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Thème:

Teaching-Learning-Based Optimization Technique for Optimal Power Flow Incorporating Renewable Energy Sources Considering the Cost, Emission, Power Loss and Voltage Profile Improvement

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Dedicated

We are very happy to dedicate this work to those who give our inspiration and will.

To our parents

To our grandparents

We dedicate it to our dear brothers and sisters

To big family **BOULIFA** and **GHANEM**

ملخص

يعد التوزيع الامثل للطاقة مشكلة معقدة غيرخطية للغاية حيث يلزم تحديد معلمات الحالة الثابتة للشبكة الكهربائية للعثور على نقطة تشغيل مستقرة ذات سياق اقتصادي، تقني وبيئي، ويزداد تعقيد المشكلة مع وجود قيود فيها.

في هذا العمل، نقدم خوارزمية تعتمد على طريقة التحسين القائم على التعلم والتعليم لدراسة متعددة الأهداف للتدفق الأمثل للطاقة الكهربائية. لبلوغ الأهداف، تم تطبيق هذه الطريقة على نظام اختبار قياسي 30 عقدة لدراسة عدة أهداف مثل تقنين تكلفة الوقود، التقليل من انبعاث الغازات السامة، تحسين انحراف الجهد، تحسين استقرار الجهد والتقليل من الضياع في الاستطاعات في الشبكة الكهربائية. تمت دراسة حالات أحادية الهدف، وحالات متعددة الأهداف للتوزيع الأمثل للطاقة باستعمال المحصلة المرجحة.

الكلمات المفتاحية: توزيع الطاقة الأمثل، طريقة التحسين القائم على التعلم والتعليم، تقنين تكلفة الوقود، تحسين انحراف الجهد والتقليل من الضياع في الاستطاعات في الشبكة الكهربائية.

Résumé

La répartition optimale de puissances (OPF) est un problème d'optimisation complexe hautement non linéaire où les paramètres en régime permanent d'un réseau électrique doivent être déterminés pour trouver un point de fonctionnement stable selon un contexte économique, technique et environnemental. La complexité du problème augmente avec la présence des contraintes dans le problème.

La méthode d'optimisation basée sur l'enseignement-apprentissage a été proposée et appliquée pour trouver des solutions optimales avec différents objectifs d'OPF, l'algorithme proposé est testé sur un réseau standard IEEE 30 JB pour étudiée plusieurs objectifs d'OPF tels que le coût du combustible, les émissions, la déviation de la tension, la stabilité de la tension et les pertes de puissances. Des cas d'OPF à objectif unique et à somme pondérée sont étudiés dans le cadre de ce mémoire.

Mots clés : Répartition optimale de puissance, optimisation basée sur l'enseignement-apprentissage, minimisation de coût du combustible, déviation de la tension et minimisation des pertes de puissance.

Abstract

Optimal power flow (OPF) is a highly nonlinear and complex optimization problem. Under the economic, technical and environmental conditions, it is necessary to determine the steady-state parameters of the power grid in order to find a stable operation point. The complexity of the problem increases with the existence of constraints.

In this work, we propose and apply a metaheuristic method to solve the optimal solutions of different objectives functions, named teaching learning based optimization technique. Several OPF targets such as fuel cost, emission, voltage deviation, voltage stability and power loss are tested on IEEE 30 bus system. In the scope of this part of work, the case of single objective and weighted sum OPF is studied.

Key words: optimal power allocation, teaching learning based optimization, optimization method, and fuel cost minimization.

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Acronyms

Symbol	Designation
ACO	Ant colony optimization
OPF	Optimal Power Flow
PQ	Load bus
PSO	Particle Swarm Optimization
TLBO	Teaching-Learning-Based Optimization
VD	Voltage deviation
DG	Distribution generation

Symbols

$\boldsymbol{P_i}$	Active power generated by unit *i*
$\boldsymbol{P_L}$	Total losses i transmission lines
$\boldsymbol{a}$, $\boldsymbol{b_i}$, $\boldsymbol{c_i}$, $\boldsymbol{d_i}$	fuel cost factors for the th generation
a_i, Q , $\boldsymbol{\gamma_i}$, m_i , $\boldsymbol{\mu_i}$	Coefficients of the emission function of th generator
$\boldsymbol{N}$	Total number of bus in the power system.
$\boldsymbol{N_g}$	Number of electricity generators
$\boldsymbol{NL}$	Number of load bus (PQ bus)
$\boldsymbol{nl}$	Number of transmission lines
$\boldsymbol{N_C}$	Number of shunt compensator
$\boldsymbol{N_T}$	Number of transformers
δ	Angle voltage
$\boldsymbol{x}$	State vector
$\boldsymbol{u}$	Control variables vector
$\mathbf{g}(\boldsymbol{x}, \boldsymbol{u})$	Equality Constraints
$(\boldsymbol{x}, \boldsymbol{u})$	Inequality constraints
$\boldsymbol{T_j}$	Ration Tap

$\boldsymbol{f_{aug}}$ Fonction objectif augmenté

$\boldsymbol{f_{pénalité}}$ Penalty function

$\boldsymbol{VD}$ Voltage Deviation

$\boldsymbol{Y_L}$, $\boldsymbol{Y_{LG}}$, $\boldsymbol{Y_{GL}}$ **et** $\boldsymbol{Y_{GG}}$ Partial matrices of the admittance matrix Y_{bus}

$\boldsymbol{G_{(ij)}}$ Conductance of branch q related the buses i and j

$\boldsymbol{B_{(ij)}}$ Susceptance of branch q connecting bus i and j.

$Q_{C_{NC}}$ Reactive powers of shunt compensators.

T_{N_T} The reports of the taps of the transformers menus of regulators on load.

P_1 Active power generated at the reference busbar (Slack bus).

Q_i Reactive power of the generator connected to node i.

V_{LP} Voltage module of p-th load node (PQ node).

S_{Lq} Apparent power flowing in the q-th branch.

NL., nl Number of load bus (PQ node) and the number of transmission lines respectively.

$\boldsymbol{f(x,u)}$ Fuel cost Function

$\boldsymbol{f(x,u)}$ Nox toxic gas emission function

$\boldsymbol{f(x,u)}$ Function of voltage deviation

$\boldsymbol{f(x,u)}$ Voltage stability Function

$\boldsymbol{f(x,u)}$ Function of active power losses

$\mathbf{P_{losses}}$ Active power losses

Lmax Voltage stability index

1. Background

Most optimization problems in real-world applications are affected by conditions that change over time, which makes the ability to solve problems in these dynamic environments both a sophisticated and very difficult task [1].

This is the case for problems in the context of electric power systems such as, economic power dispatch, toxic gas emission dispatch, reactive power scheduling and dispatch, maximum interchange, unit commitment, generation, transmission and distribution expansion planning, and maintenance planning, as well as many other problems. In recent decades, there has been considerable growth and interest in the generation, transmission and distribution of electricity, and due to strict regulations (environmental and governmental), the development of electrical installations has been limited. Since it is very uneconomical to store electrical energy over a certain period of time, industry players are continuously seeking to ensure a balance between electricity supply and demand [2].

Achieving an efficient, reliable, secure and economic allocation of consumer demand for electricity among generating units creates dynamism in the sector. In order to achieve this objective, grid operators need to constantly adjust the control variables of the power system (i.e., generator power setpoints, transformer taps, etc.). This extremely difficult task is performed by the Optimal Power Flow function at the power system's control centers [3].

Optimal power flow, often abbreviated to OPF, is therefore the basic IT tool that allows the grid operator to determine the conditions for safe and economical operation of the power system. The OPF procedure uses methods based on mathematical programming to determine the optimal setting of system control variables to meet a set of specified operational and safety requirements.

In recent years, metaheuristic methods have emerged as powerful and efficient methods for solving OPF problems because of their qualities, among which we can mention their ability to search for the solution in non-convex spaces with multiple and isolated maxima, global convergence, robustness and the natural ability of a parallel search [3].

2. Contribution

The main contributions of this thesis are as follows:

The contribution of this research work is to introduce the teaching-learning based optimization (TLBO) method, to solve the simple, bi and multi objective OPF problem. The technique is successfully tested on a standard IEEE 30-bus system.

3. Work plan

The work plan, is divided into three chapters, in the first chapter introduces the methods of solving the optimal power flow problem based on TLBO algorithm.

In the second chapter, we propose the expression of the optimal power allocation problem, and summarize the objective functions of this paper, namely, fuel cost minimization, toxic gas emissions, voltage deviation, voltage deviation and so on. Voltage stability, active and reactive power loss.

In the third chapter, the proposed method has been applied tested on IEEE 30-bus system to solve the OPF problems.

The validation of simulation results is demonstrated and discussed through seven case studies (single and multiobjective function. Finally, we will draw a general conclusion, summarize the main conclusions, and put forward some prospects and suggestions for future work.

I.1 Introduction:

Optimization is a part of nature and, inevitably, an integral part of human life. Every decision we make is an attempt to deal with an optimal or near optimal situation. From a general point of view, any optimization problem can be considered as a decision problem, and the question is whether or not there is a better solution to the problem than the one we have found. In other words, optimization means achieving the best possible solution that will lead to a better performance of the system under consideration. As described by Beightler et al. [4], optimization is a three-step decision-making process: (1) modeling the problem based on the knowledge of the problem, (2) finding measures of efficiency or objective function, and (3) optimization method or theory. It can be said that the whole field of optimization, and in particular the last stage, only benefits from the development and improvement of computers that started in the mid 1940s.

I.2 Description of the components of the Metaheuristics

There are many classification criteria for Metaheuristics, the most common of which are group-based search and single solution based search. Defining these two classes helps you become familiar with metaheuristics.

The Metaheuristics algorithms based on single solution operates and transforms the single solution through iterative search (generation and replacement) process to obtain the optimal solution. Generation refers to the generation of candidate solutions or candidate solution sets from current solutions based on a higher-level framework or mechanism. Replacement is to select a new solution or an appropriate solution from the generation set to replace the current solution in order to enter the foreground region of the search space. This iterative process continues until the stop condition is satisfied [5]. In population-based meta heuristics, iterative search process (including generation and replacement) is also applied. However, in this type of meta heuristics, a group of solutions distributed in the search space. First, initialize a set of solutions called initial population. Different strategies can be used for initialization, but the most common is to generate proxies randomly in the search space. Based on the high-level framework or search mechanism, the algorithm repeatedly operates on the current solution set to generate a new solution, and uses a specific strategy to replace the old solution with the new one. This process continues until the stop criteria are met [5]. The most common stopping criteria are the fixed number of iterations of the algorithm, the maximum number of no progress iterations of the objective function and the minimum value of the objective function. Almost all meta heuristics are based on natural phenomena, and the performance of meta heuristics is described from two aspects: the ability to detect the neighborhood of the promising region visited before, and the ability to access and detect Research [6]. These two conflicting capabilities are called development (intensive or local research) and exploration (diversified or integrated research), respectively.

The term "meta heuristic" was first introduced by Glover [7] and is widely used in such algorithms. Meta heuristic word is a combination of two ancient Greek words: heuristic verb

I.3 History of Metaheuristics

It is widely accepted that metaheuristics is the most successful and developed method among other methods to solve many practical optimization problems. Regardless of the rich literature on modifications to current metaheuristics using different mechanisms and strategies that have been ongoing, this field is witnessing the advent of a new metaheuristic, perhaps once a month.

Sorensen et all in Ref [8], have very recently described the history of metaheuristics in five distinct periods:

1. Pre-theoretical period (until c. 1940), during which heuristics and even metaheuristics were used, but were not formally introduced;

2. Early period (c. 1940-c. 1980), during which the first formal studies on heuristics appear;

3. Period focused on the method (c. 1980-c. 2000), during which the field of metaheuristics really takes off and many different methods are proposed;

4. Period centered on the frame (c. 2000-present), during which we realize that metaheuristics are more usefully described as frameworks and not as methods;

5. Scientific period (the future), during which the conception of metaheuristics becomes a science rather than an art".

Before the year 2000, evolution-based metaheuristics (evolutionary strategies, evolutionary programming, genetic algorithms, genetic programming, and differential evolution, as the best-known methods) and trajectory-based metaheuristics (such as hill climbing, simulated annealing, tabu search, iterative local search, variable neighborhood search, as the best-known ones) have been developed.

The transition period took place around the 2000s, when the best-known and most successful swarm-based metaheuristics (particle swarm optimization (PSO) and ant colony optimization (ACO)) were invented. During this period, more powerful metaheuristics as well as new frameworks for local and global search were needed.

Since 2000, which can be described as the period of application, many practical optimization problems have been formulated, modeled and optimized to arrive at optimal solutions. During this period, many works have been developed in areas such as metaheuristics for multi-modal and multi-objective optimization, parallel metaheuristics, hybrid metaheuristics, constraint processing methods for constrained optimization, metaheuristics for large-scale optimization, metaheuristics for costly optimization, synergistic metaheuristics and cloud computing [9].

On the other hand, the development of new frameworks to achieve a more efficient trade-off between exploration and exploitation was of increasing interest at that time, and thus many new nature-based metaheuristics were developed. The Fig. III.1 illustrates the classification flowchart of the most known and used metaheuristic methods in the engineering domain.

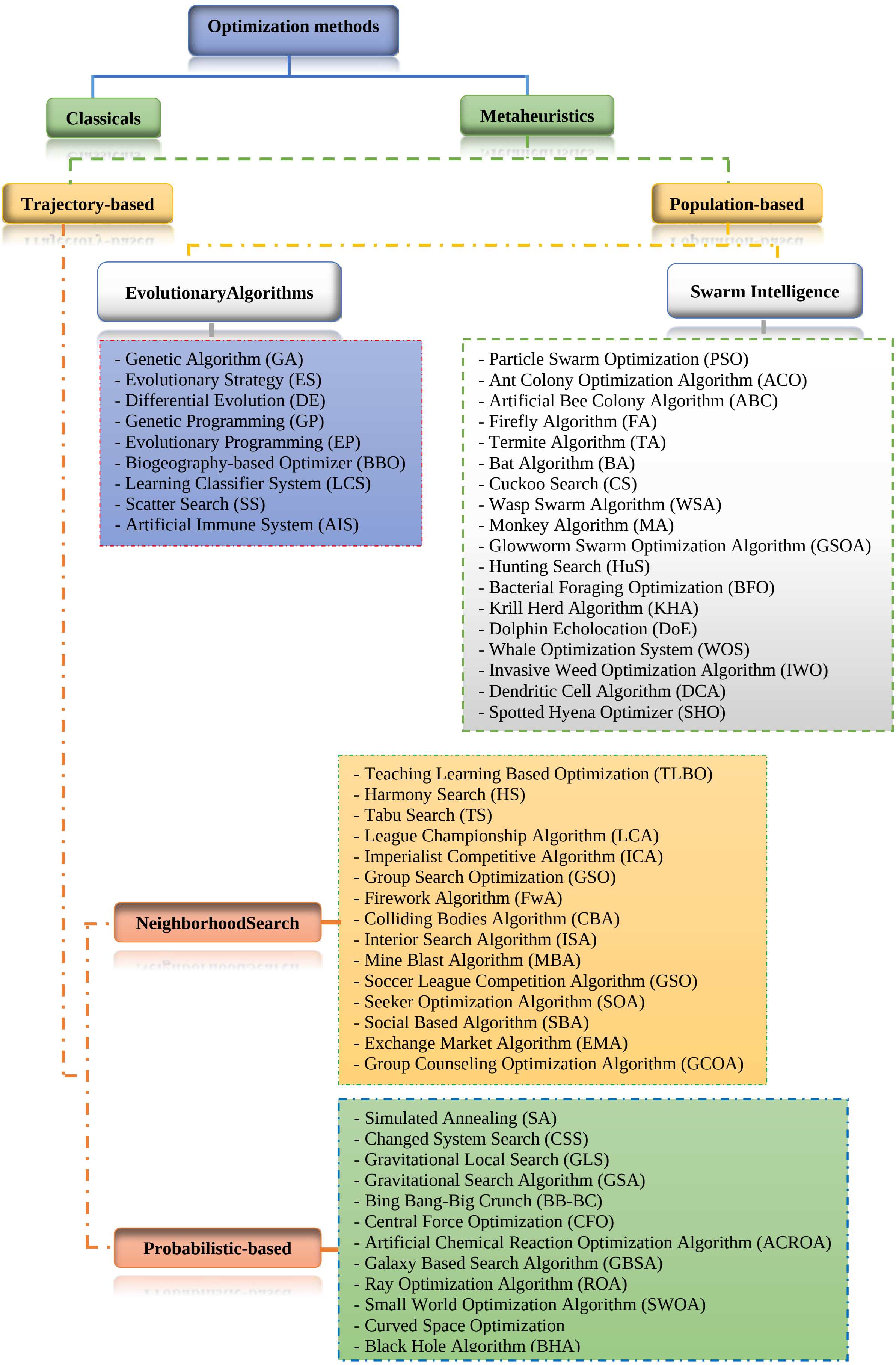


Figure I.1: Classification of the most population metaheuristics technique.

In this thesis, we choose a metaheuristic algorithm based population, named Teaching learning based optimization (TLBO) to analysis optimal power flow on electrical power system.

I.4 Teaching learning based optimization (TLBO)

I.4.1 Definition

Teaching learning based optimization (TLBO) is a metaheuristic method, which was originally developed by Rao et al. [10]. It is an algorithm based on teaching process and the influence of teachers on students' classroom output. TLBO describes two basic learning models

(i) Through teaching, it is called teaching stage;

(ii) Through interaction with other students, the so-called student stage.

In this optimization algorithm, A group of students is regarded as a group, the different subjects provided to students are regarded as the variables of the optimization problem (involving the parameters of the objective function), and the results of students are regarded as the values of the fitness function (function) [10]。 The overall optimal solution corresponds to the optimal value of the objective function and is allocated to teachers.

Different from other metaheuristics, TLBO needs to determine fewer parameters in the update process. It does not need any algorithm specific parameters, but only needs control parameters, such as population size and generation number to operate [11]. TLBO algorithm is very effective for some optimization problems.

I.4.2 Principle of TLBO algorithm

Like other population-based algorithms, TLBO starts from the initialization phase. In the initialization phase, the population of randomly generated candidate solutions is placed in the search space composed of N dimensions. Each dimension has an upper limit and a lower limit. Then the operation process of ,TLBO is divided into "Teacher Phase" and "Learner Phase", that is, learning through the interaction between students (learners). The working principle of, TLBO is explained as follows [12].

I.4.2.1Teacher Phase:

In the first stage, students learn through teachers, who (the best solution) are assigned to impart knowledge to all students to improve the classroom average. In each j iteration, the best individual (student) in the population is selected to be the T_j Professor, and the target value is defined by $\mu_{Teacher}$. Then calculate the average value of learners of each design variable v to form μ_{mean} vector. Professor $T_i$tried to improve each student's score by comparing the difference between each student's score and the group average, as follows:

$$Difference_{mean} = r_i \times \left(\mu_{Teacher} - T_F \times \mu_{mean}\right) \quad (I.1)$$

Where, r_i is a random number between 0 and 1, and $T_F$is a learning factor that determines the value of the average value to be modified. It can be 1 or 2 and is determined by an equal probability. $T_F$is not a parameter of TLBO algorithm. Equation (I.2) is used to generate T_F.

$$T_F = round\left[1 + rand(0,1)\{2-1\}\right] \quad (I.2)$$

Based on the "differential" average, update the existing solution at the teacher stage according to the following expression:

$$X'_{i,j} = X_{i,j} + Difference_{mean} \quad (I.3)$$

Where $X'_{i,j}$'is the new solution i from the first stage to iteration j. if $X'_{i,j}$is a worse solution than $X_{i,j}$, then $X_{i,j}$ will replace $X_{i,j}$ in the next phase.

I.4.2.2Learner Phase:

In the second stage, students randomly increase their knowledge by communicating with each other and using a method similar to focus group. The solution $X'_{i,j}$will be randomly compared. $X'_{i,j}$solution is compared with another random $X'_{P,j}$solution ($X'_{i,j} \neq X'_{P,j}$), as follows:

$$X''_{i,j} = \begin{cases} X'_{i,j} + r \times \left(X'_{i,j} - X'_{p,j}\right), & si \quad f\left(X'_{i,j}\right) \langle \; f\left(X'_{p,j}\right) \\ \\ X'_{i,j} + r \times \left(X'_{p,j} - X'_{i,j}\right), & si \quad f\left(X'_{p,j}\right) \langle \; f\left(X'_{i,j}\right) \end{cases} \quad (I.4)$$

Where $X''_{i,j}$ is the new solution. If the fitness function value given by solution $X''_{i,j}$is less than that given by $X''_{i,j}$, then in this case, solution $X''_{i,j}$is rejected, and $X''_{i,j}$will be the final solution in the new species group. Repeat these two stages until the stop criteria are reached. Equation (I..4) is used to minimize the optimization problem. For the maximization problem, equation (I.5)[12] is used. The flowchart of TLBO method is shown in figure (I.2).

$$X''_{i,j} = \begin{cases} X'_{i,j} + r \times \left(X'_{p,j} - X'_{i,j}\right), & si \quad f\left(X'_{p,j}\right) \langle \; f\left(X'_{i,j}\right) \\ \\ X'_{i,j} + r \times \left(X'_{i,j} - X'_{p,j}\right), & si \quad f\left(X'_{i,j}\right) \langle \; f\left(X'_{p,j}\right) \end{cases} \quad (I.5)$$

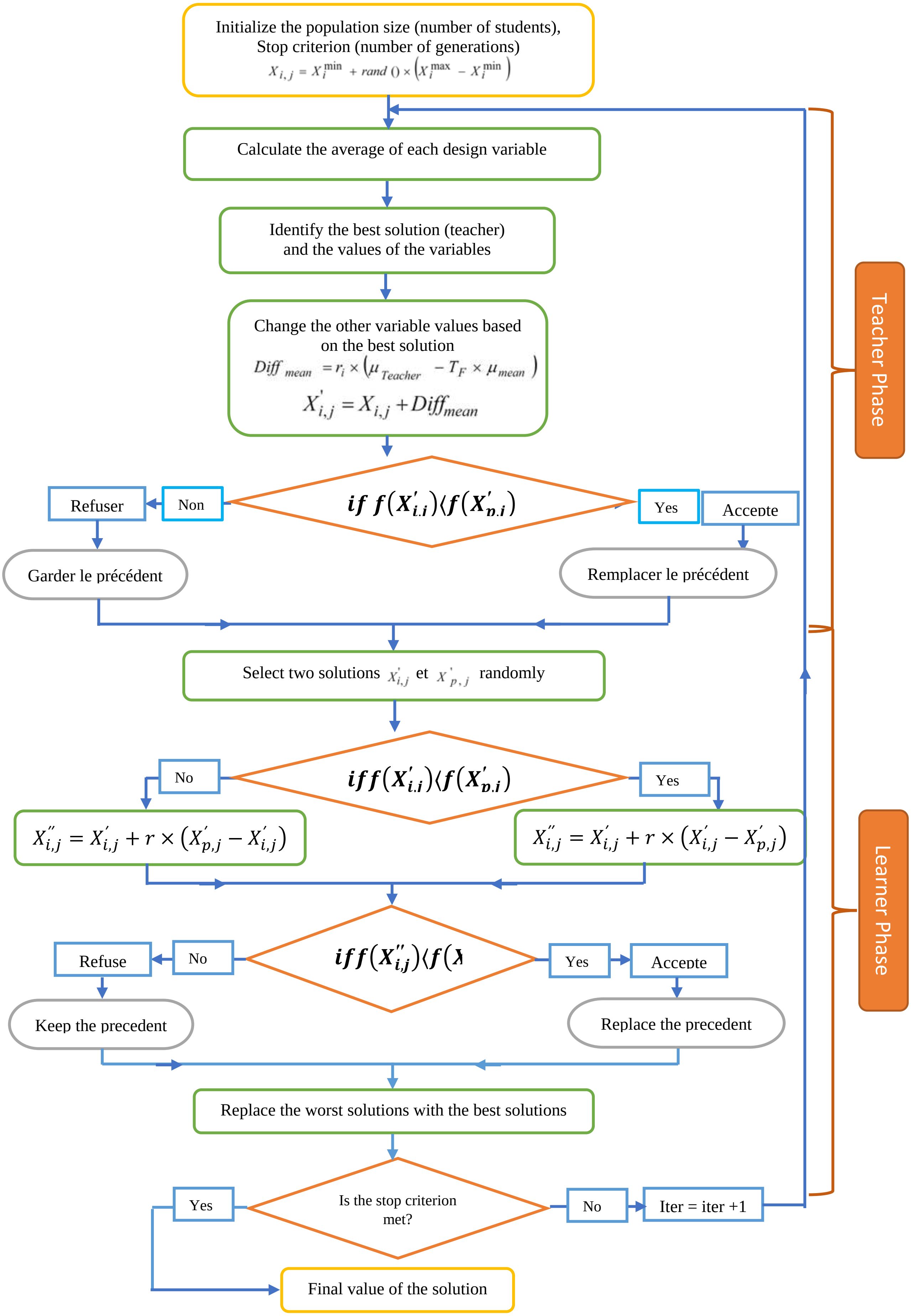


Figure I.2: Flowchart of TLBO algorithm.

I.5 conclusion

This chapter represents a general introduction to global optimization methods (metaheuristics). It gives an overview of their history, philosophies, features and benefits. Among the most known and used metaheuristic methods in engineering fields, we have studied the teaching-learning based optimization method TLBO.

II.1 Introduction

Optimal Power Flow (OPF) is a very important tool in planning and controlling the operation of modern power systems. In an OPF, the values of some or all of the control variables must be found to optimize (minimize or maximize) a predefined objective. It is also important that the appropriate definition of the problem with clearly stated objectives is given at the outset. The quality of the solution depends on the accuracy of the model studied. The objectives must be modelled and their practicality with possible solutions.

II.2. Problem of optimal power distribution

The problem of optimal power flow (OPF) has been widely studied since the 1960s. It was first introduced by Carpentier in 1962 **[13]**.

OPF aims to optimize a certain objective, such as minimizing the total fuel cost of all interconnected plants in the power system as well as the power losses subject to the power flow equations of the system and the operating limits of the system and equipment. The optimal condition is achieved by adjusting the available controls to minimize an objective function subject to specified operational and safety requirements.

II.2.1. Mathematical formula of the OPF

Optimal power dispatch is a nonlinear-nonconvex optimization problem that minimizes some objective function in the power system and satisfies several constraints. Mathematically, the OPF problem can be represented by:

$$Min \;\; f(x,u) \tag{II.1}$$

Subject to:
$$g(x,u) = 0$$
$$h(x,u) \leq 0$$

With u is the vector of control variables presented by the independent quantities of the control variables, x is the vector of state variables presented by the dependent quantities of the control variables. $f(x,u)$ is the objective function of the OPF, $g(x,u)$ and $h(x,u)$ represent the equality and inequality constraints respectively.

II.2.2. Variables

II.2.2.1. Control variables

The set of control variables, also called decision variables, that can control the power flow in the power system is represented by the following vector:

$$u = \left[P_2 \dots P_{Ng}, V_1 \dots V_{Ng}, Q_{C_1} \dots Q_{C_{N_C}}, T_1 \dots T_{N_T}\right] \tag{II.2}$$

With

$(P_2 \dots P_{Ng})$: Active power generated by Ng generators (except the reference one).

$(V_1 \dots V_{Ng})$: Voltage modules of all generator busbars (PV nodes).

II.2.2.2. State variables

The changes in the state of the power system are defined by the state variables which can be expressed by the vector x:

$$x = \left[P_1, V_{L_1} \dots V_{L_{NL}}, Q_1 \dots Q_{Ng}, S_{l_1} \dots S_{l_{nl}}\right] \tag{II.3}$$

These variables are not directly controlled in the optimization process. These are unknown variables and usually are obtained by solving the power flow equation. **[14]**.

II.2.3. Constraints

As mentioned earlier, the OPF problem has both equality and inequality constraints that must be satisfied. The constraints are separated and provided here.

II.2.3.1. Equality constraints

In the OPF, the power balance equations are the equality constraints present in the non-linear power flow equations in all branches, where the sum of the active and reactive powers injected in each bus is zero. These are represented by

$$P_i - P_{D_P} - V_i \sum_{j=1}^{N} V_j \left[G_{ij} \cos\left(\delta_{ij}\right) + B_{ij} \sin\left(\delta_{ij}\right)\right] = 0 \ \forall\, i \in N,\ p \in NL \tag{II.4}$$

$$Q_i - Q_{D_P} - V_i \sum_{j=1}^{N} V_j \left[G_{ij} \sin\left(\delta_{ij}\right) - B_{ij} \cos\left(\delta_{ij}\right)\right] = 0 \ \forall\, i \in N,\ p \in NL \tag{II.5}$$

Where, , P_i, Q_i are the generated active and reactive power, P_{Dp}, Q_{Dp} are the active and reactive power demand, G_{ij} is the conductance and B_{ij} is the susceptance of the line connecting bus i and bus j respectively, $\delta_{ij} = (\delta_i - \delta_j)$ is difference between the phase angles of the voltages of the buses i and j, N is the total number of buses in power system.

II.2.3.2. Inequality constraints

The inequality constraints in the OPF reflect the physical and technical limits of operation of the equipment present in the power system but also the limits imposed on the load lines and busbars (PQ) to guarantee the security of the system.

a) Generator constraints :

The voltage, active power and reactive power of all generating unit in power system are limited by their lower and upper limits.

$$V_i^{\min} \le V_i \le V_i^{\max} \quad \forall\, i \in Ng \tag{II.6}$$

$$P_i^{\min} \le P_i \le P_i^{\max} \tag{II.7}$$

$$Q_i^{\min} \le Q_i \le Q_i^{\max} \tag{II.8}$$

b) Transformer constraints :

The ratio of the transformer load adjuster is limited by a minimum and a maximum.

$$T_j^{\min} \le T_j \le T_j^{\max} \quad \forall\, j \in N_T \tag{II.9}$$

c) Shunt compensator constraints:

The reactive powers injected by the shunt compensation sources must be within the limits.

$$Q_{C_k}^{\min} \le Q_{C_k} \le Q_{C_k}^{\max} \quad \forall\, k \in N_C \tag{II.10}$$

d) Security constraints :

The system is said to be in a secure state if it meets the following security constraints:

The voltages of (PQ) bus must not exceed their permissible limits.

Power lines must meet transit power limits.

$$V_{L_p}^{\min} \le V_{L_p} \le V_{L_p}^{\max} \quad \forall\, p \in NL \tag{II.11}$$

$$S_{l_q} \le S_{l_q}^{\max} \quad \forall\, q \in nL \tag{II.12}$$

$S_{l_q}^{max}$: Maximum power allowed in the *q-th* branch, corresponding to the maximum value of the current flowing in the same branch.

II.3. Handling constraints

The most effective and simple way to handle constraints in optimization problems is to use penalty functions [15]. The direction of the search process and thus the quality of the optimal solution are strongly impacted by these functions. An appropriate penalty function must be chosen to solve a particular problem. The main purpose of a penalty function is to maintain system security.

These penalty functions are associated with many user-defined coefficients that must be rigorously tuned to fit the given problem.

This research used a quadratic penalty function method in which a penalty term is added to the objective function for any constraint violation. The inequality constraints which include generator constraints, reactive compensation sources and transformer constraints are combined in the objective function as a penalty term, while the equality constraints and generator reactive power limits are satisfied by the Newton-Raphson method (NR power flow). By adding the inequality constraints to the objective function $f(x,u)$ in Eq. (II.1), the augmented objective function f_{aug} to be minimized becomes:

$$f_{aug}(x,u) = f(x,u) + f_{pénalité} \tag{II.13}$$

$f_{aug}(x,u)$ is the proposed augmented objective function, f(x,u) is the objective function, $f_{pénalité}$ is the penalty function given in Eq. (II.14).

$$f_{pénalité} = \delta_P \left(P_1 - P_1^{\lim}\right)^2 + \delta_V \sum_{p=1}^{NL} \left(V_{L_P} - V_{Lp}^{\lim}\right)^2 + \delta_Q \sum_{i=1}^{Ng} \left(Q_i - Q_i^{\lim}\right)^2 + \delta_S \left(S_{lq} - S_{lq}^{\lim}\right)^2 \tag{II.14}$$

In the global objective function the P_i^{lim} , $V_{L_P}^{lim}$, Q_i^{lim} and $S_{l_q}^{lim}$ are defined in the following equations:

$$P_i^{\lim} = \begin{cases} P_i^{\min} & si \quad P_i \langle\ P_i^{\min} \\ P_i^{\max} & si \quad P_i \rangle\ P_i^{\max} \\ P_i & si \quad P_i^{\min} \langle\ P_i \langle\ P_i^{\max} \end{cases} \tag{II.15}$$

$$V_{Lp}^{\lim} = \begin{cases} V_{Lp}^{\min} & si \quad V_{Lp} \langle\ V_{Lp}^{\min} \\ V_{Lp}^{\max} & si \quad V_{Lp} \rangle\ V_{Lp}^{\max} \\ V_{Lp} & si \quad V_{Lp}^{\min} \langle\ V_{Lp} \langle\ V_{Lp}^{\max} \end{cases} \tag{II.16}$$

$$Q_i^{\lim}=\begin{cases} Q_i^{\min} & si \quad Q_i \langle\; Q_i^{\min} \\ Q_i^{\max} & si \quad Q_i \rangle\; Q_i^{\max} \\ Q_i & si \quad Q_i^{\min} \langle\; Q_i \;\langle\; Q_i^{\max} \end{cases} \tag{II.17}$$

$$S_{lq}^{\lim}=\begin{cases} S_{lq}^{\min} & si \quad S_{lq} \langle\; S_{lq}^{\min} \\ S_{lq}^{\max} & si \quad S_{lq} \rangle\; S_{lq}^{\max} \\ S_{lq} & si \quad S_{lq}^{\min} \langle\; S_{lq} \;\langle\; S_{lq}^{\max} \end{cases} \tag{II.18}$$

II.4. Objective functions

The objective function takes various forms such as fuel cost, transmission losses and reactive power source allocation. Usually, the objective function of interest is the minimization of the total cost of the generated powers of all the scheduled production units. This is the most widely used because it reflects current practice of economic dispatch and, more importantly, the cost aspect is always ranked among the operational requirements of power systems. Some well-known objectives can be identified as follows:

Objectives of the optimal active power distribution Objectives of the optimal reactive power distribution among the above objectives, fuel cost minimization and active power loss minimization are the most commonly used objectives.

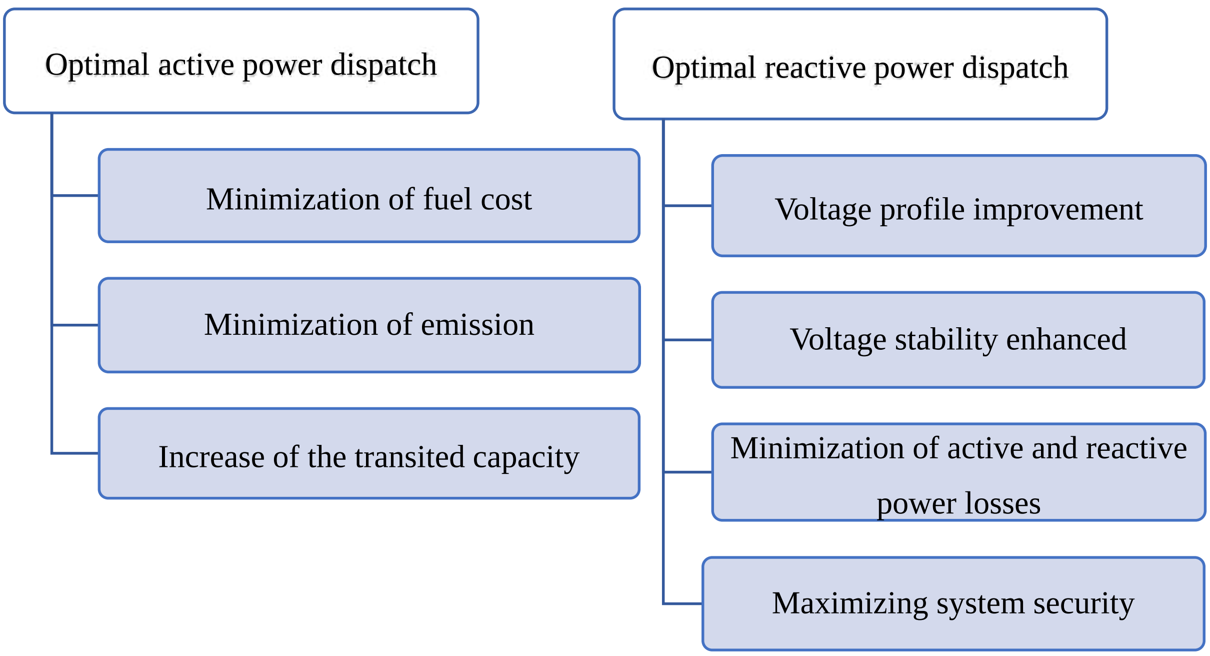


Figure II.1: Basic structure of the multi-objective OPF strategy.

II.4.1: Minimization of generation fuel cost

Fuel cost minimization is the most fundamental objective function of OPF studied in almost all literatures. The association between the fuel cost ($/h) and the quadratic relation approximately gives the generated power (MW) and thus the objective function to be minimized is described as:

$$f_1(x,u)=\sum_{i=1}^{Ng} a_i + b_i.P_i + c_i.P_i^2 \tag{II.19}$$

II.4.2. Minimization of emission

The production of electrical energy from conventional energy sources emits harmful gases into the environment, such as carbon dioxide (CO_2), nitrogen oxide (NOx), sulfur dioxide (SO_2) and mercury (Hg). The amount of emissions of these pollutants in tons per hour (t/h) increases with the increase of the power produced in (MW) according to the relation given in equation (II.20). Minimizing emissions is the goal of the OPF.

Mathematically, the emission rate of gases can be represented as an objective function of the generated power given by:

$$f_2(x,u)=\sum_{i=1}^{Ng} \alpha_i + \beta_i.P_i + \gamma_i.P_i^2 + \omega_i e^{(\mu_i P_i)} \tag{II.20}$$

Where, $\alpha_i, \beta_i, \gamma_i, \omega_i$ and μ_i are the coefficients of the emission function of each generator *i*,

II.4.3. Voltage profile improvement

The voltage deviation VD is a measure of the voltage quality in the network. The VD deviation index is also important from a safety point of view. VD is formulated as a cumulative deviation of the voltages of all load busbars (PQ bus) of a power system from the nominal voltage (1.0 p.u). Mathematically, it is expressed as follows [16]:

$$f_3(x,u)=VD=\sum_{p=1}^{NL}\left|V_{L_p} - V^{ref}\right| = \sum_{p=1}^{NL}\left|V_{L_p} - 1.0\right| \tag{II.21}$$

II.4.4. Voltage stability enhancement

Voltage stability problems are receiving increasing attention in power systems, as system collapses have been experienced in the past due to voltage instability. Under normal conditions and after being subjected to disturbances, the stability of a power system is characterized by its ability to maintain all busbar voltages within acceptable limits. On the other hand, a network enters a state of voltage instability when a disturbance, an increase in load, a change in the state of the system or damage to equipment (lines, cables, transformers, metering reducers, circuit breakers, etc.) causes a progressive and uncontrollable decrease in voltage [17]. Systems with long transmission lines and large loads are more prone to voltage instability problems. In a power system, improving the voltage stability of a system is an important aspect. As a result, much research work has been directed towards the development and control of voltage stability processes. Kessel and Glavitsch [17] have developed analyses and proposed a voltage stability index called the L-index.

The L index of each node serves as a good indicator of the stability of the power system [17]. The value of the index varies from 0 to 1, 0 being the case with no load while 1 means voltage collapse.

The index L is determined from the basic power flow equation, and which is formulated as follows [18]:

$$I_{bus} = Y_{bus} \cdot V_{bus} \tag{II.22}$$

By separating the load buses (PQ bus) from the generation bus (PV bus), equation (II.22) can be rewritten as follows:

$$\begin{bmatrix} I_L \\ I_G \end{bmatrix} = \left[Y_{bus} \right] \cdot \begin{bmatrix} V_L \\ V_G \end{bmatrix} = \begin{bmatrix} Y_{LL} & Y_{LG} \\ Y_{GL} & Y_{GG} \end{bmatrix} \cdot \begin{bmatrix} V_L \\ V_G \end{bmatrix} \tag{II.23}$$

Where, Y_{LL} , Y_{LG}, Y_{GL} andY_{GG} are the partial matrices of the admittance matrix Bus Y_{bus}; V_L, I_L are the voltages and currents of the load nodes respectively; V_G , $I_G$are the voltages and currents of the generating nodes respectively. Eq. (II.23) can be rewritten with another formula like [19],

$$\begin{bmatrix} V_L \\ I_G \end{bmatrix} = \left[H \right] \cdot \begin{bmatrix} I_L \\ V_G \end{bmatrix} = \begin{bmatrix} H_{LL} & H_{LG} \\ H_{GL} & H_{GG} \end{bmatrix} \cdot \begin{bmatrix} I_L \\ V_G \end{bmatrix} \tag{II.24}$$

Where, H is determined by the partial inversion of the admittance matrix Y_bus; Y_{bus}; H_{LL} , H_{LG}, H_{GL} and H_{GG} are sub-matrices of H.

Finally, the index L of load bus j denoted by L_j is formulated as follows:

$$L_j = \left| 1 - \sum_{i=1}^{Ng} F_{ji} * \frac{V_i}{V_j} \right|, \quad j = 1,2,\ldots, NL \tag{II.25}$$

and $F_{ji} = -[Y_{LL}]^{-1}[Y_{LG}]$

To ensure voltage stability the condition $L_j \leq 1$ must not be violated for all busbars in the network.

The voltage stability index L-index L_{max}) can be given by equation (II.26)

$$L - index = L_{\max} = \max(L_j), \quad j = 1,2,\ldots, NL \tag{II.26}$$

According to Eq. (II.26), the improvement in voltage stability can be achieved by minimizing the voltage stability index (L-index) at each bus in the system [19]. Therefore, to consider the voltage stability in the OPF problem, the objective function is given by the expression (II.27).

$$f_4(x,u) = L_{\max} = \max(L_j) \tag{II.27}$$

II.4.5. Minimization of active power losses

The total active losses dissipated in the transmission lines of an electrical network is unavoidable because the lines have an inherent resistance. The active power loss (in MW) to be minimized is expressed by:

$$f_5(x,u) = P_{loss} = \sum_{q=1}^{nl} G_{q(ij)} . \left[V_i^2 + V_j^2 - 2V_iV_j\cos(\delta_{ij})\right] \tag{II.28}$$

Where, $\delta_{ij} = (\delta_i - \delta_j)$, is the difference in voltage angles between bus i and bus j and G_(q(ij)) the conductance of the branch q connecting the two bus i and j.

II.4.6. Minimization of reactive power losses

The objective function represents total reactive losses of transmission lines; it is given by the expression,

$$f_6(x,u) = Q_{loss} = \sum_{q=1}^{nl} B_{q(ij)} . \left[-V_i^2 - V_j^2 + 2V_iV_j\cos(\delta_{ij})\right] \tag{II.29}$$

Where, B_(q(ij)) is the susceptance of the branch q connecting the two bar sets i and j.

II.5. Conclusion

In this chapter, we have presented basic notions and formulations of the OPF problems. Different objective functions were presented such as the economic dispatch function, environmental dispatch, voltage deviation improvement, voltage stability enhanced, active and reactive power loss minimization. Given the complexity of OPF problems and the limitations of deterministic methods, as they do not converge to local optima, we propose the optimization of OPF problems by metaheuristic methods and this will be the subject of the next chapter.

III .1. Simulation results and discussion

In order to evaluate the performance of TLBO algorithm, we will study several cases with different goals. This optimization method has been applied to IEEE 30 bus standard test system. Table (III .1) summarizes the main components and other useful parameters installed in the test system. In this test network. In power flow research, the function of is swing us the active and reactive power of the system by satisfying the power swing equations (II. 4) and (II. 5). For convenience, the voltage modulus of the slack bus is considered to be 1.0 p.u., and the voltage phase angle is 0 degrees. All other bus voltage and their angles are expressed as values relative to equilibrium bus, which are obtained at the end of the load flow study. Finally, the performance of TLBO optimization algorithm is compared. The advantages and disadvantages of each algorithm will be analyzed according to different performance standards. The single line scheme corresponding to IEEE 30 bus test system is shown in Figure (III .1).

Table III.1: Summary of major components installed in the studied system [21].

Terme	Value	Details
Bus	30	[21]
Branches	41	[21]
Generation	6	Bus : 1 (Slack bus), 2, 5, 8, 11 and 13
Compensator shunt	9	Bus : 10, 12, 15, 17, 20, 21, 23, 24 and 29
Transformer on load regulator menu	4	Branche : 11, 12, 15 and 16
Control variables	24	-
Connected load	-	283,4 MW, 126,2 Mvar
Voltage profile (PQ)	24	[0,95 – 1,05] p.u.
Transformer ratio limite	-	[0,90 – 1,10] p.u.
The power range of QC compensator shunt	-	[0 – 5] Mvar.

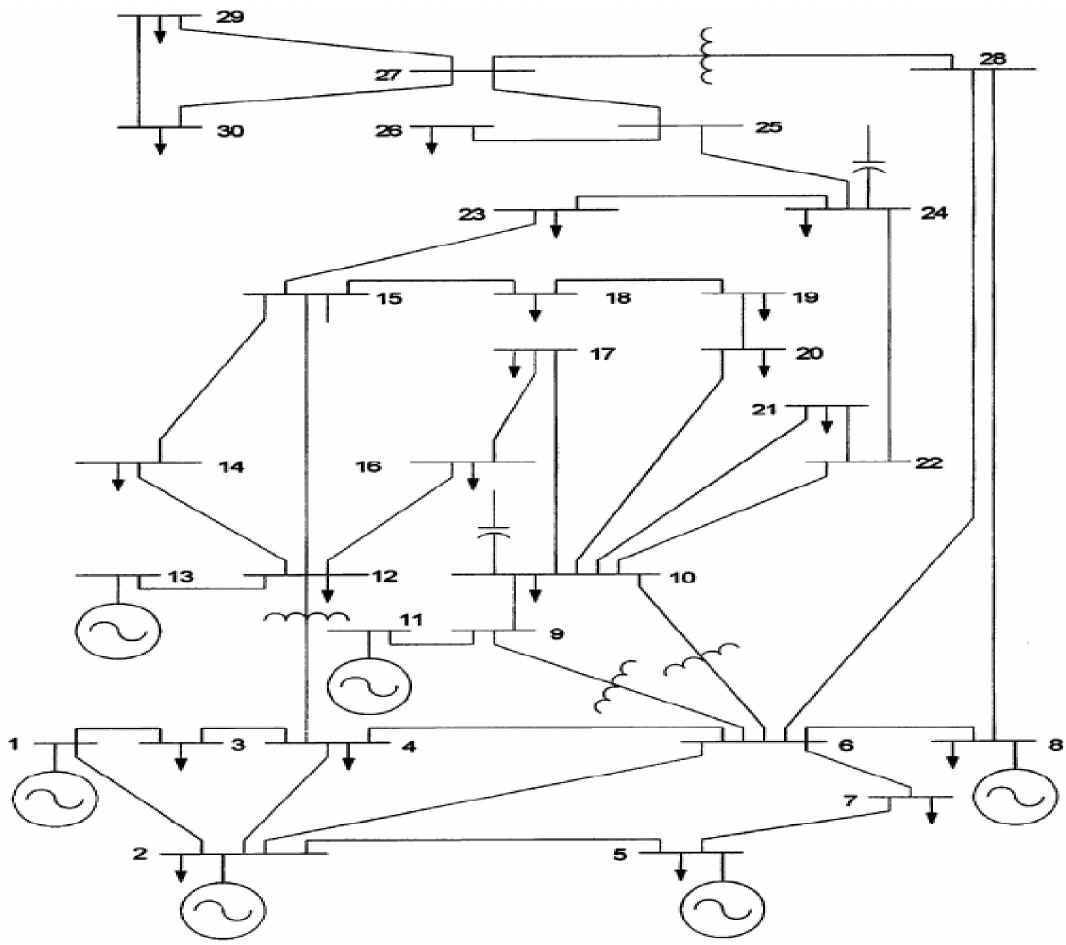


Figure III.1: Single line diagram of the IEEE 30-bus test system.

III.2. TLBO algorithm to OPF problems:

The main steps in solving the OPF problem by TLBO are:

Step 1: Enter all power system data such as generator limits, transformer limits and safety constraints. Population size and number of generations are also introduced.

Step 2: Initialize the control variables.

Step 3: Apply the power flow by the Newton-Raphson method (fast decoupled method), check if the inequality constraints are violated and sanction the violations.

Step 4: Calculate the new objective function with the penalized violations.

Step 5: Update the new control variables using Eq. (I. 1) And (I. 3)

Step 6: Obtain a new solution of the power flow, using the new control variables.

Step 7: Repeat step 4 to update the lens function.

Step 8: Compare the results obtained in step 7 with step 4.

Step 9: If the new value of the objective function is better than the previous one, update the control variables with the better parameters.

Step 10: Update the new control variables using Eq (I. 4)

Step 11: Repeat step 3 for the power flow calculation update.

Step 12: Repeat step 4 to update the target function.

Step 13: Compare the results obtained in step 12 with step 7.

Step 14: If the new value of the objective function is better than the previous one, update the control variables with the better parameters.

Step 15: Repeat the above procedures from step 2 for the maximum number of iterations.

III.3. Simulation and interpretation of results:

In this work, the optimization parameters of the TLBO algorithm are given in Table V.2. The OPF problem consists of optimizing six objective functions that are realized for the system for eleven study cases, five cases aim at optimizing single objective functions and the remaining cases concern multi-objective optimizations that are converted into single objective functions by introducing weighting factors as in many previous studies and reproduced here.

Table III .2: Simulation parameters for TLBO algorithms.

TLBO	Parameters
Population size	50
Max Iter	200/500

The OPF problem consists of optimizing six conflicting objectives that are:

$f_1(x,u)$: Function of fuel cost (Eq. II.19).

$f_2(x,u)$: NOxtoxic gas emission function (Eq. II.20).

$f_3(x,u)$: Function of the voltage deviation (Eq. II.21).

$f_4(x,u)$: Voltage stability function (Eq. II.27).

$f_5(x,u)$: Active power loss function (Eq. II.28).

Table III .3: Summary of the studied (minimized) cases for the IEEE 30 bus test network.

Cases	Fuel cost	Emission	Voltage profile improvement	Voltage stability enhanced	Active power losses
Cas 1	✓				
Cas 2	✓	✓			
Cas 3	✓		✓		
Cas 4	✓			✓	
Cas 5					✓
Cas 6	✓				✓
Cas 7	✓	✓	✓		✓

III.3.1.Case 1: Minimization of generation fuel cost

$$Fobj1 = f_1(x,u) + f_{Pénalité} \tag{III.1}$$

III.3.2. Case 2: Minimization of fuel cost and emissions:

$$fobj2 = F_{TC} = \alpha \times f_1(x,u) + (1-\alpha) \times \lambda_{NOx} \times f_2(x,u) + f_{Pénalité} \tag{III.2}$$

III .3.3. Case 3: Minimization of fuel cost and Voltage profile improvement:

$$Fobj3 = f_1(x,u) + \lambda_{VD} \times f_3(x,u) + f_{Pénalité} \tag{III.3}$$

III.3.4.Case 4: Minimization fuel cost and Voltage stability enhancement

$$Fobj4 = f_1(x,u) + \lambda_L \times f_4(x,u) + f_{Pénalité} \tag{III.4}$$

III.3.5. Case 5: Minimization of active power transmission losses

$$Fobj5 = f_5(x,u) + f_{Pénalité} \tag{III.5}$$

III .3.6.Case 6: Minimization of generation fuel cost and power Losses

$$fobj6 = f_1(x,u) + \lambda_P \times f_5(x,u) + f_{Pénalité} \tag{III.6}$$

III .3.7. Case7: Minimization of generation fuel cost, emission, voltage deviation and power Losses

$$fobj7 = f_1(x,u) + \lambda_E \times f_2(x,u) + \lambda_{VD} \times f_3(x,u) + \lambda_P \times f_5(x,u) + f_{Pénalité} \tag{III.7}$$

Table III .4: Solutions of optimal control variables obtained in all cases

Control variables	Min limit	Max limit	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7
P_1	50	200	177,352	129,9966	176,0794	178,8177	51,2796	103,9616	123,5530
P_2	20	80	48,6967	57,0573	49,2533	48,45910	80,0000	55,4105	52,5099
P_5	15	50	21,3053	25,4941	21,8119	21,2470	49,9999	37,1901	30,9506
P_8	10	35	21,0801	35,0000	22,1795	19,9840	35,0000	35,0000	35,0000
P_{11}	10	30	11,8841	22,3181	12,1101	11,5271	30,0000	30,0000	26,2761
P_{13}	12	40	12,0000	19,3745	12,0000	12,2049	39,9998	26,4318	20,5345
V_1	0.95	1.1	1,1000	1,1000	1,0407	1,1000	1,1000	1,1000	1,1000
V_2	0.95	1.1	1,0879	1,0909	1,0233	1,0866	1,0976	1,0923	1,0883
V_5	0.95	1.1	1,0617	1,0667	1,0150	1,0689	1,0798	1,0713	1,0629
V_8	0.95	1.1	1,0694	1,0776	1,0015	1,0831	1,0868	1,0807	1,0721
V_{11}	0.95	1.1	1,1000	1,1000	1,0112	1,0998	1,1000	1,1000	1,0129
V_{13}	0.95	1.1	1,1000	1,1000	0,9873	1,1000	1,1000	1,1000	1,0290
$T_{6\text{-}9}$	0.90	1.1	1,0449	1,0420	1,0043	1,0078	1,0609	1,0492	1,1000
$T_{6\text{-}10}$	0.90	1.1	0,9000	0,9000	0,9508	0,9144	0,9000	0,9000	0,9902
$T_{4\text{-}12}$	0.90	1.1	0,9864	0,9805	0,951	0,9907	0,9842	0,9787	1,0721
$T_{28\text{-}27}$	0.90	1.1	0,9659	0,9663	0,9789	0,9718	0,9791	0,9736	1,0349
Q_{C10}	0.00	5.00	5,0000	4,9998	0,7345	4,9968	1,8326	4,5886	4,9935
Q_{C12}	0.00	5.00	5,0000	5,0000	4,5466	4,9448	1,7239	8,16E-04	0,0252
Q_{C15}	0.00	5.00	4,9991	4,9999	4,8922	4,8788	4,6965	4,9890	4,0884
Q_{C17}	0.00	5.00	5,0000	5,0000	4,1130	4,9952	0,0048	4,9998	5,0000
Q_{C20}	0.00	5.00	5,0000	4,9991	3,8201	4,9931	4,9933	0,0363	4,9995
Q_{C21}	0.00	5.00	5,0000	5,0000	1,6385	4,9826	0,0197	3,6415	4,9987
Q_{C23}	0.00	5.00	3,8387	3,8440	-47,1476	5,0000	14,3364	-18,1663	4,1657
Q_{C24}	0.00	5.00	5,0000	5,0000	3,2170	4,9902	1,1548	0,0032	5,0000
Q_{C29}	0.00	5.00	2,7589	2,6820	2,4220	4,8964	4,5499	4,9988	2,5432
Fuel cost ($/hr)	NA	NA	**799,068**	817,1843	**813,6568**	**799,4257**	**967,1354**	**856,0143**	**827,5184**
Emission (ton/h)	NA	NA	0,3656	0,2706	0,3675	0,3736	0,3194	0,2362	0,2590
P_{losses} (MW)	NA	NA	8,6246	**5,8417**	11,9215	8,8412	2,8807	4,5949	5,4247
Q_{losses} (Mvar)	NA	NA	4,1695	-6,4214	13,3469	4,9430	-18,8437	-13,2481	-13,8374
VD (p.u)	NA	NA	1,8568	1,9867	1,0969	2,0678	2,0108	1,5856	0,4545
Lmax	NA	NA	0,1164	0,1152	0,1626	0,1134	0,1147	0,1228	0,1343

The optimal control variables obtained from TLBO are shown in Table III.4. Finally, the calculation results of minimum generation cost, gas emission, voltage deviation, stability index and active and reactive power loss are given. Obviously, the optimal solution of case 1 is obtained by the proposed TLBO method. The results show that the TLBO algorithm can obtain the optimal minimum cost (799.068 US $/h). Under this minimum cost, the voltage deviation is 1.8568 (p.u.). The voltage stability index is 0.1164 p.u. the total active and reactive losses are 8.6246 MW and 4.1695 Mvar, respectively.

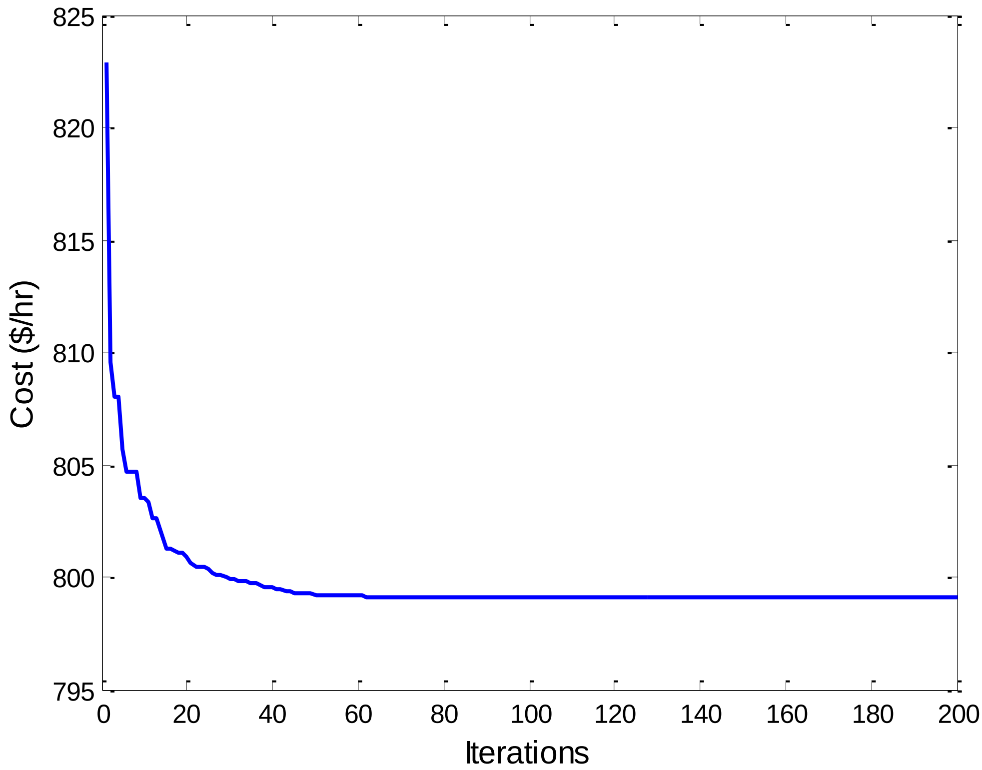


Figure III .2: fuel cost convergence characteristics with TLBO.

The optimal control parameters obtained from TLBO are shown in Table III.4. Finally, the results of minimum production cost, emission (T/h), voltage deviation, stability index and active and reactive power loss are given. It can be inferred from Table III.4 that the optimal emission value obtained by TLBO algorithm is 0.2706 (T / h). Compared with the optimal value of 0.3675 T / h obtained by the same algorithm in case 1, the optimal value is lower. In this case, the minimum combustion cost (813,6568$/h) obtained by TLBO is higher than that (799 $/h). In this case, the active and reactive power losses of TLBO are 11,9215 MW and 13,3469 Mvar respectively, while VD and Lmax are 1,0969 (p.u.) and 0,1626 respectively.

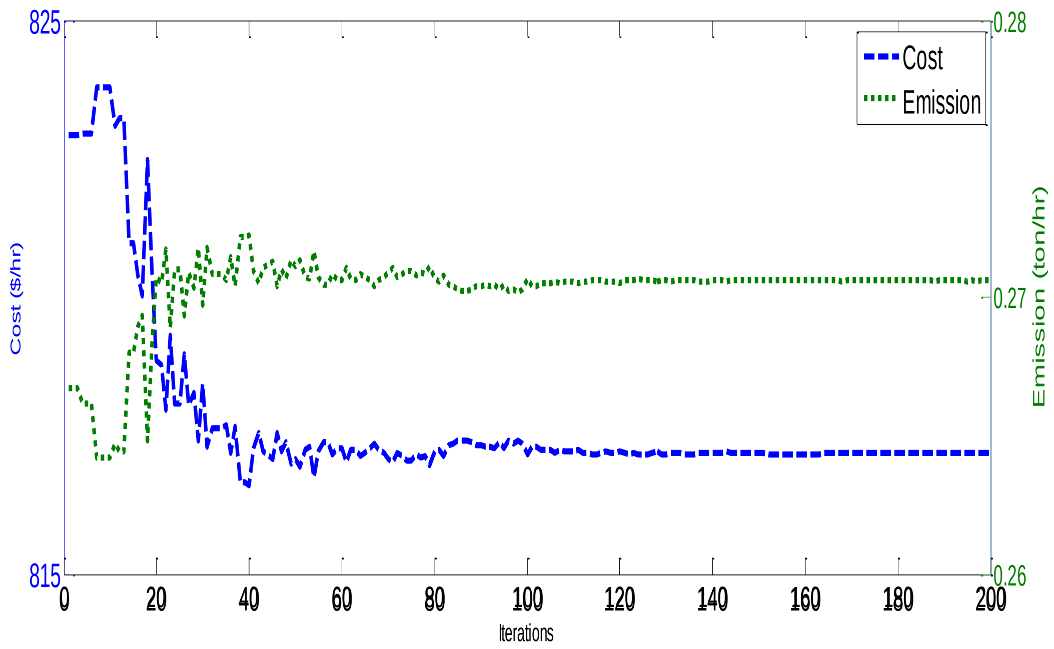


Figure III .3: fuel cost and Emission characteristics approximate production with TLBO

- Case 3: The table (III.4) in the case 3 show the changes in fuel cost and voltage deviation during.
- The iteration determined by the proposed method.
- This shows that the proposed TLBO method has good convergence. Statistics of cost, voltage deviation and objective function. In this case.
- The fuel cost and VD obtained with TLBO are 813.6568 \$/h and 1.0969 p.u respectively. As for result of emission 0.3675 (ton/h) and P_{losses} are 11.9215 MW.

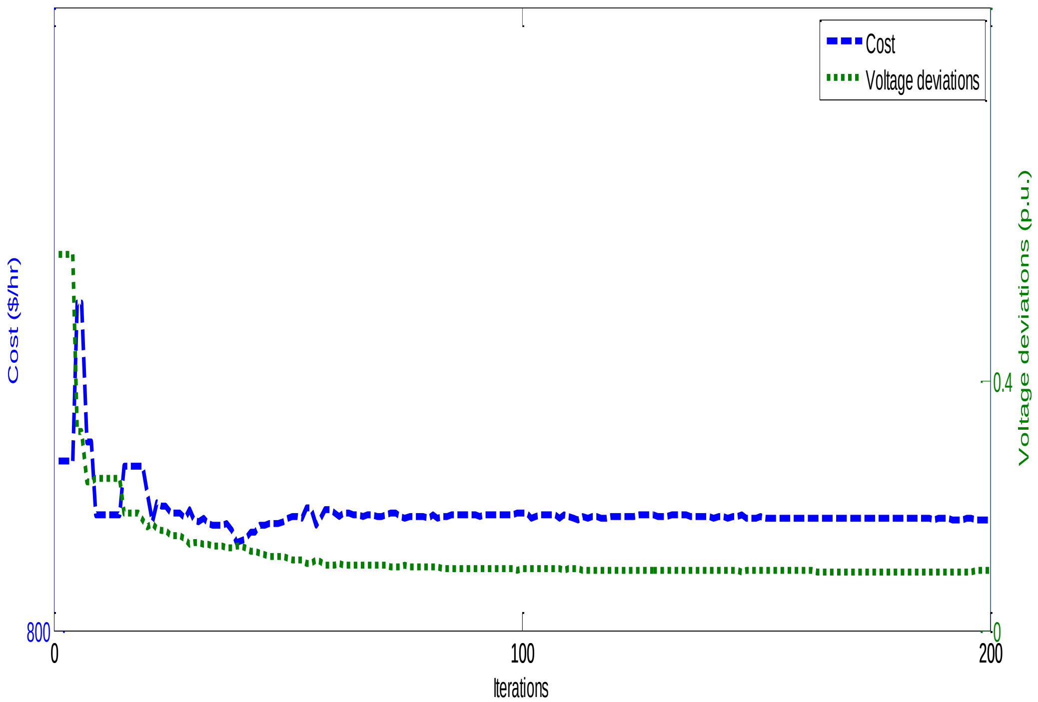


Figure III .4: variation of fuel cost and voltage deviation obtained by TLBO.

- Case 4: Of the case 4 according to Table (III.4), the solution found is within the acceptable range and meets all security constraints.
- The minimum values of fuel cost and (L_{max}) obtained are 799.4257 \$/h and 0.1134 respectively.
- As for result of emission 0.3736 (ton/h). While VD and P_{losses} are 2.0678 p.u and 8.8412MW respectively.

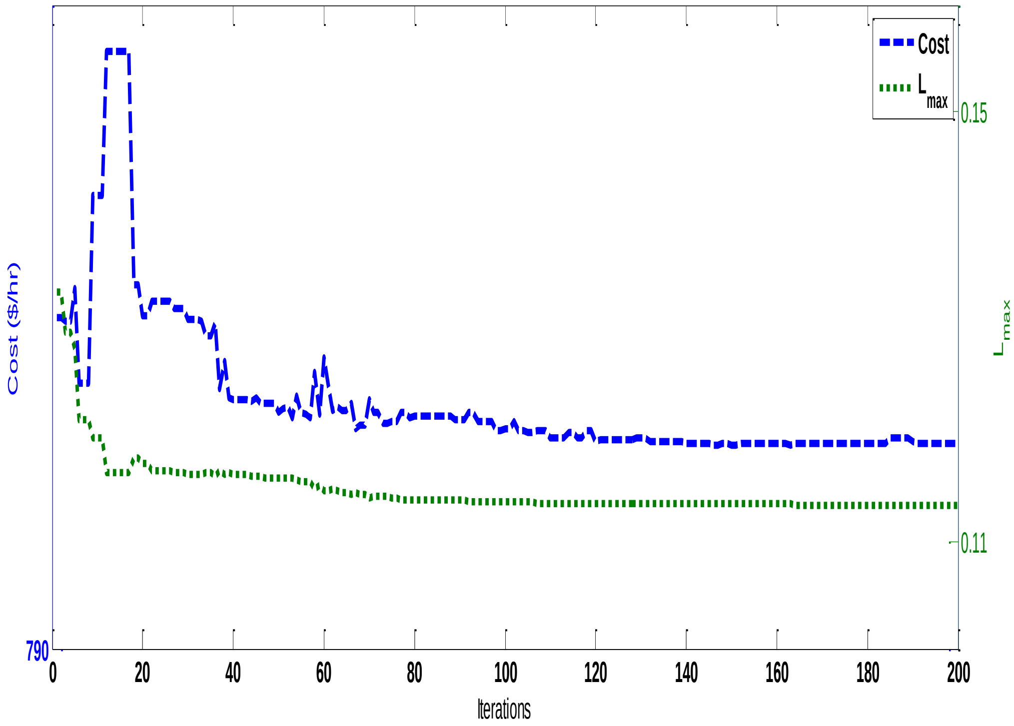


Figure III .5: convergence of production cost and the stability index with TLBO

- Case 5: The optimal values of control variables of case 5 obtained by the two algorithms are shown in table (III.4) For case 4.
- All the optimal solutions are within the allowable range.

The optimal P_{losses} of TLBO method is 2.8807MW, and 66.95% lower than 8.6246MW of TLBO method in case 1.

- The fuel cost of this case 96.1354$/h, as VD and L_{max} were 2.0108 and 0.114 (p.u) respectively.

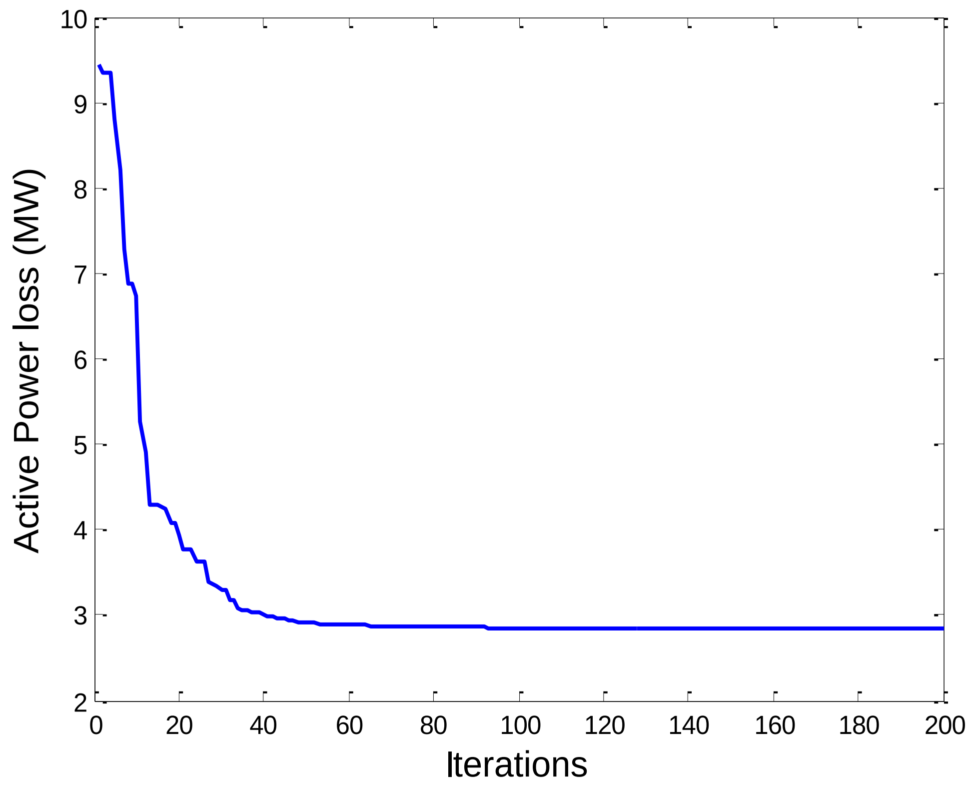


Figure III .6: Minimization of active power losses with TLBO

- Case6: it can be inferred from compared to previous state (case5) of the table (III.4), we notice an increase in the value P_{losses} and Lmax and emission are 4.5949 MW and 0.1228 and 0.2362 (ton/h) respectively.
- As for fuel cost result is 856.0143($/hr) and for VD is 1.5856 p.u

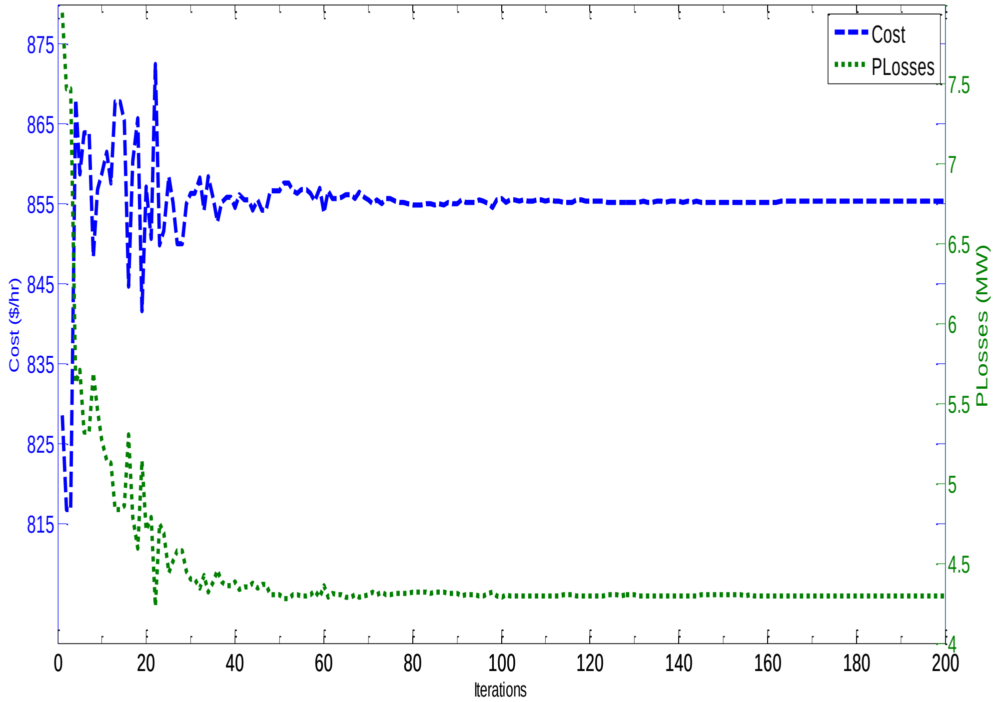


Figure III .7: Minimization of fuel cost and active power losses with TLBO.

- Case7: compared the case7 with the previous case6, we note the cost of fuel obtained (827.5184 $/h).
- The control variables are also in the allowable range.
- The fuel cost of increased from US 799.068 $/h (case 1), we note that the emission is the only one that has decreased by 0.2590(ton/hr). VD is 0.4545 p.u, as for P_{losses} and Lmax are 5.4247 MW and 0.1343 respectively.

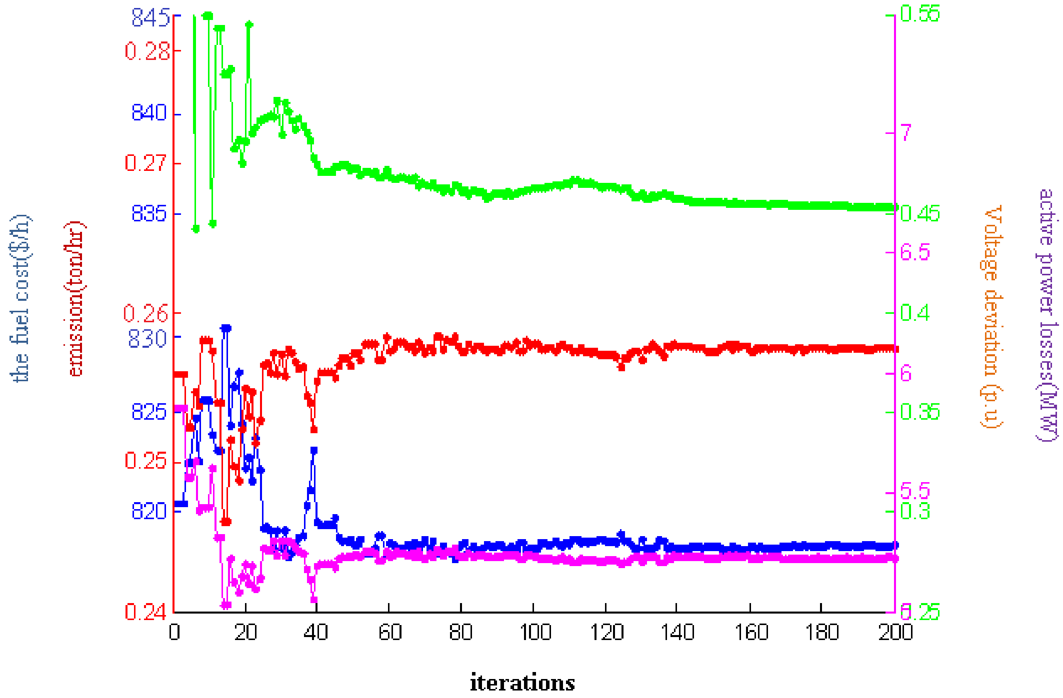


Figure III 1: Variations in all components of total cost during iterations by TLBO

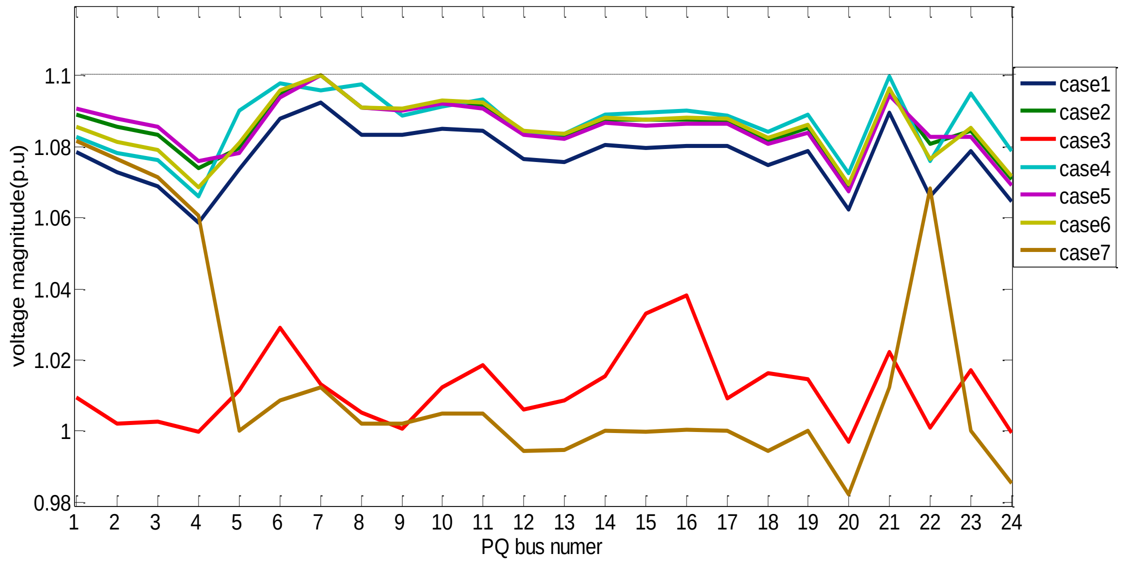
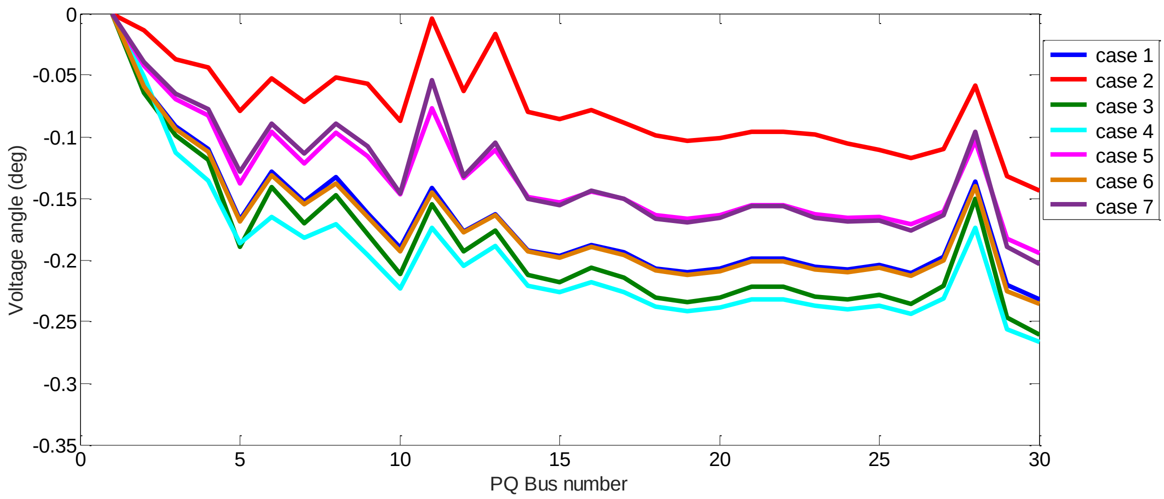


Figure III.9: Voltage magnitude of PQ bus from case 1 to case7.



FigureIII.10: Voltage angles obtained of all buses for the all cases.

III.4 OPF problems solution with DG unit

Table III .5: Solutions of optimal control variables obtained with added DG.

Control variables	Min limit	Max limit	Case 8	Case 9	Case 10	Case 11
P_1	50	200	175,163	175,1258	177,0614	122,277
P_2	20	80	48,0774	48,6624	47,9513	51,9393
P_5	15	50	21,4892	21,5514	21,1783	30,7634
P_8	10	35	20,5964	21,2368	18,4212	35,0000
P_{11}	10	30	12,1334	12,0678	12,4346	25,9208
P_{13}	12	40	12,0033	12,0034	12,9493	20,3231
V_1	0.95	1.1	1,1000	1,0397	1,0994	1,1000
V_2	0.95	1.1	1,0895	1,0238	1,0847	1,0883
V_5	0.95	1.1	1,0610	1,0149	1,0983	1,0629
V_8	0.95	1.1	1,0707	1,0081	1,0900	1,0721
V_{11}	0.95	1.1	1,1000	0,9874	1,0797	1,0129
V_{13}	0.95	1.1	1,0970	1,0003	1,1000	1,0290
T_{6-9}	0.90	1.1	0,9921	1,0004	0,9685	1,1000
T_{6-10}	0.90	1.1	0,9710	0,9003	0,9442	0,9902
T_{4-12}	0.90	1.1	0,9994	0,9583	0,9805	1,0721
T_{28-27}	0.90	1.1	0,9897	0,9685	0,9797	1,0349
Q_{C10}	0.00	5.00	2,9764	5,0000	4,9943	4,9935
Q_{C12}	0.00	5.00	3,0463	0,0019	5,0000	0,1952
Q_{C15}	0.00	5.00	3,4643	4,9962	4,9848	4,3597
Q_{C17}	0.00	5.00	5,0000	0,0000	4,9831	5,0000
Q_{C20}	0.00	5.00	4,1928	4,9997	4,9790	4,9995
Q_{C21}	0.00	5.00	1,9885	4,9995	4,9964	4,9987
Q_{C23}	0.00	5.00	1,8E-05	4,9942	5,0000	4,1657
Q_{C24}	0.00	5.00	1,4321	4,9999	4,9745	5,0000
Q_{C29}	0.00	5.00	4,3463	1,7685	4,9498	2,5432
Fuel cost ($/hr)	NA	NA	**790,489**	**794,6783**	**791,9808**	**827,5184**
Emission (ton/h)	NA	NA	0,3636	0,3634	0,3686	0,2590
P_{losses} **(MW)**	NA	NA	8,4634	9,7810	9,0036	5,4247
Q_{losses} **(Mvar)**	NA	NA	2,1502	10,0727	5,1523	-13,8374
VD (p.u)	NA	NA	1,1518	0,0919	2,1432	0,4545
Lmax	NA	NA	0,1065	0,1194	0,0982	0,1343

III .4.1.Case 8: Minimization of fuel cost with DG:

- Case 8: the results Minimization of generation fuel cost in electrical power system using distributed generator decrease the cost (to 790.489$/hr) and active power losses (to 8.4634MW) and voltage deviation (to 1.1518 p.u) and Lmax (to 0.1065) . as for emission, they have not changed.

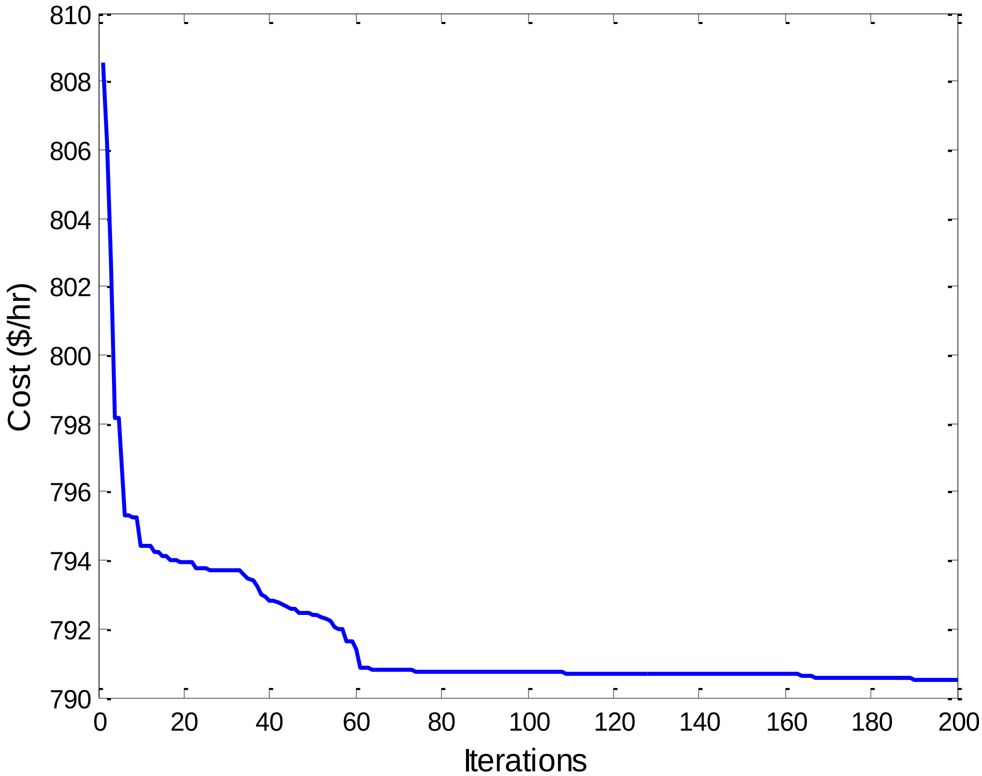


Figure III .11: Fuel cost characteristics changes with DG.

III .4.2.Case 9: Minimization of fuel cost and voltage profile improvement

- Case 9: the results Voltage profile improvement in electrical power system using distributed generator decrease.
- The cost and active power losses (to 794.6783$/hr/ 9.7810MW) straight and voltage deviation (to 1.1518 p.u) and Lmax (to 0.1065).
- As for emission, they are almost unchanged.

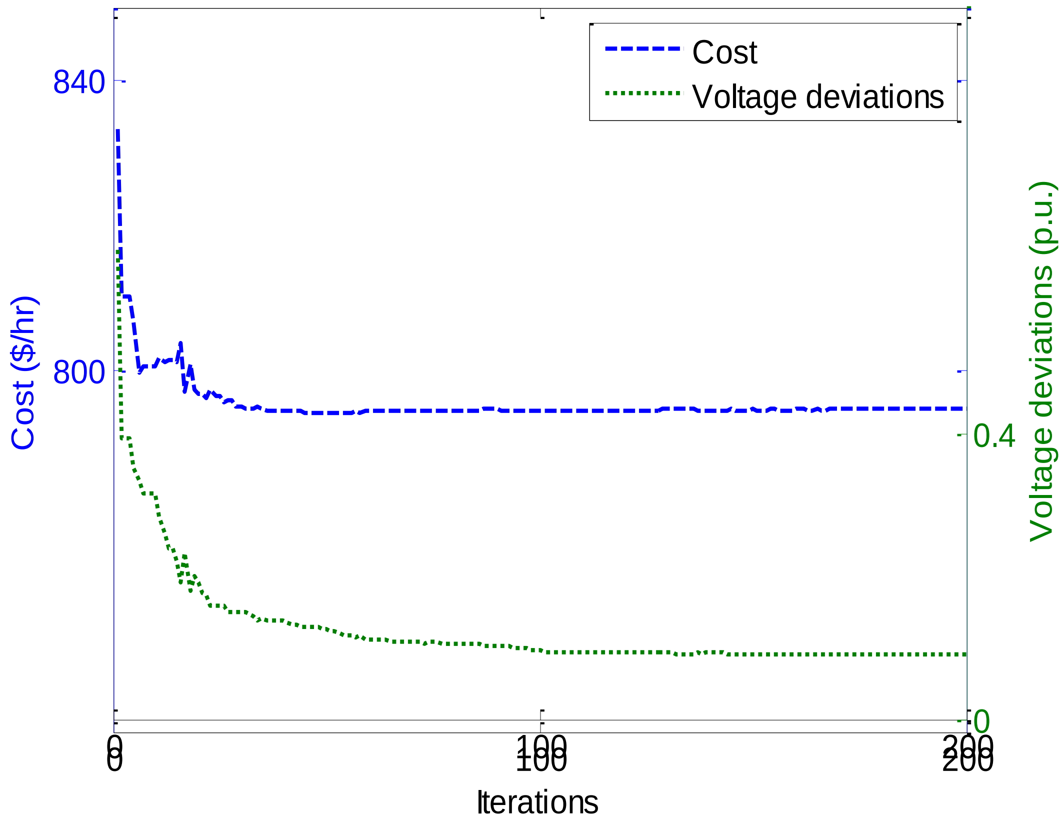


Figure III .12: Variation in voltage deviation obtained by TLBO with DG.

III .4.3. Case 10: Minimization of fuel cost and voltage stability enhancement with DG

- Case 10: the results Voltage stability enhancement in electrical power system using distributed generator decrease the cost and active power losses (to 799.4257 $/hr/ and 8.412 MW) respectively.
- The voltage deviation (to 2.0678p.u) and Lmax (to 0.1134).
- As for emission, they have not changed.

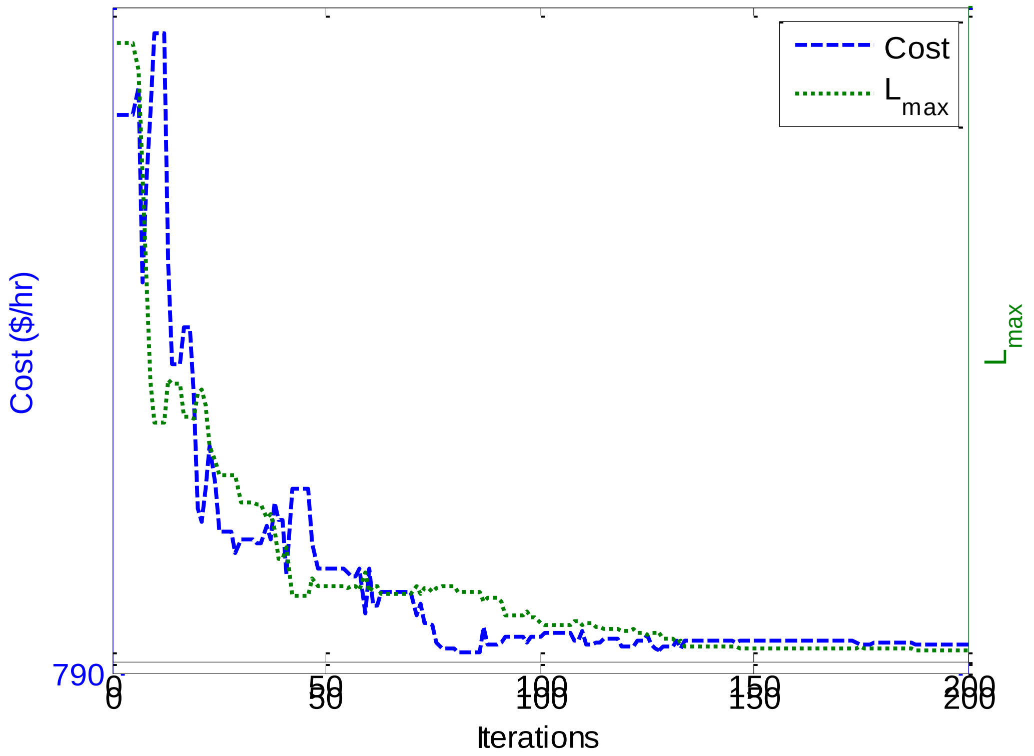


Figure III .13: Convergence of production cost and the stability index with DG.

III.4.4. Case 11: Minimization of generation fuel cost, emission, voltage deviation and power Losses with DG

- Case 11: the results Minimization of generation fuel cost, emission, voltage deviation and power Losses in electrical power system using distributed generator decrease the cost and active power losses (to 827.5184$/hr/ 5.4247MW) straight and voltage deviation (to 0.4545p.u) and Lmax (to 0.1343). as for emission, they have not changed

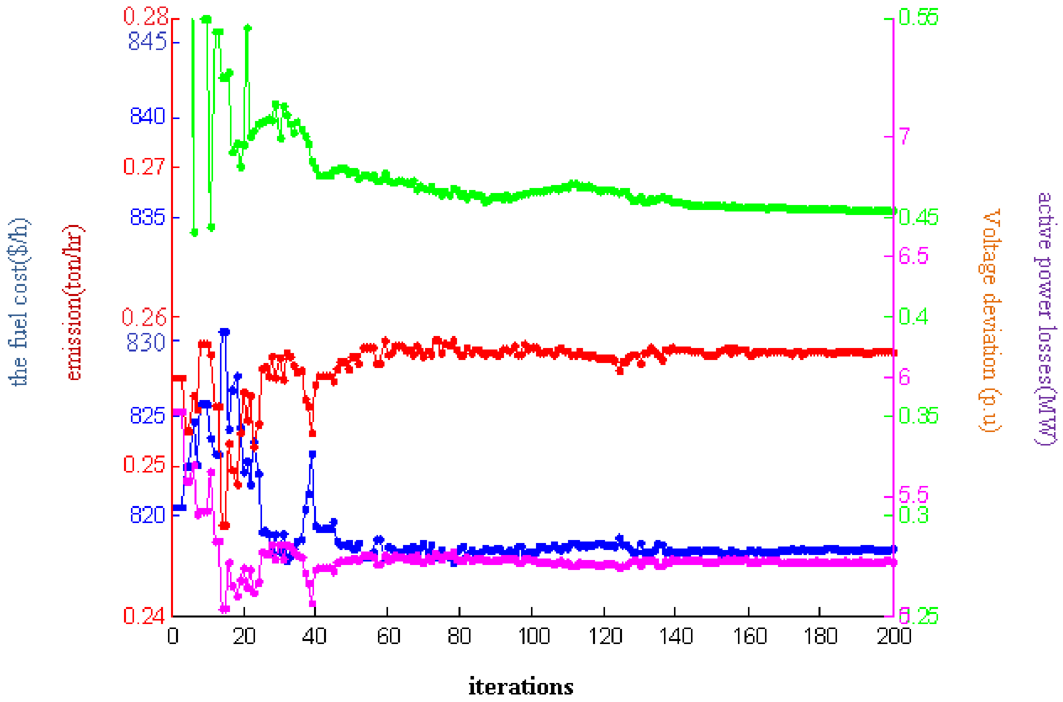


Figure III 2: Variations in all components of total cost during iterations after added DG unit.

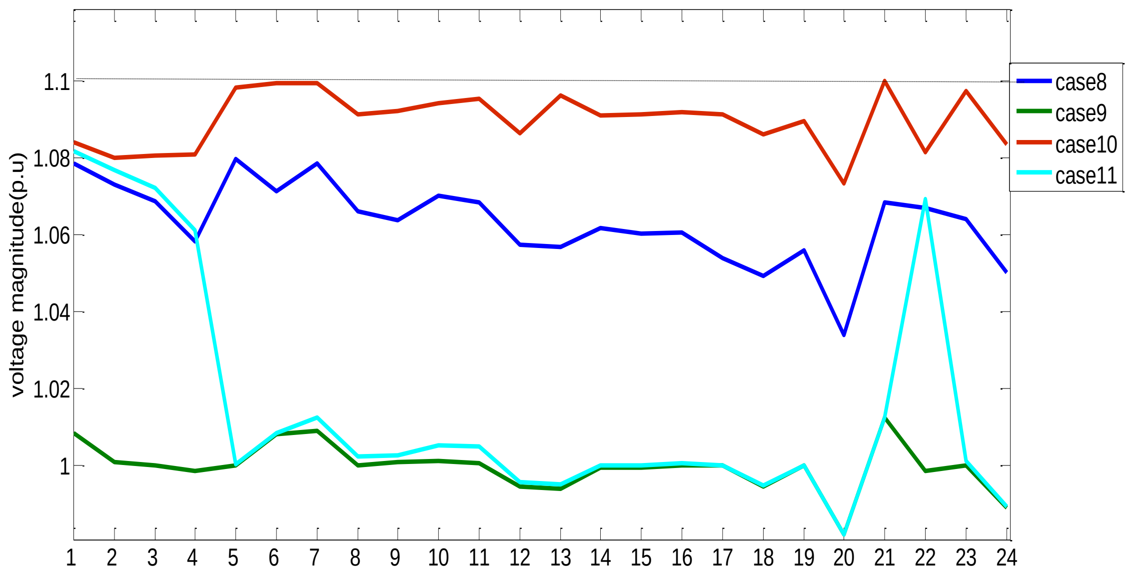


Figure III.15: Voltage magnitude of PQ bus from case 8 to case11 after added DG unit.

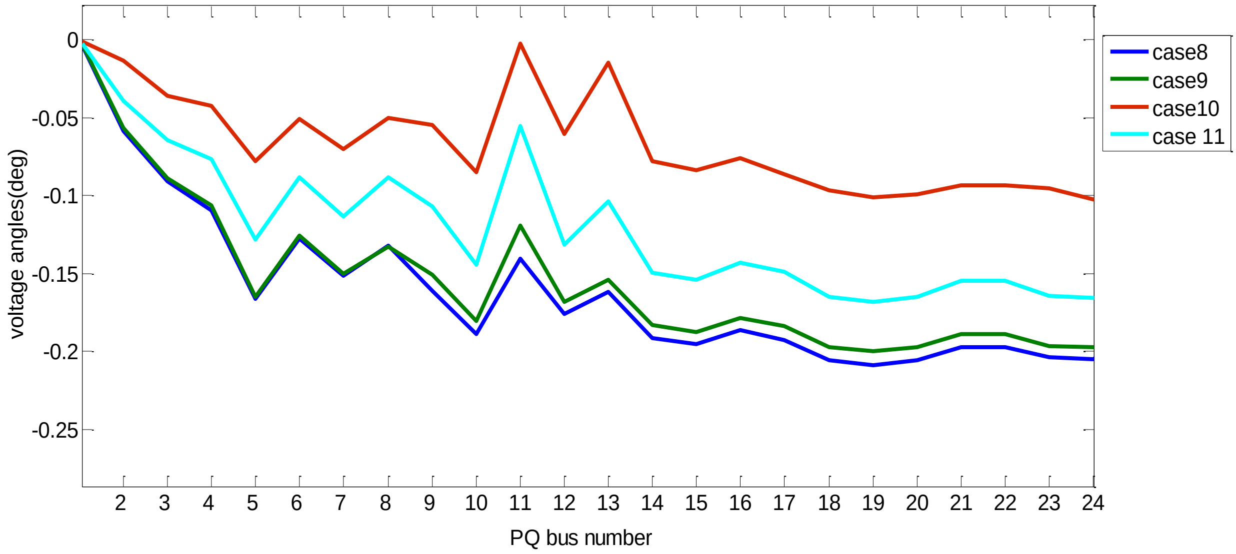


Figure III.16: Voltage angles of PQ bus from case 8 to case 11 after added DG unit.

III .5 Conclusion

The goal of this chapter is the optimization of the power flow using the metaheuristic method: the TLBO teaching-learning based optimization method. Seven cases were studied, four cases optimize simple objective functions, namely fuel cost, active and reactive power losses and toxic gas emission rate. For the other cases, the optimization is performed in such a way that two and four objective functions are optimized simultaneously, namely, fuel cost, emission rate, voltage deviation and voltage stability index at busbar level.

General conclusion

The research work of this thesis is right Optimization of power grid operation. The goal is to apply metaheuristic algorithm for solving optimal power flow problems. For donations, the contribution of this work is the optimization of OPF problem by using teaching-learning based optimization technique (TLBO).

The objective is to minimize one or more "objective" functions while satisfying a set of equality and inequality constraints.

The OPF problem consists in optimizing a simple objective, bi-objective and multi-objective. The main difficulty of such an optimization problem is related to the presence of conflicts between several objective functions, while satisfying a set of constraints. For this purpose, in this work, we have transformed any bi or multiobjective problem into a single objective function, by introducing weighting factors.

The simulation results show that, the TLBO approach using in this thesis has an acceptable accuracy from the practiced point of view successful in the OPF problem.

The research work presented in this thesis can be continued in several directions. Here we cite some of these directions:

We propose the hybridization of TLBO algorithm with deterministic techniques such as the IP interior point method, and then with modern evolutionary methods such as IACS, ANS, GWO.

Extend the application of TLBO method to solve OPF problems for more extensive power systems (IEEE 57 bus, IEEE 118 bus, IEEE 300 bus and above) in the presence of others renewable energy sources and FACTS devices, such as SVC, STATCOM, UPFC.

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