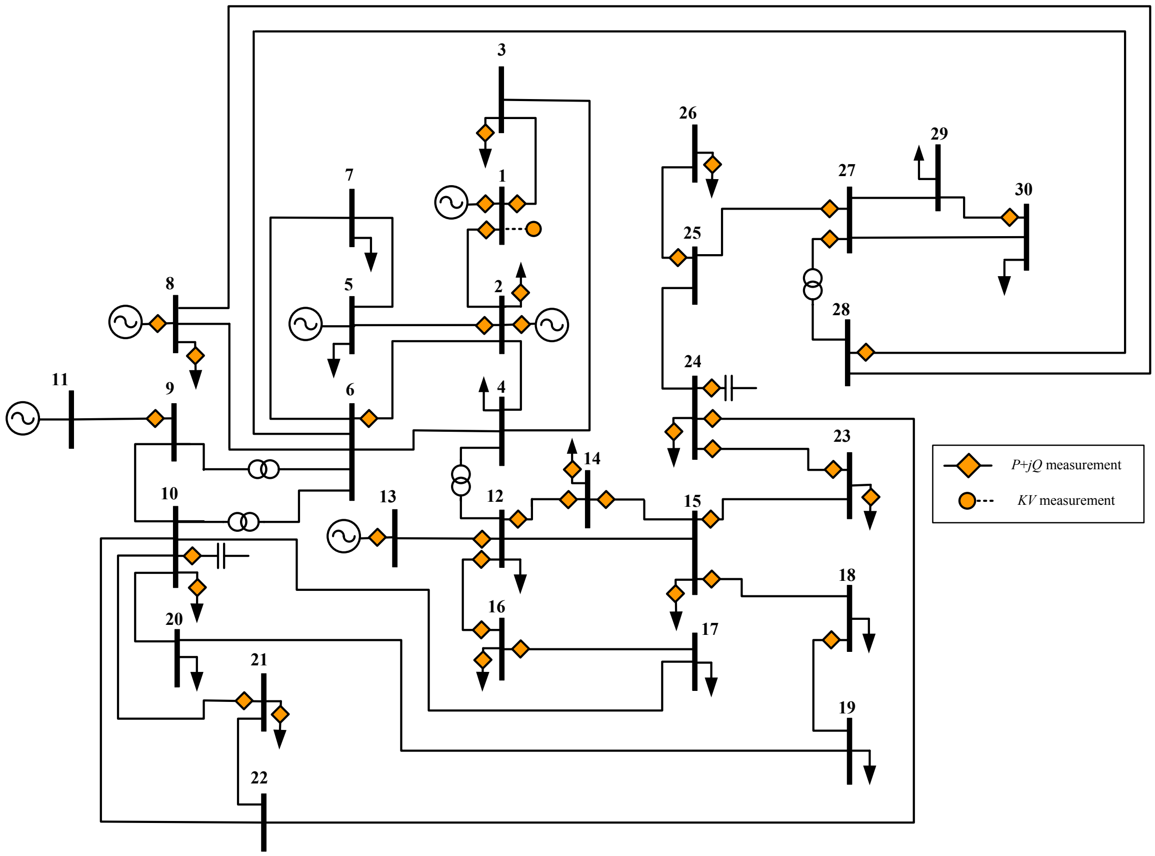

Figure 4.4.2: IEEE 30 Bus Test System with Measurement Locations

Table 4.4.9 presents the true system state variables which were obtained running an AC power flow routine. The true values of quantities to be measured were calculated by means of (4.2.3)-(4.2.6) using the mentioned true state variables. These values are shown in Table 4.4.10.

Table 4.4.7: Bus Data

No.	Voltage		Power Demand		Power Generation	Power Limits (MVAR)		Shunt Susceptance	No.	Voltage		Power Demand		Power Generation	Power Limits (MVAR)		Shunt Susceptance
	$\lvert V\rvert$	δ	MW	MVAR	MW	Min	Max	MVAR		$\lvert V\rvert$	δ	MW	MVAR	MW	Min	Max	MVAR
1	1.06	0.00	0.00	0.00	0.00	0	0	0.0	16	-	-	3.50	1.80	0.00	-	-	0.0
2	1.04	-	21.70	12.70	40.00	-40	50	0.0	17	-	-	9.00	5.80	0.00	-	-	0.0
3	-	-	2.40	1.20	0.00	-	-	0.0	18	-	-	3.20	0.90	0.00	-	-	0.0
4	-	-	7.60	1.60	0.00	-	-	0.0	19	-	-	9.50	3.40	0.00	-	-	0.0
5	1.01	-	94.20	19.00	0.00	-40	40	0.0	20	-	-	2.20	0.70	0.00	-	-	0.0
6	-	-	0.00	0.00	0.00	-	-	0.0	21	-	-	17.50	11.20	0.00	-	-	0.0
7	-	-	22.80	10.90	0.00	-	-	0.0	22	-	-	0.00	0.00	0.00	-	-	0.0
8	1.01	-	30.00	30.00	0.00	-10	60	0.0	23	-	-	3.20	1.60	0.00	-	-	0.0
9	-	-	0.00	0.00	0.00	-	-	0.0	24	-	-	8.70	6.70	0.00	-	-	4.3
10	-	-	5.80	2.00	0.00	-	-	19.0	25	-	-	0.00	0.00	0.00	-	-	0.0
11	1.08	-	0.00	0.00	0.00	-6	24	0.0	26	-	-	3.50	2.30	0.00	-	-	0.0
12	-	-	11.20	7.50	0.00	-	-	0.0	27	-	-	0.00	0.00	0.00	-	-	0.0
13	1.07	-	0.00	0.00	0.00	-6	24	0.0	28	-	-	0.00	0.00	0.00	-	-	0.0
14	-	-	6.20	1.60	0.00	-	-	0.0	29	-	-	2.40	0.90	0.00	-	-	0.0
15	-	-	8.20	2.50	0.00	-	-	0.0	30	-	-	10.60	1.90	0.00	-	-	0.0

Table 4.4.8: Branch Data

Branch		R	X	½ B	Tap Changing	Branch		R	X	½ B	Tap Changing
From Bus	To Bus	pu	pu	pu	Setting	From Bus	To Bus	pu	pu	pu	Setting
1	2	0.0192	0.0575	0.0264	-	15	18	0.1073	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	0.978	23	24	0.1320	0.2700	0.0000	-
6	10	0.0000	0.5560	0.0000	0.969	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	0.932	28	27	0.0000	0.3960	0.0000	0.968
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	0.0650	-
16	17	0.0824	0.1923	0.0000	-						

The measurements data are given in Table 4.4.11. Note that the quantity of available measurements is relatively less than the first case study. Moreover, the measurements generated have significant errors. However, the proposed method should have the ability to estimate with good accuracy the true system state. The algorithm control parameters used in this case study are the same as those used in the first case study.

Table 4.4.9: True State Variables of the System

Voltage								
Bus No.	|V| (pu)	δ (degree)	Bus No.	|V| (pu)	δ (degree)	Bus No.	|V| (pu)	δ (degree)
1	1.060	0.000	11	1.087	-14.431	21	1.033	-16.466
2	1.043	-5.498	12	1.057	-15.292	22	1.033	-16.452
3	1.021	-7.999	13	1.071	-15.292	23	1.027	-16.654
4	1.012	-9.655	14	1.043	-16.181	24	1.022	-16.823
5	1.010	-14.387	15	1.038	-16.270	25	1.019	-16.411
6	1.011	-11.389	16	1.045	-15.874	26	1.001	-16.830
7	1.003	-13.147	17	1.040	-16.185	27	1.025	-15.897
8	1.008	-12.090	18	1.028	-16.877	28	1.010	-12.046
9	1.052	-14.431	19	1.026	-17.047	29	1.005	-17.122
10	1.045	-16.023	20	1.030	-16.848	30	0.994	-18.002

Table 4.4.10: True Values to Be Measured

Voltage and Power Injection							
Bus No.	KV	MW	MVAR	Bus No.	KV	MW	MVAR
1	243.8	261.01	-16.80	15	-	-8.23	-2.52
2	-	18.29	36.84	16	-	-3.49	-1.77
3	-	-2.42	-1.28	21	-	-17.61	-11.45
8	-	-30.03	-2.34	23	-	-3.19	-1.60
10	-	-5.78	17.19	24	-	-8.72	-2.42
13	-	0.00	10.40	26	-	-3.49	-2.29
14	-	-6.21	-1.62				
Power Flow							
Branch		MW	MVAR	Branch		MW	MVAR
From Bus	To Bus			From Bus	To Bus		
1	2	177.82	-22.16	16	12	-7.13	-3.10
1	3	83.19	5.35	16	17	3.64	1.33
2	5	83.03	1.70	18	19	2.77	0.70
6	2	-59.86	2.79	21	10	-15.68	-9.77
9	11	0.00	-17.46	23	24	1.77	1.27
12	13	0.00	-10.27	24	22	-5.68	-2.90
12	14	7.85	2.43	24	23	-1.76	-1.26
12	16	7.18	3.21	25	26	3.54	2.36
14	12	-7.78	-2.28	27	25	4.86	0.72
14	15	1.57	0.66	27	28	-17.56	4.60
15	18	5.98	1.65	28	6	-18.78	-3.91
15	23	4.99	2.94	30	29	-3.67	-0.54

Table 4.4.11: Measurements Data

Voltage and Power Injection Measurements							
Bus No.	KV	MW	MVAR	Bus No.	KV	MW	MVAR
1	243.2	261.3	-19.02	15	-	-11.7	-8.5125
2	-	17.8	39.572	16	-	0.8	-1.899
3	-	-6.6	2.8781	21	-	-11.2	-11.984
8	-	-28.5	4.3856	23	-	-11.2	-9.6205
10	-	-12.5	4.451	24	-	-15.9	-5.4135
13	-	3.6	13.766	26	-	-0.6	-7.5825
14	-	1.9	4.354				
Power Flow Measurements							
Branch		MW	MVAR	Branch		MW	MVAR
From Bus	To Bus			From Bus	To Bus		
1	2	173.8	-21.9	16	12	-5.3	-0.1
1	3	85.9	8.5	16	17	-1.4	5.4
2	5	84.1	4.5	18	19	2.7	5.5
6	2	-64.5	1.9	21	10	-15.9	-14.6
9	11	-10.9	-17.5	23	24	1.8	2.4
12	13	-0.3	-11.8	24	22	-7.2	-1.5
12	14	2.8	-4.9	24	23	3.7	-6.3
12	16	10.3	2.2	25	26	-5.8	-1.3
14	12	-5.2	-1.7	27	25	7.0	6.2
14	15	10.0	2.3	27	28	-13.7	-4.8
15	18	9.0	9.0	28	6	-15.1	-1.5
15	23	1.8	1.2	30	29	-0.8	-0.1
Meters Precision							
Measurement				Variance (σ^2)			
Voltage Magnitude, *V*				3.83 KV			
Real Power, *P*				5 MW			
Reactive Power, *Q*				5 MVAR			

Due to the dimensionality of this problem, the classic EP could confront potential stagnations in local minimums or slow convergence rate. For this reason, it is desirable to know what mutation operator is optimum for this type of problems. Therefore, a convergence comparison between Gaussian mutation, Lévy mutation (α =1.2) and Adaptive mutation was first carried out in order to select the best mutation operator. Figure 4.4.3 shows the average convergence of EP based in 50 independent runs while solving state estimation with the WLS formulation for the 30 bus test system. Here, each of the mutation operators mentioned was tested separately.

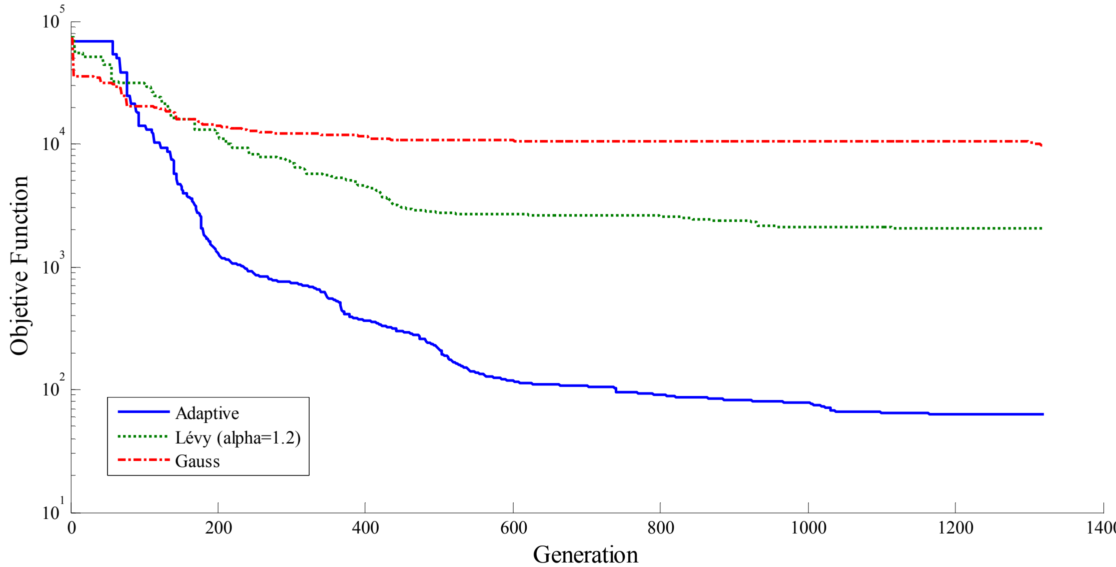

Figure 4.4.3: Convergence rate of EP with several mutation operators.

It is obvious that Gaussian mutation (α =2.0) is not recommendable to solve this problem, due to its stagnation in a bad local minimum. Still, Lévy mutation (α =1.2) provides a poor solution for this problem. Moreover, no fixed value of α (i.e. $1.0 < \alpha < 2.0$) could provide a mutation that guarantee satisfactory results for this problem. Therefore, the adaptive mutation operator was selected to perform this case study.

Tables 4.4.12 and 4.4.13 show the final solution obtained by the proposed method with both, WLS and WLAV formulation. In order to facilitate the visual comparison for the reader, only the estimated values corresponding to the true values shown in Table 4.4.10 are included in Table 4.4.13. The best objective function values reached by the proposed method with both, WLS and WLAV formulation were of 61.41 and 72.81, respectively. Note that the estimated values of both formulations have some similarity and provide a good estimate of the system state.

Table 4.4.12: Solution of EP for the State Estimation Problem

State Variable									
Bus No.	|V| (pu)		δ (degree)		Bus No.	|V| (pu)		δ (degree)	
	WLS	WLAV	WLS	WLAV		WLS	WLAV	WLS	WLAV
1	1.060	1.060	0.00	0.00	16	1.049	1.048	-15.88	-15.88
2	1.043	1.045	-5.50	-5.50	17	1.037	1.035	-16.19	-16.19
3	1.022	1.022	-8.00	-8.00	18	1.028	1.028	-16.88	-16.88
4	1.012	1.012	-9.66	-9.66	19	1.023	1.018	-17.05	-17.05
5	1.010	1.010	-14.38	-14.38	20	1.029	1.029	-16.85	-16.85
6	1.009	1.017	-11.40	-11.40	21	1.030	1.030	-16.47	-16.47
7	1.003	1.003	-13.15	-13.15	22	1.030	1.029	-16.49	-16.54
8	1.008	1.014	-12.12	-12.12	23	1.027	1.029	-16.95	-16.74
9	1.055	1.054	-14.43	-14.43	24	1.019	1.020	-17.11	-16.80
10	1.044	1.044	-16.02	-16.02	25	1.019	1.019	-16.64	-16.33
11	1.087	1.081	-14.43	-14.43	26	1.002	1.010	-16.84	-16.84
12	1.059	1.058	-15.30	-15.30	27	1.029	1.020	-15.99	-15.81
13	1.071	1.071	-15.30	-15.30	28	1.011	1.015	-12.06	-12.06
14	1.046	1.042	-16.19	-16.19	29	1.009	1.000	-17.49	-17.21
15	1.038	1.038	-16.28	-16.28	30	0.995	0.995	-18.01	-18.01

Table 4.4.13: Estimated Values Corresponding to the Final Solution of EP

Estimation of Voltages and Power Injections													
Bus No.	KV		MW		MVAR		Bus No.	KV		MW		MVAR	
	WLS	WLAV	WLS	WLAV	WLS	WLAV		WLS	WLAV	WLS	WLAV	WLS	WLAV
1	243.80	243.80	260.98	260.11	-17.30	-21.05	15	-	-	-7.28	-7.55	-4.94	-3.04
2	-	-	18.78	20.11	38.33	41.06	16	-	-	-1.80	-1.38	2.13	3.06
3	-	-	-1.59	-1.13	1.36	2.82	21	-	-	-16.10	-11.09	-14.17	-11.72
8	-	-	-29.12	-31.35	3.48	-2.94	23	-	-	-5.07	-3.57	0.01	0.68
10	-	-	-2.78	-1.70	19.66	20.91	24	-	-	-11.29	-7.83	-2.38	-3.85
13	-	-	0.00	0.00	9.18	10.33	26	-	-	-2.76	-2.79	-2.74	-0.54
14	-	-	-5.06	-6.67	-0.17	-2.22							

Estimation of Power Flows											
Branch		MW		MVAR		Branch		MW		MVAR	
From Bus	To Bus	WLS	WLAV	WLS	WLAV	From Bus	To Bus	WLS	WLAV	WLS	WLAV
1	2	177.78	176.92	-22.15	-25.90	16	12	-6.74	-6.54	-2.31	-1.92
1	3	83.20	83.20	4.85	4.85	16	17	4.94	5.17	4.44	4.99
2	5	82.99	83.43	1.70	2.80	18	19	3.66	5.07	2.57	5.45
6	2	-60.26	-59.79	1.38	4.75	21	10	-16.75	-16.54	-12.11	-11.66
9	11	0.00	0.00	-16.18	-13.88	23	24	2.09	1.69	2.02	2.64
12	13	0.00	0.00	-9.08	-10.20	24	22	-7.30	-4.33	-1.48	-2.57
12	14	7.58	8.03	1.79	2.80	24	23	-2.08	-1.67	-2.00	-2.62
12	16	6.78	6.58	2.40	2.01	25	26	2.80	2.81	2.80	0.57
14	12	-7.51	-7.95	-1.65	-2.64	27	25	6.44	3.80	1.34	-1.29
14	15	2.45	1.28	1.48	0.41	27	28	-18.01	-17.14	5.16	1.95
15	18	6.05	6.05	1.81	1.81	28	6	-17.00	-19.26	2.48	-4.71
15	23	7.21	5.29	2.12	2.03	30	29	-2.81	-2.86	-1.50	0.41

The *MSE* analysis was again carried out for the shown estimated values, Table 4.4.14 summarizes the results of this analysis.

Table 4.4.14: Mean Square Error Results

MSE			
		WLS	WLAV
Voltage		0.0000	0.0000
Real Power	Injection	2.2110	5.6368
	Flow	0.8291	0.6185
Reactive Power	Injection	6.4870	7.7855
	Flow	3.0524	3.9698
All Values		**2.7497**	**3.7948**

The *MSE* analysis reveals that the proposed method reaches better results using the WLS formulation. It is important to observe that the *MSE* values obtained here are greater than those obtained in the first case study. Although the above statements could be fixed finding better set of independent control parameters for each formulation, it is obvious that the quantity of existing measurements represent an important control variable. Thus, the proposed algorithm would be able to reach better solutions if more measurements were available.

CHAPTER 5
UNIT COMMITMENT IN DEREGULATED POWER SYSTEMS

5.1 Introduction

Electric power systems experience load levels which can be forecasted according to their corresponding pre-stored statistical data. In many countries the load demand for electricity is higher during the daytime and lower during the late evening and early morning. This cyclical load demand requires that utility companies plan for generation of power on an hourly basis. Before the power market restructuring, unit commitment was defined as the process of scheduling generation units in a power system by the electric utility companies. Generation units have different operational costs and maintenance requirements. Therefore, electric utilities have to decide in advance which generators to start up and when to connect them to the network. Also, a great deal of money can be saved by turning units off when they are not needed. In general, the traditional unit commitment (UC) planned for the most economical set of generation units to be available to supply the predicted or forecasted load of the system over a future time period observing spinning reserve and limits of operation of the units.

UC problem can be very complex to solve in large scale power systems. The most typical approaches for its solution are Priority-list Schemes, Dynamic Programming and Lagrange Relaxation [14]. References [42]-[44] present several approaches for solving UC based in EP formulations. The general formulation of UC is shown below:

$$\min \quad TC = \sum_{i=1}^{N}\sum_{t=1}^{T}\left[\left\{F_i\left(P_{it}\right) + ST_i\left(1 - X_{i(t-1)}\right)\right\}X_{it} + SD_i\left(1 - X_{it}\right)X_{i(t-1)}\right] \qquad (5.1.1)$$

Subject to the following constraints:

a) Demand constraints

$$\sum_{i=1}^{N} P_{it}X_{it} = D_t \qquad \forall t = 1,...,T \qquad (5.1.2)$$

b) Reserve constraints

$$\sum_{i=1}^{N} P_{i(\max)}X_{it} \geq D_t + SR_t \qquad \forall t = 1,...,T \qquad (5.1.3)$$

c) Real power operating limits

$$P_{i\min} \leq P_i \leq P_{i\max} \qquad \forall i = 1,...,N \qquad (5.1.4)$$

d) Minimum up/down time constraints

$$T_i^{\text{on}} \geq T_{iup} \qquad (5.1.5)$$

$$T_i^{\text{off}} \geq T_{idown} \qquad (5.1.6)$$

e) Maximum ramp up/down rate constraints

$$P_{it} - P_{i(t-1)} \leq UR_i \qquad (5.1.7)$$

$$P_{i(t-1)} - P_i \leq DR_i \qquad (5.1.8)$$

where the variables are defined as follows:

TC is total production cost,

N is the number of generator units,

T is the number of hours,

F_i is fuel cost function of generator i,

P_{it} is real power output of generator i at hour t,

ST_i is startup cost of generator i,

SD_i is shutdown cost of generator i,

X_{it} is the on/off status of generator i at hour t,

D_t is load demand at hour t,

SR_t is spinning reserve at hour t,

$P_{i\min}$ is minimum generation limit of generator i,

$P_{i\max}$ is maximum generation limit of generator i.

T_i^{on} is the minimum time which the generator i have been continuously On.

T_i^{off} is the minimum time which the generator i have been continuously Off.

T_{iup} is the minimum up time of generator i,

T_{idown} is the minimum down time of generator i.

UR_i is the maximum ramp-up rate limit of generator i.

DR_i is the maximum ramp-down rate limit of generator i.

The electricity industry throughout the world, which has long been dominated by vertically integrated utilities, is undergoing enormous changes. The electricity industry is evolving into a distributed and competitive industry in which market forces drive the price of electricity and reduce the net cost through increased competition.

Power system restructuring has resulted in the decomposition of its three major components: generation, transmission and distribution. At the same time, a new entity has been introduced, the so called Independent System Operator (ISO) with the objective of overseeing the operation of the grid. As part of their inherent functions in a power market, some entities use modified models of UC as decision tools; they are the ISO and the Generation Companies (GENCOS). The following sections explain the details related to the modified models of UC as well as the EP based approaches developed in order to solve them.

5.2 Profit-Based Unit Commitment

The restructuring of electric power systems has resulted in market-based competition by creating an open market environment [45]-[46]. A restructured system allows the power supply to function competitively, as well as allowing consumers to choose suppliers of electric energy. The Generation Companies (GENCOS) compete for selling energy and ancillary services to customers by submitting competitive bids to the power market. These companies can now run UC not for minimizing total production cost as before, but for maximizing their own profits. Moreover, in the vertically integrated power systems, utilities had an obligation to serve their customers. That means all demand and spinning reserve had to be met. However, this is not necessary in the restructured system. The GENCOS can now consider a schedule for their generating units that produce less than the predicted load demand and reserve, but creates a maximum profit. This type of UC is known as Profit-Based Unit Commitment (PBUC). Several publications show techniques to solve PBUC which are based in hybrids methods [45]-

[47], classical methods [48]-[56] and heuristic methods [57]-[58]. Others publications [59]-[64] include PBUC in a framework that develop market strategies. The mathematic formulation of PBUC is stated as follows:

The objective function is:

$$\max \quad PF = RV - TC \tag{5.2.1}$$

Demand and reserve constraints are redefined as follows:

$$\sum_{i=1}^{N} P_{it} X_{it} \le D'_t \qquad \forall t = 1,...,T \tag{5.2.2}$$

$$\sum_{i=1}^{N} R_{it} X_{it} \le SR'_t \qquad \forall t = 1,...,T \tag{5.2.3}$$

Real power operating limits (5.1.4), minimum up/down time constraints (5.1.5), (5.1.6) and maximum ramp up/down rate constraints (5.1.7), (5.1.8) are kept in their traditional way.

Two additional constraints are added, these constraints are:

$$0 \le R_i \le \left(P_{i\max} - P_{i\min}\right), \qquad \forall i = 1,...,N \tag{5.2.4}$$

$$\left(R_i + P_i\right) \le P_{i\max}, \qquad \forall i = 1,...,N \tag{5.2.5}$$

where the variables are defined as follows:

PF is the total profit of GENCO,

RV is the total revenue of GENCO,

R_{it} is reserve generation of generator i at time t,

D'_t is forecasted demand at hour t,

SR_t' is forecasted reserve at hour t.

Forecasted demand, forecasted reserve, expected spot price, reserve price and the strategies for selling power and reserve are important parameters to solve profit-based UC for deregulated power market. They are used to determine the expected revenue, which directly affects the expected profit. Demand, reserve and price are forecasted by other methods which are out of the scope of this work; hence it is assumed that all forecasted data are given.

In the restructured system, GENCO will sell power in a energy market sell reserve in a reserve market. The exact scheduling plan of power and reserve depends on the way reserve payments are made. In the real market there are many kinds of payment method. This work will focus in the two types of reserve markets discussed in [45] and [46].

5.2.1 Reserve Market 1: Payment for Reserve Power Delivered

In this scenario, reserve power is paid only when reserve is actually used. Therefore, the reserve price is higher than the spot price. For this payment method, the revenue and cost for GENCO can be calculated from:

$$RV = \sum_{i=1}^{N}\sum_{t=1}^{T}\left(P_{it} \cdot SP_t\right)X_{it} + r\sum_{i=1}^{N}\sum_{t=1}^{T}\left(R_{it} \cdot RP_t\right)X_{it} \tag{5.2.6}$$

$$TC = \begin{cases} (1-r)\sum_{i=1}^{N}\sum_{t=1}^{T}F_i\left(P_{it}\right) + r\sum_{i=1}^{N}\sum_{t=1}^{T}F_i\left(P_{it}+R_{it}\right) \\ +\sum_{i=1}^{N}\sum_{t=1}^{T}\left[ST_i\left(1-X_{i(t-1)}\right)X_{it} + SD_i\left(1-X_{it}\right)X_{i(t-1)}\right] \end{cases} \tag{5.2.7}$$

where:

SP_t is the forecasted spot price at hour t,

RP_t is the forecasted reserve price at hour t,

r is the probability that the reserve power is called and generated.

5.2.2 Reserve Market 2: Payment for Reserve Power Allocated

In this scenario, GENCO receives the reserve price per unit of reserve power for every time period that the reserve is allocated and not used. If the reserve is used, GENCO will receive the spot price for the reserve power that is generated. In this payment method, reserve price is much lower than the spot price. The revenue for GENCO can be calculated from:

$$RV = \sum_{i=1}^{N}\sum_{t=1}^{T}\left(P_{it} \cdot SP_t\right)X_{it} + \sum_{i=1}^{N}\sum_{t=1}^{T}\left[\left(1-r\right)RP_t + r \cdot SP_t\right]R_{it} \cdot X_{it} \tag{5.2.8}$$

the cost for GENCO can be calculated by (5.2.7).

5.2.3 EP Model for PBUC

The profit-based UC has two groups of variables, binary variables (i.e. status of the units) and continuous variables (i.e. output power and reserve). Therefore, the profit-based UC is a mixed problem. The above fact adds complexity to the conventional day ahead scheduling, whose own dimensionality is relatively high. Hence, the development of approaches with good balance between accuracy and computational effort is desirable. The EP model for PBUC shown here is conceived in order to meet the above necessity. The problem is decomposed in three parts, a first sub-problem which tries to optimize the status of the generating units, a second sub-problem which attends to optimize the bid of reserve power after the first sub-problem is done, and finally a third sub-problem which optimizes the power dispatch in the spot market depending of the type of reserve market. Figure 5.2.1 shows a schematic of the whole process.

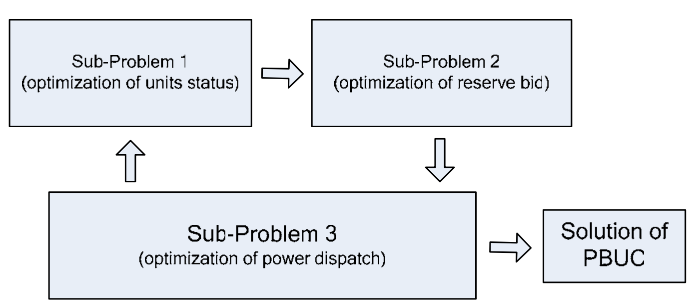

Figure 5.2.1: Structure of the proposed EP model for PBUC

The original configuration of EP is applied as it was explained in Chapter 2. Here, the structure of the individuals, the mutation process, the fitness function used to evaluate each individual, and the selection process are fully explained.

5.2.3.1 Sub-Problem 1: Optimization of Units Status

5.2.3.1.1 Statements

Each individual (parents and offspring) are structured as a matrix $\mathbf{X}^k$, $\forall k \in \{1,...,\mu_1\}$ with dimension N x T. Here, μ is the same as defined in Chapter 2. $\mathbf{X}$ is the matrix of binary variables to optimized. This matrix represents a trial solution of UC schedule and its elements represent the operational status of the units (i.e. "1" if the unit is on or "0" if the unit is off). Figure 5.2.2 shows the structure of a trial solution of UC schedule.

$\mathbf{X}^k$

Unit \ Hour	1	2	3	4	5	6	7	8	•	t	•	T
1	1	1	1	1	1	0	0	0	•	0	•	1
2	0	0	0	1	1	1	1	0	•	0	•	0
•	•	•	•	•	•	•	•	•	•	1	•	•
i	0	1	1	1	1	0	0	0	•	0	•	1
•	•	•	•	•	•	•	•	•	•	1	•	•
N	1	1	1	0	0	0	1	1	•	1	•	0

Figure 5.2.2: Structure of a trial solution of UC schedule.

The time coupling constraints (5.5)-(5.6) are the most difficult to meet [42], [65]-[66]. Hence, in order to satisfy these constraints, the variables of each trial UC schedule is generated in sets of p variables, which are randomly arrayed along the T. The procedure developed here to generate and to arrange these sets is based in the approach presented in [42]. The following discussion fully explains this procedure.

Suppose that unit i of the trial UC schedule $\mathbf{X}^k$ has a minimum up time of 4 hours and a minimum down time of 2 hours. Subsequently, the quantity of binary variables per set is selected according to $p \geq \max\left\{T_{iup}, T_{idown}\right\}$, where p must be a divisor of T. In the case of $T = 24$, p is selected equal to 4. A binary system is generated whose binary numbers have p bits (Fig. 5.2.3a).

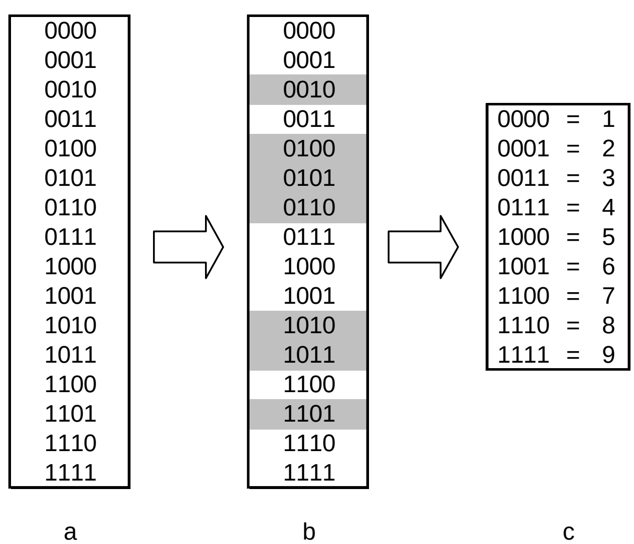

Figure 5.2.3: Construction of sets of status.

Then, the binary numbers that violate the minimum up and/or minimum down time constraints are eliminated (Fig. 5.2.3b). Finally, the feasible combinations are coded (Fig. 5.2.3c), where each code corresponds to one set of unit status (i.e. the status of unit i along p hours of operation).

The array of the sets of status must be made in order to provide a feasible operation of unit i along the T. For instance, a feasible combination of sets of status for unit i could be:

Unit \ Hour	1 2 3 4	5 6 7 8	9 10 11 12	13 14 15 16	17 18 19 20	21 22 23 24
i	[0 0 1 1]	[1 1 1 0]	[0 1 1 1]	[1 1 0 0]	[0 0 1 1]	[1 1 1 1]
	[3]	[8]	[4]	[7]	[3]	[9]

For this example, the possible sets of status that can be selected for a given set of status are shown in Table 5.2.1. The procedure is repeated for the N units to be scheduled until the trial UC schedule is formed. Once formed, the matrix $\mathbf{X}^k$ is processed by means of (5.2.9) in order to verify if it is able to meet the constraints (5.1.7), (5.1.8) and (5.2.2).

$$\sum_{i=1}^{N} X_{it}^{k}\left(P_{i\max}\right) > D_t' \text{ and } \sum_{i=1}^{N} X_{it}^{k}\left(P_{i\min}\right) < D_t' \tag{5.2.9}$$

$\forall k \in \{1,...,\mu_1\}$, $\forall t \in \{1,...,T\}$, here X_{it}^{k} denotes the it^{th} status of the k^{th} matrix of UC schedule among the μ_1 population of parents. If $\mathbf{X}^k$ does not satisfy (5.1.9), it is generated anew.

Table 5.2.1: Feasible combinations of sets of status for unit *i*.

Current Set	Next Feasible Sets
1	1, 2, 3, 4, 9
2	8, 9
3	7, 8, 9
4	5, 6, 7, 8, 9
5	1, 2, 3, 4, 9
6	8, 9
7	1, 2, 3, 4, 9
8	1, 2, 3, 4, 9
9	1, 2, 3, 5, 6, 7, 8, 9

5.2.3.1.1.1 Power Dispatch

Once that the trial UC schedule $\mathbf{X}^k$ satisfies (5.2.9), the following step is to assign the output power level to each commitment unit in order to obtain profit maximization. A way to calculate these output powers is setting the real generation level of each unit until their marginal costs equal a "pseudo-price." This pseudo-price is the hourly forecasted price modified to account for transition and fixed costs [67]. For the frequently used quadratic cost function, the output power level of each unit is calculated as follows:

$$P_{it} = X_{it}\left(\frac{\lambda_t - \beta_i}{2\gamma_i}\right) \tag{5.2.10}$$

$\forall i \in \{1,...,N\}$, $\forall t \in \{1,...,T\}$, where;

$$\lambda_t = SP_t - \zeta \left[\frac{\sum_{i=1}^{N} \sum_{t=1}^{T} \left[ST_i \left(1 - X_{i(t-1)}\right) X_{it} + SD_i \left(1 - X_{it}\right) X_{i(t-1)} + \alpha_i X_{it} \right]}{\sum_{t=1}^{T} D'_t} \right] \quad (5.2.11)$$

and the variables are defined as follows:

λ_t is the system marginal cost at hour t,

α_i is the constant term in the quadratic cost curve of the unit i

β_i is the linear term in the quadratic cost curve of the unit i

γ_i is the quadratic term in the quadratic cost curve of the unit i

ζ is the dispatch factor which help account the type of reserve market by modifying the initial energy offer (more details about this factor in section 5.2.3.3)

If when applying the above criteria, there is an output power that violates the real power limits constraint (5.1.4), this output power is set equal to the corresponding violated limit. For the hours where the demand constraint (5.2.2) is violated, the output powers of the commitment units are adjusted until they reach the demand level. This is done iteratively by adjusting the system marginal cost as shown below [40]:

$$\lambda_t^{(k+1)} = \lambda_t^{(k)} + \Delta\lambda_t^{(k)} \quad (5.2.12)$$

where

$$\Delta\lambda_t^{(k)} = \frac{\Delta P_{it}^{(k)}}{\sum_{i=1}^{N} \frac{1}{2\gamma_i}} \tag{5.2.13}$$

$$\Delta P_{it}^{(k)} = D_t' - \sum_{i=1}^{N} P_{it}^{(k)} \tag{5.2.14}$$

Once the output power level of all commitment units is settled along the T, it is necessary to verify if their ramp up/down limit constraints (5.1.7), (5.1.8) are met [68]. If not, their output power levels are set according to:

$$P_{iq} = \begin{cases} UR_i \text{ if } X_{i(q-1)} = 0 \text{ and } X_{iq} = 1, \quad q = t \\ DR_i \text{ if } X_{iq} = 1 \text{ and } X_{i(q+1)} = 0, \quad q = (t-1) \end{cases} \tag{5.2.15}$$

$\forall i = 1,...,N_V$, here, the subscript V indicates the number of units that violate the ramp up/down constraints. Soon, the dispatch process explained above is performed for the rest of the online units at the modified hour (i.e. t or $t-1$). If after this, there are some online units with $X_{i(t-1)} = 1$ and $X_{it} = 1$ that still violate (5.1.7) or (5.1.8) at hour t, then their output power levels are set according to:

$$P_{it} = \begin{cases} P_{i(t-1)} + UR_i & \text{for ramping up} \\ P_{i(t-1)} - DR_i & \text{for ramping down} \end{cases} \tag{5.2.16}$$

Finally, the dispatch is performed again for the rest of non-fixed online units at hour t.

5.2.3.1.2 Mutation Process

From each UC schedule $\mathbf{X}^k$, $\forall k \in \{1,\ldots,\mu\}$ a new trial UC schedule $\mathbf{X}'^k$ is created by modifying the schedule of each unit in $\mathbf{X}^k$. This process is made by modifying the set of status of each generating unit as follows: First, it is selected at random one set of unit status, then including this selected set, it is initialized a forward replacement of the following sets along T according with the process prescribed in section 5.2.3.1.1. Thus for our example, if the random selector chooses the third set of unit i, then, the new trial UC schedule could to include the following schedule for this unit:

X_i	[0 0 1 1]	[1 1 1 0]	[**0 1 1 1**]	[1 1 0 0]	[**0 0 1 1**]	[1 1 1 1]
	[3]	[8]	[**4**]	[7]	[**3**]	[9]

$$\Downarrow$$

X'_i	[0 0 1 1]	[1 1 1 0]	[**0 0 1 1**]	[1 1 0 0]	[**0 0 0 1**]	[**1 1 1 0**]
	[3]	[8]	[**3**]	[7]	[**2**]	[**8**]

Each new UC schedule is verified in order to ensure that it meets the requirements of (5.2.9). Then, the output power levels of these new trial solutions are established as it was explained in section 5.2.3.1.1.1.

5.2.3.1.3 Fitness Function

The fitness score of each of the $2\mu_1$ trial UC schedule is evaluated to the light of the fitness function, the fitness function is defined as follows:

$$\max \quad PF_1^k = RV_1^k - \left(C_F^k + C_T^k\right) \tag{5.2.17}$$

where:

$$RV_1^k = \sum_{i=1}^{N}\sum_{t=1}^{T}\left(P_{it}^k \cdot SP_t\right) \tag{5.2.18}$$

$$C_F^k = \sum_{i=1}^{N}\sum_{t=1}^{T} F_i\left(P_{it}^k\right) \tag{5.2.19}$$

$$C_T^k = \sum_{i=1}^{N}\sum_{t=1}^{T}\left[ST_i\left(1 - X_{i(t-1)}^k\right)X_{it}^k + SD_i\left(1 - X_{it}^k\right)X_{i(t-1)}^k\right] \tag{5.2.20}$$

and the variables are defined as follows:

PF_1^k is the k^{th} trial profit of GENCO in problem 1,

RV_1^k is the k^{th} trial revenue in problem 1,

C_F^k is the k^{th} trial total fuel cost of units in problem 1,

C_T^k is the k^{th} trial total transition cost of units in problem1.

5.2.3.1.4 Competition and Selection

A selected number of pair-wise comparisons over all the $2\mu_1$ individuals are conducted. For each individual, q_1 individuals are chosen uniformly at random from all the $2\mu_1$ population to be its opponents. For each comparison, if the fitness score of the selected individual is greater than its opponents, it wins the competition. The μ_1

individuals that have the most win, out of all the $2\mu_1$ population to be the parents of the next generation.

5.2.3.1.5 <u>Stopping Criterion</u>

The Sub-Problem 1 terminates if the fitness score of the best individual does not change for a predefined interval of generations, that is:

$$\left| \frac{PF_1'^{\text{best}} - PF_1^{\text{best}}}{PF_1'^{\text{best}}} \right| \leq \varepsilon_1 \tag{5.2.21}$$

for g_1 successive generations, here ε_1 is a sufficiently small positive value. Otherwise, the process is repeated beginning from section 5.2.3.1.2.

5.2.3.2 Sub-Problem 2: Optimization of Reserve Bid

From Sub-Problem 1, the following values are imported: $\mathbf{P}^{\text{best}}$, RV_1^{best}, C_F^{best} and C_T^{best}, where $\mathbf{P}^{\text{best}}$ is the matrix of output power levels corresponding to the best UC schedule found.

5.2.3.2.1 <u>Statements</u>

Each individual (parents and offspring) are structured as a pair of matrices $\left(\mathbf{R}^k, \boldsymbol{\eta}^k\right)$, $\forall k \in \{1,...,\mu_2\}$, with dimension N x T. Here, $\boldsymbol{\eta}$ and μ are the same as defined in Chapter 2. $\mathbf{R}$'s are matrices of trial reserve powers whose elements are the variables to be optimized. Initially these variables are selected at random such that they meet the constraints (5.2.4) and (5.2.5) as follows:

$$R_{it}^{k} = \begin{cases} \upsilon_{it}^{k} \cdot \min\left\{\left(P_{i\max} - P_{it}^{\text{best}}\right), SR_{t}'\right\} & \text{if } P_{it}^{\text{best}} \neq 0 \\ 0 & \text{otherwise} \end{cases} \tag{5.2.22}$$

where υ_{it}^{k} is a random number whose value is uniformly distributed in the interval $(0,1)$. This random number is generated anew for each it^{th} variable in the k^{th} individual. Once formed, the matrix $\mathbf{R}^{k}$ is processing by means of (5.2.23) in order to verify if it is able to meet the unit coupling constraint (5.2.3).

$$\sum_{i=1}^{N} R_{it}^{k} \leq SR_{t}' \tag{5.2.23}$$

$\forall k \in \{1,\ldots,\mu_{2}\}$, $\forall t = 1,\ldots,T$. Here R_{it}^{k} denotes the it^{th} reserve power of the k^{th} matrix of reserve power among the μ_{2} population of parents. If $\mathbf{R}^{k}$ does not satisfy (5.2.23), it is generated anew.

5.2.3.2.2 Mutation Process

From each of the μ_{2} parents $\left(\mathbf{R}^{k}, \boldsymbol{\eta}^{k}\right)$, one offspring is generated by:

$$\eta_{it}'^{k} = \begin{cases} \eta_{it}^{k} \cdot \exp\left(\tau' \cdot \nu^{k} + \tau \cdot \nu_{it}^{k}\right) & \text{if } R_{it}^{k} \neq 0 \\ 0 & \text{otherwise} \end{cases} \tag{5.2.24}$$

$$R_{it}'^{k} = \begin{cases} R_{it}^{k} + \left(\eta_{it}'^{k} \cdot \nu_{it}^{k}\right) & \text{if } R_{it}^{k} \neq 0 \\ 0 & \text{otherwise} \end{cases} \tag{5.2.25}$$

$\forall k \in \{1,...,\mu_2\}$, $\forall i \in \{1,...,N\}$, $\forall t \in \{1,...,T\}$, where ν, τ and τ' are the same as defined in Chapter 2. In order to ensure the fulfillment of constraints (5.2.3)-(5.2.5), each offspring is submitted to the following process:

$$R_{it}'^{k} = \begin{cases} \min\left\{\left(P_{i\max} - P_{it}^{\text{best}}\right), SR_t'\right\} & \text{if } R_{it}'^{k} > \min\left\{\left(P_{i\max} - P_{it}^{\text{best}}\right), SR_t'\right\} \\ 0 & \text{if } R_{it}'^{k} < 0 \\ R_{it}'^{k} & \text{otherwise} \end{cases} \tag{5.2.26}$$

Once evaluated in (5.2.26), the matrix $\mathbf{R}'^{k}$ is verified by means of :

$$\sum_{i=1}^{N} R_{it}'^{k} \leq SR_t' \tag{5.2.27}$$

$\forall k \in \{1,...,\mu_2\}$, $\forall t = 1,...,T$. Here $R_{it}'^{k}$ denotes the it^{th} reserve power of the k^{th} matrix of reserve power among the μ_2 population of parents. If $\mathbf{R}'^{k}$ does not satisfy (5.2.27), it is generated anew.

5.2.3.2.3 Fitness Function

The fitness score of each of the $2\mu_2$ individuals is evaluated by means of (5.2.1), where (5.2.6)-(5.2.8) are rearranged as follows:

$$RV^k = \begin{cases} RV_1^{\text{best}} + r\sum_{i=1}^{N}\sum_{t=1}^{T}\left(R_{it}^k \cdot RP_t\right) & \text{if } S=1 \\ RV_1^{\text{best}} + \sum_{i=1}^{N}\sum_{t=1}^{T}\left[\left(1-r\right)RP_t + r\cdot SP_t\right]R_{it}^k & \text{if } S=2 \end{cases} \tag{5.2.28}$$

$$TC^k = \left(1-r\right)C_F^{\text{best}} + C_T^{\text{best}} + r\sum_{i=1}^{N}\sum_{t=1}^{T}F_i\left(P_{it}^{\text{best}} + R_{it}^k\right) \tag{5.2.29}$$

here S indicates the type of reserve market.

5.2.3.2.4 <u>Competition, Selection and Stopping Criteria</u>

The same competition and selection process used in problem 1 is applied here. The Sub-Problem 2 end if the fitness scores of the best individual of μ_2 does not change for a predefined interval of generations, that is:

$$\left|\frac{PF'^{\text{best}} - PF^{\text{best}}}{PF'^{\text{best}}}\right| \leq \varepsilon_2 \tag{5.2.30}$$

for successive generations g_2, here ε_2 is a sufficiently small positive value. Otherwise, the process is repeated beginning from section 5.2.3.2.2.

5.2.3.3 Sub-Problem 3: Optimization of Power Dispatch

The dispatch factor ζ was introduced in (5.2.11), whose original structure only take into account the energy market [67]. In a two commodities environment (i.e. energy and reserve power), it is necessary to evaluate if offering less energy in the spot market and more reserve in the reserve market, the final profit is greater than doing the opposite. The

Sub-Problem 3 was created with the intention of guaranteeing that the proposed algorithm performs this evaluation.

In this part of the algorithm ζ is generated as a random number whose value is uniformly distributed in the interval $(0,1)$. Then, this number is exported to Sub-Problem 1. For each value of ζ exported to Sub-Problem 1, is obtained $\mathbf{P}^{\text{best}}$, $\mathbf{R}^{\text{best}}$ and PF^{best} from Sub-Problem 2. This process is performed for a determined number of iterations, while an elitist selection decides what the best solution of PBUC is.

5.2.4 Case Study

In order to test its effectiveness, the proposed method (EPUCM) is tested in a GENCO with three generating units. This company wishes to know the optimum quantity of energy and reserve power that it can offer in a deregulated power market with the intention of maximizing profit. The data of the units and the system are taken from [45]. The results will be compared with those obtained via the traditional unit commitment algorithm (TUC) and the hybrid profit-based unit commitment algorithm (EPLR) developed in [45].

The system data are given in Tables 5.2.2-5.2.3. Table 5.2.4 shows the units data, Table 5.2.5 illustrates the control variables of the proposed algorithm used for this study. Tables 5.2.6-5.2.10 show the final solution of the methods to be compared.

The best known solution for this case study was obtained from EPLR. Hence, the differences between the best solution obtained with the proposed method and that obtained with EPLR were included in Table 5.2.10. These differences were calculated as percentage error:

$$\text{Error}\left(\%\right)=100\left(\frac{PF_{\text{EPUCM}}^{t}-PF_{\text{EPLR}}^{t}}{PF_{\text{EPUCM}}^{t}}\right) \tag{5.2.31}$$

where PF_{EPUCM}^{t} is the profit obtained for the proposed algorithm at hour t. The results shown in Table 5.2.10 indicate that maximum deviation of the proposed method is 0.0494% occurred at hour 9 for the reserve market 2.

Table 5.2.2: Forecasted Prices for Energy and Reserve Power for 12 Hours

Hour	Forecasted Spot Price ($/MWh)	Forecasted Reserve Price Payment Method 1 ($/MWh)	Forecasted Reserve Price Payment Method 2 ($/MWh)
1	10.55	31.65	0.422
2	10.35	31.05	0.414
3	9.00	27.00	0.360
4	9.45	28.35	0.378
5	10.00	30.00	0.400
6	11.25	33.75	0.450
7	11.30	33.90	0.452
8	10.65	31.95	0.426
9	10.35	31.05	0.414
10	11.20	33.60	0.448
11	10.75	32.25	0.430
12	10.60	31.80	0.424

Table 5.2.3: Forecasted Demand and Reserve for 12 Hours

Hour	Forecasted Demand (MW)	Forecasted Reserve (MW)
1	170	20
2	250	25
3	400	40
4	520	55
5	700	70
6	1050	95
7	1100	100
8	800	80
9	650	65
10	330	35
11	400	40
12	550	55

Table 5.2.4: Unit Data

Parameter	Unit 1	Unit 2	Unit 3
P_{max}	600	400	200
P_{min}	100	100	50
α (\$/h)	500	300	100
β (\$/MWh)	10	8	6
γ (\$/MW^{2}h)	0.0020	0.0025	0.0050
Min ON time (h)	3	3	3
Min OFF time (h)	3	3	3
Startup cost ($)	450.00	400.00	300.00
Shutdown cost ($)	0.00	0.00	0.00
Initial status (h)	-3	3	3

The results obtained show that the proposed method is able to reach the best known solution for the sample problem illustrated here. In order to test the quality of the solutions for the above problem, 50 independent runs were executed. This experiment gives the success rate illustrated in Table 5.2.11. Moreover, Figure 5.2.4 illustrates the average convergence of the proposed approach for reserve market 1.

Table 5.2.5: Control Parameters for the Proposed EP Algorithm.

Control Variable	Value			Description
	Sub-Problem 1	Sub-Problem 2	Sub-Problem 3	
μ	40	30	-	Number of individuals
η_1	-	5	-	Initial perturbation
q	10	6	-	Number of opponents in stochastic ranking
ε	$1x10^{-4}$	$1x10^{-4}$	-	Error tolerance
g	40	30	10	Generation tolerance
r	-	0.005	-	Probability that the reserve is called and generated

Table 5.2.6: Power Generation of the Final Solution (Reserve Market 1)

Hour	Power (MW)								
	Unit 1			Unit 2			Unit 3		
	TUC	EPLR	EPUCM	TUC	EPLR	EPUCM	TUC	EPLR	EPUCM
1	0	0	0	100	0	0	70	170	170
2	0	0	0	100	0	0	150	200	200
3	0	0	0	200	0	0	200	200	200
4	0	0	0	320	0	0	200	200	200
5	100	0	0	400	379.9	380.73	200	200	200
6	450	0	0	400	400	400	200	200	200
7	500	0	0	400	400	400	200	200	200
8	200	0	0	400	400	400	200	200	200
9	100	0	0	350	400	400	200	200	200
10	100	0	0	100	130	130	130	200	200
11	100	0	0	100	200	200	200	200	200
12	100	0	0	250	350	350	200	200	200

Table 5.2.7: Reserve Generation of the Final Solution (Reserve Market 1)

Hour	Reserve (MW)								
	Unit 1			Unit 2			Unit 3		
	TUC	EPLR	EPUCM	TUC	EPLR	EPUCM	TUC	EPLR	EPUCM
1	0	0	0	0	0	0	20	20	20
2	0	0	0	0	0	0	25	0	0
3	0	0	0	40	0	0	0	0	0
4	0	0	0	55	0	0	0	0	0
5	70	0	0	0	20.1	19.268	0	0	0
6	95	0	0	0	0	0	0	0	0
7	100	0	0	0	0	0	0	0	0
8	80	0	0	0	0	0	0	0	0
9	15	0	0	50	0	0	0	0	0
10	0	0	0	0	35	35	35	0	0
11	0	0	0	40	40	40	0	0	0
12	0	0	0	55	50	50	0	0	0

Table 5.2.8: Power Generation of the Final Solution (Reserve Market 2)

Hour	Power (MW)								
	Unit 1			Unit 2			Unit 3		
	TUC	EPLR	EPUCM	TUC	EPLR	EPUCM	TUC	EPLR	EPUCM
1	0	0	0	100	0	0	70	170	170
2	0	0	0	100	0	0	150	200	200
3	0	0	0	200	0	0	200	200	200
4	0	0	0	320	0	0	200	200	200
5	100	0	0	400	330	330.36	200	200	200
6	450	0	0	400	400	400	200	200	200
7	500	0	0	400	400	400	200	200	200
8	200	0	0	400	400	400	200	200	200
9	100	0	0	350	387.2	400	200	200	200
10	100	0	0	100	130	130	130	200	200
11	100	0	0	100	200	200	200	200	200
12	100	0	0	250	350	350	200	200	200

Table 5.2.9: Reserve Generation of the Final Solution (Reserve Market 2)

Hour	Reserve (MW)								
	Unit 1			Unit 2			Unit 3		
	TUC	EPLR	EPUCM	TUC	EPLR	EPUCM	TUC	EPLR	EPUCM
1	0	0	0	0	0	0	20	20	20
2	0	0	0	0	0	0	25	0	0
3	0	0	0	40	0	0	0	0	0
4	0	0	0	55	0	0	0	0	0
5	70	0	0	0	70	69.643	0	0	0
6	95	0	0	0	0	0	0	0	0
7	100	0	0	0	0	0	0	0	0
8	80	0	0	0	0	0	0	0	0
9	15	0	0	50	12.8	0	0	0	0
10	0	0	0	0	35	35	35	0	0
11	0	0	0	40	40	40	0	0	0
12	0	0	0	55	50	50	0	0	0

Table 5.2.10: Expected Profit Based in the Sale of Energy and Reserve

Hour	Profit ($)							
	Reserve Payment Method 1				Reserve Payment Method 2			
	TUC	EPLR	EPUCM	Error (%)	TUC	EPLR	EPUCM	Error (%)
1	126.50	531.40	531.39	0.0019	132.80	537.70	537.67	0.0056
2	352.90	570.00	570.00	0.0000	360.60	570.00	570.00	0.0000
3	103.60	300.00	300.00	0.0000	114.30	300.00	300.00	0.0000
4	303.10	390.00	390.00	0.0000	318.60	390.00	390.00	0.0000
5	-363.20	201.00	201.00	0.0000	-342.30	215.70	215.65	0.0232
6	1,017.80	1,350.00	1,350.00	0.0000	1,049.70	1,350.00	1,350.00	0.0000
7	1,040.90	1,380.00	1,380.00	0.0000	1,074.50	1,380.00	1,380.00	0.0000
8	548.40	990.00	990.00	0.0000	573.80	990.00	990.00	0.0000
9	308.10	810.00	810.00	0.0000	328.10	810.40	810.00	0.0494
10	91.10	818.10	818.10	0.0000	102.80	829.80	829.78	0.0024
11	159.70	804.60	804.63	0.0037	172.50	817.40	817.44	0.0049
12	359.90	929.20	929.23	0.0032	377.30	945.00	945.03	0.0032
Total	4,048.80	9,074.30	9,074.35	0.0006	4,262.70	9,136.00	9,135.57	0.0047

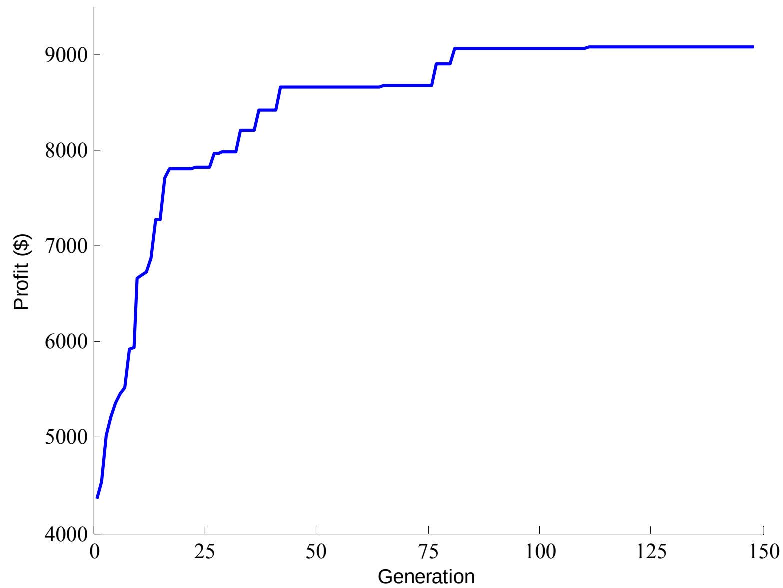

Figure 5.2.4: Average Convergence of the EPUCM for the Case Study

Table 5.2.11: Capture Rate of the Proposed Method for the Case Study

Reserve Market 1		Reserve Market 2	
Expected Profit ($)	Success Rate (%)	Expected Profit ($)	Success Rate (%)
9,073.20	8.00	9,115.20	2.00
9,074.10	8.00	9,117.40	2.00
9,074.35	84.00	9,124.50	2.00
		9,129.00	4.00
		9,135.57	90.00

The final values of the dispatch factor ζ found by the proposed method for the reserve markets 1 and 2 were 0.1667 and 0.6000, respectively. The results shown highlight the effectiveness of the proposed method in solving UC for deregulated power system market. The values obtained by means of the traditional UC algorithm were shown in order to confirm that TUC is no longer effective in market environment. Hence, the values obtained by the proposed method were compared with those obtained by the EPLR method.

5.3 Unit Commitment with Network Flow Constraints

A competitive power market needs an independent operational control of the network. The entity that guarantees this class of control is known as the Independent System Operator (ISO). This entity has the authority to commit and dispatch the necessary system resources as well as to perform load shedding in order to maintain the system reliability.

Among the most typical functions of the ISO is to plan the day ahead schedule using a UC routine. However, in circumstances where most of the commitment units are located in one part of the system, it becomes more difficult to keep the normal operation level of the system because it becomes more congested. For these cases, the incorporation of network flow constraints in the UC formulation is a valuable decision. Several publications show research in this area, where UC includes as additional constraints, the network flows [69]-[72]. Moreover, other system constraints have been included [73]-[87]. As a contribution for the ISO, this section presents an EP model based in Unit Commitment with Network Flows Constraints (UCFC) in order to plan an effective and secure day-ahead schedule. The formulation of UCFC is the same as the traditional UC, with the objective function (5.1.1) and the constraints (5.1.2)-(5.1.8), the difference here is the addition of the branch flow constraints:

$$\left|P_{ut}\right| \leq P_u^{\max} \tag{5.3.1}$$

$\forall t \in \{1,...,T\}$, $\forall u \in \{1,...,br\}$; where br is the number of branches in the system and $P_u^{\max}$ is the maximum real power operating limit of the branch u.

5.3.1 EP Model for UCFC

The variables which control the real power network flows are the status of the units (UC), the output power level of theses units, and the phase shifter controls. For the purpose of UC, the consideration of changes in the output power level of units and phase shifter controls is very complex task [72]. Including these considerations provide a suboptimal security solution when there is a significant deviation between the real system requirements and the forecasted one. Accounting for the status of units to control the network flows provides a conservative solution, which is a desire for this stage of the planning process. The proposed method is designed to provide this kind of solution. The methodology of this technique is explained in the following sections.

5.3.1.1 Statements

An initial population μ of matrices of trial UC schedules is generated as it was explained in section 5.2.3.1.1. The difference here is the way the output power level to each online unit is assigned. In this case these output powers are set until the marginal cost of each unit equals the system marginal cost. Equation (5.2.10) continues being used to calculate the output power. λ_t is obtained by means of an iterative process performed for (5.2.12)-(5.2.14), but in this case (5.2.14) is redefined as follows:

$$\Delta P_{it}^{(k)} = \left(D_t + L_t\right) - \sum_{i=1}^{N} P_{it}^{(k)} \tag{5.3.2}$$

where L_t are the system power losses at hour t, which for this study are estimated as a percentage of the system demand. The initial value of λ_t is found by means of:

$$\lambda_t = \frac{\left(D_t + L_t\right) + \sum_{i=1}^{N} \frac{\beta_i}{2\gamma_i}}{\sum_{i=1}^{N} \frac{1}{2\gamma_i}} \tag{5.3.3}$$

5.3.1.2 Mutation Process

From each UC schedule $\mathbf{X}^k$, $\forall k \in \{1,...,\mu\}$ a new trial UC schedule $\mathbf{X}'^k$ is created according to section 5.2.3.1.3. The output power levels of these new trial solutions are established as was explained in section 5.3.1.1.

5.3.1.3 Fitness Function

The fitness score of each of the 2μ trial UC schedule is evaluated by means of the following fitness function:

$$\Phi\left(\mathbf{X}^k\right)=\begin{cases}\displaystyle\sum_{i=1}^{N}\sum_{t=1}^{T}\left[\left\{F_i\left(P_{it}\right)+ST_i\left(1-X_{i(t-1)}\right)\right\}X_{it}+SD_i\left(1-X_{it}\right)X_{i(t-1)}\right]\\ \displaystyle+p_0\left[\sum_{u=1}^{br}\sum_{t=1}^{T}\left\{g_{ut}^{+}\left(\mathbf{X}^k\right)\right\}^2\right]\end{cases}\tag{5.3.4}$$

$\forall k\in\{1,\ldots,\mu\}$. Here, p_0 is a fixed penalty parameter and $g_{ut}^{+}\left(\mathbf{X}^k\right)$ is the magnitude of the overflow in branch u at time t, which can be calculated as follows:

$$g_{ut}^{+}\left(\mathbf{X}^k\right)=\max\left\{\left(\left|P_{ut}\right|-P_u^{\max}\right),0\right\}\tag{5.3.5}$$

The value of P_{ut} is found running an AC power flow routine and calculating the branch flows of the system for each hour along T. The reason why the AC power flow is used is due to the fact the proposed model is developed for MVA violations. Here, the model considers only the MW violations so that comparisons can be made with published results. Since the system losses are estimated, the little deviation between this estimation and the real value of the losses will be adjusted by the unit connected to the slack bus. For this reason, the slack bus is selected as that which has the unit with more spinning reserve in the system.

5.3.1.4 Competition and Selection

A selected number of pair-wise comparisons over all the 2μ UC schedules are conducted. For each UC schedule, q UC schedules are chosen uniformly at random from all the 2μ population for to be its opponents. For each comparison, if the fitness score of the UC schedule is less than its opponents, it wins the competition. The μ UC schedules that have the most wins, out of all the 2μ population be the parents of the next generation.

5.3.1.5 Stopping Criterion

The algorithm end if the fitness scores of the best UC schedule of μ individuals does not change for a predefined interval of generations, that is:

$$\left| \frac{\Phi\left(\mathbf{X}'^{\text{best}}\right) - \Phi\left(\mathbf{X}^{\text{best}}\right)}{\Phi\left(\mathbf{X}'^{\text{best}}\right)} \right| \leq \varepsilon \tag{5.3.6}$$

for successive generations g, here ε is a sufficiently small positive value. Otherwise, the process is repeated beginning from section 5.3.1.3.

5.3.2 Case Studies

In order to test the effectiveness of the proposed method (UCFC), the following two case studies were performed:

5.3.2.1 6 Bus Test System

This case study has the intention of comparing the results of the proposed method with those obtained by means of a Bender Decomposition Security Constrained Unit Commitment approach (BCUC) (case 2 of [87]). This last approach assigns the output power level by means of an optimal power flow routine (OPF). The six bus test system is shown in Figure 5.3.1. The system data are given in Tables 5.3.1-5.3.3. Table 5.3.4 shows the units data, while Table 5.3.5 illustrates the control variables used for the proposed algorithm in this study.

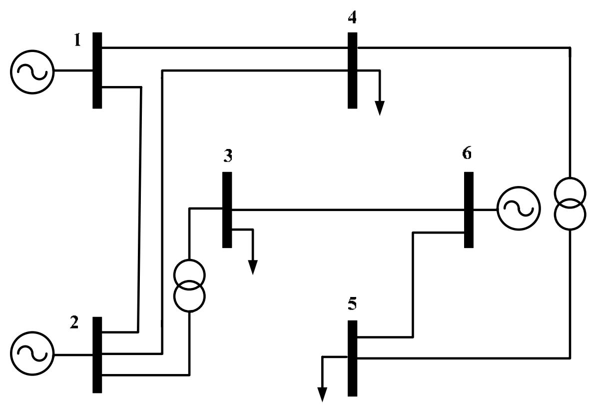

Figure 5.3.1: Six Bus Test System

Table 5.3.1: Hourly Load and Spinning Reserve

Hour	Load		Spinning Reserve	Hour	Load		Spinning Reserve
	MW	MVAR	MW		MW	MVAR	MW
1	175.19	50.37	1.75	13	242.18	69.63	2.42
2	165.15	47.48	1.65	14	243.60	70.03	2.44
3	158.67	45.62	1.59	15	248.86	71.55	2.49
4	154.73	44.49	1.55	16	255.79	73.54	2.56
5	155.06	44.58	1.55	17	256.00	73.60	2.56
6	160.48	46.14	1.60	18	246.74	70.94	2.47
7	173.39	49.85	1.73	19	245.97	70.72	2.46
8	177.60	51.06	1.90	20	237.35	68.24	2.37
9	186.81	53.71	2.06	21	237.31	68.23	2.37
10	206.96	59.50	2.17	22	232.67	66.89	2.27
11	228.61	65.73	2.29	23	195.93	56.33	2.01
12	236.10	67.88	2.36	24	195.60	56.23	1.97

The system losses were estimated as 0.48% of the system demand along of T. The UC schedule for this system without network flow constraints was obtained in [87]. For this solution, the output power level of each unit was calculated as was explained in section 5.3.1.1. The results obtained are shown in Table 5.3.6. This schedule produces violations in lines 1-4 at some hours, as it is shown in Table 5.3.7. With the intention to repair these violations, reference [87] indicates that the BCUC approach should be run again, now considering the network flows constraints.

Table 5.3.2: Network Data

Branch		R (pu)	X (pu)	Tap Changing	Flow Limit (MW)
From Bus	To Bus				
1	2	0.0050	0.1700	1.00	200
1	4	0.0030	0.2580	1.00	100
2	3	0.0000	0.0370	0.95	100
2	4	0.0070	0.1970	1.00	100
4	5	0.0000	0.0370	0.95	100
5	6	0.0020	0.1400	1.00	100
3	6	0.0005	0.0180	1.00	100

Table 5.3.3: Load Distribution Profile

Bus	Percentage of Total Load	
	MW	MVAR
3	20.00%	23.00%
4	40.00%	38.50%
5	40.00%	38.50%

Table 5.3.4: Generator Data

Bus	Pmin (MW)	Pmax (MW)	Qmin (MVAR)	Qmax (MVAR)	Start up Cost ($)	Cost Coefficients			Ramp (MW/h)	Min up/down time (h)	Initial State (h)
						α ($)	β ($/MWh)	γ ($/MW^{2}h)			
1	100	220	-40	50	124.69	220.58	16.833	0.1247	55	4	4
2	10	100	-40	50	249.22	161.87	40.623	0.1246	50	2	2
6	10	20	-40	50	0	171.23	21.933	0.1246	20	2	2

Based in this last solution of BCUC, the output power level is assigned again to each online unit according with the classical economic dispatch approach (ED) shown in section 5.3.1.1. The results obtained are shown in Table 5.3.8. For this solution, a little overflow of 0.819 MW persists in line 1-4 at hour 22. This line is the most loaded of the system, with an average load level of 84.88% along T.

Table 5.3.5: Control Parameter of the Proposed Algorithm

Control Variable	Value	Description
μ	40	Number of individuals
p_0	100	Penalty parameter
q	10	Number of opponents in stochastic ranking
ε	$1\text{x}10^{-4}$	Error tolerance
g	30	Generation tolerance

Table 5.3.6: Hourly Dispatch without Network Constraints by BCUC

Hour	Generation (MW)			Hour	Generation (MW)		
	Unit 1 (Bus 1)	Unit 2 (Bus 2)	Unit 3 (Bus 6)		Unit 1 (Bus 1)	Unit 2 (Bus 2)	Unit 3 (Bus 6)
1	135.69	40.34	0.00	13	173.24	50.00	20.00
2	165.94	0.00	0.00	14	160.05	64.72	20.00
3	159.43	0.00	0.00	15	162.69	67.36	20.00
4	155.47	0.00	0.00	16	166.17	70.84	20.00
5	155.80	0.00	0.00	17	166.28	70.95	20.00
6	161.25	0.00	0.00	18	161.63	66.30	20.00
7	174.22	0.00	0.00	19	177.15	50.00	20.00
8	178.45	0.00	0.00	20	218.49	0.00	20.00
9	187.71	0.00	0.00	21	218.45	0.00	20.00
10	207.95	0.00	0.00	22	213.79	0.00	20.00
11	209.71	0.00	20.00	23	196.87	0.00	0.00
12	217.23	0.00	20.00	24	196.54	0.00	0.00

Table 5.3.7: Flow in Line 1-4 (MW)

Hour	12	20	21	22
Flow	102.370	102.940	102.920	100.820
Violation	2.3738	2.94	2.917	0.820

Table 5.3.8: Hourly Dispatch with Network Constraints by BCUC

Hour	Generation (MW)			Hour	Generation (MW)		
	Unit 1 (Bus 1)	Unit 2 (Bus 2)	Unit 3 (Bus 6)		Unit 1 (Bus 1)	Unit 2 (Bus 2)	Unit 3 (Bus 6)
1	135.69	40.34	0.00	13	159.34	64.00	20.00
2	165.94	0.00	0.00	14	160.05	64.72	20.00
3	159.43	0.00	0.00	15	162.69	67.36	20.00
4	155.47	0.00	0.00	16	166.17	70.84	20.00
5	155.80	0.00	0.00	17	166.28	70.95	20.00
6	161.25	0.00	0.00	18	161.63	66.30	20.00
7	174.22	0.00	0.00	19	161.24	65.91	20.00
8	178.45	0.00	0.00	20	156.91	61.58	20.00
9	187.71	0.00	0.00	21	168.45	50.00	20.00
10	207.95	0.00	0.00	22	213.79	0.00	20.00
11	209.71	0.00	20.00	23	196.87	0.00	0.00
12	167.24	50.00	20.00	24	196.54	0.00	0.00

Table 5.3.9: Hourly Dispatch by Means of the Proposed Method (UCFC)

Hour	Generation (MW)			Hour	Generation (MW)		
	Unit 1 (Bus 1)	Unit 2 (Bus 2)	Unit 3 (Bus 6)		Unit 1 (Bus 1)	Unit 2 (Bus 2)	Unit 3 (Bus 6)
1	125.70	30.33	20.00	13	159.34	64.00	20.00
2	145.94	0.00	20.00	14	160.05	64.72	20.00
3	139.43	0.00	20.00	15	162.69	67.36	20.00
4	135.47	0.00	20.00	16	166.17	70.84	20.00
5	115.59	20.22	20.00	17	166.28	70.95	20.00
6	128.31	32.94	0.00	18	161.63	66.30	20.00
7	134.79	39.43	0.00	19	161.24	65.91	20.00
8	158.45	0.00	20.00	20	156.91	61.58	20.00
9	167.71	0.00	20.00	21	156.89	61.56	20.00
10	141.65	46.30	20.00	22	164.56	69.23	0.00
11	152.52	57.18	20.00	23	146.11	50.76	0.00
12	156.29	60.95	20.00	24	135.95	40.59	20.00

On the other hand, Table 5.3.9 shows the hourly dispatch result of the proposed method. Here, no branch overflows were found. The most loaded branch was line 1-4 with an average load level of 77.35% along T. Moreover, the total operating cost here is *$200,540.00,* versus the *$206,980.00* calculated for the UC schedule found by BCUC with network constraints. Based in 50 independents runs, Figure 5.3.2 shows the convergence rate of UCFC, where the worst, the average and the best solution are highlighted. Note that the worst solution is still better than the solution reached by the BCUC with network constraints method.

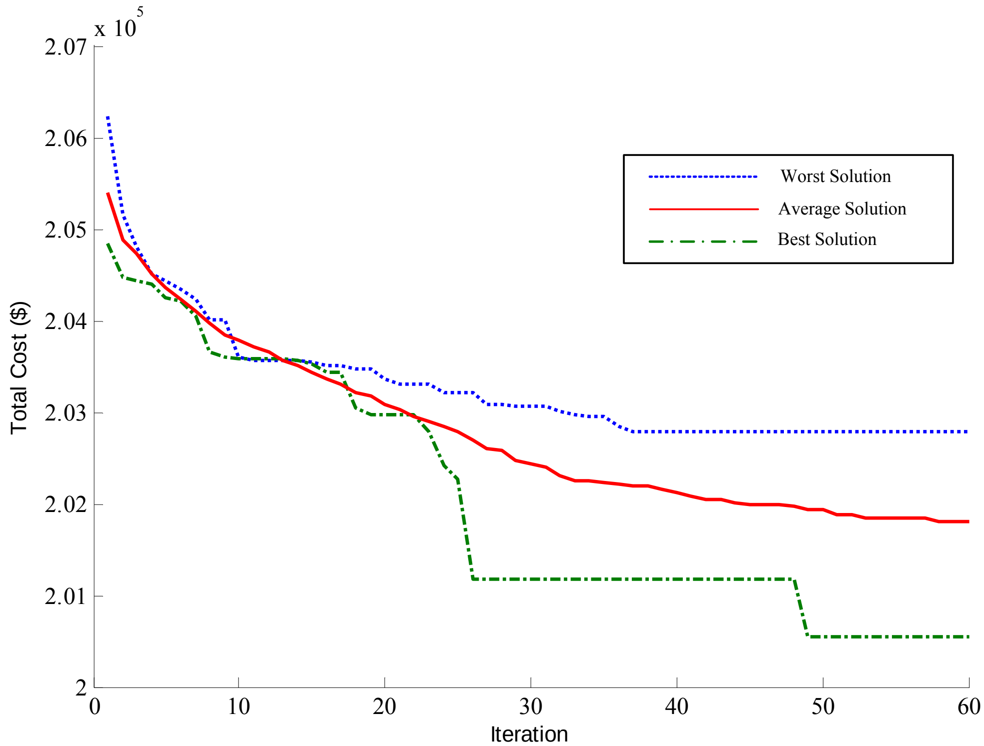

Figure 5.3.2: Convergence of UCFC

5.3.2.2 Modified IEEE 30 Bus Test System

The proposed method is tested again, now with the intention to show its ability to solve effectively larger systems. Figure 5.3.3 shows the system that was used for this test. The network and some generator data are taken from [88], and are shown in Tables 5.3.10-5.3.11. The hourly system load and spinning reserve, as well as the load distribution profile are shown in Tables 5.3.12 and 5.3.13. Table 5.3.14 illustrates the control variables of the proposed method which were used in this case study.

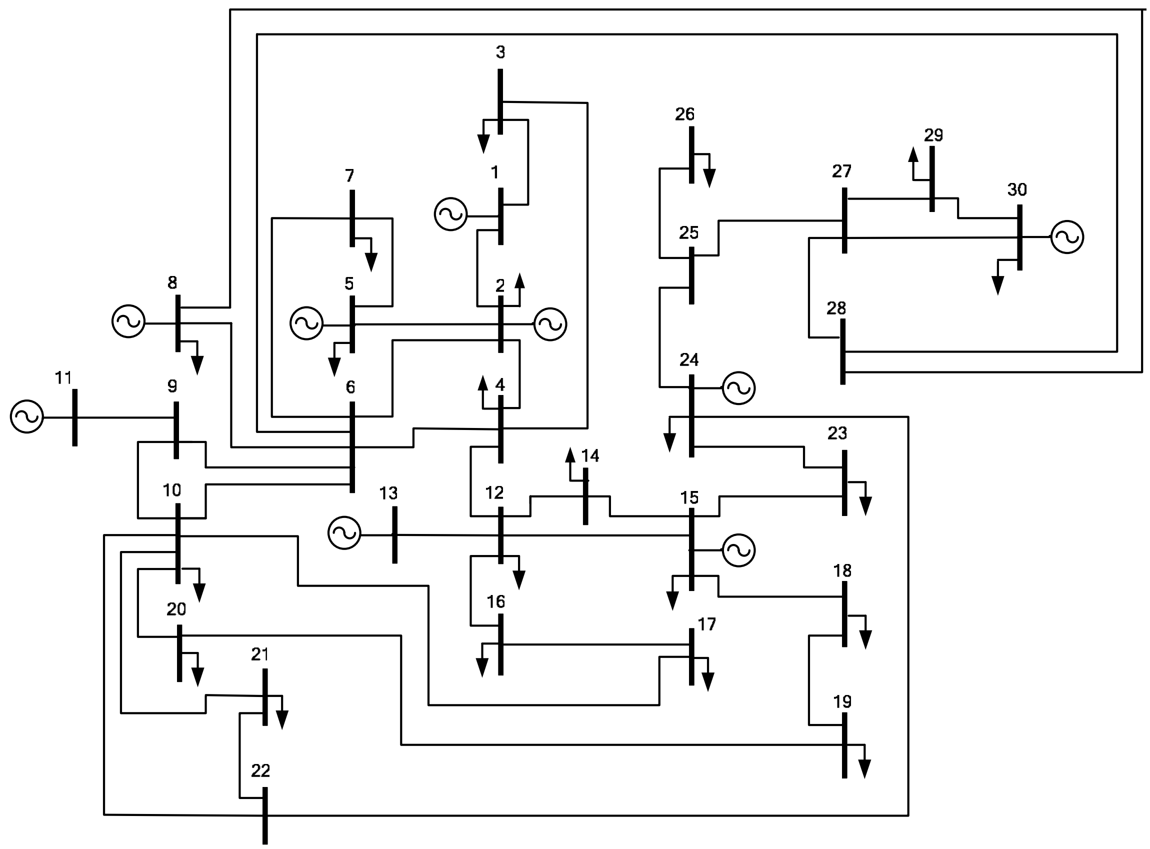

Figure 5.3.3: Modified IEEE 30 Bus Test System

The system losses were estimated as 2.00 % of the system demand along of T. The test system was solved first by UCFC without network flows constraints, that is, setting the penalty function (5.2.5) to zero. The hourly dispatch found is shown in Table 5.3.15. The total operating cost of this solution is *$86,955.00.* However, this solution is not feasible due to overloads in several lines. Table 5.3.16 shows the flows of these lines which are expressed as percentage of their own ratings.

Table 5.3.10: Network Data

Branch From Bus	Branch To Bus	R (pu)	X (pu)	Flow Limit (MW)	Branch From Bus	Branch To Bus	R (pu)	X (pu)	Flow Limit (MW)
1	2	0.0192	0.0575	30	15	18	0.1073	0.2185	16
1	3	0.0452	0.1852	30	18	19	0.0639	0.1292	16
2	4	0.0570	0.1737	30	19	20	0.0340	0.0680	32
3	4	0.0132	0.0379	30	10	20	0.0936	0.2090	32
2	5	0.0472	0.1983	30	10	17	0.0324	0.0845	32
2	6	0.0581	0.1763	30	10	21	0.0348	0.0749	30
4	6	0.0119	0.0414	30	10	22	0.0727	0.1499	30
5	7	0.0460	0.1160	30	21	22	0.0116	0.0236	30
6	7	0.0267	0.0820	30	15	23	0.1000	0.2020	16
6	8	0.0120	0.0420	30	22	24	0.1150	0.1790	30
6	9	0.0000	0.2080	30	23	24	0.1320	0.2700	16
6	10	0.0000	0.5560	30	24	25	0.1885	0.3292	30
9	11	0.0000	0.2080	30	25	26	0.2544	0.3800	30
9	10	0.0000	0.1100	30	25	27	0.1093	0.2087	30
4	12	0.0000	0.2560	65	28	27	0.0000	0.3960	30
12	13	0.0000	0.1400	65	27	29	0.2198	0.4153	30
12	14	0.1231	0.2559	32	27	30	0.3202	0.6027	30
12	15	0.0662	0.1304	32	29	30	0.2399	0.4533	30
12	16	0.0945	0.1987	32	8	28	0.0636	0.2000	30
14	15	0.2210	0.1997	16	6	28	0.0169	0.0599	30
16	17	0.0824	0.1923	16					

Table 5.3.11: Generator Data

Bus	Pmin (MW)	Pmax (MW)	Qmin (MVAR)	Qmax (MVAR)	Start up Cost ($)	Cost Coefficients α ($)	Cost Coefficients β ($/MWh)	Cost Coefficients γ ($/MW^{2}h)	Ramp (MW/h)	Min up/down time (h)		Initial State (h)
1	20	100	12	57	200	142.73	10.694	0.0046	70	5	3	5
2	10	80	6	49	100	218.34	18.1	0.0061	60	4	2	-2
5	10	50	6	31	80	81.136	13.327	0.0087	25	3	2	3
8	10	50	6	31	80	81.298	13.353	0.0089	25	3	2	3
11	5	20	3	12	30	118.82	37.889	0.0143	20	1	1	-1
13	10	70	6	43	95	287.14	19.327	0.0103	55	4	2	-2
15	10	60	6	37	90	230	18.3	0.0071	60	4	2	4
24	5	20	3	12	30	128.82	39.889	0.0163	20	1	1	-1
30	10	20	6	12	70	187.36	49.327	0.0243	20	3	2	-2

Table 5.3.12: Hourly System Load and Spinning Reserve

Hour	Load		Spinning Reserve	Hour	Load		Spinning Reserve
	MW	MVAR	MW		MW	MVAR	MW
1	202.86	90.32	10.14	13	233.71	103.87	11.69
2	186.86	83.34	9.34	14	228.57	101.82	11.43
3	176.57	78.42	8.83	15	226.29	100.59	11.31
4	165.71	76.36	8.29	16	226.29	100.59	11.31
5	160.57	73.90	8.03	17	236.57	105.10	11.83
6	160.57	73.90	8.03	18	260.00	115.78	13.00
7	165.71	76.36	8.29	19	257.14	114.55	12.86
8	181.71	80.88	9.09	20	252.00	112.08	12.60
9	208.00	92.38	10.40	21	244.57	108.80	12.23
10	228.57	101.82	11.43	22	238.86	106.34	11.94
11	233.71	104.28	11.69	23	226.29	100.59	11.31
12	236.57	105.10	11.83	24	210.29	93.61	10.51

Table 5.3.13: Load Distribution Profile

Bus	Percentage of Total Load		Bus	Percentage of Total Load	
	MW	MVAR		MW	MVAR
2	7.66%	10.06%	17	3.18%	4.60%
3	0.85%	0.95%	18	1.13%	0.71%
4	23.85%	1.27%	19	3.35%	2.69%
5	12.07%	15.06%	20	0.78%	0.55%
7	8.05%	8.64%	21	6.18%	8.87%
8	10.59%	23.77%	23	1.13%	1.27%
10	2.05%	1.58%	24	3.07%	5.31%
12	3.95%	5.94%	26	1.24%	1.82%
14	2.19%	1.27%	29	0.85%	0.71%
15	2.89%	1.98%	30	3.74%	1.51%
16	1.24%	1.43%			

Table 5.3.14: Control Parameter of the Proposed Algorithm

Control Variable	Value	Description
μ	30	Number of individuals
p_0	100	Penalty parameter
q	7	Number of opponents in stochastic ranking
ε	$1x10^{-4}$	Error tolerance
g	25	Generation tolerance

The test system was solved again by full UCFC (i.e. considering network flow constraints). Table 5.3.17 shows the hourly dispatch of the final solution, for which no overloads were found in the network. The total operating cost here is *$108,340.00.*

Table 5.3.15: Hourly Dispatch by UCFC without Network Constraints

Hour	Generation (MW)								
	Unit 1 (Bus 1)	Unit 2 (Bus 2)	Unit 3 (Bus 5)	Unit 4 (Bus 8)	Unit 5 (Bus 11)	Unit 6 (Bus 13)	Unit 7 (Bus 15)	Unit 8 (Bus 24)	Unit 9 (Bus 30)
1	100.00	0.00	50.00	50.00	6.92	0.00	0.00	0.00	0.00
2	100.00	0.00	41.50	39.10	0.00	10.00	0.00	0.00	0.00
3	100.00	0.00	33.66	31.44	5.00	10.00	0.00	0.00	0.00
4	100.00	0.00	28.06	25.97	5.00	10.00	0.00	0.00	0.00
5	100.00	0.00	27.94	25.85	0.00	10.00	0.00	0.00	0.00
6	100.00	0.00	27.94	25.85	0.00	10.00	0.00	0.00	0.00
7	100.00	0.00	35.64	33.38	0.00	0.00	0.00	0.00	0.00
8	100.00	0.00	38.84	36.51	0.00	0.00	10.00	0.00	0.00
9	100.00	0.00	50.00	50.00	0.00	0.00	12.16	0.00	0.00
10	100.00	0.00	50.00	50.00	0.00	0.00	33.14	0.00	0.00
11	100.00	0.00	50.00	50.00	0.00	0.00	38.38	0.00	0.00
12	100.00	0.00	50.00	50.00	5.00	0.00	36.30	0.00	0.00
13	100.00	33.38	50.00	50.00	5.00	0.00	0.00	0.00	0.00
14	100.00	18.14	50.00	50.00	5.00	10.00	0.00	0.00	0.00
15	100.00	10.82	50.00	50.00	0.00	10.00	10.00	0.00	0.00
16	100.00	10.82	50.00	50.00	0.00	10.00	10.00	0.00	0.00
17	100.00	0.00	50.00	50.00	0.00	10.00	31.30	0.00	0.00
18	100.00	0.00	50.00	50.00	5.20	0.00	60.00	0.00	0.00
19	100.00	57.28	50.00	50.00	5.00	0.00	0.00	0.00	0.00
20	100.00	52.04	50.00	50.00	5.00	0.00	0.00	0.00	0.00
21	100.00	49.46	50.00	50.00	0.00	0.00	0.00	0.00	0.00
22	100.00	43.64	50.00	50.00	0.00	0.00	0.00	0.00	0.00
23	100.00	0.00	50.00	50.00	0.00	0.00	30.82	0.00	0.00
24	100.00	0.00	46.00	43.50	5.00	10.00	10.00	0.00	0.00

The results shown in Table 5.3.17 demonstrate that in order to avoid overloads in the network, the proposed method decided to turnoff permanently the less expensive unit 1, which produces the most overloads to its neighboring lines. This decision caused the commitment for more hours of the more expensive units 2, 5, 7 and 8. Hence the total operating cost eventually increased.

Table 5.3.16: Percentage of Load in Several Lines of the Test System

Hour	Flows in Overloaded Lines (%)						
	1-2	1-3	2-4	3-4	2-6	5-7	9-10
1	211.90	121.43	83.65	113.50	71.44	87.32	83.98
2	214.23	119.10	79.46	111.81	72.50	74.96	58.83
3	216.21	117.13	75.58	110.25	71.37	62.60	62.76
4	217.73	115.60	73.20	109.11	71.28	54.99	58.53
5	217.91	115.42	73.66	109.01	72.35	56.55	48.89
6	217.91	115.42	73.66	109.01	72.35	56.55	48.89
7	214.46	118.88	78.73	112.26	74.34	68.52	59.11
8	214.19	119.14	78.55	112.08	72.33	70.64	56.22
9	211.78	121.55	82.83	113.60	71.13	85.03	64.30
10	214.33	119.00	78.86	110.52	68.07	81.01	54.87
11	214.98	118.36	77.86	109.76	67.30	80.00	52.52
12	214.94	118.39	77.74	109.74	66.46	79.09	63.17
13	192.88	140.46	115.46	130.77	104.35	95.77	92.43
14	202.11	131.23	98.35	122.33	86.91	89.30	81.34
15	206.83	126.50	90.39	117.88	79.54	86.19	64.41
16	206.83	126.50	90.39	117.88	79.54	86.19	64.41
17	215.31	118.03	77.16	109.39	67.03	79.43	51.88
18	217.94	115.40	73.09	106.15	63.09	74.56	51.10
19	178.71	154.62	137.53	143.67	127.21	103.09	101.07
20	181.84	151.50	132.67	140.85	122.16	101.47	99.18
21	183.10	150.23	131.19	139.77	121.20	102.18	88.08
22	186.56	146.77	125.79	136.62	115.61	100.38	86.06
23	214.05	119.28	79.30	110.86	68.41	81.44	55.92
24	213.72	119.61	79.01	111.73	69.92	77.20	67.12

The EP model for UC with network constraints shown in this section demonstrated it effectiveness not only minimizing the total operating cost, but also the network flows violations. Two case studies were analyzed in which the proposed method was able to find an optimal solution. The system requirements used in planning analysis are mainly forecasted, therefore, the planning tools must be designed in order to obtain conservative results that cover deviations in forecasted data. The proposed method also demonstrated that the solution found using as decision variable only the unit status for controlling the network flows is more conservative than more structured approaches. Moreover, the necessary computational requirements of UCFC are evidently smaller.

Table 5.3.17: Hourly Dispatch by Full UCFC

Hour	Generation (MW)								
	Unit 1 (Bus 1)	Unit 2 (Bus 2)	Unit 3 (Bus 5)	Unit 4 (Bus 8)	Unit 5 (Bus 11)	Unit 6 (Bus 13)	Unit 7 (Bus 15)	Unit 8 (Bus 24)	Unit 9 (Bus 30)
1	0.00	62.40	50.00	50.00	5.00	0.00	39.52	0.00	0.00
2	0.00	53.62	50.00	50.00	5.00	0.00	31.98	0.00	0.00
3	0.00	47.97	50.00	50.00	5.00	0.00	27.13	0.00	0.00
4	0.00	59.02	50.00	50.00	5.00	0.00	0.00	5.00	0.00
5	0.00	58.78	50.00	50.00	0.00	0.00	0.00	5.00	0.00
6	0.00	58.78	50.00	50.00	0.00	0.00	0.00	5.00	0.00
7	0.00	59.02	50.00	50.00	5.00	0.00	0.00	5.00	0.00
8	0.00	75.34	50.00	50.00	5.00	0.00	0.00	5.00	0.00
9	0.00	62.53	50.00	50.00	5.00	0.00	39.64	5.00	0.00
10	0.00	76.50	50.00	50.00	5.00	0.00	51.64	0.00	0.00
11	0.00	79.32	50.00	50.00	5.00	0.00	54.06	0.00	0.00
12	0.00	78.20	50.00	50.00	0.00	10.00	53.10	0.00	0.00
13	0.00	76.63	50.00	50.00	0.00	10.00	51.75	0.00	0.00
14	0.00	80.00	50.00	50.00	0.00	53.14	0.00	0.00	0.00
15	0.00	80.00	50.00	50.00	0.00	50.82	0.00	0.00	0.00
16	0.00	75.25	50.00	50.00	5.00	0.00	50.57	0.00	0.00
17	0.00	80.00	50.00	50.00	5.00	0.00	56.30	0.00	0.00
18	0.00	80.00	50.00	50.00	20.00	0.00	60.00	5.20	0.00
19	0.00	80.00	50.00	50.00	17.28	0.00	60.00	5.00	0.00
20	0.00	80.00	50.00	50.00	5.00	10.00	57.04	5.00	0.00
21	0.00	80.00	50.00	50.00	0.00	64.46	0.00	5.00	0.00
22	0.00	80.00	50.00	50.00	0.00	58.64	0.00	5.00	0.00
23	0.00	80.00	50.00	50.00	0.00	45.82	0.00	5.00	0.00
24	0.00	63.78	50.00	50.00	0.00	10.00	40.71	0.00	0.00

CHAPTER 6
CONCLUSIONS, RECOMMENDATIONS AND FUTURE WORK

6.1 General Conclusions

This thesis has presented novel optimization models based in Evolutionary Programming (EP) with the intention of solving several complex power systems optimization problems. These problems are Branch Outage Simulation for contingency studies, Power System State Estimation, Profit-based Unit Commitment and Unit Commitment with Network Flows Constraints. In general, the models developed were successful in finding good optimal solutions while providing a good convergence rate. Each model was tested with one or more case studies. Results were compared with those obtained by classical approaches available in the literature reviewed.

The major characteristics of the developed EP models for the addressed power system engineering areas covered in this work are highlighted next:

1. <u>Branch Outage Simulation for Power System Contingency Studies:</u> This EP model relies on a single branch outage model for $Q-V$ quantities which are used for both line and transformer outages instead of two different models developed in the literature reviewed [18]-[22]. This model was not only able to identify post outage bus voltage magnitude violations effectively, but also found the post-outage bus voltage magnitude values with satisfactory accuracy. Due to the use of a full AC

base-case load flow and the DC distribution factors, the computational effort is not significant, allowing the proposed method being applicable in contingency studies.

2. Power System State Estimation: The EP model developed to solve this problem demonstrated its effectiveness when its results were compared to those obtained using Gradient-Newton method for the WLS State Estimation [39]. Also, the model shown its flexibility for solving a larger system with few available and noised measurements in both WLS and WLAV state estimation formulations. The main advantage of this model is its capacity to improve the found estimated values by tuning its control variables.

3. Profit Base Unit Commitment: The profit-based UC is one of the more complex optimization problem due to it mixed variables and its high dimensionality as well. The EP model developed to solve this problem offers a good balance between accuracy and computational effort. The model decomposes the problem into three sub-problems. The first one optimizes the status of the generating units with an initial power dispatch, the second one optimizes the bid of reserve power after the first sub-problem is done, and finally a third one optimizes the initial power dispatch by varying the dispatch factor ζ added in the equation used to set the initial output power level. It was demonstrated that the developed EP model with this formulation was able to find the best known solution for the test case studied.

4. Unit Commitment with Network Flow Constraints: The EP model developed for this problem was designed to provide conservative solutions accounting only the unit status in the optimization process instead of real power level, phase shifter control and unit status used as control variables in traditional approaches [87]. In general, the solutions reached by the model were more conservative in the security sense that those reached by the classical method found in the literature reviewed.

According with the successful implementation of the developed models in the addressed problems, we can summarize that these models represent a valuable contribution to the modern heuristics research applied to the current power system structure.

Evolutionary Algorithms (EA) including EP, are stochastic optimization methods. Therefore, they do not guarantee an optimal solution at all times. However, an adequate mutation operator along with a correct set of control parameters (such as the number of individuals in the population, the values between which these individuals are generated, the initial strategy parameters, and the number of opponent in the stochastic ranking) may lead to very successful results in reasonable computational times.

6.2 Recommendations

The following are recommendations about how to handle the algorithm control variables in order to achieve better performance in the search of solutions to optimization problems.

The number of individuals in the population (μ) is a parameter used to control the quality of the search. Few individuals in the population may cause poor searching performance, whereas many individuals in the population increase the computational requirements without a significant improvement in the searching performance. The optimal selection of this parameter is that it offers good searching performance with a minimum number of individuals. According with the acquired experience working with the problems studied in this thesis, values between 30 and 80 individuals per population are considered good.

The variables of the individuals in the population are generated at random between pre-selected minimum and maximum values. These values must be selected according to the presumable solution space, and are used to control the exploration performance of the algorithm. Thus, small range between these values may cause premature stagnations in local optimums. On the other hand, a big range between these values may cause a slow convergence rate. Therefore, the optimum setting of this parameter is the one which offers good convergence rate with a significant reduction of potential stagnations.

The strategy parameter (η) is used by the mutation operator to generate the offspring. This parameter behaves like the standard deviation of the fitness score of the population. For instance, big values of strategy parameters mean individuals further different between them. Obviously, as the evolution process advances, the values of this parameter tend to become small. The initial values of this parameter are usually set as constant values. These initial values should be sufficiently big to aid the algorithm to escape initial local optimums.

The number of opponents (q) in the stochastic ranking is used by the selection operator in order to select the parents in the next generation. The opponents are selected at random with the intention of providing diversity in the surviving population and this way guarantee a better exploration of the search space. Selecting a big number of opponent converts the selection process in one elitist due to the lesser probability of an individual with a bad fitness being selected as a parent for the next generation. On the other hand, few opponents produce instability in the convergence because the algorithm could select as the best individual one with worse fitness than that selected as best individual in the previous generation. An optimum number of opponents is the one in the range of 10%-25% of the number the individuals in the population.

Penalty strategy selection for constraint evaluation is very important for the success and performance of EP. Different penalty strategies may lead to different results in solution type, accuracy or algorithm performance. The use of fixed penalty functions is not suitable for all constraints, but they improve simulations since they require less floating point operations than the dynamic penalty parameter. Dynamic penalty functions give the algorithm a better understanding of the solution space but increase the computational time.

6.3 Future Work

This thesis provides simulation tools which expand the usability of Evolutionary Programming in the field of Power Systems Engineering. Several problems within two areas of this field (i.e., operation and planning) were studied and solved efficiently with EP. As a general recommendation for future work, it is suggested to study the applicability of EP in others power system engineering problems which have arisen with power market deregulation. Also, it is recommended to include the control parameters of EP in the optimization process in order to obtain a high performance algorithm which could be used by people without knowledge in evolutionary computation field. Finally, is desirable to enhance the algorithm code in order to reduce the execution time.

For the EP model developed for the problems addressed in this thesis, the specific recommendations for future work are the following:

Branch Outage Simulation:

- To consider reactive power limit violations in PV buses
- To develop an approach which mixes Branch Outage Simulation with an online application of generator outages.

Power System State Estimation

- To investigate what is the minimum number of measurements and their location that provides a good system estimate based in a predefined *MSE* tolerance.

Unit Commitment

- To develop a mutation operator for binary variables still more effective than the one developed here so that it allows exploring the solution space more completely in order to find a global optimum.
- Once the above mutation operator is designed, to explore the possibility of performing the profit-based unit commitment in a parallel way.

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