*Electric Power Components and Systems*, 00(00):1–16, 2016

ISSN: 1532-5008 print / 1532-5016 online
DOI: 10.1080/15325008.2015.1115919

# Optimal Power Flow Using an Improved Electromagnetism-like Mechanism Method

Houssem Rafik El-Hana Bouchekara,[1] Mohammad Ali Abido,[2] and Alla Eddine Chaib[1]
[1]Constantine Electrical Engineering Laboratory, LEC, Department of Electrical Engineering, University of Constantine 1, Constantine, Algeria
[2]Electrical Engineering Department, King Fahd University of Petroleum and Minerals, Dhahran, Saudi Arabia



**CONTENTS**



Keywords: optimal power flow, electromagnetism-like mechanism, power system optimization, metaheuristic, voltage stability

Received 23 December 2014; accepted 25 October 2015

Address correspondence to H. R. E.-H. Bouchekara, Constantine Electrical Engineering Laboratory, LEC, Department of Electrical Engineering, University of Constantine 1, 25000, Constantine, Algeria. E-mail: bouchekara.houssem@gmail.com

Color versions of one or more of the figures in the article can be found online at www.tandfonline.com/uemp.

**Abstract**—In this article, an improved version of the electromagnetism-like mechanism is developed and proposed to find the optimal solution for the optimal power flow problem in a power system. To show the effectiveness of the developed method, it has been demonstrated on standard IEEE 30-bus and IEEE 57-bus test systems for seven different objectives that reflect fuel cost minimization with generators that may have either convex or non-convex fuel cost characteristics, voltage profile improvement, voltage stability enhancement, and active and reactive power transmission losses minimization. The results obtained using the improved version of the electromagnetism-like mechanism method are compared with those obtained using different methods reported in the literature. Considering the quality of these results, the proposed method is a quite promising alternative approach for solving optimal power flow problems.

## 1. INTRODUCTION

Optimal analysis, control, and monitoring of power system operation and planning require special tools. The majority of these tools are appropriately formulated as some sort of optimization problem [1]. Optimal power flow (OPF) is the backbone tool that has been widely investigated since its introduction in 1960 [2, 3]. The OPF term was first introduced by Dommel and Tinney in 1968 [4] as reported in [1]. Generally, the OPF problem is a large-scale highly constrained non-linear non-convex optimization problem [5]. In other words, the main purpose of the OPF problem is to optimize a predefined function by adjusting a set of control variables while satisfying certain physical, operational, and policy constraints [6]. Many OPF models have been developed and adopted to formulate different kinds of optimization problems to optimize different types of objective functions using different sets of controls and under different kinds of constraints [7].

Among a number of different objectives for which an OPF problem may be formulated, find real and reactive power losses minimization, load shedding, bus voltage deviation, emission of generating units, voltage stability enhancement, and fuel cost minimization are found to be the most common and widely considered.

The OPF problem has been rigorously investigated over the past few decades, and many optimization techniques have emerged and been applied to solve this problem [8]. Earlier, many traditional (deterministic) optimization techniques have been successfully used, the most popular of which were gradient-based methods, Newton-based method, the simplex method, sequential linear programming, sequential quadratic programming, and interior point methods. Surveys of the most commonly used conventional optimization algorithms applied to solve the OPF problem were given in [9–12]. Although some of these deterministic techniques have excellent convergence characteristics and many of them are widely used in the industry, they suffer from some shortcomings. Some of their drawbacks are that they cannot guarantee global optimality (*i.e.*, they may converge to local optima), they cannot readily handle binary or integer variables, and they are developed with some theoretical assumptions (such as convexity, differentiability, and continuity, among other things) that may not be suitable for actual OPF conditions [1, 12].

Furthermore, the rapid developments of recent computational intelligence tools have motivated significant research in the area of metaheuristic optimization methods to solve the OPF problem in the past two decades [1]. Many of these techniques have been applied to OPF problems, including ant colony optimization (ACO), bacterial foraging algorithms (BFAs), biogeography-based optimization (BBO), differential evolution (DE), the genetic algorithm (GA), particle swarm optimization (PSO), simulated annealing (SA), and tabu search (TS). These methods are known for their capabilities of finding global solutions and avoiding being trapped with local ones, their ability of fast search of large solution spaces, and their ability to account for uncertainty in some parts of the power system. A review of some of these optimization techniques applied to solve the OPF problem was given in [1, 13].

The electromagnetism-like mechanism (EM) algorithm, proposed by Birbil and Fang [14], is a new optimization algorithm based on the attraction–repulsion mechanism of electromagnetism theory [15]. This method is applicable for non-linear problems with bounded variables. It considers each point as a charged particle. Each particle is impressed by other particles and consequently moved to a better solution space [15]. Due to its characteristics and performances, the EM has been garnering attention and been extended and applied in many works, with most reporting its promising performance [15].

The main contributions of this article can be summarized as follows:

1) An improved EM (IEM) method is proposed.
2) The proposed IEM method has been formulated and implemented to solve the OPF problem.

The remainder of the article is organized as follows. First, the OPF is formulated then the EM and the IEM are presented. Next, the EM and IEM are applied to solve the OPF problem to optimize the power system operating conditions. Finally, some final remarks and points conclude.

## 2. OPF FORMULATION

As mentioned earlier, OPF is a power flow problem that gives the optimal settings of the control variables for a given settings of load by optimizing a predefined objective function while respecting some constraints. Hence, the OPF problem can be formulated as a non-linear constrained optimization problem as follows [16–18]:

$$\begin{array}{ll} \text{minimize} & J(\mathbf{x}, \mathbf{u}), \\ \text{subjectto} & g(\mathbf{x}, \mathbf{u}) = 0 \ , \\ \text{and} & h(\mathbf{x}, \mathbf{u}) \leq 0, \end{array} \quad (1)$$

where $J(\mathbf{x}, \mathbf{u})$ is the objective function, $g(\mathbf{x}, \mathbf{u})$ is the set of equality constraints, $h(\mathbf{x}, \mathbf{u})$is the set of inequality constraints, $\mathbf{u}$ is the vector of independent variables or control variables stated in Eq. (2), and $\mathbf{x}$ is the vector of dependent variables or state variables stated in Eq. (3) respectively.

### 2.1. Control Variables

Control variables are the set of variables that can be modified to satisfy the load flow equations; thus, the vector of control variables $\mathbf{u}$ can be expressed as follows:

$$\begin{aligned} \mathbf{u}^T = & \left[\left\{P_{G_2} \cdots P_{G_{NG}}\right\}, \left\{V_{G_1} \cdots V_{G_{NG}}\right\}, \{T_1 \cdots T_{NT}\}, \right. \\ & \left. \times \{QC_1 \cdots QC_{NC}\}\right], \end{aligned} \quad (2)$$

where

$\{P_{G_2} \cdots P_{G_{NG}}\}$ are the active power generations at the PV buses except at the slack bus;
$\{V_{G_1} \cdots V_{G_{NG}}\}$ are the voltage magnitudes at the PV buses;
$\{T_1 \cdots T_{NT}\}$ are the tap settings of transformers;
$\{QC_1 \cdots QC_{NC}\}$ are the shunt VAR compensations; and
$NG$, $NT$, and $NC$ are the number of generators, regulating transformers, and VAR compensators, respectively.

It is worth mentioning that transformer tap and shunt compensation control variables are discrete in nature. However, these variables can be handled as continuous and set to their nearest discrete value after the optimization for simplicity [19].

### 2.2. State Variables

State variables are the set of variables that describe any unique state of the system; hence, the vector of dependent variables **x** can be expressed as follows:

$$\mathbf{x}^T = \left[P_{G_1}, \left\{V_{L_1} \cdots V_{L_{NL}}\right\}, \left\{Q_{G_1} \cdots Q_{G_{NG}}\right\}, \left\{S_{l_1} \cdots S_{l_{nl}}\right\}\right], \tag{3}$$

where

$P_{G1}$ is the active power output at the slack bus,
$\left\{V_{L_1} \cdots V_{L_{NL}}\right\}$ are the voltage magnitudes at the PQ buses,
$\left\{Q_{G_1} \cdots Q_{G_{NG}}\right\}$ are the reactive power outputs of all generator units,
$\left\{S_{l_1} \cdots S_{l_{nl}}\right\}$ are the transmission line loadings (or lines flow), and
*NL* and *nl* are the number of load buses and transmission lines, respectively.

### 2.3. Objective Constraints

There are two types of OPF constraints: equality and inequality constraints.

#### 2.3.1. Equality Constraints.

The equality constraints of the OPF reflect the physics of the power system represented by the typical power flow equations and are given by

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{NB} V_j \left[G_{ij} \cos\left(\theta_{ij}\right) + B_{ij} \sin\left(\theta_{ij}\right)\right] = 0, \tag{4}$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{NB} V_j \left[G_{ij} \sin\left(\theta_{ij}\right) - B_{ij} \cos\left(\theta_{ij}\right)\right] = 0, \tag{5}$$

where

$\theta_{ij} = \theta_i - \theta_j$, *NB* is the number of buses,
$P_G$ is the active power generation,
$Q_G$ is the reactive power generation,
$P_D$ is the active load demand,
$Q_D$ is the reactive load demand, and
$G_{ij}$ and $B_{ij}$ are the elements of the admittance matrix $\left(Y_{ij} = G_{ij} + jB_{ij}\right)$, representing the conductance and susceptance between bus *i* and bus *j*, respectively.

#### 3.3.2. Inequality Constraints.

The inequality constraints of the OPF reflect the limits on physical devices present in the power system as well as the limits created to guarantee system security. These inequality constraints are as follows:

$$V_{G_i}^{\min} \le V_{G_i} \le V_{G_i}^{\max}, \mathrm{i} = 1, \ldots, NG, \tag{6}$$
$$P_{G_i}^{\min} \le P_{G_i} \le P_{G_i}^{\max}, \mathrm{i} = 1, \ldots, NG, \tag{7}$$
$$Q_{G_i}^{\min} \le Q_{G_i} \le Q_{G_i}^{\max}, \mathrm{i} = 1, \ldots, NG, \tag{8}$$
$$T_i^{\min} \le T_i \le T_i^{\max}, \mathrm{i} = 1, \ldots, NT, \tag{9}$$
$$Q_{C_i}^{\min} \le Q_{C_i} \le Q_{C_i}^{\max}, \mathrm{i} = 1, \ldots, NC, \tag{10}$$
$$V_{L_i}^{\min} \le V_{L_i} \le V_{L_i}^{\max}, \mathrm{i} = 1, \ldots, NL, \tag{11}$$
$$\mathrm{S}_{l_i} \le S_{l_i}^{\max}, \mathrm{i} = 1, \ldots, nl, \tag{12}$$

where Eqs. (6), (7), and (8) represent the generators constraints; Eq. (9) represents the transformers constraints; Eq. (10) represents the shunt VAR compensators constraints; and Eqs. (11) and (12) represent security constraints.

It is worth mentioning that control variables are self-constrained while constraints on state variables can be included into the objective function as quadratic penalty terms, as follows:

$$Penalty = \lambda_P \left(P_{G_1} - P_{G_1}^{\lim}\right)^2 + \lambda_V \sum_{i=1}^{NL} \left(V_{L_i} - V_{L_i}^{\lim}\right)^2 + \lambda_Q \sum_{i=1}^{NG} \left(Q_{G_i} - Q_{G_i}^{\lim}\right)^2 + \lambda_S \sum_{i=0}^{nl} \left(S_{l_i} - S_{l_i}^{\max}\right)^2 \tag{13}$$

and

$$J_{\text{Augmented}} = J + Penalty, \tag{14}$$

where $J_{Augmented}$ is the augmented objective function, *i.e.*, after the inclusion of constraints; $\lambda_P$, $\lambda_V$, $\lambda_Q$, and $\lambda_S$ are penalty coefficients, and $x^{\lim}$ is the limit value of dependent variable *x*. *Penalty* equals 0 if the solution is feasible; otherwise, it takes a value to penalize solutions that are outside the feasible set.

If *x* is higher than the upper limit, $x^{\lim}$ takes the value of this one; likewise, if *x* is lower than the lower limit, $x^{\lim}$ takes the value of this limit.

## 3. EM

### 3.1. Overview

As aforesaid, the EM is a flexible and effective population-based metaheuristic to search for the optimal solution of global optimization problems, by Birbil and Fang in 2003 [14]. It is based on the attraction–repulsion principle of the electromagnetism theory where the population is considered as electrically charged particles spread inside the solution space.

### 3.2. The Initial Version EM

The initial EM method was proposed by Birbil and Fang [14]. In this initial version, the heuristic EM consisted of four stages:

initialization, calculation of the total force exerted on each particle, movement along the direction of the force, and application of local search to exploit the local minima [14]. A fifth stage is now added before initialization: bounds normalization. Each of these five stages is detailed in the flowing sections. The pseudocode of the EM method is given in Algorithm 1. It is worth mentioning that in the present implementation of the EM method, some improvements are added, which are pointed out along with the description of the EM in the following sections.

#### 3.2.1. Bounds Normalization.

The variables to be optimized have different ranges of variation; for example, the power can vary between 50 and 200 MW, while the voltage can vary between 0.95 and 1.1 p.u. To normalize all ranges, *i.e.*, the new range of all variables will be [0, 1], a new stage is introduced—bounds normalization—which can be optional depending on the value of the bounds normalization index called *NormIndex*. If *NormIndex* is selected as ON, bounds normalization is activated; otherwise, if it is selected as OFF, there is no bounds normalization. The most robust approach for transforming variables, regardless of their original ranges, is given as follows:

$$Variable_i^{Normalized} = \frac{Variable_i - Lower\ bound_i}{Upper\ bound_i - Lower\ bound_i}. \tag{15}$$

This stage has improved the convergence speed of the EM.

#### 3.2.2. Initialization.

In the initial version of the EM, this stage consisted of generating $m$ sample points (charges) in a random manner inside the feasible domain consisting of $n$ dimensions, where each dimension is limited by an upper and a lower bound. After a charge is generated, the objective function value for that charge is calculated; the charge that has the best function value is then stored in $x^{best}$ [14, 20]. However, in the developed version, a new parameter $m_0 > m$ is added, called the initial number of charges. Hence, the new initialization stage consists of first generating in a random way $m_0$ charges and evaluating their objective functions, then sorting these objective functions and selecting the first $m$ charges, and finally storing the best charge in $x^{best}$.

The goal of this modification is to use a high number of charges in the initialization stage to have a better distribution of charges in the solution domain. Removing some of these charges for the remaining stages will then consequently reduce the time of simulation.

#### 3.2.3. Local Search.

After the determination of the initial solutions, the second stage is to conduct a local search. A local search can be divided into three kinds: no local search, local search only on current better particle, and local search on all particles [21]. Random selection near the original solution of all points is proposed in the initial version of the EM algorithm [20]. In the developed version of the EM algorithm, a new parameter—*LSIndex*—is added to the program. The role of this index is to specify the nature of the local search to be conducted. Hence, *LSIndex* $= 0$ can be selected for no local search, *LSIndex* $= 1$ can be specified for local search on all particles, and *LSIndex* $= 2$ can be selected for local search on current better charge only.

#### 3.2.4. Total Force Calculation.

In this stage, the force exerted on each charged particle is calculated using the proportion of the charges of that particle and the inverse proportion of the distance between the particles [20]. Hence, the total force exerted on the $i$th particle is determined by

$$F^i = \sum_{\substack{j=1 \\ j \neq i}}^{m} \left\{ \begin{array}{l} \left(x^j - x^i\right) \times \dfrac{q^i q^j}{x^j - x^{i2}} iff \left(x^j\right) < f\left(x^i\right) \\ \left(x^i - x^j\right) \times \dfrac{q^i q^j}{x^j - x^{i2}} iff \left(x^j\right) \geq f\left(x^i\right) \end{array} \right\}, \ \forall i, \tag{16}$$

where $f(x^j) < f(x^i)$ represents attraction and $f(x^j) \geq f(x^i)$ represents repulsion; the virtual charge $q^i$ of the $i$th particle, which determines the power of attraction or repulsion of a particle, is determined by

$$q^i = \exp\left(-n \times \frac{f\left(x^i\right) - f\left(x^{best}\right)}{\sum_{k=1}^{m}\left(f\left(x^k\right) - f\left(x^{best}\right)\right)}\right), \forall i, \tag{17}$$

where $f(x^{best})$ denotes the best cost function value. The particle with the largest charge (*i.e.*, best cost function value) is called the "optimum particle." A particle will have stronger attraction, as it appears near the optimum particle. The particle attracts other particles with better cost function values and repels other particles with the worse cost function values [21]. To improve the efficiency and accuracy by exploring the attraction–repulsion mechanism of the EM algorithm, a study on the effect of charges associated with each particle in the population was reported in [22].

It is obvious that a particle will not produce the force to affect itself. Further, in general, the force in Eq. (16) is normalized as

$$F^i = \frac{F^i}{\| F^i \|}, \forall i. \tag{18}$$

This stage is represented in Algorithm 1 between lines 8 and 20.

In [23], a modified expression a force was proposed. Therefore, an index in the EM method is introduced—*CalcFIndexM*. If $CalcFIndexM = 1$, the original expression of force is used, and if $CalcFIndexM = 2$, the modified expression of force is used.

3.2.5. Movement of Particles.

The final stage involves moving along the orientation of the resultant force. After calculating the total force on one particle, this particle moves by a random step length in the path of the force to cause the particles to move into any unvisited zones along this path.

The update of each particle depends on the resultant force and is given by

$$x^i = \begin{cases} x^i + \alpha \times F^i \times \left(b_{upper} - x^i\right) if F^i > 0 \\ x^i + \alpha \times F^i \times \left(x^i - b_{lower}\right) if F^i \leq 0 \end{cases}, \forall i; \mathrm{i} \neq best, \tag{19}$$

where $b_{upper}$ is the upper bound, $b_{lower}$ is the lower bound, and $\alpha$ is a random value uniformly distributed between 0 and 1. If the resultant force is positive, the particle moves toward the upper bound by a random step length $\alpha$, whereas it moves toward the lower bound if the resultant force is negative. In the mechanism, the optimum particle of the population does not move, because it has the best cost function value and then attracts all other particles [21].

This stage is represented in Algorithm 1 between lines 21 and 33.

3.2.6. Termination Criterion.

The second through the fifth stages are repeated until a termination criterion is reached. The termination criterion can be:

- the maximum number of iterations and/or
- the amount of iterations performed without replacing the current optimal solution.

For the second criterion, the decision of stopping the algorithm has to be studied carefully since the algorithm may be stopped before converging to the global optimum. In this study, the maximum number of iterations is used as stopping criterion as in the initial version of the EM.

Algorithm 1: The pseudocode of the EM.

1. $n$: dimension of the problem
2. $m$: population size
3. *MAXITER*: maximum number of iterations
4. BoundsNormalization()
5. $[x, x^{best}]$ = Initialization()
6. while $ITER < MAXITER$
7. LocalSearch()
   Total force calculation
8. for $i = 1{:}\ m$
9. $\quad q^i = \exp\left(-n \times \frac{f(x^i)-f(x^{best})}{\sum_{k=1}^{m}\left(f(x^k)-f(x^{best})\right)}\right)$
10. $\quad F^i \leftarrow 0$
11. End for
12. for $i = 1{:}\ m$
13. $\quad$ for $j = 1{:}\ m$
14. $\quad\quad$ if $f\left(x^j\right) < f\left(x^i\right)$
15. $\quad\quad\quad F^i \leftarrow F^i + \left(x^j - x^i\right) \times \frac{q^i q^j}{\|x^j - x^i\|^2}$
16. $\quad\quad$ else
17. $\quad\quad\quad F^i \leftarrow F^i - \left(\|x^j - x^i\|\right) \times \frac{q^i q^j}{\|x^j - x^i\|^2}$
18. $\quad\quad$ end if
19. $\quad$ end for
20. end for
21. for $i = 1{:}\ m$ Movement of particles
22. $\quad\quad$ if $i \neq$ best
23. $\quad\quad\quad \alpha \leftarrow$ rand (0, 1)
24. $\quad\quad\quad F^i \leftarrow \frac{F^i}{\|F^i\|}$
25. $\quad\quad\quad$ for $k = 1{:}\ n$
26. $\quad\quad\quad\quad$ if $F^i > 0$
27. $\quad\quad\quad\quad\quad x^i + \alpha \times F^i \times \left(b_{upper} - x^i\right)$
28. $\quad\quad\quad\quad$ else
29. $\quad\quad\quad\quad\quad x^i + \alpha \times F^i \times \left(x^i - b_{lower}\right)$
30. $\quad\quad\quad\quad$ end if
31. $\quad\quad\quad$ end for
32. $\quad\quad$ end if
33. $\quad$ end for
34. end while

### 3.3. The Improved Version of IEM

The pseudocode of the IEM method is shown in Algorithm 2. In this version, the initialization stage remains the same; however, the local search stage is removed. Moreover, the force calculation stage has changed; a particle $i$ interacts with two other particles $j$ and $k$ ($i \neq j \neq k$) randomly selected as shown in lines 9 and 10 in Algorithm 2. It is assumed that all charges have a virtual value of $q^i = 1$. Hence, the total force exerted on the $i$th particle is the sum of the forces exerted by particles $j$ and $k$, determined by

$$F^i = \frac{\left(x^j - x^i\right)}{\|x^j - x^i\|^3} + \frac{\left(x^k - x^i\right)}{\|x^k - x^i\|^3}. \tag{20}$$

Likewise, for particles $j$ and $k$, the total forces exerted on them are given by

$$F^j \leftarrow \frac{\left(x^i - x^j\right)}{\|x^i - x^j\|^3} + \frac{\left(x^k - x^j\right)}{\|x^k - x^j\|^3}, \tag{21}$$

$$F^k \leftarrow \frac{\left(x^i - x^k\right)}{\|x^i - x^k\|^3} + \frac{\left(x^j - x^k\right)}{\|x^j - x^k\|^3}. \tag{22}$$

After calculating the total force on the three particles ($i$, $j$, $k$), these particles move according to the following equations:

$$x^i \leftarrow x^i + \text{rand}(0,1) \times \left(x^{best} - x^i\right) + \text{rand}(0,1) \times F^i, \tag{23}$$

$$x^j \leftarrow x^j + \text{rand}(0,1) \times \left(x^{best} - x^j\right) + \text{rand}(0,1) \times F^j, \tag{24}$$

$$x^k \leftarrow x^k + \text{rand}(0,1) \times \left(x^{best} - x^k\right) + \text{rand}(0,1) \times F^k. \tag{25}$$

After that, the new best particle is recalculated (line 17), and a comparison between the "best particle" and the newly calculated "best particle" is done to keep or update the best particle. Thus, if $f\left(x^{best}_{New}\right) < f\left(x^{best}\right)$, then the best particle is updated; *i.e.*, $x^{best} \leftarrow x^{best}_{New}$.

Finally, the termination criteria in the IEM are the same as in the EM.

Algorithm 2: The pseudocode of the IEM.

1. $n$: dimension of the problem
2. $m$: population size
3. *MAXITER*: maximum number of iterations
4. BoundsNormalization()
5. $[x, x^{best}]$ = Initialization()
6. while $ITER < MAXITER$
7.     for $i = 1{:}\ m$
8.         $j \leftarrow \text{rand}i(m)$ $(j \neq i)$
9.         $k \leftarrow \text{rand}i(m)$ $(k \neq i)$ and $(k \neq j)$
10.         $F^i \leftarrow \frac{\left(x^j - x^i\right)}{\|x^j - x^i\|^3} + \frac{\left(x^k - x^i\right)}{\|x^k - x^i\|^3}$
11.         $F^j \leftarrow \frac{\left(x^i - x^j\right)}{\|x^i - x^j\|^3} + \frac{\left(x^k - x^j\right)}{\|x^k - x^j\|^3}$
12.         $F^k \leftarrow \frac{\left(x^i - x^k\right)}{\|x^i - x^k\|^3} + \frac{\left(x^j - x^k\right)}{\|x^j - x^k\|^3}$
13.         $x^i \leftarrow x^i + \text{rand}(0,1) \times \left(x^{best} - x^i\right) + \text{rand}(0,1) \times F^i$
14.         $x^j \leftarrow x^j + \text{rand}(0,1) \times \left(x^{best} - x^j\right) + \text{rand}(0,1) \times F^j$
15.         $x^k \leftarrow x^k + \text{rand}(0,1) \times \left(x^{best} - x^k\right) + \text{rand}(0,1) \times F^k$
16.         $x^{best}_{New} \leftarrow argmin\left(f\left(x^i\right), \forall i\right)$
17.         if $f\left(x^{best}_{New}\right) < f\left(x^{best}\right)$
18.         $x^{best} \leftarrow x^{best}_{New}$
19.         end if
20.     end for
21. end while

In addition to these modifications and improvements, there are some other general improvements of the initial version that have been made herein. Obviously, the EM has been initially developed to solve optimization problems with a mathematical function as objective functions, *i.e.*, where the computation time is very small. However, in this application, the simulation time is crucial; therefore, some numerical improvements in the IEM code have been done, helping to decrease significantly the simulation time. In this study, the simulation time has been reduced by almost 80%.

## 4. RESULTS AND DISCUSSIONS

To assess the effectiveness of the proposed IEM method, it has been applied to solve the OPF problem for different cases and has been tested on the standard IEEE 30-bus and IEEE 57-bus test systems. To show the improvements achieved using the IEM method, its results are presented along with those of the EM method for the investigated cases. Furthermore, in Section 4.3, a detailed comparison is made between these two methods.

The developed program is implemented using the MATLAB (The MathWorks, Natick, Massachusetts, USA) computing environment, applied on a 2.20-GHz i7 laptop with 8.00 GB-RAM (Lenovo, Beijing, China). Initially, several runs have been done with different key parameters of the EM to identify the best combination. In the present study, the EM parameters are summarized in Table 1.

### 4.1. The IEEE 30-bus Test System

This test system has 30 buses, 41 branches, 6 generators, 9 shunts, 4 transformers, and, consequently, 24 control variables.

| Name | Value | Description |
|---|---|---|
| $x_0$ | Initial operating conditions | Initial value if any |
| $n$ | 24 | Dimension of the problem |
| $m_0$ | 100 | Number of initial sample points |
| $m$ | 10 | Number of sample points |
| *MAXITER* | 500 | Maximum number of iterations |
| *LSITER* | 10 | Maximum number of local search iterations |
| $\delta$ | 0.05 | Local search parameter∈ [0, 1] |
| $\nu$ | 0.5 | Parameter for the EM algorithm |
| *LSIndex* | — | Index for local search method; 0: no local search, 1: local search only on current better particle, and 2: local search on best values only |
| *Calc FIndexM* | — | Index for force calculation method; 1: initial method and 2: modified method |
| *NormIndex* | — | Index for normalization of bounds: ON: bounds normalization and OFF: no bounds normalization |

**TABLE 1.** EM key parameters

Therefore, the vector of control variables can be expressed as follows:

$$\boldsymbol{u}^T = \begin{bmatrix} \{P_{G_2}, P_{G_5}, P_{G_8}, P_{G_{11}}, P_{G_{13}}\} \\ \{V_{G_1}, V_{G_2}, V_{G_5}, V_{G_8}, P_{G_{11}}, V_{G_{13}}\} \\ \{T_{11}, T_{12}, T_{15}, T_{36}\} \\ \{Q_{c_{10}}, Q_{c_{12}}, Q_{c_{15}}, Q_{c_{17}}, Q_{c_{20}}, Q_{c_{21}}, Q_{c_{23}}, Q_{c_{24}}, Q_{c_{29}}\} \end{bmatrix} . \quad (26)$$

More details about this system can be found in [24–26].

4.1.1. Case 1: Minimization of Generation Fuel Cost.

In this case, the minimization of the generation fuel cost is considered. Hence, objective function $J$ represents the total fuel cost of all generator units, expressed as follows:

$$J_{\text{Augmented}} = \sum_{i=1}^{NG} f_i + \text{Penalty}, \quad (27)$$

where $f_i$ is the fuel cost of the $i$th generator, expressed by the following quadratic function:

$$f_i = a_i + b_i P_{Gi} + c_i P_{Gi}^2 \,(\$/\text{hr}), \quad (28)$$

where $a_i$, $b_i$, and $c_i$ are the basic, linear, and quadratic cost coefficients of the $i$th generator; the values of these coefficients were given in [26]. The penalty coefficients, λ, are selected as $1 \times 10^6$ to exclude the unfeasible solutions. The procedure of how to select penalty terms was explained in [27].

The variation of total fuel cost (representing the convergence characteristic of the proposed IEM method) is depicted in Figure 1. This figure shows the excellent convergence performance of the IEM method. The optimal settings of control variables obtained using the EM method are given in Table 2, and those obtained using the IEM method are given in Table 3 The total fuel cost obtained by the EM and IEM methods are \$800.0781/hr and \$799.1821/hr, respectively. This shows the superiority if the proposed IEM over the EM. The total fuel cost obtained using the IEM method is considerably reduced (11.39%) compared to the initial operating point (\$901.9516/hr). It is worth mentioning that the initial operating point has voltage violation at buses {19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, and 30}. Using the IEM method, these voltage violations have been alleviated.

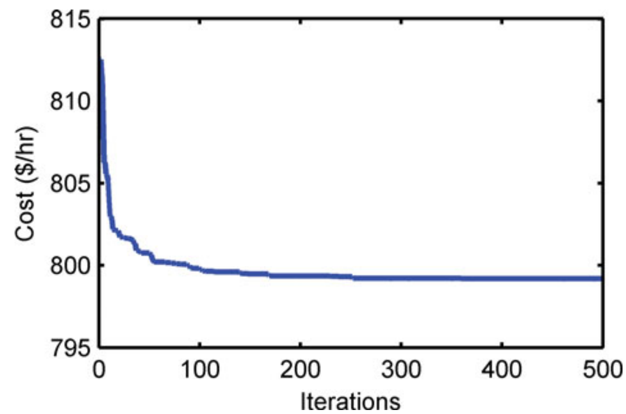


**FIGURE 1.** Fuel cost variation for Case 1.

It is worth mentioning here that the results found in this case using the EM method have been carried out using a local search only on current better particle (*i.e.*, *LSIndex* = 2), the first method for force calculation (*i.e.*, *CalcFIndexM* = 1), and with bound normalization (*i.e.*, *NormIndex* = ON). Using *LSIndex* = 0, *CalcFIndexM* = 2, and *NormIndex* = ON gives a total fuel cost of \$800.4837/hr. However, since there in no local search, the calculation time is reduced. Using *LSIndex* = 0, *CalcFIndexM* = 2, and *NormIndex* = OFF gives a total fuel cost of \$801.2197/hr. This last result shows the improvement obtained using the bound normalization step.

Using the same conditions (control variables limits, initial conditions, and system data), the results obtained in Case 1 using the EM and IEM methods are compared to some other methods reported in the literature, as shown in Table 4 It is clear from Table 4 that the IEM method outperforms many other methods used to solve the OPF problem. In addition, a comparison study of the computational time between the proposed IEM and other well-known optimization methods has been carried out for this case. The results show that the proposed method has lower computational time, as given in Table 5

| | Minimum | Maximum | Initial | Case 1 | Case 2 | Case 3 | Case 4 | Case 5 | Case 6 |
|---|---|---|---|---|---|---|---|---|---|
| $P_{G_1}$ | 50 | 200 | 99.2230 | 174.4387 | 177.1969 | 164.0252 | 56.5403 | 64.0008 | 139.9484 |
| $P_{G_2}$ | 20 | 80 | 80 | 48.1710 | 48.9791 | 45.8153 | 78.3450 | 75.0319 | 54.9924 |
| $P_{G_5}$ | 15 | 50 | 50 | 20.8907 | 20.5304 | 19.8823 | 48.9589 | 48.1465 | 25.8824 |
| $P_{G_8}$ | 10 | 35 | 20 | 20.5925 | 17.9008 | 31.3544 | 34.6278 | 32.7775 | 32.4979 |
| $P_{G_{11}}$ | 10 | 30 | 20 | 13.4993 | 13.2958 | 13.9006 | 29.3071 | 28.9746 | 14.3995 |
| $P_{G_{13}}$ | 12 | 40 | 20 | 14.4318 | 15.4706 | 17.2284 | 38.7976 | 37.9527 | 23.1257 |
| $V_{G_1}$ | 0.95 | 1.1 | 1.05 | 1.0908 | 1.0535 | 1.0712 | 1.0946 | 1.0927 | 1.0378 |
| $V_{G_2}$ | 0.95 | 1.1 | 1.04 | 1.0788 | 1.0329 | 1.0578 | 1.0884 | 1.0885 | 1.0295 |
| $V_{G_5}$ | 0.95 | 1.1 | 1.01 | 1.0520 | 1.0157 | 1.0472 | 1.0732 | 1.0764 | 1.0030 |
| $V_{G_8}$ | 0.95 | 1.1 | 1.01 | 1.0604 | 1.0096 | 1.0702 | 1.0825 | 1.0910 | 1.0187 |
| $V_{G_{11}}$ | 0.95 | 1.1 | 1.05 | 1.0853 | 0.9867 | 1.0767 | 1.0996 | 1.0160 | 1.0630 |
| $V_{G_{13}}$ | 0.95 | 1.1 | 1.05 | 1.0845 | 0.9974 | 1.0739 | 1.0989 | 1.0659 | 1.0610 |
| $T_{11}$ | 0.9 | 1.1 | 1.078 | 1.0359 | 0.9845 | 1.0746 | 0.9511 | 1.0874 | 1.0107 |
| $T_{12}$ | 0.9 | 1.1 | 1.069 | 0.9227 | 0.9304 | 1.0665 | 1.0895 | 0.9879 | 0.9444 |
| $T_{15}$ | 0.9 | 1.1 | 1.032 | 1.0049 | 0.9359 | 0.9352 | 1.0783 | 1.0232 | 1.0183 |
| $T_{36}$ | 0.9 | 1.1 | 1.068 | 0.9814 | 0.9632 | 0.9307 | 1.0093 | 1.0461 | 0.9842 |
| $Q_{C10}$ | 0 | 5 | 0 | 3.6724 | 4.0498 | 4.3110 | 4.9422 | 3.2124 | — |
| $Q_{C12}$ | 0 | 5 | 0 | 4.4120 | 0.6815 | 4.1757 | 0.0530 | 4.7420 | — |
| $Q_{C15}$ | 0 | 5 | 0 | 3.9357 | 4.2492 | 4.0770 | 2.2453 | 4.1200 | — |
| $Q_{C17}$ | 0 | 5 | 0 | 4.4873 | 1.4505 | 4.1075 | 4.8953 | 1.8437 | — |
| $Q_{C20}$ | 0 | 5 | 0 | 4.5202 | 4.3856 | 4.2206 | 0.0086 | 3.1539 | — |
| $Q_{C21}$ | 0 | 5 | 0 | 3.7935 | 3.6199 | 4.1565 | 0.3414 | 3.2219 | — |
| $Q_{C23}$ | 0 | 5 | 0 | 3.9689 | 4.0993 | 4.2233 | 0.0085 | 4.6849 | — |
| $Q_{C24}$ | 0 | 5 | 0 | 4.5687 | 4.3813 | 4.1191 | 4.9958 | 3.1210 | — |
| $Q_{C29}$ | 0 | 5 | 0 | 3.3512 | 1.9145 | 4.1472 | 4.8063 | 2.8779 | — |
| Fuel cost (\$/hr) | — | — | 901.9516 | **800.0781** | **804.2600** | **802.9516** | 954.3150 | 939.4832 | **650.9371** |
| Active power loss (MW) | — | — | 5.8219 | 8.6232 | 9.9735 | 9.3428 | **3.1775** | 3.4851 | 7.4449 |
| Reactive power loss (MVAR) | — | — | –4.6066 | 2.7154 | 10.4977 | 6.7435 | –16.8510 | **–22.0196** | 2.1658 |
| Voltage deviations | — | — | 1.1496 | 1.3829 | **0.1270** | 1.6033 | 1.2599 | 0.7773 | 0.3375 |
| $L_{\max}$ | — | — | 0.1723 | 0.1221 | 0.1379 | **0.1156** | 0.1253 | 0.1330 | 0.1515 |

**TABLE 2.** Optimal settings of the control variables obtained using EM for Cases 1 through 6

Bold indicates the best value for each objective function.



4.1.2. Case 2: Voltage Profile Improvement.

In Case 1, the objective was the minimization of total fuel cost, which may give a feasible solution to the OPF problem. However, there is no guarantee on the quality of buses voltage, which represents one of the most important and significant safety and service quality indexes. Therefore, the second case tries to minimize the fuel cost and improve voltage profile at the same time. The fuel cost is considered as the sum of all generator costs represented by quadratic functions (as in Case 1), while the improvement of voltage profile is represented by the voltage deviation of load buses from the unity 1.0. Thus, the objective function can be expressed as follows:

$$J_{Cost} = \sum_{i=1}^{NG} f_i, \tag{29}$$

$$J_{Voltage\ Deviation} = \sum_{i=1}^{NL} |V_i - 1.0|, \tag{30}$$

$$J_{\text{Augmented}} = J_{Cost} + wJ_{Voltage\ Deviation} + Penalty, \tag{31}$$

where $w$ is a suitable weighting factor that has to be selected carefully to give a weight or an importance to each one of the

| | Case 1 | Case 2 | Case 3 | Case 4 | Case 5 | Case 6 |
|---|---|---|---|---|---|---|
| $P_{G_1}$ | 177.3818 | 172.8769 | 182.8306 | 51.4431 | 51.4349 | 139.7899 |
| $P_{G_2}$ | 48.8881 | 49.4273 | 54.9068 | 80.0000 | 80.0000 | 54.8879 |
| $P_{G_5}$ | 20.9802 | 22.0231 | 20.5406 | 50.0000 | 50.0000 | 29.4862 |
| $P_{G_8}$ | 20.7776 | 21.6505 | 12.0129 | 35.0000 | 35.0000 | 23.4057 |
| $P_{G_{11}}$ | 12.0755 | 13.2805 | 10.4990 | 30.0000 | 30.0000 | 22.5204 |
| $P_{G_{13}}$ | 12.0591 | 13.7104 | 12.2902 | 40.0000 | 40.0000 | 20.8819 |
| $V_{G_1}$ | 1.1000 | 1.0418 | 1.0984 | 1.1000 | 1.1000 | 1.0318 |
| $V_{G_2}$ | 1.0882 | 1.0260 | 1.0849 | 1.1000 | 1.1000 | 1.0220 |
| $V_{G_5}$ | 1.0594 | 1.0056 | 1.0868 | 1.0847 | 1.0939 | 1.0132 |
| $V_{G_8}$ | 1.0663 | 1.0070 | 1.0799 | 1.0900 | 1.1000 | 1.0134 |
| $V_{G_{11}}$ | 1.0931 | 1.0494 | 1.0951 | 1.1000 | 1.1000 | 0.9990 |
| $V_{G_{13}}$ | 1.0930 | 0.9930 | 1.0979 | 1.1000 | 1.1000 | 0.9999 |
| $T_{11}$ | 0.9693 | 1.0407 | 1.0743 | 0.9659 | 1.0121 | 1.0659 |
| $T_{12}$ | 1.0188 | 0.9088 | 0.9369 | 1.1000 | 0.9000 | 0.9882 |
| $T_{15}$ | 1.0261 | 0.9400 | 0.9858 | 1.0991 | 0.9870 | 1.0185 |
| $T_{36}$ | 0.9676 | 0.9551 | 0.9603 | 1.0106 | 0.9816 | 0.9853 |
| $Q_{C10}$ | 2.1615 | 3.5190 | 4.5861 | 5.0000 | 0.6417 | 0.0000 |
| $Q_{C12}$ | 1.4157 | 4.0677 | 2.1986 | 4.7616 | 0.0299 | 0.0000 |
| $Q_{C15}$ | 2.1081 | 2.1899 | 4.2670 | 1.8196 | 4.4270 | 0.0000 |
| $Q_{C17}$ | 3.5840 | 1.9084 | 4.9519 | 4.9851 | 0.0000 | 0.0000 |
| $Q_{C20}$ | 0.3146 | 4.3662 | 4.6863 | 3.9828 | 5.0000 | 0.0000 |
| $Q_{C21}$ | 4.5322 | 2.9480 | 3.0805 | 2.5397 | 4.9813 | 0.0000 |
| $Q_{C23}$ | 2.4954 | 3.5070 | 2.0383 | 2.1150 | 0.0098 | 0.0000 |
| $Q_{C24}$ | 4.2871 | 2.8149 | 4.9788 | 0.0123 | 0.0225 | 0.0000 |
| $Q_{C29}$ | 0.0476 | 1.3276 | 4.8540 | 5.0000 | 4.0354 | 0.0000 |
| Fuel cost ($/hr) | **799.1821** | **804.1084** | **799.8349** | 967.1147 | 967.2229 | **649.6309** |
| Active power loss (MW) | 8.6591 | 9.9423 | 8.9477 | **2.8699** | 2.9186 | 7.2769 |
| Reactive power loss (MVAR) | –3.2917 | 6.3781 | –2.4154 | –24.8978 | –**25.1422** | –2.5608 |
| Voltage deviations | 1.7698 | **0.1063** | 1.9227 | 1.9830 | 2.0860 | 0.5941 |
| $L_{max}$ | 0.1176 | 0.1371 | **0.1144** | 0.1156 | 0.1162 | 0.1294 |

**TABLE 3.** Optimal settings of the control variables obtained using IEM for Cases 1 through 6.

Bold indicates the best value for each objective function.

two terms of the objective function. In this study, $w$ is chosen as 100.

The IEM method has been applied to solve this case; the variation of total fuel cost over the iterations is sketched in Figure 2 From Tables 2 and 3, the fuel cost and voltage deviation obtained using the IEM are \$804.1084/hr and 0.1063 p.u., respectively, while those obtained using the EM are \$804.2600/hr and 0.1270 p.u., respectively. The system voltage profile in this case is compared with that of Case 1 in Figure 3 It can be noticed that the voltage profile is greatly improved compared with that of Case 1. It is reduced from 1.3829 p.u. in Case 1 to 0.1063 p.u., representing a reduction of 92.31% n Case 2 using the IEM method (a reduction of 90.82% is obtained using the EM method). However, in this case, the fuel cost is slightly increased compared to Case 1.

The results obtained in this case using the EM method have been carried out using $LSIndex = 2$, $CalcFIndexM = 1$, and $NormIndex =$ ON. Good results are also obtained using $LSIndex = 0$, $CalcFIndexM = 2$, and $NormIndex =$ ON (the fuel cost and the voltage deviation obtained are \$804.7737/hr and 0.1319 p.u., respectively).

Using the same operating conditions, the results of this case are compared to some other methods reported in the literature, as shown in Table 6 It is clear from this table that the IEM method gives excellent results for solving the OPF problem by minimization of generation fuel cost and improvement of voltage profile at the same time.

| Method/description | Cost | Reference |
|---|---|---|
| IEM | 799.1821 | |
| League championship algorithm (LCA) | 799.1974 | [28] |
| DE | 799.2891 | [26] |
| SA | 799.45 | [29] |
| EM | 800.078 | |
| Genetic evolving ant direction HDE (EADHDE) | 800.1579 | [30] |
| Evolving ant direction DE (EADDE) | 800.2041 | [31] |
| PSO | 800.41 | [24] |
| Fuzzy PSO (FPSO) | 800.72 | [32] |
| Improved GA (IGA) | 800.805 | [33] |
| PSO | 800.96 | [32] |
| Fuzzy GA (GAF) | 801.21 | [32] |
| Imperialist competitive algorithm (ICA) | 801.843 | [34] |
| Enhanced GA (EGA) | 802.06 | [35] |
| TS | 802.2900 | [36] |
| Modified DE (MDE) algorithm | 802.376 | [37] |
| Improved evolutionary programming (IEP) | 802.465 | [38] |
| Evolutionary programming (EP) | 802.62 | [39] |
| Refined GA (RGA) | 804.02 | [40] |
| Gradient method (GM) | 804.853 | [25] |
| GA | 805.94 | [40] |

**TABLE 4.** Comparison of the simulation results for Case 1.

### 4.1.3. Case 3: Voltage Stability Enhancement.

Influenced by many economic and environmental constraints, transmission systems are forced more and more often to work close to their security limits. However, one important characteristic of the power system is its ability to conserve constantly acceptable voltage at each bus under normal operating conditions, after load increase, following system configuration changes or when the system is being subjected to a disturbance. However, the non-optimized control variables

| Method | Execution time for one iteration |
|---|---|
| IEM | 0.5688 |
| GA | 0.5733 |
| DE | 0.8870 |
| PSO | 1.0402 |

**TABLE 5.** Comparison of the simulation results for Case 1.

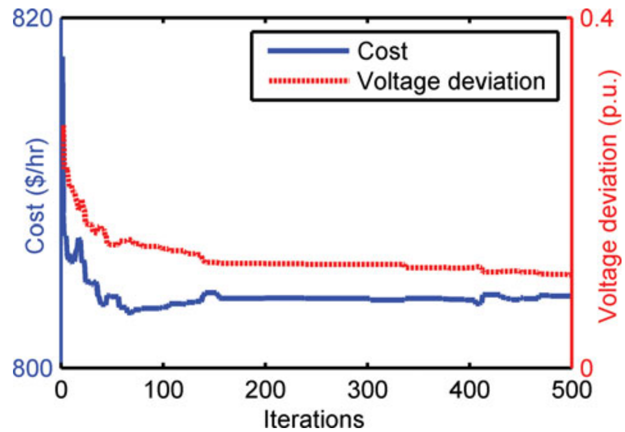


**FIGURE 2.** Fuel cost variation for Case 2.

may lead to progressive and uncontrollable drop in voltage, resulting in an eventual widespread voltage collapse [41].

Consequently, voltage stability studies have become a subject of paramount importance and an issue to be addressed by electric utility. Many works have been made to assess voltage stability of a given network; accordingly Kessel and Glavitsch [42] developed a voltage stability index based on the feasibility of power flow equations for each node.

For a power system with $NB$, $NG$, and $NL$ buses representing the total number of buses, total number of generator buses, and total number of load buses, respectively, buses can be separated into two parts: generator buses at the head and load buses at the tail, as follows:

$$\begin{bmatrix} I_L \\ I_G \end{bmatrix} = [Y_{bus}] \begin{bmatrix} V_L \\ V_G \end{bmatrix} = \begin{bmatrix} Y_{LL} & Y_{LG} \\ Y_{GL} & Y_{GG} \end{bmatrix} \begin{bmatrix} V_L \\ V_G \end{bmatrix}, \tag{32}$$

where $Y_{LL}$, $Y_{LG}$, $Y_{GL}$, and $Y_{GG}$ are submatrices of $Y_{bus}$.

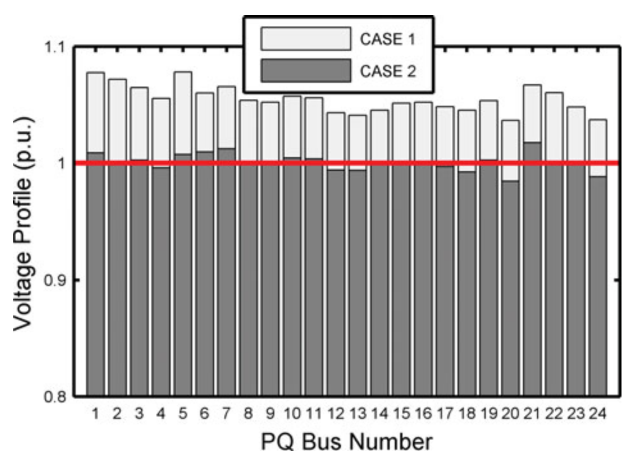


**FIGURE 3.** System voltage profile improvement.

| Methods | Cost | Voltage deviation |
|---|---|---|
| IEM | 804.1084 | 0.1063 |
| EM | 804.26 | 0.127 |
| BBO | 804.9982 | 0.102 |
| DE | 805.2619 | 0.1357 |
| PSO | 806.38 | 0.0891 |

**TABLE 6.** . Comparison of the simulation results for Case 2.

The following hybrid system of equations can be written:

$$\begin{bmatrix} V_L \\ I_G \end{bmatrix} = [H]\begin{bmatrix} I_L \\ V_G \end{bmatrix} = \begin{bmatrix} H_{LL} & H_{LG} \\ H_{GL} & H_{GG} \end{bmatrix}\begin{bmatrix} I_L \\ V_G \end{bmatrix}, \tag{33}$$

where

$H$ is generated by the partial inversion of $Y_{bus}$;
$H_{LL}$, $H_{LG}$, $H_{GL}$, and $H_{GG}$ are sub matrix of $H$; and
$V_G$, $I_G$, $V_L$, and $I_L$ are voltage and current vector of generator buses and load buses, respectively.

The matrix $H$ is given by

$$[H] = \begin{bmatrix} Z_{LL} & -Z_{LL}Y_{LG} \\ Y_{GL}Z_{LL} & Y_{GG} - Y_{GL}Z_{LL}Y_{LG} \end{bmatrix} Z_{LL} = Y_{LL}^{-1}. \tag{34}$$

Therefore, the stability index of bus $j$, denoted by $L_j$, is represented by

$$L_j = \left| 1 - \sum_{i=1}^{NG} H_{LGji} \frac{V_i}{V_j} \right| j = 1, 2, \ldots, NL. \tag{35}$$

For stable situations, condition $L_j \leq 1$ must not be violated for any bus $j$; hence, a global indicator $L_{\max}$ describing the stability of the complete system is given by [42]

$$L_{\max} = \max\left(L_j\right) j = 1, 2, \ldots, NL. \tag{36}$$

Recall that the $L$ index of a bus indicates the proximity of that bus to the voltage collapse condition. It varies between 0 and 1, corresponding to no load and voltage collapse, respectively. The lower the $L$ is in a bus, the more stable the bus is. Thus, the minimization of global index $L_{\max}$ enhances the stability of the whole system.

Since the objective of this case is the minimization of the total fuel cost and enhancement of the voltage stability of the system, it can be expressed as follows:

$$J_{Cost} = \sum_{i=1}^{NG} f_i, \tag{37}$$

$$J_{Voltage\ Stability\ Enhancement} = L_{\max}, \tag{38}$$

$$J_{\text{Augmented}} = J_{Cost} + wJ_{Voltage\ Stability\ Enhancement} + Penalty, \tag{39}$$

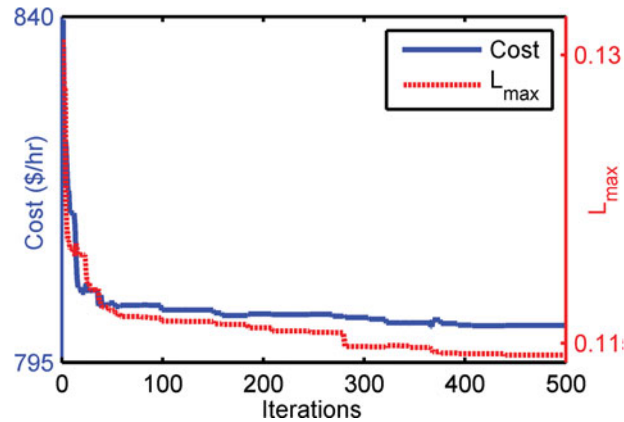


**FIGURE 4.** Fuel cost variation for Case 3.

where $w$ is a weighting factor, set as 6000 in this study, as in [8, 26].

After applying the IEM method, it can be seen from Table 3 that the value of $L_{\max}$ is significantly reduced in this case compared to Case 1 and Case 2. Consequently, distance from collapse point is increased. Figure 4 shows the variation of fuel cost over iterations.

It is worth mentioning that the results obtained in this case using the EM method have been carried out using $LSIndex = 2$, $CalcFIndexM = 1$, and $NormIndex = \text{ON}$.

The obtained results in this case are compared with some other methods reported in the literature, as shown in Table 7 It is clear from this table that the proposed IEM method gives excellent results for solving the OPF problem by simultaneous minimization of generation fuel cost and enhancement of voltage stability.

### 4.1.4. Case 4: Minimization of Active Power Transmission Loss.

In this case, the OPF problem goal is to minimize the active power transmission loss; thus, the objective function can be expressed as follows:

$$J_{\text{Augmented}} = \sum_{i=1}^{NB} P_{Gi} - \sum_{i=1}^{NB} P_{Di} + Penalty$$

| Methods | Cost | $L_{\max}$ |
|---|---|---|
| IEM | 799.8349 | 0.1144 |
| EM | 805.058 | 0.1167 |
| BBO | 805.7252 | 0.1104 |
| DE | 807.5272 | 0.1219 |
| PSO | 801.16 | 0.1246 |

**TABLE 7.** Comparison of the simulation results for Case 3.

$$= \sum_{i=1}^{NB} P_i + Penalty. \quad (40)$$

Figure 5 shows the trend for minimizing the total active power transmission loss using the proposed IEM method. The optimal settings of control variables using the EM and IEM methods are given in Table 2 and 3, respectively. Compared with the initial case, the total active power transmission loss has decreased 45.42% using the EM method, from 5.8219 to 3.1775 MW, and 49.87% using the IEM method, from 5.8219 to 2.9186 MW. However, other objective functions became slightly worse, for example, the total fuel cost.

#### 4.1.5. Case 5: Minimization of Reactive Power Transmission Loss.

The reactive power transmission loss is minimized using the following equation:

$$J_{\text{Augmented}} = \sum_{i=1}^{NB} Q_{Gi} - \sum_{i=1}^{NB} Q_{Di} + Penalty = \sum_{i=1}^{NB} Q_i + Penalty. \quad (41)$$

Notice that the reactive power loss is not necessarily positive.

After optimization, the optimal settings of control variables are given in Tables 2 and 3. The reactive power loss minimization study has resulted in –22.0196 MVAR using the EM method and –25.1422 MVAR using the IEM method. However, other objective functions in this case became worse, for example, the total cost. Figure 6 shows the trend for minimizing the reactive power transmission loss using the IEM method.

#### 4.1.6. Case 6: Piecewise Quadratic Fuel Cost Curve.

In practice, many thermal generating units may be supplied with multiple fuel sources. Therefore, the fuel cost functions (curves) can be divided as piecewise quadratic cost functions

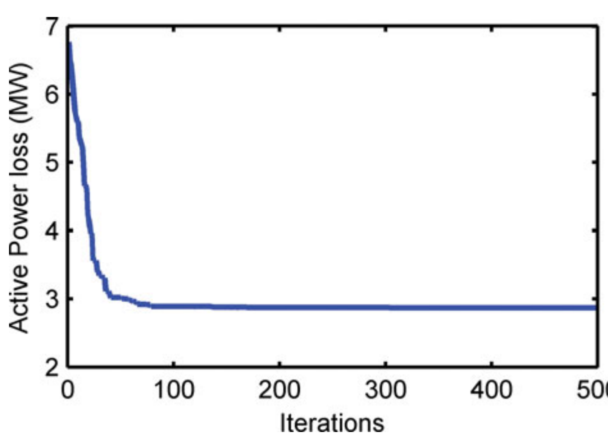


**FIGURE 5.** Minimization of active power transmission loss.

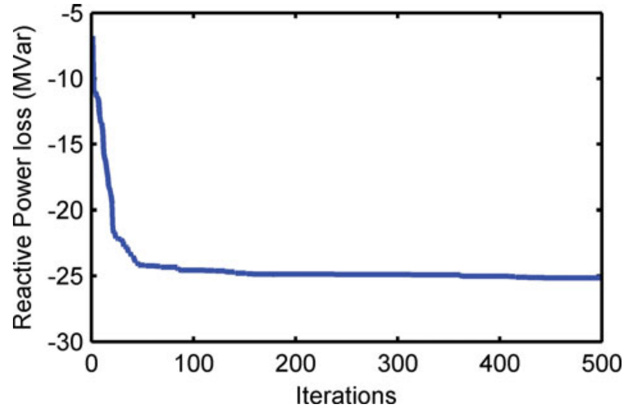


**FIGURE 6.** Minimization of reactive power transmission loss.

for various fuel types [26]. Thus, the problem is no longer a convex one, which can lead traditional methods to be trapped into local optimal solutions. In this case, the fuel cost function is given as follows:

$$J_{\text{Augmented}} = \sum_{i=1}^{NG} f_i + Penalty, \quad (42)$$

where the fuel cost curve is expressed by the following piecewise quadratic function:

$$f_i = a_{ik} + b_{ik}P_i + c_{ik}P_i^2 \text{if } P_{ik}^{\min} \le P_i \le P_{ik}^{\max}, \quad (43)$$

where $k$ is the fuel option.

In this study, the generators of buses 1 and 2 have two fuel options, and hence, $k = 2$. The fuel cost coefficients of these generators were given in [26], while the coefficients of the remaining generators are those of Case 1. To compare the results with those reported in [26] the upper limit of voltage magnitude at bus 1 is set as 1.05 and no reactive compensation is considered.

The optimal settings of control variables are given in Tables 2 and 3 The fuel cost minimization study has resulted in \$649.6309/hr using the IEM method and \$650.9371/hr using the EM method. Figure 7 shows the trend for minimizing the fuel cost objective function over iterations using the IEM method.

Using the same conditions, the results obtained in Case 6 are compared with the DE method, as shown in Table 8 It is clear from Table 8 that the proposed method presents excellent results to solve the OPF problem by minimization of generation fuel cost with piecewise cost functions.

### 4.2. The IEEE 57-bus Test System

To test the scalability of the EM and IEM to larger systems, they have been applied to the IEEE 57-bus test system. This test system has 57 buses, 80 branches, 7 generators, 3 shunts, 17

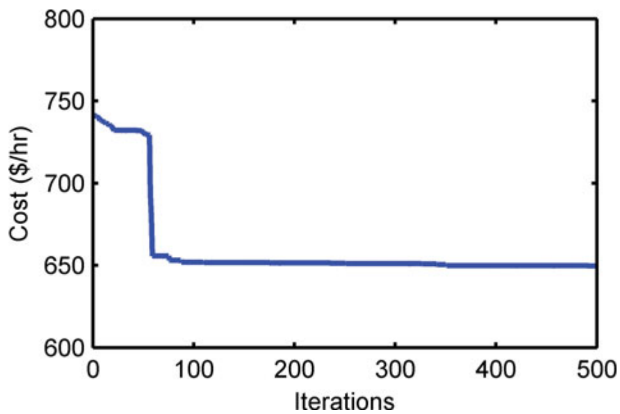


**FIGURE 7.** Fuel cost variation for Case 6.

transformers, and, consequently, 33 control variables. Therefore, the vector of control variables can be expressed as follows:

$$\boldsymbol{u}^T = \begin{bmatrix} \{P_{G_2}, P_{G_3}, P_{G_6}, P_{G_8}, P_{G_9}, P_{G_{12}}\} \\ \{V_{G_2}, V_{G_2}, V_{G_3}, V_{G_6}, V_{G_8}, V_{G_9}, V_{G_{12}}\} \\ \{T_{19}, T_{20}, T_{31}, T_{35}, T_{36}, T_{37}, T_{41}, T_{46}, T_{54}, T_{58} \\ \quad T_{59}, T_{65}, T_{66}, T_{71}, T_{73}, T_{76}, T_{80}\} \\ \{QC_{18}, QC_{25}, QC_{53}\} \\ \end{bmatrix} \tag{44}$$

Cost coefficients and more details about this system can be found in [43] and in MATPOWER software [44].

4.2.1. Case 7: Minimization of Generation Fuel Cost.

The objective function of this case is given by Eq. (27). The IEM has been run to solve the OPF problem of this case, and the results are given in Table 9. Moreover, the IEM is compared to some other optimization methods in Table 10. It can be seen from this table that the IEM has better results than some other optimization methods when minimizing the fuel cost of the IEEE 57-bus test system. It is worth mentioning that the EM was not even able to solve this case; *i.e.*, it did not converge.

### 4.3. Comparison Between the EM and the IEM Methods

The results obtained using the IEM method are compared with those obtained using the EM in Table 11. This comparison highlights the improvements made in the proposed IEM method compared with the initial EM method. This can be evidently seen when solving the OPF for larger systems like in Case 7, where the EM was not even able to converge.

| Methods | Cost |
|---|---|
| IEM | 649.6309 |
| EM | 650.9371 |
| DE | 650.8224 |

**TABLE 8.** Comparison of the simulation results for Case 6.

| | Case 7 |
|---|---|
| $P_{G1}$ | 432.3304 |
| $P_{G2}$ | 104.4437 |
| $P_{G3}$ | 49.1121 |
| $P_{G6}$ | 408.6548 |
| $P_{G8}$ | 37.8805 |
| $P_{G9}$ | 101.4132 |
| $P_{G12}$ | 156.7219 |
| $V_{G1}$ | 1.0998 |
| $V_{G2}$ | 1.0978 |
| $V_{G3}$ | 1.0867 |
| $V_{G6}$ | 1.0992 |
| $V_{G8}$ | 1.0864 |
| $V_{G9}$ | 1.0644 |
| $V_{G12}$ | 1.0674 |
| $T_{19(4\text{-}18)}$ | 1.0720 |
| $T_{20(4\text{-}18)}$ | 0.9123 |
| $T_{31(21\text{-}20)}$ | 0.9976 |
| $T_{35(24\text{-}25)}$ | 0.9868 |
| $T_{36(24\text{-}25)}$ | 0.9680 |
| $T_{37(24\text{-}26)}$ | 0.9985 |
| $T_{41(7\text{-}29)}$ | 0.9701 |
| $T_{46(34\text{-}32)}$ | 0.9824 |
| $T_{54(11\text{-}41)}$ | 1.0134 |
| $T_{58(15\text{-}45)}$ | 0.9672 |
| $T_{59(14\text{-}46)}$ | 0.9698 |
| $T_{65(10\text{-}51)}$ | 1.0099 |
| $T_{66(13\text{-}49)}$ | 0.9494 |
| $T_{71(11\text{-}43)}$ | 0.9627 |
| $T_{73(40\text{-}56)}$ | 0.9014 |
| $T_{76(39\text{-}57)}$ | 1.0791 |
| $T_{80(9\text{-}55)}$ | 0.9854 |
| $Q_{C18}$ | 4.1676 |
| $Q_{C25}$ | 4.4852 |
| $Q_{C53}$ | 4.9713 |
| Fuel cost ($/hr) | 4810.2161 |
| Active power loss (MW) | 39.7565 |
| Reactive power loss (MVAR) | 174.3065 |
| Voltage deviations | 2.2971 |
| $L_{\max}$ | 0.2778 |

**TABLE 9.** Optimal settings of the control variables obtained using IEM for Case 7.

| Methods | Cost |
|---|---|
| IEM | 4812.6667 |
| BBO | 4814.4904 |
| ABC | 4833.3172 |
| PSO | 5438.6105 |
| GA | 5440.9830 |
| EM | Not able to converge |

**TABLE 10.** Comparison of the simulation results for Case 7.

|  |  | Best | Mean | Median | Worst | *SD* |
|---|---|---|---|---|---|---|
| Case 1 | EM | 1 | 1.0019 | 1.0018 | 1.0045 | 0.0007 |
|  | IEM | 1 | 1.0004 | 1.0004 | 1.0008 | 0.0002 |
| Case 2 | EM | 1 | 1.0040 | 1.0037 | 1.0093 | 0.0019 |
|  | IEM | 1 | 1.0041 | 1.0040 | 1.0066 | 0.0013 |
| Case 3 | EM | 1 | 1.0067 | 1.0053 | 1.0321 | 0.0052 |
|  | IEM | 1 | 1.0057 | 1.0053 | 1.0140 | 0.0028 |
| Case 4 | EM | 1 | 1.0974 | 1.0891 | 1.2399 | 0.0440 |
|  | IEM | 1 | 1.0233 | 1.0202 | 1.1284 | 0.0183 |
| Case 5 | EM | 1 | 1.0587 | 1.0578 | 1.1299 | 0.0250 |
|  | IEM | 1 | 1.0114 | 1.0107 | 1.0307 | 0.0052 |
| Case 6 | EM | 1 | 1.0139 | 1.0066 | 1.1205 | 0.0270 |
|  | IEM | 1 | 1.0165 | 1.0066 | 1.1190 | 0.0361 |
| Case 7 | EM | Not able to converge |  |  |  |  |
|  | IEM | 1 | 1.0356 | 1.015 | 1.2637 | 0.0478 |

**TABLE 12.** Efficiency of the proposed IEM method after 50 trials.

Another advantage of the IEM over the EM is that the IEM method has no internal or key parameters to tune while the EM method has several, such as *LSITER*, $\delta$, $\nu$, *LSIndex*, *CalcFIndexM*, and *NormIndex*.

To assess the robustness of the proposed IEM method, a statistical study has been carried out. Thus, the IEM has been run 50 times. The obtained best, mean, median, worst, and standard deviation (*SD*) using the IEM method are displayed in Table 12 along with those obtained using the EM method (for comparison purposes). It is worth mentioning that the mean, median, worst, and *SD* values are normalized with respect to the best value.

It can be noticed that the best, mean, median, and worst values for the 50 trials are very close, which is also shown by the low *SD* values. This study reveals the robustness of the proposed technique and its ability to reach either to optimum value or very near to it in almost every trial.

## 5. CONCLUSION

In this article, an improved version of the EM method has been developed, implemented, and successfully applied to solve different OPF problems with various types of complexities. Different objective functions have been considered. The simulation results demonstrate the effectiveness and robustness of the proposed method. Moreover, the results obtained using the IEM method have been compared with those obtained using the initial EM method and with other methods previously reported in the literature. The comparison confirms the superiority of the proposed IEM method over many other methods used to solve the OPF in terms of solution quality. The results obtained are promising, and implementing a multi-objective IEM is a possible extension of the current work.

## FUNDING

Dr. M. A. Abido would like to acknowledge the support provided by King Abdulaziz City for Science and Technology (KACST) through the Science and Technology Unit at King Fahd University of Petroleum and Minerals (KFUPM) for funding this work (project 14-ENE265-04) as a part of the National Science Technology and Innovation Plan (NSTIP).

## REFERENCES

[1] AlRashidi, M. R., and El-Hawary, M. E., "Applications of computational intelligence techniques for solving the revived opti-

|  | Case 1 | Case 2 | Case 3 | Case 4 | Case 5 | Case 6 | Case 7 |
|---|---|---|---|---|---|---|---|
| IEM | 799.1821 | 804.1084 0.1063 | 799.8349 0.1144 | 2.8699 | – 25.1422 | 649.6309 | 4810.2161 |
| EM | 800.0781 | 804.2600 0.1270 | 802.9516 0.1156 | 3.1775 | – 22.0196 | 650.9371 | Not able to converge |

**TABLE 11.** Comparison between the initial and improved versions of the EM optimization method.

mal power flow problem," *Electr. Power Syst. Res.*, Vol. 79, No. 4, pp. 694–702, 2009.

[2] Squires, R. B., "Economic dispatch of generation directly from power system voltages and admittances," *IEEE Trans. Power App. Syst.*, Vol. 79, No. 3, pp. 1235–1245, 1961.

[3] Carpentier, J., "Contribution à l'étude du Dispatching Economique," *Bull. Soc. Franc. Electric.*, Vol. 8, pp. 431–447, 1962.

[4] Dommel, H. W., and Tinney, W. F., "Optimal power flow solutions," *IEEE Trans. Power App. Syst.*, Vol. 87, No. 10, pp. 1866–1876, 1968.

[5] Shabanpour-Haghighi, A., Seifi, A. R., and Niknam, T., "A modified teaching–learning based optimization for multi-objective optimal power flow problem," *Energy Convers Manag.*, Vol. 77, pp. 597–607, 2014.

[6] Niknam, T., Narimani, M. R., Jabbari, M., and Malekpour, A. R., "A modified shuffle frog leaping algorithm for multi-objective optimal power flow," *Energy*, Vol. 36, No. 11, pp. 6420–6432, 2011.

[7] Li, X., Li, Y., and Zhang, S., "Analysis of probabilistic optimal power flow taking account of the variation of load power," *IEEE Trans. Power Syst.*, Vol. 23, No. 3, pp. 992–999, 2008.

[8] Bhattacharya, A., and Chattopadhyay, P. K., "Application of biogeography-based optimisation to solve different optimal power flow problems," *IET Gener. Transm. Distrib.*, Vol. 5, No. 1, pp. 70–80, 2011.

[9] Huneault, M., and Galiana, F. D., "A survey of the optimal power flow literature," *IEEE Trans. Power Syst.*, Vol. 6, No. 2, pp. 762–770, 1991.

[10] Momoh, J. A., Adapa, R., and El-Hawary, M. E., "A review of selected optimal power flow literature to 1993. I. Nonlinear and quadratic programming approaches," *IEEE Trans. Power Syst.*, Vol. 14, No. 1, pp. 96–104, 1999.

[11] Momoh, J. A., El-Hawary, M. E., and Adapa, R., "A review of selected optimal power flow literature to 1993. II. Newton, linear programming and interior point methods," *IEEE Trans. Power Syst.*, Vol. 14, No. 1, pp. 105–111, 1999.

[12] Frank, S., Steponavice, I., and Rebennack, S., "Optimal power flow: A bibliographic survey I, Formulations and deterministic methods," *Energy Syst.*, Vol. 3, No. 3, pp. 221–258, 2012.

[13] Frank, S., Steponavice, I., and Rebennack, S., "Optimal power flow: A bibliographic survey II, Non-deterministic and hybrid methods," *Energy Syst.*, Vol. 3, No. 3, pp. 259–289, 2012.

[14] Birbil, S. I., and Fang, S. C., "An electromagnetism-like mechanism for global optimization," *J. Global Optim.*, Vol. 25, pp. 263–282, 2003.

[15] Jolai, F., Tavakkoli-Moghaddam, R., Golmohammadi, A., and Javadi, B., "An electromagnetism-like algorithm for cell formation and layout problem," *Expert Syst. Appl.*, Vol. 39, No. 2,, pp. 2172–2182 2012.

[16] Bouchekara, H. R. E.-H., and Abido, M. A., "Optimal power flow using differential search algorithm," *Electr. Power Compon. Syst.*, Vol. 42, pp. 1683–1699, 2014.

[17] Bouchekara, H. R. E. H., "Optimal power flow using black-hole-based optimization approach," *Appl. Soft Comput. J.*, Vol. 24, pp. 879–888, 2014.

[18] Bouchekara, H. R. E. H., Abido, M. A., and Boucherma, M., "Optimal power flow using teaching-learning-based optimization technique," *Electr. Power Syst. Res.*, Vol. 114, pp. 49–59, 2014.

[19] Robbins, B. A., Zhu, H., and Dominguez-Garcia, A. D., "Optimal tap settings for voltage regulation transformers in distribution networks," *Proceedings of the North American Power Symposium*, Manhattan, KS, 22–24 September 2013.

[20] Su, C. T., and Lin, H. C., Applying electromagnetism-like mechanism for feature selection," *Inf. Sci.*, Vol. 181, No. 5, pp. 972–986, 2011.

[21] Lee, K.-C., and Jhang, J.-Y., "Application of electromagnetism-like algorithm to phase-only syntheses of antenna arrays," *Prog. Electromagn. Res.*, Vol. 83, pp. 279–291, 2008.

[22] Rocha, M. A. C., and Fernandes, E., "On charge effects to the electromagnetism-like algorithm," *Proceedings of Euro Mini Conference Continuous Optimization and Knowledge-Based Technologies*, pp. 198–203, Neringa, Lithuania, 20–23 May 2008.

[23] Shang, Y., Chen, J., and Wang, Q., "Improved electromagnetism-like mechanism algorithm for constrained optimization problem," *International IEEE Conference on Computational Intelligence and Security (CIS)*, pp. 165–169, Nanning, China, 11–14 December 2010.

[24] Abido, M. A., "Optimal power flow using particle swarm optimization," *Int. J. Electr. Power Energy Syst.*, Vol. 24, No. 7, pp. 563–571, 2002.

[25] Lee, K., Park, Y., and Ortiz, J., "A united approach to optimal real and reactive power dispatch," *IEEE Trans. Power Appar. Syst.*, Vol. 104, No. 5, pp. 1147–1153, 1985.

[26] Abou El Ela, A. A., and Abido, M. A., "Optimal power flow using differential evolution algorithm," *Electr. Power Syst. Res.*, Vol. 80, No. 7, pp. 878–885, 2010.

[27] Hendrix, E. M. T., and Toth, B. G., *Introduction to Nonlinear and Global Optimization*, Berlin: Springer, 2010.

[28] Bouchekara, H. R. E. H., Abido, M. A., Chaib, A. E., and Mehasni, R., "Optimal power flow using the league championship algorithm: A case study of the Algerian power system," *Energy Convers. Manag.*, Vol. 87, pp. 58–70, 2014.

[29] Roa-Sepulveda, C. A., and Pavez-Lazo, B. J., "A solution to the optimal power flow using simulated annealing," *Int. J. Electr. Power Energy Syst.*, Vol. 25, No. 1, pp. 47–57, 2003.

[30] Vaisakh, K., and Srinivas, L. R., "Genetic evolving ant direction HDE for OPF with nonsmooth cost functions and statistical analysis," *Expert Syst. Appl.*, Vol.. 38, pp. 2046–2062, 2011.

[31] Vaisakh, K., and Srinivas, L. R., "Evolving ant direction differential evolution for OPF with non-smooth cost functions," *Eng. Appl. Artif. Intell.*, Vol. 24, pp. 426–436, 2011.

[32] Liang, R.-H., Tsai, S.-R., Chen, Y.-T., and Tseng, W.-T., "Optimal power flow by a fuzzy based hybrid particle swarm optimization approach," *Electr. Power Syst. Res.*, Vol. 81, No. 7, pp. 1466–1474, July 2011.

[33] Lai, L. L., Ma, J. T., Yokoyama, R., and Zhao, M., "Improved genetic algorithms for optimal power flow under both normal and contingent operation states," *Int. J. Electr. Power Energy Syst.*, Vol. 19, No. 5, pp. 287–292, 1997.

[34] Ghanizadeh, A. J., Mokhtari, G., Abedi, M., and Gharehpetian, G. B., "Optimal power flow based on imperialist competitive algorithm," *Int. Rev. Electr. Eng., Part B*, Vol. 6, No. 4, pp. 1847–1582, June 2011.

[35] Bakirtzis, A. G., Biskas, P. N., Zoumas, C. E., and Petridis,

V., "Optimal power flow by enhanced genetic algorithm," *IEEE Trans. Power Syst.*, Vol. 17, No. 2, pp. 229–236, 2002.

[36] Abido, M. A., "Optimal power flow using tabu search algorithm," *Electr. Power Compon Syst.*, Vol. 30, pp. 469–483, 2002.

[37] Sayah, S., and Zehar, K., "Modified differential evolution algorithm for optimal power flow with non-smooth cost functions," *Energy Convers. Manag.*, Vol. 49, No. 11, pp. 3036–3042, 2008.

[38] Ongsakul, W., and Tantimaporn, T., "Optimal power flow by improved evolutionary programming," *Electr. Power Compon. Syst.*, Vol. 34, No. 1, pp. 79–95, 2006.

[39] Yuryevich, J., and Wong, K. P., "Evolutionary programming based optimal power flow algorithm," *IEEE Trans. Power Syst.*, Vol. 14, No. 4, pp. 1245–1250, 1999.

[40] Paranjothi, S. R., and Anburaja, K., "Optimal power flow using refined genetic algorithm," *Electr. Power Compon. Syst.*, Vol. 30, pp. 1055–1063, 2002.

[41] Belhadj, C. A., and Abido, M. A., "An optimized fast voltage stability indicator," *Electric Power International Conference on Engineering (PowerTech)*, pp. 79–83, Budapest, 29 August–2 September1999.

[42] Kessel, P., and Glavitsch, H., "Estimating the voltage stability of a power system," *IEEE Trans. Power Del.*, Vol. 1, No. 3, pp. 346–354, 1986.

[43] Basu, M., "Multi-objective optimal power flow with FACTS devices," *Energy Convers. Manag.*, Vol. 52, pp. 903–910, 2011.

[44] Zimmerman, R. D., Murillo-Sánchez, C. E., and Thomas, R. J., "MATPOWER: Steady-state operations, planning and analysis tools for power systems research and education," *IEEE Trans. Power Syst.*, Vol. 26, No. 1, pp. 12–19, February 2011.

## BIOGRAPHIES

**Houssem Rafik El-Hana Bouchekara** received his B.Sc. in electrical engineering from University Mentouri Constantine, Algeria, in 2004; his Master's degree in electronic systems and electrical engineering from Polytechnic School of the University of Nantes, France, in 2005; and his Ph.D. degree in electrical engineering from Grenoble Electrical Engineering Laboratory, France, in 2008. After graduation, he joined the Electrical Engineering Department of Umm Al-Qura University, Saudi Arabia, for 3 years. After that, he moved to University of Constantine 1, Algeria. He is currently an associate professor in the Electrical Engineering Department of University of Constantine 1. His research interests include power systems, optimization techniques, magnetic refrigeration, and electromagnetics.

**Mohammad Ali Abido** received his B.Sc. (honors with first class) and M.Sc. in electrical engineering from Menoufiya University, Egypt, in 1985 and 1989, respectively, and his Ph.D. from KFUPM, Saudi Arabia, in 1997. He has been with the Electrical Engineering Department, Menoufiya University, as an assistant professor since 1998. He is currently a Distinguished University Professor at KFUPM. He is the recipient of the KFUPM Excellence in Research Award in 2002, 2007, and 2012; the KFUPM Best Project Award in 2007 and 2010; the First Prize Paper Award from IEEE Industry Applications Society in 2003; the Abdel-Hamid Shoman Prize for Young Arab Researchers in Engineering Sciences in 2005; the Best Applied Research Award of 15thGCC-CIGRE Conference, Abu-Dhabi, UAE, in 2006; and the Best Poster Award at ICREPQ'13, Bilbao, Spain, in 2013. He has published more than 250 papers in reputable journals and international conferences. His research interests are power system stability, operation, and optimization techniques.

**Alla Eddine Chaib** is currently a Ph.D. student in the Electrical Engineering Department of University of Constantine 1, Algeria. He received his B.Sc. in electrical engineering from University Mentouri Constantine, Algeria, in 2009. He received the magisterial degree in electromagnetic systems and electrical engineering from the military Polytechnic School of Algeria in 2013. His research interests are OPF, metaheuristics, and electromagnetic compatibility.