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True Multi-Objective Optimal Power Flow in a Deregulated Environment Using Intelligent Technique

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Abstract—in this paper, a Multi-Objective Particle Swarm optimization (MOPSO) technique is proposed for solving the Optimal Power Flow (OPF) problem in a deregulated environment. The OPF problem is formulated as a nonlinear constrained multiobjective optimization problem where the fuel cost and wheeling cost are to be optimized simultaneously. MVA-km method is used to calculate the wheeling cost in the system. The proposed approach handles the problem as a true multiobjective optimization problem. The results demonstrate the capabilities of the proposed approach to generate true and well-distributed Pareto-optimal solutions of the multiobjective OPF problem in one single run. In addition, the effectiveness of the proposed approach and its potential to solve the multiobjective OPF problem are confirmed. IEEE 30 bus system is considered to demonstrate the suitability of this algorithm.

Index Terms— Optimal power flow, Particle swarm optimization, Wheeling cost, Fuel cost, Multiobjective optimization.

I INTRODUCTION

The Optimal Power Flow (OPF) problem is one of the most widely studied subjects in the power system field. Still researchers are working on OPF problems for the present day challenges of power system such as a liberalized market or microgrid. The OPF requirements have become more complex than it was and the classical power systems concepts and practices are overruled by the management of economic market, due to the deregulation of electricity market and consideration of dynamic system properties [1].

In deregulated electricity market, OPF research result can be extended into many research fields: electricity transmission fee computation, locational real-time pricing, available transfer capability estimation, network congestion management, etc. [2].

The most common methods for OPF: Linear Programming, Nonlinear Programming, Quadratic Programming, Newton-Raphson, Interior Point and Artificial Intelligence (AI) methods. AI methods include Genetic Algorithm (GA), Evolutionary Programming (EP), Artificial Neural Network, Ant Colony, Fuzzy Logic Method and Particle Swarm Optimization (PSO) [3]-[4].

The power transfer allocation is one of the important issues in deregulated power industry. The most common methods for allocation payment of electricity transmission systems: MVA-mile, MW-mile, contract path, postage-stamp rate, unused transmission capacity, counter-flow, and distribution factors [5]. The results of GA, EP and PSO were promising and encouraging for further research for solving OPF problem [6]-[8].

In a standard OPF problem, several objectives can be defined. The multiobjective OPF problem was converted to a single objective problem by linear combination of different objectives as a weighted sum. However, this requires multiple runs depending on the number of desired Pareto-optimal solutions (POS). Additionally, this method cannot be used to find POS in problems having a non-convex Pareto-optimal front. Evolutionary algorithms can be efficiently used to eliminate most of the difficulties of conventional methods [9]-[11]. Since they use a population of solutions in their search, multiple POS can be found in one single run. The multiobjective evolutionary algorithms have been proposed for different optimization problems of power system with impressive success [12]-[15].

Generally, in a multiobjective optimization the major challenges are generating uniform distributed Pareto set with maximum diversity, selecting the best compromise solution from the Pareto set as well as the computational efficiency. Several methods have been proposed to solve mutliobjective optimization problems [16]-[19].

In this paper, Multi-Objective Particle Swarm Optimization (MOPSO) technique is utilized to solve the OPF problem. The OPF problem is formulated as a nonlinear constrained multiobjective optimization problem where the fuel cost and wheeling cost are treated as competing objectives. A hierarchical clustering technique is implemented to manage Pareto-optimal set size. Furthermore, for choosing the best compromise solution from Pareto optimal solutions the Fuzzy theory is proposed. As well as several runs have been carried out on the standard IEEE 30-bus test system.

The rest of this paper is organized as follows. The problem statement is described in section II. Whereas multi-objective optimization and the proposed approach are described in sections III and IV respectively. The implementation of the proposed technique is described in section V. Finally, the results and conclusions are made in sections VI and VII respectively.

II Problem Statement

A. Problem Objectives

1. Minimization of Fuel Cost: The generator cost curves can be represented as

$$f_i = a_i + b_i P_{Gi} + c_i P_{Gi}^2 \quad (\$/\text{Hour}) \tag{1}$$

Where f_i is the fuel cost of the i^{th} generator, a_i, b_i, and c_i are the cost coefficients of the i^{th} generator. Table I contains the values of these coefficients. P_{Gi} is the real power output of the i^{th} generator.

In this study, J_1 represents the total fuel cost, *i.e.*,

$$J_1 = F(P_G) = \sum_{i=1}^{NG} f_i \quad (\$/\text{Hour}) \tag{2}$$

Where NG is the number of generators.

2. Minimization of Wheeling Cost: The wheeling cost is represented by the following equation

$$C_i = W_f \; S_i \; L_i \quad (\text{Cent/Hour}) \tag{3}$$

Where W_f is weighting factor and it's unit is cent/(hour. MVA. km), S_i is the average apparent power flow in branch i (MVA) and L_i is the length of branch i (km).

The J_2 represents the total wheeling cost (CT).

$$J_2 = CT = \sum_{i=1}^{Nb} W_f \; S_i \; L_i \tag{4}$$

Where Nb is the number of branches.

B. Problem Constraints

Equality Constraints are the load flow equations:

$$P_{G_i} - P_{D_i} - V_i \sum_{j=1}^{NB} V_j [G_{ij}\cos(\delta_i - \delta_j) + B_{ij}\sin(\delta_i - \delta_j)] = 0 \tag{5}$$

$$Q_{G_i} - Q_{D_i} - V_i \sum_{j=1}^{NB} V_j [G_{ij}\sin(\delta_i - \delta_j) - B_{ij}\cos(\delta_i - \delta_j)] = 0 \tag{6}$$

where i= 1,…NB, NB is the number of buses; P_G and Q_G are the generator real and reactive power respectively; P_D and Q_D are the load real and reactive power respectively; G_{ij} and B_{ij} are the transfer conductance and susceptance between bus i and bus j respectively [12].

Inequality Constraints are the system operating constraints:

- *Generation constraints:* V_G and Q_G represent generator voltages and reactive power outputs, respectively. These constraints are restricted by their lower and upper limits as follows:

$$V_{G_i}^{\min} \le V_{G_i} \le V_{G_i}^{\max}, \quad i = 1,\dots, NG \tag{7}$$

$$Q_{G_i}^{\min} \le Q_{G_i} \le Q_{G_i}^{\max}, \quad i = 1,\dots, NG \tag{8}$$

where NG is number of generators.

- *Transformer constraints:* represent the transformer tap (T) settings, which are bounded as follows:

$$T_i^{\min} \le T_i \le T_i^{\max}, \quad i = 1,\dots, NT \tag{9}$$

where NT is the number of transformers.

- *Switchable VAR sources constraints:* Switchable VAR compensations Q_C are restricted by their limits as follows:

$$Q_{ci}^{\min} \le Q_{ci} \le Q_{ci}^{\max}, \quad i = 1,\dots, NC \tag{10}$$

where NC is the number of switchable VAR sources.

- *Security constraints:* These include the constraints of voltages at load buses and transmission line loadings as follows:

$$V_{L_i}^{\min} \le V_{L_i} \le V_{L_i}^{\max}, \quad i = 1,\dots, NL \tag{11}$$

Where NL is the number of load buses

$$S_{l_i} \le S_{l_i}^{\max}, \quad i = 1,\dots, Nb \tag{12}$$

C. Problem Formulation

The multiobjective optimization problem can be mathematically formulated as a nonlinear constrained as follows.

$$\textit{Minimize}\ [J_1, J_2] \tag{13}$$

Subject to:

$$g(\mathrm{x},\mathrm{u}) = 0 \tag{14}$$

$$h(\mathrm{x},\mathrm{u}) \le 0 \tag{15}$$

where:

x: is the vector of dependent variables consisting of real power generated at slack bus, load bus voltages (V_L), generator reactive power outputs (Q_G), and transmission line loadings S_l. Hence, x can be expressed as

$$\mathrm{x}^T = [P_{G_1}, V_{L_1} \dots V_{L_{NL}}, Q_{G_1} \dots Q_{G_{NG}}, S_{l_1} \dots S_{l_{Nb}}] \tag{16}$$

u: is the vector of control variables consisting of generator voltages V_G, transformer tap settings T, and shunt compensations Q_c. Hence, u can be expressed as

$$u^T = [V_{G_1} \dots V_{G_{NG}}, P_{G_2} \dots P_{G_{NG}}, T_1 \dots T_{NT}, Q_{c_1} \dots Q_{c_{NC}}] \tag{17}$$

g: is the equality constraints.

h: is the inequality constraints.

III Multiobjective Optimization

Generally, multiobjective optimization problem consists of a number of objectives to be optimized simultaneously and is associated with a number of equality and inequality constraints [11]-[12], [19]. It can be formulated as follows:

$$\textit{Minimize} \quad f_i(x) \quad i = 1,\dots, N_{obj} \tag{18}$$

$$\textit{Subject to}: \begin{cases} g_j(x) = 0 & j = 1,\dots, M \\ h_k(x) \le 0 & k = 1,\dots, K \end{cases} \text{Constraints} \tag{19}$$

where f_i is the i^{th} objective functions, x is a decision vector that represents a solution, and N_{obj} is the number of objectives.

In a multiobjective optimization problem, a minimization problem, a solution x^1 dominates a solution x^2 if and only if:

$$1.\ \forall i \in \{1, 2, ..., N_{obj}\}: f_i(x^1) \le f_i(x^2) \qquad (20)$$

$$2.\ \exists j \in \{1, 2, ..., N_{obj}\}: f_j(x^1) < f_j(x^2) \qquad (21)$$

The nondominated solutions are denoted as Pareto optimal set or Pareto optimal front.

IV THE PROPOSED APPROACH

A. Overview

MOPSO technique is proposed for solving the OPF problem [20]-[24]. The OPF problem is formulated as a nonlinear constrained multiobjective optimization problem where the fuel cost and wheeling cost are treated as competing objectives. A hierarchical clustering technique is implemented to manage Pareto optimal set size [25]. Furthermore, the Fuzzy set theory has been used to find best compromise solution since for the decision making purpose and practical reasons, one is interested in only one solution [26], [27]. The detailed flow chart of the proposed MOPSO is shown in Fig.1.

The basic elements of the proposed MOPSO technique are briefly stated and defined as follows [17],[28]-[34]: -

- **Nondominated local set, $S_j^*(t)$,:**

It is a set that stores the nondominated solutions obtained by the jth particle up to the current time. As the j^{th} particle moves through the search space, its new position is added to this set and the set is updated to keep only the nondominated solutions. An average linkage based hierarchical clustering algorithm is employed to reduce the nondominated local set size if it exceeds a certain prespecified value.

- **Nondominated global set, S**(t),:**

It is a set that stores the nondominated solutions obtained by all particles up to the current time. First, the union of all nondominated local sets is formed. Then, the nondominated solutions out of this union are members in the nondominated global set.

- **External set:**

It is an archive that stores a historical record of the nondominated solutions obtained along the search process. This set is updated continuously after each iteration by applying the dominance conditions to the union of this set and the nondominated global set. Then, the nondominated solutions of this union are members in the updated external set.

- **Local best, Xj *(t), and global best, Xj**(t),:**

In order to guide the search towards the Pareto-optimal front, the global and local best individuals are selected as follows. The individual distances between members in nondominated local set of the j^{th} particle, $S_j*(t)$, and members in nondominated global set, $S**(t)$, are measured in the objective space. If $X_j*(t)$ and $X_j**(t)$ are the members of $S_j*(t)$ and $S**(t)$ respectively that give the minimum distance, they are selected as the local best and the global best of the j^{th} particle respectively.

B. MOPSO Steps

The steps for MOPSO can be summarized as following:-

Step 1: Initialization:

Set the time counter t=0 and generate randomly n particles, $\{X_j(0), j=1, \ldots, n\}$, where $X_j(0)=[x_{j,1}(0), \ldots, x_{j,m}(0)]$. where m is the number of optimized parameters. $x_{j,k}(0)$ is generated by randomly selecting a value with uniform probability over the k^{th} optimized parameter search space $[x_k^{min}, x_k^{max}]$. Similarly, generate randomly initial velocities of all particles, $\{V_j(0), j=1, \ldots, n\}$, where $V_j(0)=[v_{j,1}(0), \ldots, v_{j,m}(0)]$. $v_{j,k}(0)$ is generated by randomly selecting a value with uniform probability over the k^{th} dimension $[-v_k^{max}, v_k^{max}]$. Each particle in the initial population is evaluated using the objective functions. For each particle, set $Sj*(0)=\{Xj(0)\}$ and the local best $Xj*(0)=Xj(0)$, j=1, …, n. Search for the nondominated solutions and form the nondominated global set $S**(0)$. The nearest member in $S**(0)$ to $Xj*(0)$ is selected as the global best $Xj**(0)$ of the j^{th} particle. Set the external set equal to $S**(0)$. Set the initial value of the inertia weight $w(0)$.

Step 2: Time updating:

Update the time counter $t = t+1$.

Step 3: Weight updating:

Update the inertia weight $w(t) = \alpha\, w(t-1)$.

Where α is a decrement constant smaller than but close to 1

Step 4: Velocity updating:

Using the global best and individual best of each particle, the j^{th} particle velocity in the k^{th} dimension is updated according to equation (22):

$$v_{j,k}(t) = w(t)\, v_{j,k}(t-1) + c_1 r_1 (x^*_{j,k}(t-1) - x_{j,k}(t-1)) + c_2 r_2 (x^{**}_{j,k}(t-1) - x_{j,k}(t-1)) \qquad (22)$$

Step 5: Position updating:

Based on the updated velocities, each particle changes its position according to equation (23).

$$x_{j,k}(t) = v_{j,k}(t) + x_{j,k}(t-1) \qquad (23)$$

If a particle violates its position limits in any dimension, set its position at the proper limit.

Step 6: Nondominated local set updating:

The updated position of the j^{th} particle is added to $Sj*(t)$. The dominated solutions in $Sj*(t)$ will be truncated and the set will be updated accordingly. If the size of $Sj*(t)$ exceeds a prespecified value, the clustering algorithm will be invoked to reduce the size to its maximum limit.

Step 7: Nondominated global set updating:

The union of all nondominated local sets is formed and the nondominated solutions out of this union are extracted to be members in the nondominated global set *S**(t)*. The size of this set will be reduced by clustering algorithm if it exceeds a prespecified value.

Step 8: External set updating:
The external Pareto-optimal set is updated as follows.
Copy the members of *S**(t)* to the external Pareto set.

1. Search the external Pareto set for the nondominated individuals and remove all dominated solutions from the set.
2. If the number of the individuals externally stored in the Pareto set exceeds the maximum size, reduce the set by means of clustering.

Step 9: Local best and global best updating:
The individual distances between members in $S_j*(t)$, and members in $S**(t)$, are measured in the objective space. If $X_j*(t)$ and $X_j**(t)$ are the members of $S_j*(t)$ and $S**(t)$ respectively that give the minimum distance, they are selected as the local best and the global best of the j^{th} particle respectively.

Step 10: Stopping criteria:
If the number of iterations exceeds its maximum preset limit then stop, else go to step 2.

C. Reducing Pareto Set by Clustering

The hierarchical clustering algorithm is utilized to manage the Pareto optimal set. From the decision maker's point of view, reducing the size of the Pareto optimal set without affecting the trade-off front is desirable. [35].

D. Best Compromise Solution

The decision maker making the final judgment based on the best compromise solution that is selected from among the Pareto optimal solutions using the Fuzzy set theory [36]. To formulate fuzzy membership function, decision maker is asked to assess an unacceptable value of an objective F denoted by $F_i^{\max}$, and a satisfactory value of F denoted by $F_i^{\min}$. Here membership value 0 means least satisfaction whereas 1 indicates maximum satisfaction. Mathematically fuzzy membership function for each objective can be defined as:

$$\mu_i = \begin{cases} 1 & F_i \le F_i^{\min} \\ \dfrac{F_i^{\max} - F_i}{F_i^{\max} - F_i^{\min}} & F_i^{\min} < F_i < F_i^{\max} \\ 0 & F_i \ge F_i^{\max} \end{cases} \tag{24}$$

The normalized membership function (μ^k) is calculated as:

$$\mu^k = \frac{\sum_{i=1}^{N_{obj}} \mu_i^k}{\sum_{k=1}^{M} \sum_{i=1}^{N_{obj}} \mu_i^k} \tag{25}$$

Where M is number of nondominated solutions. The best compromise solution is that attains the maximum value of μ^k.

E. Proportional Sharing Principle

The proportional sharing principle has been used to trace the power flow. Fig.2 shows this principle, where f_1 and f_2 represent the outflow at connected node whereas f_a and f_b represent the inflow [37].

F. Upstream Looking Algorithm

In this study, the tracing algorithm for the electricity flow looks at the flows inflowing to the network nodes so that it is referred to as upstream looking.

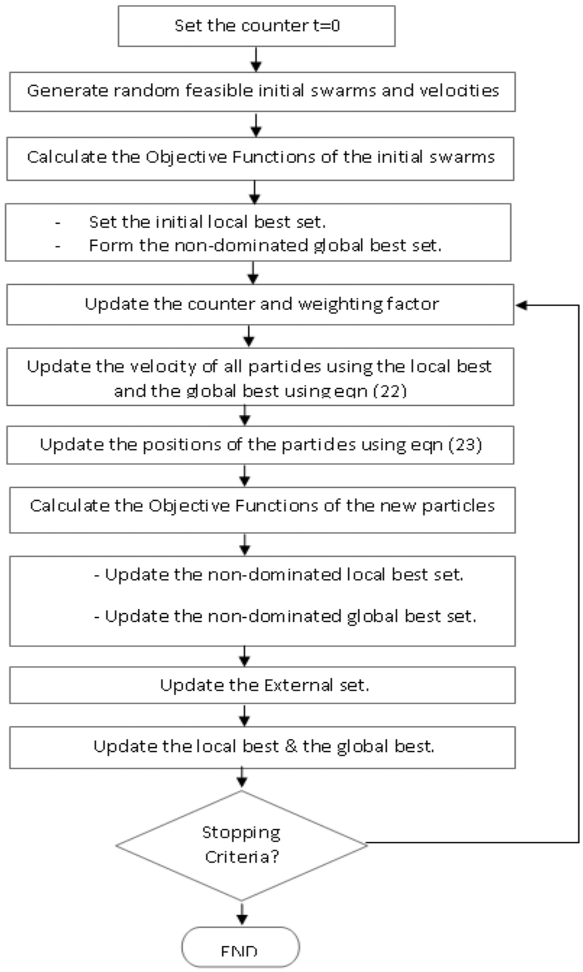
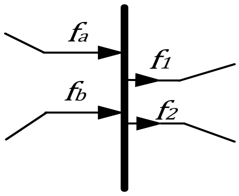


Figure1: Flow chart of the proposed approach.



$$f_1 = f_1 \frac{f_a}{f_a + f_b} + f_1 \frac{f_b}{f_a + f_b}$$
$$f_2 = f_2 \frac{f_a}{f_a + f_b} + f_2 \frac{f_b}{f_a + f_b}$$

Figure 2: Proportional Sharing Principle.

Upstream looking technique develops a set of real and reactive power contribution factors, which uses the results of AC power flow and the law of conservation of apparent power. According to these contribution factors, the generation portion of each generator in each transmission line and the generation portion of each generator in the transmission losses can be calculated. This algorithm determines the gross power flow that shows how the power output from each generator would be distributed among the lines and loads [37]–[40].

For reactive power flow, a transmission line is considered as its π equivalence and its charging capacitance effects is included in its terminal bus loads according to AC power flow solution. The reactive power flow at the two terminals of the line have different directions. Virtual bus has been added at the middle of each transmission line. This bus acts as reactive sources or sinks responsible for line generation or consumption [37]. Fig. 3 shows the virtual bus model.

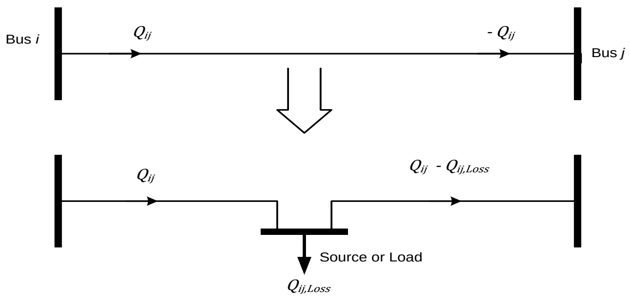


Figure 3: Virtual bus model.

G. MVA-km Methodology

MVA-km method is AC power flow based method. This method is an extended version of the MW-km method. It considers both real power and reactive power. MVA-km method allocates the wheeling cost based on the magnitude of power and the geographical distance between the delivery point and the receipt point [41]-[43]. The total transmission network cost can now be calculated using (3) and (4).

H. Implementation of the Proposed Approach

In this study, the techniques used were developed and implemented using MATLAB software. On all optimization runs, the population size is 50 and the maximum number of generations is 500. The maximum size of the Pareto optimal set and the local best set size were selected as 20 and 10 respectively. The clustering technique is used when the size of Pareto optimal set in global best set and local best set exceeds the respective bound.

I. Results and Discussions

The IEEE 30-bus system has been used to investigate the effectiveness of the proposed approach. Fig. 4 shows the single line diagram of the test system, and the detailed data is given in [44]. The system has six generators at buses 1, 2, 5, 8, 11, and 13 and four transformers with off-nominal tap ratio in lines 6-9, 6-10, 4-12, and 27-28. The Table II has the lower and upper limits, the initial settings of the control variables and the initial values of objective functions.

At first, the fuel cost and wheeling cost objectives are optimized individually and the best results of fuel cost and wheeling cost objectives are given in the Table II. Convergence of fuel cost and wheeling cost objectives are shown in Fig. 5 and Fig. 6 respectively.

The problem was handled as a multiobjective optimization problem where both objectives were optimized simultaneously with the proposed approach. In this study, two cases have been simulated:

Case 1: The generator cost curves are represented by quadratic functions as shown in (1). The values of the coefficients are given in Table II. The diversity of the Pareto optimal set over the trade-off surface is shown in Fig. 7. The best fuel cost, the best wheeling cost and the best compromise solution are given in Table I and shown in Fig.7.

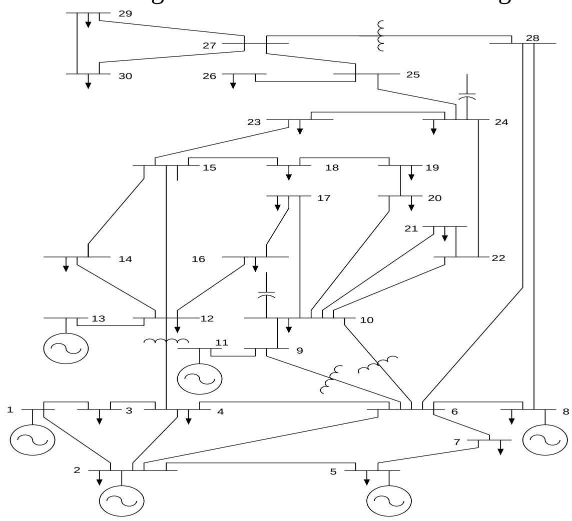


Figure 4: Single-line diagram of IEEE 30-bus test system.

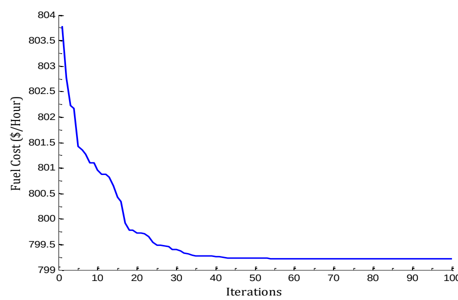


Figure5: Fuel cost optimization for IEEE 30-bus test system.

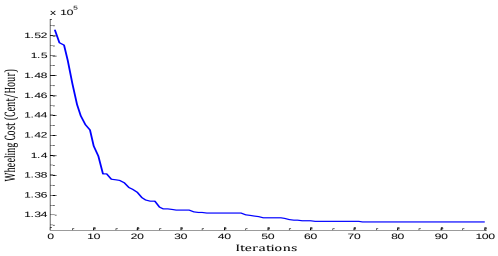


Figure 6: Wheeling cost optimization for IEEE 30-bus test system.

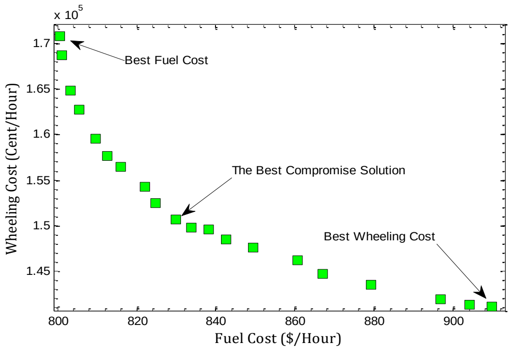


Figure7: Multiobjective optimization for IEEE 30-bus test system of case1.

Case 2: In this case, the cost curves of the generators at busses 1 and 2 are represented by piecewise quadratic functions as given in Table III [45]. The result of case is shown in Fig.8.

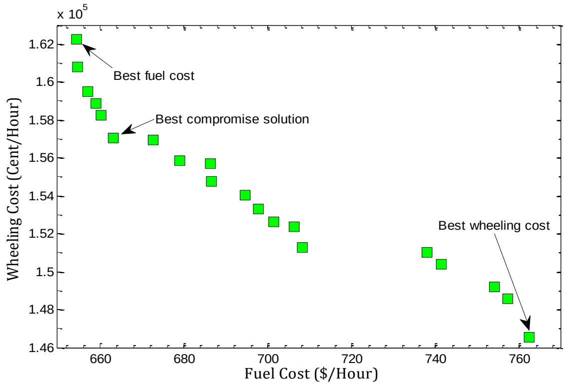


Figure8: Multiobjective optimization for IEEE 30-bus test system of case2.

TABLE II

Optimal Settings of Control Variables

Variables		Limits: Lower	Limits: Upper	Base Case [21]	Individual Optimization: Best Fuel Cost	Individual Optimization: Best Wheeling Cost	Proposed MOPSO Approach: Best Fuel Cost	Proposed MOPSO Approach: Best Wheeling Cost	Proposed MOPSO Approach: Best Compromise solution
Generators Output (MW)	P_1	50	200	99.226	177.24	74.25	169.27	78.72	135.08
	P_2	20	80	80.000	48.77	80.00	49.05	77.25	45.83
	P_5	15	50	50.000	21.33	50.00	21.73	47.23	35.99
	P_8	10	35	20.000	21.19	35.00	24.89	35.00	33.59
	P_{11}	10	30	20.000	11.55	30.00	14.79	30.00	27.01
	P_{13}	12	40	20.000	12.00	18.07	12.00	19.09	12.00
Generators Voltage (p.u.)	V_1	0.95	1.10	1.050	1.10	1.05	1.10	1.10	1.07
	V_2	0.95	1.10	1.040	1.04	1.00	1.04	1.06	1.03
	V_5	0.95	1.10	1.010	1.06	1.04	1.05	1.07	1.02
	V_8	0.95	1.10	1.010	1.10	1.09	1.05	1.07	1.07
	V_{11}	0.95	1.10	1.050	1.10	1.00	1.04	1.04	1.03
	V_{13}	0.95	1.10	1.050	1.10	1.03	1.04	1.05	1.03
Transformer Taps Position	T_{6-9}	0.90	1.10	1.078	0.94	0.98	1.01	1.01	1.00
	T_{6-10}	0.90	1.10	1.069	1.10	0.91	0.95	0.90	0.91
	T_{4-12}	0.90	1.10	1.032	1.03	1.01	1.03	1.02	1.01
	T_{28-27}	0.90	1.10	1.068	0.98	1.00	1.00	1.01	1.01
Shunt Elements (MVAR)	Qc_{10}	0.00	5.00	0.0	5.00	3.19	4.39	3.04	3.26
	Qc_{12}	0.00	5.00	0.0	4.96	5.00	3.39	3.82	3.21
	Qc_{15}	0.00	5.00	0.0	5.00	5.00	2.35	4.66	4.10
	Qc_{17}	0.00	5.00	0.0	3.49	3.96	3.92	3.19	4.67
	Qc_{20}	0.00	5.00	0.0	3.24	2.26	2.87	1.43	1.89
	Qc_{21}	0.00	5.00	0.0	5.00	5.00	3.09	5.00	3.63
	Qc_{23}	0.00	5.00	0.0	0.52	5.00	2.13	2.25	3.07
	Qc_{24}	0.00	5.00	0.0	5.00	5.00	4.14	2.05	3.02
	Qc_{29}	0.00	5.00	0.0	2.51	4.62	4.52	3.48	2.66
Fuel Cost ($/hour)				*901.84*	***799.21***	*926.24*	***800.65***	*909.73*	*829.97*
Wheeling Cost ($/hour)				*1,796.81*	*1,835.04*	***1,333.21***	*1,707.65*	***1,411.15***	*1,506.58*

TABLE I
Generator Cost Coefficients

	G_1	G_2	G_5	G_8	G_{11}	G_{13}
a	0.0	0.0	0.0	0.0	0.0	0.0
b	200	175	100	325	300	300
c	37.5	175	625	83.4	250	250

TABLE III
Generator Cost Coefficients for Case 2.

	From MW	**To MW**	**Cost Coefficients**		
			a	**b**	**c**
G_1	50	140	55.0	0.70	0.0050
	140	200	82.5	1.05	0.0075
G_2	20	55	40.0	0.30	0.0100
	55	80	80.0	0.60	0.0200

V Conclusion

Multi-objective particle swarm optimization technique has been employed to obtain a multi-objective solution to the optimal power flow problem of the IEEE 30-bus power system model. On all optimization runs, the swarm size is taken as 50 and the maximum number of generations is set at 500. The fuel cost and wheeling cost have been considered as competing objectives. Furthermore, non-smooth fuel cost curve has been considered. A clustering technique has been employed to manage the number of the Pareto optimal solution. Moreover, The Fuzzy set theory has been utilized to extract the best compromise solution over the trade-off curve. The results show the performance and efficiency of the proposed technique to solve multiobjective optimal power flow problem simultaneously.

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