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# Optimal Power Flow by Using New Multi Parent Crossover

**Krishna Aitha[1] and V. Sunil Kumar[2]**

Department of EEE, St.Martin's Engineering College, Hyderabad, T.S.

[1]*St.Martin's Engg.College, Hyderabad, T.S, e-Mail: aitha.krishna217@gmail.com*

[2]*St.Martin's Engg.College, Hyderabad, T.S, e-Mail: Vskumar20@gmail.com*



**Abstract - This paper proposed a new genetic algorithm for solving problem of optimal power flow problem with both continuous and discrete variables. Over the last twenty years there are different genetic algorithms were introduced to solve optimization problems. Due to the unevenness of the characteristics of different optimization problems no method gives consistent performance over real world problems. The search operators are the heart of Genetic algorithm. In this paper we used a new multi-parent crossover in addition with diversity factor instead of mutation operator and also maintain an archive pool for best solutions.**

**The effectiveness and robustness of the proposed method was tested on IEEE 30 bus test system with different objective functions like minimization of fuel cost and voltage profile improvement. The results obtained with the proposed method are compared with the methods which were included in the literature.**

**Keywords – Optimal power flow (OPF), Genetic Algorithm, Multi Parent Crossover (MPC).**

## 1. INTRODUCTION

The Genetic Algorithm (GA) is widely used for solving many practical optimization problems. GA has the ability to deal with both continuous and discrete variables, is well suited for parallel computing, and can deal with optimization of extremely complex fitness landscapes. GA has also been successfully applied to noisy problems. However, GA is known to be slow, and sometimes GA cannot convergence to the global optimal.

Over the last few decades, although many GA's have been introduced for solving constrained optimization problems, their performance varies when considered a wide range of problems. In some cases, they do not even perform better than other EAs such as differential evolution and particle swarm algorithms. In this research, our objective is to improve the performance of genetic algorithms by introducing a new crossover with a randomized operator to replace mutation. The proposed crossover uses three parents to generate three new offspring, two of which are to help exploitation, while the third offspring is for promoting exploration. The randomized operator can help to escape from the optima and premature convergence.

The idea of multi-parent crossover is not new in the literature. There are different crossovers suitable for continuous problems, such as unimodal distribution crossover(UNDX) [11], simplex crossover (SPX) [12], parent centric crossover (PCX) [13] and Triangular crossover (TC) [14].UNDX uses multiple parents and creates offspring solutions around the centre of mass of these parents. A small probability is assigned to solutions away from the centre of mass. UNDX has shown excellent performance for highly epistasis problems. On the other hand, there are some areas where the UNDX cannot generate offspring with a given initial population, such as when the population size is small relative to the search space. UNDX also has difficulty to find an optimal solution near boundaries [11]. Simplex crossover (SPX) is a multi-parent recombination operator for real-coded GAs. The SPX operator assigns a uniform probability distribution for creating offspring in a restricted search space around the region marked by the parents. SPX uses the property of a simplex in the search space. SPX has a balance between exploration and exploitation. The simplex crossover works well on functions having multimodality and/or epistasis with a medium number of parents, such as three parents on a low dimensional function and four parents on a high dimension function [12] [13]. However, SPX fails on functions that consist of tightly linked sub-functions [12].PCX allows a large probability of creating a solution near each parent, rather than near the centre of the parents. PCX is a self adaptive type of approach, where a new solution vector keeps moving towards the optimum [14]; however GA with PCX has difficulty in solving separable multimodal problems whereas DE can solve them successfully [16]. TC uses three parents (where two parents must be feasible and one infeasible) and generate three random numbers to generate three new off spring. Each offspring is generated as a linear combination of those three parents. TC works well where the optimal solution lies on the boundary of the feasible region of problems that have a single bounded feasible region in the continuous domain. It is important to mention here that our proposed crossover neither uses a mean-centric probability distribution, such as UNDX and SPX, nor uses a parent centric approach, such as PCX.

The proposed genetic algorithm is named as GA-MPC. In GA-MPC, first, an initial population with size *PS* is generated randomly, and the best *m* individuals are stored in an archive pool, based on the objective function and/or constraint violation. A tournament selection with size *TC* is performed to select good solutions which are stored into the selection pool for performing crossover. In the crossover operations, with crossover rate ($c_r$), three individuals are used to generate three new offspring. A randomized operation is applied for each new offspring with a probability ($p$). The generated offspring are merged with the individuals of the archive pool to select the best *PS* individuals, based on the objective function and/or constraint violations, to build the new population for the next generation, and the archive pool is concurrently updated. The algorithm also shows consistently better performance as compared to the state-of-the-art algorithm.

This paper is organized as follows. After this first section which is the introduction, the second section focuses on the formulation of the OPF problem. The third section of this paper presents the concept and main steps of the developed MPC approach. Next, we apply the GA-MPC approach to solve the OPF problem in order to optimize the power system operating conditions. Finally, the conclusions are drawn in the fifth section.

## 2. OPTIMAL POWERFLOW FORMULATION

As aforesaid, OPF is a power flow problem which gives the optimal settings of the control variables for a given settings of load by minimizing a predefined objective function such as the cost of active power generation or transmission losses. The majority of OPF formulations may be represented using the following standard form [5]:

Minimize J(**x**, **u**) (1)

Subject to g(**x**, **u**) = 0 (2)

and h(**x**, **u**) ≤ 0 (3)

where **u** represents the vector of independent variables or control variables. **x** represents the vector of dependent variables or state variables. J(**x**,**u**) represents the system's optimization goal or the objective function. g(**x**,**u**) represents the set of equality constraints. h(**x**,**u**) represents the set of inequality constraints. The control variables **u** and the state variables **x** of the OPF problem are stated in (4) and (5), respectively.

### 2.1. Control variables

These are the set of variables which can be modified to satisfy the load flow equations. The set of control variables in the OPF problem formulation are:

-$P_G$: represents the active power generation at the PV buses except at the slack bus.
-$V_G$: represents the voltage magnitude at PV buses.
-T: represents the tap settings of transformer.
-$Q_C$: represents the shunt VAR compensation.

Hence, **u** can be expressed as:

$$\mathbf{u}^T = [P_{G_2} \cdots P_{G_{NG}}, V_{G_1} \cdots V_{G_{NG}}, Q_{C_1} \cdots Q_{C_{NC}}, T_1 \cdots T_{NT}] \quad (4)$$

where NG, NT and NC are the number of generators, the number of regulating transformers and the number of VAR compensators, respectively.

### 2.2. State variables

All OPF formulations require variables to represent the electrical state of the system [5]. Most often, the state variables for the OPF problem formulation are:

- $P_{G1}$: represents the active power output at slack bus.
- $V_L$: represents the voltage magnitude at PQ buses; load buses.
- $Q_G$: represents the reactive power output of all generator units.
- $S_l$: represents the transmission line loading (or line flow).

Hence, **x** can be expressed as:

$$\mathbf{x}^T = [P_{G_1}, V_{L_1} \cdots V_{L_{NL}}, Q_{G_1} \cdots Q_{G_{NG}}, S_{l_1} \cdots S_{l_{nl}}] \quad (5)$$

Where NL, and nl are the number of load buses, and the number of transmission lines, respectively.

### 2.3. Constraints

OPF constraints can be classified into equality and inequality constraints, which are detailed in the following sections.

#### 2.3.1. Equality constraints

The equality constraints of the OPF reflect the physics of the power system. These equality constraints are as follows.

2.3.1.1. Real power constraints.

$$P_{Gi} - P_{Di} - V_i \sum_{j=i}^{NB} V_j [G_{ij} \cos(\theta_{ij}) + B_{ij} \sin(\theta_{ij})] = 0$$

(6)

2.3.1.2. Reactive Power Constraints.

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=i}^{NB} V_j [G_{ij} \sin(\theta_{ij}) + B_{ij} \cos(\theta_{ij})] = 0$$

(7)

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, QD is the reactive load demand, $G_{ij}$ and $B_{ij}$ are the elements of the admittance matrix ($Y_{ij} = G_{ij} + jB_{ij}$) representing them conductance and susceptance between bus i and bus j, respectively.

2.3.2. 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.

2.3.2.1. Generator constraints.

For all generators including the slack: voltage, active and reactive outputs ought to be restricted by their lower and upper limits as follows:

$$V_{G_i}^{\min} \le V_{G_i} \le V_{G_i}^{\max}, \quad i = 1, \ldots, NG$$

(8)

$$P_{G_i}^{\min} \le P_{G_i} \le P_{G_i}^{\max}, \quad i = 1, \ldots, NG \qquad (9)$$

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

(10)

2.3.2.2. Transformer constraints.

Transformer tap settings ought to be restricted within their specified lower and upper limits as follows:

$$T_i^{\min} \le T_i \le T_i^{\max}, \quad i = 1, \ldots, NT$$

(11)

2.3.2.3. Shunt VAR compensator constraints.

Shunt VAR compensators must be restricted by their lower and upper limits as follows:

$$Q_{C_i}^{\min} \le Q_{GC_i} \le Q_{C_i}^{\max}, \quad i = 1, \ldots, NG$$

(12)

2.3.2.4. Security constraints.

These contain the constraints of voltage magnitude at load buses and transmission line loadings. Voltage of each load bus must be restricted within its lower and upper operating limits. Line flow through each transmission line ought to be restricted by its capacity limits. These constraints can be mathematically formulated as follows:

$$V_{L_i}^{\min} \le V_{L_i} \le V_{L_i}^{\max}, \quad i = 1, \ldots, NL$$

(13)

$$S_{l_i} \le S_{l_i}^{\max}, \quad i = 1, \ldots, nl \qquad (14)$$

It is worth mentioning that control variables are self constrained. The inequality constraints of dependent variables which contain load bus voltage magnitude; real power generation output at slack bus, reactive power generation output and line loading can be included into an objective function as quadratic penalty terms. In these terms, a penalty factor multiplied with the square of the disregard value of dependent variable is added to the objective function and any unfeasible solution obtained is declined.

Mathematically, penalty function can be expressed as follows:

$$J_{aug} = J + \lambda_P (P_{G_1} - P_{G_1}^{\lim})^2 + \lambda_V \sum_{i=1}^{NL} (V_{L_i} - V_{L_i}^{\lim})^2 + \lambda_Q \sum_{i=1}^{NG}$$
$$+ \lambda_S \sum_{i=0}^{nl} (S_{l_i} - S_{l_i}^{\max})^2 \qquad (15)$$

where $\lambda_P$, $\lambda_V$, $\lambda_Q$ and $\lambda_S$ are penalty factors and $x^{\lim}$ is the limit value of the dependent variable x. 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 hence:

$$x^{\lim} = \begin{cases} x^{\max}; & x > x^{\max} \\ x^{\min}; & x < x^{\min} \end{cases} \qquad (16)$$

## 3. NEW MULTIPARENT CROSSOVER

In GA, the crossover should have the ability for exploiting information about the search space in generating new offspring. The distribution of offspring should neither be extremely narrow nor extremely wide when compared to their parents. If the generated offspring are distributed extremely narrower than the parents, they may lose diversity and converge prematurely. On contrast if the offspring are distributed extremely widely, they may be too diverse and take too long in converging to optimality [11]. So it should be appropriate to generate offspring that satisfy a balance of exploration and exploitation.

Based on the above principle, we propose the following multi-parent crossover, named here as (MPC). The idea behind MPC comes from the heuristic crossover [18] and the mutation operator in DE [4].

The steps of MPC are:

1- Select three parents based on a selection rule.

2- If one of the selected individuals is the same as another, then replace it with a random individual from the selection pool.

3- Rank these three individuals from the best ($x_1$) to the worst ($x_3$), based on their fitness functions and/or constraint violations.

4- Generate a random number **β** that follows a normal distribution with mean value μ and standard deviation **σ**.

5- Generate three offspring ($o_i$):

$$o_1 = x_1 + \beta \times (x_2 - x_3) \qquad (17)$$
$$o_2 = x_2 + \beta \times (x_3 - x_1) \qquad (18)$$
$$o_3 = x_3 + \beta \times (x_1 - x_2) \qquad (19)$$

In equation 17, the worst individual $x_3$ is subtracted from $x_2$, then the difference is multiplied by **β** and then the total is added to the best individual $x_1$. This allows $o_1$ to be generated in the direction of a better part of the search space. The same situation applies in equation 19; $f(x_1) \leq f(x_2) \leq f(x_3)$ this allows $o_3$ to be generated to a better point. In equation 18, we subtract the best point $x_1$ from an inferior point $x_3$, this ensures that $f(o_2) \leq f(x_2)$, and therefore that it will extend to a diverse point. The reason for using $x_3 - x_1$ instead of $x_1 - x_3$ in equation 18, is that moving towards the best individual may let the algorithm to become stuck in a local minimum.

In GA-MPC, first an initial population is generated randomly, with size *PS*. Then an archive pool is filled with the best *m* individuals (based on their constrained violations and/or fitness function). Then a tournament selection procedure with size *TC* takes place, in the vectors and saved in the selection pool. For the crossover operation, with a crossover rate (*cr*), for each three consecutive individuals in the selection pool, three offspring are generated as described before. After we generate all offspring, we use a randomized operator with a probability *p* to escape from possible local minima. After that we merge the individuals from the archive pool with all of the offspring, and the best *PS* individuals are selected as a new population for the next generation. Also to ensure more diversity, if any individual in the population is the same to another one, then one of them is shifted within the boundary with probability ***N***(0.5 x u, 0.25*u), where u ϵ (0,1).

## 3.1. MULTI PARENT CROSSOVER PROCEDURE

**STEP 1:** In generation t=0**,** generate an initial random population of size PS. The variables in each individual (*i*) must be within the range as shown below:

$$x_{i,j} = L_j + u \times (U_j - L_j)$$

Where $L_j$, $U_j$ are the lower and upper bound for decision variable $x_j$, and u is a random number, u ϵ (0, 1).

**STEP 2:** Sort all individuals based on their constraint violations and/or objective function, and save the best *m* individuals in the archive pool (A).

**STEP 3:** Apply a tournament selection with size *TC* (randomly 2 or 3), and fill the selection pool.

**STEP 4:** For each three consecutive individuals, If u ϵ (0, 1) < *cr*

i) Rank these three individuals from
$$f(x_i) \le f(x_{i+1}) \le f(x_{i+2})$$

ii) If one of the selected individuals is the same to another, then replace one of them with a random individual from the selection pool.

iii) Calculate β = *N* (μ, σ), where μ=0.7, and σ =0.1.

iv) Generate three offspring ($o_i$)

$$o_1 = x_1 + \beta \times (x_2 - x_3)$$
$$o_2 = x_2 + \beta \times (x_3 - x_1)$$
$$o_3 = x_3 + \beta \times (x_1 - x_2)$$

**STEP 5:** For each $o^j_i$, generate a random number u ϵ (0, 1). If u ϵ (0, 1) then $o'^j_i = x^j_{arch}$. Where integer $arch \in \{1, m\}$.

**STEP 6:** If there is any duplicate individual, then
$x_{ijk} = x_{ijk} + N(0.5 \times u, 0.25 * u)$, where $u \in [0,1]$

**STEP 7:** Stop if the termination criterion is met; **else** set t=t+1 and go to **STEP 2**

## 4. APPLICATION AND RESULTS

The Multi Parent Crossover technique has been applied to solve the OPF problem for the IEEE 30-Bus test system and for two cases with different objective functions. The developed software program is written in MATLAB computing environment and run the program up to 200 iterations.

### 4.1. IEEE 30-BUS TEST SYSTEM

The effectiveness of the proposed new Multi Parent Crossover approach, it has been tested first on the standard IEEE 30-bus test system shown in Fig. 1. The standard IEEE 30-bus system chosen in this has the following characteristics: six generators at buses 1, 2, 5, 8, 11 and 13, four transformers with off-nominal tap ratio at lines 11, 12, 15 and 36, nine shunt VAR compensation buses at buses 10, 12, 15, 17, 20, 21, 23, 24 and 29.

Further, the line data, bus data, generator data and the minimum and maximum limits for the control variables.

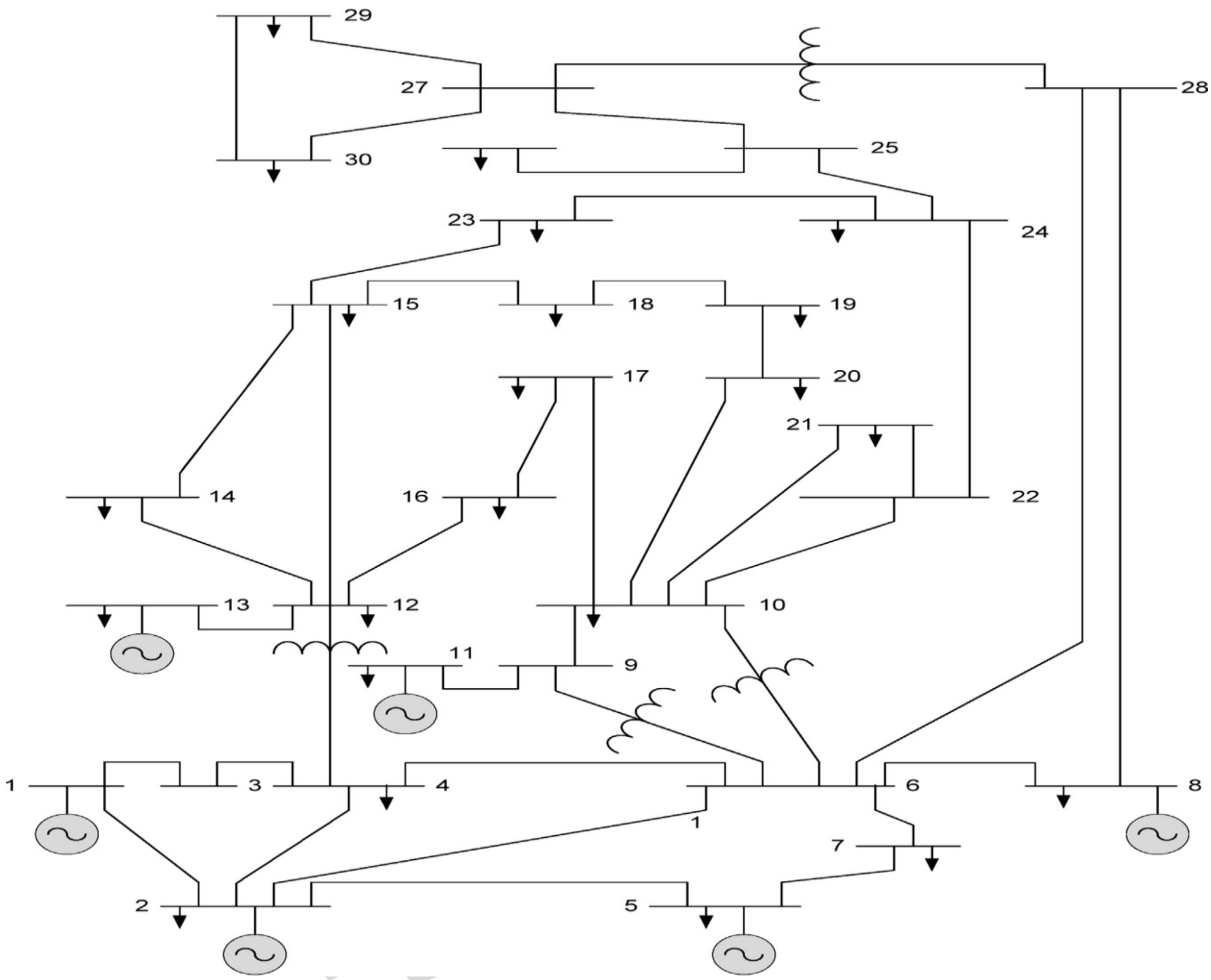


Fig. 1. Single Line Diagram of IEEE 30-Bus Test System



For this test system, two different cases have been studied with different objectives and the obtained results are summarized in Table 1. The first column of this table represents the optimal control settings found where:

- $P_{G1}$ through $P_{G6}$ and $V_{G1}$ through $V_{G6}$ represent the powers and the voltages of generator 1 through generator 6.
- T11, T12, T15 and T36 are the tap settings of transforms included between lines 11, 12, 15 and 36.
- QC10, QC12, QC15, QC17, QC20, QC21, QC23, QC24 and QC29 represent the shunt VAR compensations connected to buses 10, 12, 15, 17, 20, 21, 23, 24 and 29.

Further, fuel cost ($/h), active power losses (MW), reactive power losses (MVar), voltage deviation and Lmax represent the total fuel cost of the system, the total active transmission losses, the total reactive transmission losses, the deviation of load voltages from 1 and the index of stability, respectively.

*4.1.1. Case 1: Minimization of generation fuel cost*

In this first case the minimization of the generation fuel cost, which is the most common OPF objective, is considered. Hence, the objective function J represents the total fuel cost of all generator units and it is expressed as follows:

$$J = \sum_{i=1}^{NG} f_i (\$/h) \quad (20)$$

Where $f_i$ is the fuel cost of the $i^{th}$ generator. Generally, the OPF generation fuel cost curve is expressed by a quadratic function. Therefore, $f_i$ can be expressed as follows:

$$f_i = a_i + b_i P_{Gi} + c_i P_{G_i}^2 (\$/h) \quad (21)$$

where $a_i$, $b_i$ and $c_i$ are the basic, the linear and the quadratic cost coefficients of the ith generator, respectively.

It appears that the proposed approach has excellent convergence characteristics. The optimal settings of control variables are given in Table 1. The total fuel cost obtained by the proposed MPC approach is ($799.2614). Compared to the initial case ($901.9516), the total fuel cost is considerably reduced by 11.39%.

Using the same conditions (control variables limits, initial conditions, and system data), the results obtained in Case 1 using the GA-MPC approach are compared to some other techniques reported in the literature .There is some evidence, that the proposed approach outperforms many techniques used to solve the OPF problem by minimization of generation fuel cost. For instance, the results obtained by the GA-MPC are better than the ones obtained the well-known BHBO and other techniques.

*4.1.2. Case 2: Voltage Profile Improvement*

Bus voltage is one of the most important and significant safety and service quality indices. Minimizing only the total cost in the OPF problem as in Case 1 may result in a feasible solution, but voltage profile may not be acceptable.

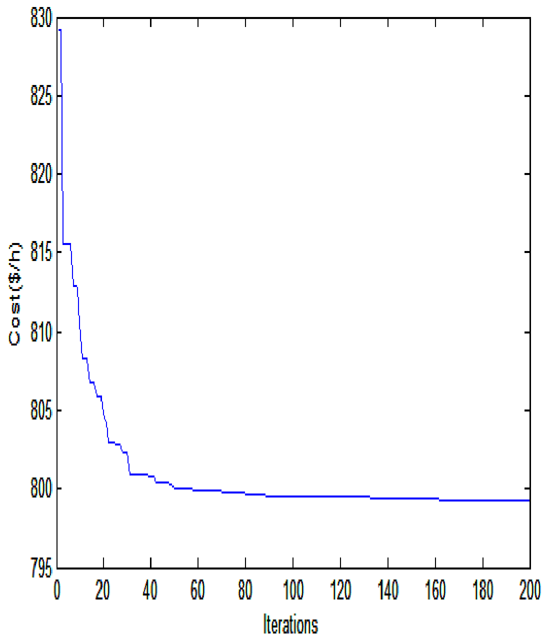


Fig. 2 Fuel Cost Variation of Case1

Therefore, in this second case a twofold objective function is considered. The objective here is to minimize the fuel cost and improve voltage profile at the same time by minimizing the voltage deviation of PQ buses from the unity 1.0. Thus, the objective function can be expressed as follows:

$$J = J_{Cost} + w J_{Voltage\ Deviation} \quad (22)$$

where w is a suitable weighting factor, to be selected by the user to give a weight (an importance) to each one of the two terms of the objective function. In this study w is chosen as 100. $J_{Cost}$ and $J_{Voltage\ Deviation}$ are given as follows:

$$J_{Voltage\ Deviation} = \sum_{i=1}^{NL} |V_i - 1.0| \quad (23)$$

$$J_{Cost} = \sum_{i=1}^{NG} f_i \quad (24)$$

Table 1
Optimal settings of control variables.

| | Min | Max | Initial | Case 1 | Case 2 |
|---|---|---|---|---|---|
| $P_{G1}$ | 50 | 200 | 99.223 | 176.5621 | 168.1600 |
| $P_{G2}$ | 20 | 80 | 80 | 49.2601 | 54.5900 |
| $P_{G3}$ | 15 | 50 | 50 | 21.1880 | 19.1200 |
| $P_{G4}$ | 10 | 35 | 20 | 19.8840 | 17.5600 |
| $P_{G5}$ | 10 | 30 | 20 | 12.8864 | 15.7500 |
| $P_{G6}$ | 12 | 40 | 20 | 12.2735 | 17.9900 |
| $V_{G1}$ | 0.95 | 1.1 | 1.05 | 1.1000 | 1.0324 |
| $V_{G2}$ | 0.95 | 1.1 | 1.04 | 1.0871 | 1.0214 |
| $V_{G3}$ | 0.95 | 1.1 | 1.01 | 1.0635 | 1.0079 |
| $V_{G4}$ | 0.95 | 1.1 | 1.01 | 1.0682 | 1.0059 |
| $V_{G5}$ | 0.95 | 1.1 | 1.01 | 1.0994 | 0.9965 |
| $V_{G6}$ | 0.95 | 1.1 | 1.05 | 1.0953 | 1.0020 |
| T11 | 0.9 | 1.1 | 1.078 | 0.9677 | 1.0000 |
| T12 | 0.9 | 1.1 | 1.069 | 1.0403 | 0.9125 |
| T15 | 0.9 | 1.1 | 1.032 | 1.0161 | 0.9625 |
| T36 | 0.9 | 1.1 | 1.068 | 0.9774 | 0.9750 |
| QC10 | 0 | 5 | 0 | 5.0000 | 3.0000 |
| QC12 | 0 | 5 | 0 | 0.7100 | 1.0000 |
| QC15 | 0 | 5 | 0 | 3.5700 | 4.0000 |
| QC17 | 0 | 5 | 0 | 5.0000 | 3.0000 |
| QC20 | 0 | 5 | 0 | 3.5700 | 5.0000 |
| QC21 | 0 | 5 | 0 | 5.0000 | 5.0000 |
| QC23 | 0 | 5 | 0 | 2.8600 | 5.0000 |
| QC24 | 0 | 5 | 0 | 5.0000 | 5.0000 |
| QC29 | 0 | 5 | 0 | 2.1400 | 5.0000 |
| Fuel cost ($/h) | - | - | 901.952 | 799.2614 | 807.1928 |
| Active power losses(MW) | - | - | 5.8219 | 8.6500 | 9.1000 |
| Reactive Power losses (MVar) | | | -4.6066 | 1.7200 | -4.6300 |
| Voltage deviation | - | - | 1.1496 | 1.5057 | 0.1040 |

Table 2
Comparision of the simulation results of case 1

| Method | Cost | Method description |
|---|---|---|
| MPC | 799.2614 | Multi parent crossover |
| BHBO | 799.9217 | Black-Hole-Based Optimization |
| DE | 799.2891 | Differential Evolution |
| SA | 799.45 | Simulated Annealing |
| EM | 800.078 | Electromagnetism-Like Mechanism |
| EADHDE | 800.1579 | Genetic Evolving Ant Direction HDE |
| EADDE | 800.2041 | Evolving Ant Direction Differential Evolution |
| PSO | 800.41 | Particle Swarm Optimization |
| IGA | 800.805 | Improved Genetic Algorithms |
| EGA | 802.06 | Enhanced Genetic Algorithm |
| MDE | 802.376 | Modified Differential Evolution Algorithm |
| IEP | 802.465 | Improved Evolutionary Programming |
| EP | 802.62 | Evolutionary Programming |
| GM | 804.853 | Gradient Method |

The MPC approach has been applied to search for the optimal solution of the problem. The variations of fuel cost and voltage deviation over the iterations are sketched in Fig. 3. The optimal settings of control variables are given in Table 1. Using MPC the fuel cost and the voltage deviation obtained are ($807.1928) and (0.1040 p.u.), respectively.

The system voltage profile in this case 2 is compared to that of Case 1 as shown in Fig. 4. It appears that the voltage profile is greatly improved compared to that of Case 1. It is reduced from 1.5057p.u. in Case 1 to 0.1040 p.u. in Case 2, which yields a reduction of 93.91%. However, in Case 2 the fuel cost is slightly increased by 0.58% compared to Case 1.

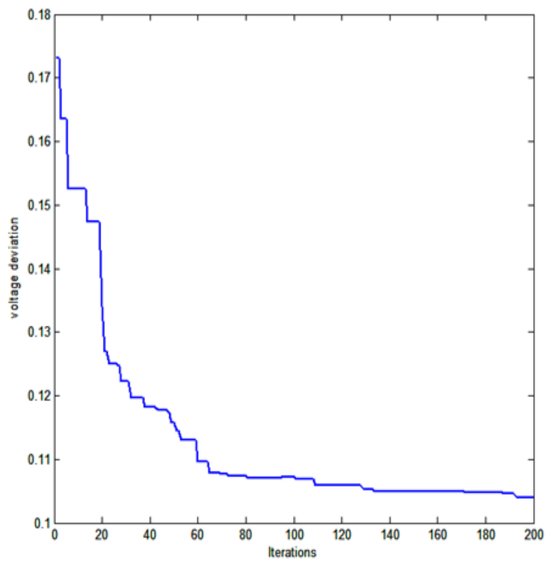


Fig. 3. Variation of Voltage Deviation for Case 2

In Fig.4 shows the variation of the voltage profile of loadbuses in case 1 is having greater value but fuel cost is less over 200 iterations. But in the case 2 a twofold objective function is considered to obtained the voltage deviation is minimum and fuel cost is acceptable of feasible solution of MPC approach.

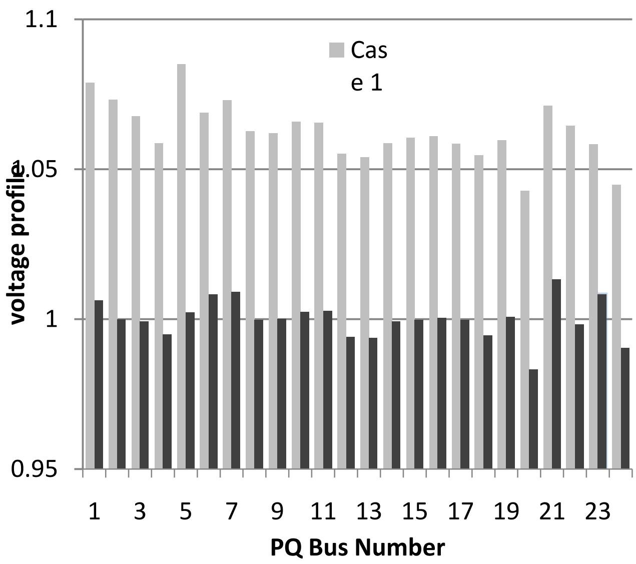


Fig.4. System Voltage Profile Improvement

## 5. CONCLUSION

During the past few decades, many evolutionary algorithms have been introduced to solve optimal power flow problems. In this paper, we used a new multi-parent crossover in addition with diversity factor instead of mutation operator and also maintain an archive pool for best solutions.

It has been successfully applied to find the optimal settings of the control variables of the standard IEEE 30- bus system. The simulation results demonstrate the effectiveness and robustness of proposed MPC approach compared with the other methods in the reported literature to solve the OPF in terms of solution quality. In this MPC technique, minimization of generation fuel cost and voltage profile improvement. Another advantage is that it can be easily coded to work on parallel computers. The results obtained are promising and implementing multiobjective MPC is a possible extension of the current work.

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