Multiobjective Bees Algorithm for Optimal Power Flow Problem

Pornrapeepat Bhasaputra[1],
Sumeth Anantasate[2], and **Woraratana Pattaraprakorn**[3], Non-members

ABSTRACT

This paper presents a multiobjective bees algorithm (MOBA) for solving the multiobjective optimal power flow. The multiobjective optimal power flow is to simultaneously minimize total fuel cost and environmental pollution of generation with considering various constraints i.e. limits on generator real and reactive power outputs, bus voltages, transformer tap-setting and power flow of transmission lines. The proposed multiobjective bees algorithm is developed by using principle of multiobjective optimization. A clustering algorithm is applied for multiobjective bees algorithm in order to manage the size of the Pareto-optimal set. The proposed approach has been tested on the standard IEEE 30-bus system. The multiobjective bees algorithm produces true and well-distributed Pareto-optimal fronts in a single run. The results show that multiobjective bees algorithm has effectiveness and potential for solving multiobjective optimal power flow problem.

Keywords: Bees Algorithm (BA), Multiobjective Optimal Power Flow (MOOPF), Multiobjective Bees Algorithm (MOBA)

1. INTRODUCTION

In the past decade, optimal load flow (OPF) has dealt to minimize only one objective such as fuel cost [1-3]. However, due to the fact that real life problems involve several objectives and that the traditional optimization techniques have disadvantages. The application of new multiobjective optimization techniques appear in the recent studies.

Traditionally, multiobjective optimization problem was treated as a single objective optimization problem. The objective function was formed as a weighted sum of all objectives using suitable scaling/weighting factors. This approach has the disadvantage of finding only a single solution which does not express the trade-off between the different objectives [4]. Generating multiple solutions using this approach requires several runs with different weighting factors and hence elongates the running time [5]. As an alternative to this approach, recent studies consider the OPF as a true multi-objective optimization problem in which the objectives are treated simultaneously and independently [5-9]. This, however, makes the problem more complicated, whereas traditional optimization techniques have several weakness and drawbacks such as linearization, continuity, differentiability, local optima and constraints handling. Therefore, new optimization techniques such as genetic algorithms (GA), particle swarm optimization (PSO), bees algorithm (BA) are recently introduced and also applied in the field of power systems with promising success [7-13].

The literature includes several OPF studies that are dealt with multi-objectives and applied conventional and new optimization techniques. The OPF problem is generally an optimization problem with non-convex, non-smooth and non-differentiable objective functions. These properties become more evident and dominant if the effects of the valve-point loading of thermal generators and the nonlinear behaviour. A wide variety of optimization techniques have been applied to solve the OPF problems [14-23] such as quadratic programming, linear programming, nonlinear programming, interior point methods, and Newton-based techniques [14-18]. Generally, Quadratic programming based techniques have some disadvantages associated with the piecewise quadratic cost approximation. Linear programming methods have some disadvantages associated with the piecewise linear cost approximation. Nonlinear programming based procedures have many drawbacks such as insecure convergence properties and algorithmic complexity. Interior point methods have been reported as computationally efficient; however, if the step size is not chosen properly, the sub-linear problem may have a solution that is infeasible in the original nonlinear domain [18]. Newton-based techniques have a drawback of the convergence characteristics that are sensitive to the initial conditions and they may fail to converge due to the inappropriate initial conditions. For more discussions on these techniques, it can be consulted by the survey presented in [19].

Generally, the conventional optimization methods

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[1,2] The authors are with Department of Electrical and Computer Engineering, Thammasart University, Thailand, E-mail:bporr@engr.tu.ac.th and sumetha@pttep.com

[3] The author is with Department of Chemical Engineering, Thammasart University, Thailand, E-mail:pworarat@engr.tu.ac.th

that make use of derivatives and gradients are not able to locate or identify the global optimum. On the other hand, many mathematical assumptions such as convex, analytic and differential objective functions have to be given to simplify the problem. Hence, it becomes essential to develop optimization techniques that are efficient to overcome these drawbacks and difficulties. Heuristic algorithms such as genetic algorithms (GA), evolutionary programming, and particle swarm optimization (PSO) [20-22] have been proposed for solving the OPF problem.

Reference [4] presented a particle swarm optimization based OPF incorporating several objective as a weighted sum. Reference [5] proposed differential evolution based multiobjective economic environmental power dispatch, solved using the weighted sum approach. In references [7-11], a true multiobjective with competing fuel cost and power plant emissions were successfully formulated and produced promising results.

This paper presents a multiobjective bees algorithm (MOBA) based optimization approach to solve the multiobjective optimal power flow (MOOPF) problem. The MOOPF problem is formulated as a constrained nonlinear multiobjective optimization problem, where the fuel cost and emission are treated as competing objectives. A clustering algorithm is also applied to manage the size of the Pareto set. An algorithm based on fuzzy set theory is used to extract the best compromise solution.

2. PROBLEM FORMULATON

The MOOPF problem is to minimize two objective functions of fuel cost and emission with several equality and inequality constraints. Generally, the problem can be formulated as follows.

2.1 Multiobjective Formulation

Aggregating the objectives and constraints, the problem can be mathematically formulated as a constrained nonlinear mulitiobjective optimization problem as follows.

$$\text{Minimize} \quad [f(x,u), e(x,u)] \tag{1}$$

Subject to:

$$g(x,u) = 0 \tag{2}$$

$$h(x,u) \leq 0 \tag{3}$$

where $g(x,u)$ is the equality constraints, $h(x,u)$ is the system inequality constraints.

x is the vector of dependent variables (state variables) consisting of:

1. Generator active power output at slack bus P_{G1}.
2. Load bus voltage V_L.
3. Generator reactive power output Q_{G1}.
4. Transmission line loading S_l.

Hence, x can be expressed as:

$$x^T = [P_{G1}, V_{L1} \dots V_{LNB}, Q_{G1} \dots Q_{GNG}, S_{l1} \dots S_{lNL}] \tag{4}$$

where NB,NG and NL are the number of load buses, the number of generators, and the number of transmission lines, respectively.

u is the vector of independent variables (control variables) consisting of:

1. Generator active power output P_G at PV buses except at the slack bus P_{G1}.
2. Generation bus voltages V_G.
3. Transformer tap settings T.

Hence, u can be expressed as:

$$u^T = [P_{G2} \dots P_{GNG}, V_{G1} \dots V_{GNG}, T_1 \dots T_{NT}] \tag{5}$$

where NT is the number of the regulating transformers.

2.1.1 Objective of Fuel Cost

The total US$/h fuel cost $f(x,u)$ can be expressed by quadratic functions as follows.

$$f(x,u) = \sum_{i=1}^{NG} (a_i + b_i P_{Gi} + c_i P_{Gi}^2) \tag{6}$$

where a_i,b_i and c_i are the cost coefficients of the i^{th} generator, and P_{Gi} is the real power output of the i^{th} generator.

2.1.2 Objective of emission

The environmental pollutants such as sulphur oxides (SO_X) and nitrogen oxides (NO_X) caused by fossil-fuel units can be modelled separately. However, for comparison purposes, the total ton/h emission $e(x,u)$ of these pollutants can be expressed as follows.

$$e(x,u) = \sum_{i=1}^{NG} (10^{-2}(\alpha_i + \beta_i P_{Gi} + \gamma_i P_{Gi}^2) + \xi_i \exp(\lambda_i P_{Gi})) \tag{7}$$

where $\alpha_i, \beta_i, \gamma_i, \xi_i$ and λ_i are coefficients of the i^{th} generator emission characteristics.

2.2 Problem Constraints

2.2.1 Equality Constraints

Power balance is equality constraint. The total power generation must cover the total demand (P_D) and real power loss in transmission lines (P_{loss}). It can be expressed as follows.

$$\sum_{i=1}^{NG} = (P_{Gi} - P_D - P_{loss}) = 0 \quad (8)$$

The calculation of P_{loss} implies solving the load flow problem with equality constraints on real and reactive power at each bus as follows [24].

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{NB} V_j \Big[G_{ij} \cos(\delta_i - \delta_j) + B_{ij} \sin(\delta_i - \delta_j) \Big] = 0 \quad (9)$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{NB} V_j \Big[G_{ij} \sin(\delta_i - \delta_j) + B_{ij} \cos(\delta_i - \delta_j) \Big] = 0 \quad (10)$$

P_{Gi}, Q_{Gi} are real and reactive power generated at the i^th bus. P_{Di}, Q_{Di} are demand real and reactive power generated at the i^{th} bus. G_{ij}, B_{ij} are the transfer conductance and susceptance between i^{th} bus and j^{th} bus. V_i, V_j are the voltage magnitudes at i^{th} bus and j^{th} bus. δ_i, δ_j are the voltage angles at i^{th} bus and j^{th} bus.

Then, power loss in transmission lines can be calculated as follows.

$$P_{loss} = \sum_{k=1}^{NL} g_k \left[V_j^2 + V_j^2 - 2V_iV_j \cos(\delta_i - \delta_j) \right] \quad (11)$$

where g_k is the conductance of the k^{th} line that connects i^{th} bus and j^{th} bus.

2.2.2 Inequality Constraints

2.2.2.1 Generation Constraints

For stable operation, generator voltage, real power output and reactive power output are restricted by the lower and upper limit as follows.

$$V_{Gi}^{min} \leq V_{Gi} \leq V_{Gi}^{max} \quad ,i = 1, \dots, NG \quad (12)$$
$$P_{Gi}^{min} \leq P_{Gi} \leq P_{Gi}^{max} \quad ,i = 1, \dots, NG \quad (13)$$
$$Q_{Gi}^{min} \leq Q_{Gi} \leq q_{Gi}^{max} \quad ,i = 1, \dots, NG \quad (14)$$

where NG is the number of generators.

2.2.2.2 Transformer Constraints

Transformer tap settings are restricted by the minimum and maximum limits as follows.

$$T_i^{min} \leq T_i \leq T_i^{max} \quad ,i = 1, \dots, NT \quad (15)$$

where NT is the number of regulating transformers.

2.2.2.3 Security Constraints

These incorporate the constraints of voltage magnitudes of load buses as well as transmission line loadings as follows [25].

$$V_{Li}^{min} \leq V_{Li} \leq V_{Li}^{max} \quad ,i = 1, \dots, NB \quad (16)$$
$$S_u \leq S_u^{max} \quad ,i = 1, \dots, NL \quad (17)$$

where NB is the number of buses. NL is the number of transmission lines.

3. MULTIOBJECTIVE OPTIMIZATION PRINCIPLE

Many real world problems involve simultaneous optimization of several objective functions. Generally, these functions are non-commensurable and often competing and conflicting objectives. Multiobjective optimization with such conflicting objectives functions gives rise to a set of optimal solutions, instead of one optimal solution. The reason for the optimality of many solutions is that no one can be considered to be better than any others with respect to all objective functions. These optimal solutions are known as Pareto-optimal solution [26-29].

For a multiobjective optimization problem, any two solutions x_1 and x_2 can have one of two possibilities, which one dominates the other or does not dominate the other. In a minimization problem, without loss of generality, a solution x_1 will dominate x_2, if the following two conditions are satisfied.

$$\forall_i \epsilon \{1, 2, \dots, N_{obj}\} : \ f_i(x_1) \leq f_{x_2} \quad (18)$$
$$\exists_i \epsilon \{1, 2, \dots, N_{obj}\} : \ f_i(x_1) \leq f_{x_2} \quad (19)$$

If any of the above condition is violated, the solution x_1 will not dominate the solution x_2. If x_1 dominates the solution x_2, x_1 will be called the nondominated solution. The solutions that are nondominated within the entire search space are denoted as Pareto-optimal and constitute the Pareto-optimal set. This set is also known as Pareto-optimal front.

4. THE PROPOSED APPROACH

4.1 Overview of Bees Optimization

Bees algorithm (BA) was proposed by Pham D.T [12] optimizing numerical problems in 2006. The algorithm mimics the food foraging behaviour of swarms of honey bees. Honey bees use several mechanisms like waggle dance to optimally locate food sources and to search new ones. This makes them a good candidate for developing new intelligent search algorithms. It is a very simple, robust and population based stochastic optimization algorithm.

In BA, the colony of artificial bees contains two groups of bees, which are scout and employed bees. The scout bees have the responsibility, which is to find a new food source. The responsibility of employed bees is to determine a food source within the neighbourhood of the food source in their memory and share their information with other bees within the hive.

In recent year, BA has been presented as an efficient population based heuristic technique with a flexible and robustness. However, changing conventional single objective BA to MOBA requires some adaptation. In MOBA, there is no only one global solution, but it is a set of non-dominated global solutions. Thus, the process of Pareto-optimal set shall be applied to proposed algorithm of MOBA.

4.2 BA Solving Single Objective OPF Problem (BA-OPF)

An application of BA is described for solving the single objective OPF problem. Especially, a suggestion about how to deal with the equality and inequality constraints of the OPF problem, when each search point is modified in the BA, is also given.

The algorithm requires a number of parameters to be set, namely: NC is the number of iterations, n_s is the number of scout bees, m is the number of sites selected out of n_s visited sites, e is the number of best sites out of m selected sites, nep is the number of bees recruited for best e sites, nsp is the number of bees recruited for the other $(m-e)$ selected sites, ngh is initial size of patches which includes site and its neighborhood and stopping criterion.

The initial objective solution is calculated from initial and state solution in formula (6) for fuel cost function or formula (7) for emission objective individually. Note that it is very important to create a set of solution satisfying the equality and inequality constraints.

To handle the inequality constraints of state variables including slack bus real and reactive power, load bus voltage magnitudes and transmission line loading of each single objective function, the extended objective function or fitness function can be defined as:

$$M = f_c + K_p(P_{G1} - P_{G1}^{lim})^2 + K_Q(Q_{G1} - Q_{G1}^{lim})^2 + K_V\sum_{i=1}^{NB}(V_{Li} - V_{Li}^{lim})^2 + K_s\sum_{i=1}^{NL}(S_{Li} - S_{Li}^{lim})^2 \quad (20)$$

where
$f_c = f(x,u)$, if fuel cost objective function is handled, or
$f_c = e(x,u)$, if emission objective function is handled
K_P,K_Q,K_V and K_P are the penalty factors of penalty function
x^{lim} is the limit value of the dependent variable x given as:

$$x^{lim} = \begin{cases} x^{max} & if x > x^{max} \\ x^{min} & if x > x^{min} \end{cases} \quad (21)$$

It should be noted that the constraints on the reactive power at each generator excluding slack bus are not included in the fitness function because they are controlled in power flow program. The process of BA-OPF can be summarized as follows:

Step 1: Generate randomly the initial populations of n_s scout bees. These initial populations must be feasible candidate solutions that satisfy the constraints. Set $NC = 0$.
Step 2: Run power flow and evaluate the fitness value of the initial populations.
Step 3: Select m best solutions for neighbourhood search.
Step 4: Separated the m best solutions to two groups, the first group have e best solutions and another group has $(m-e)$ best solutions.
Step 5: Determine the size of neighbourhood search of each best solutions (ngh).
Step 6: Generate solutions around the selected within solutions neighbourhood size.
Step 7: Run power flow and evaluate generated solutions and select the fittest solution from each patch.
Step 8: Check the stopping criterion. If satisfied, terminate the search, else $NC = NC + 1$.
Step 9: Assign the $(n-m)$ population to generate new solutions. Go to Step 2.

4.3 Proposed MOBA Solving Multiobjective Optimal Power Flow Problem

An application of proposed MOBA is described for solving the MOOPF problem with the equality and inequality constraints. The control variables of MOBA used for solving MOOPF are the same as single objective OPF as mentioned above. Then the two initial objective solutions are simultaneously calculated from initial and state solutions in formula (6) for fuel cost objective function and formula (7) for emission objective function.

To handle inequality constraints of state variables of multiobjective function of fuel cost and emission, the extended objective function can be defined as:

$$F = f_{x,u} + K_p(P_{G1} - P_{G1}^{lim})^2 + K_Q(Q_{G1} - Q_{G1}^{lim})^2 + K_V\sum_{i=1}^{NB}(V_{Li} - V_{Li}^{lim})^2 + K_s\sum_{i=1}^{NL}(S_{Li} - S_{Li}^{lim})^2 \quad (22)$$

$$E = e_{x,u} + K_p(P_{G1} - P_{G1}^{lim})^2 + K_Q(Q_{G1} - Q_{G1}^{lim})^2 + K_V\sum_{i=1}^{NB}(V_{Li} - V_{Li}^{lim})^2 + K_s\sum_{i=1}^{NL}(S_{Li} - S_{Li}^{lim})^2 \quad (23)$$

The basic elements of the proposed MOBA technique are briefly stated and defined as follows:

Step 1: Generate randomly the initial populations of n_s scout bees. These initial populations must be feasible candidate solutions that satisfy the constraints. Set $NC = 0$.

Step 2: Run power flow and evaluate the fuel cost and emission fitness value of the initial populations.

Step 3: Search for non-dominated solutions from initial solution by using non-dominated function and find m best solutions for neighbourhood search by using fuzzy c-mean clustering (FCM) [30].

Step 4: Separated the m best solutions to two groups, the first group are e best solutions by using compromise fuzzy and another group is other selected $(m - e)$ solutions.

Step 5: Determine the size of neighbourhood search of each best solutions (ngh).

Step 6: Generate solutions around the selected solutions within neighbourhood size.

Step 7: Run power flow and evaluate the fuel cost and emission fitness value of the generated solution.

Step 8: Search for non-dominated solutions from all solution by using non-dominated function. If non-dominated solution is over the limit, then uses FCM.

Step 9: Check the stopping criterion. If satisfied, terminate the search, else $NC = NC + 1$.

Step10: Assign the $(n - m)$ population to generate new solutions and add it with last best solution. Go to Step 2.

Upon having the Pareto-optimal set of non-dominated solution, fuzzy-based mechanism to extract the best compromise solution is imposed to present one solution to decision maker. The computation flow chart of the proposed MOBA method is depicted in Figure 1.

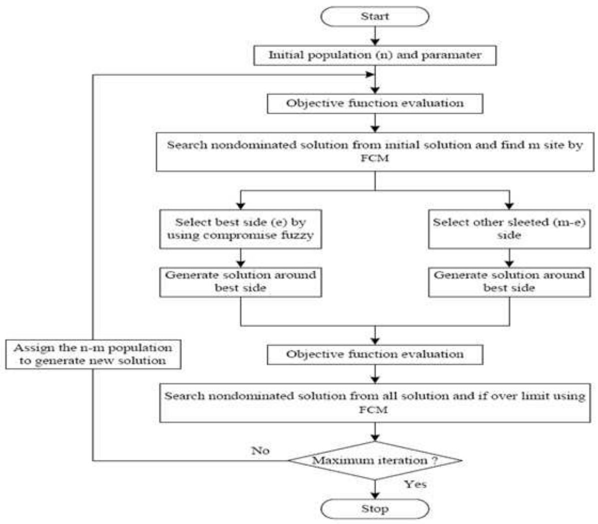

Fig.1: *Computation flow chart of the proposed MOBA*

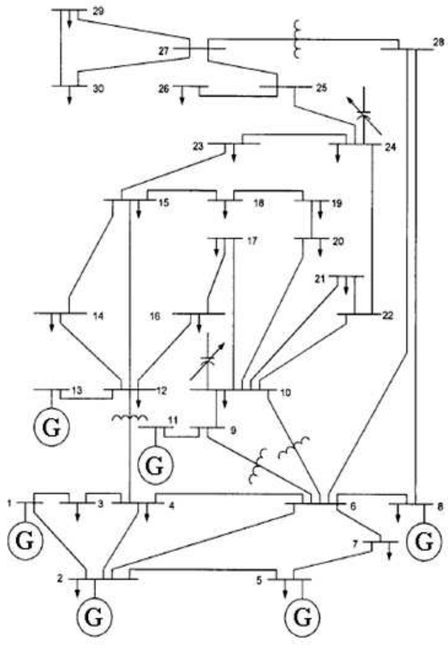

Fig.2: *IEEE 30-bus system*

5. SIMULATION RESULTS AND DISCUSSIONS

The BA-OPF and proposed MOBA have been tested on the IEEE 30-bus test system shown in Figure 2. The IEEE 30-bus system consists of 41 transmission lines, 6 power generation units and 4 tap-changing transformers. The generator coefficients of fuel cost and emission in (6) and (7) are given in Table 1. Table 2 shows the values of the parameters adopted for BA-OPF and MOBA. They are computed by Pentium core 2 duo 2.2 GHz, processer 2 GB ram, under Matlab? program.

Table 1: *Fuel cost and emission coefficients*

Unit	Cost Coefficients			Emission Coefficients				
	a	b	c	α_i	β_i	γ_i	ξ_i	λ_i
1	0	2.00	0.0038	4.09	-5.554	6.49	2.0E-4	2.86
2	0	1.75	0.0175	2.54	-6.047	5.64	5.0E-4	3.33
3	0	1.00	0.0625	4.26	-5.094	4.59	1.0E-6	8.00
4	0	3.25	0.0083	5.33	-3.550	3.38	2.0E-3	2.00
5	0	3.00	0.0250	4.26	-5.094	4.59	1.0E-6	8.00
6	0	3.00	0.0250	6.13	-5.555	5.15	1.0E-5	6.67

5.1 Results of Single Objective Optimization Using BA-OPF

The value of parameter adopted for BA-OPF has been shown in Table 2. The values were decided empirically. The algorithm was initialized with all weight values set randomly within the range 0 to 1.

The BA-OPF is tested to 100 runs for solving the single objective OPF problem. The best solution of individual cost function and emission function, when are optimized individually using BA-OPF is shown in Table 3, with following setup: population = 20, patch size = 0.01, maximum iteration = 50.

Table 2: *Estimated rate, $R_{GMM}(D)$ in (12), and empirical average encoding rate of $SVQZ_8$ at various step sizes*

Bees Method parameters	**Symbol**	**BA-OPF**	**MOBA**
Population	n_s	20	40
Number of selected sites	m	5	7
Number of elite site	e	1	1
Patch size	ngh	0.01	0.01
Number of bees around elite site	nep	15	10
Number of bees around other selected site	nsp	1	5
Maximum number of iteration	$itermax$	50	50
Penalty factor of slack bus active power	K_P	100	100
Penalty factor of slack bus reactive power	K_Q	100	100
Penalty factor of voltage magnitude	K_V	100,000	100,000
Penalty factor of transmission line loadings	K_S	100,000	100,000

Table 3: *$R_{class}(D)4$ corresponding to Table 4 (bits per sample)*

Variable	**Limit**		**Best Result**	
	Lower	**Upper**	**Fuel cost**	**Emission cost**
P_{G1}(MW)	50	200	176.467	65.016
P_{G2}(MW)	20	80	48.736	66.980
P_{G3}(MW)	15	50	21.730	49.979
P_{G4}(MW)	10	35	21.272	35.00
P_{G5}(MW)	10	30	12.128	30.00
P_{G6}(MW)	12	40	12.532	40.00
V_{G1}(p.u.)	0.95	1.05	1.050	1.037
V_{G2}(p.u.)	0.95	1.10	1.035	1.000
V_{G5}(p.u.)	0.95	1.10	0.949	1.019
V_{G8}(p.u.)	0.95	1.10	0.947	0.998
V_{G11}(p.u.)	0.95	1.10	0.961	0.953
V_{G13}(p.u.)	0.95	1.10	0.961	0.953
T_{11}	0.90	1.10	0.949	1.019
T_{12}	0.90	1.10	0.947	0.998
T_{15}	0.90	1.10	0.961	0.953
T_{36}	0.90	1.10	0.961	0.953
Fuel cost ($/h)			**802.305**	944.172
Emission (ton/h)			0.364	**0.2049**
Transmission losses (MW)			9.467	3.585
CPU time (sec)			16.34	16.10
Performance of BA-OPF				
Worst			803.364	0.2052
Average			802.601	0.2051
Best			802.305	0.2049
Standard deviation			0.228	0.00008

For comparison purpose, the results using evolutionary programming algorithm (EP) [22] and modified differential evolution algorithm (MDE) [25] comparing to single objective result of BA-OPF are shown in Table 4. The simulation results show that the BA-OPF has obtained the least cost of all. The performance of BA-OPF shows that it has good solution in each run. The convergence of BA-OPF solutions are individually shown in Figure 3 for single objective of fuel cost [31] and Figure 4 for single objective of emission. The fast convergence of the BA-OPF technique is quiet evident as it take only few iteration to reach the optimal solution.

Table 4: *Comparison between $R_{GMM}(D$ in (12) and average rate using RE_8 in AMR-WB+*

Variable	**EP [22]**	**MDE [25]**	**BA-OPF**
P_{G1}(MW)	173.84	175.974	176.467
P_{G2}(MW)	49.998	48.884	48.736
P_{G3}(MW)	21.386	21.510	21.730
P_{G4}(MW)	22.630	22.240	21.272
P_{G5}(MW)	12.928	12.251	12.128
P_{G6}(MW)	12.000	12.000	12.532
Total generation (MW)	292.79	292.859	292.865
Fuel cost ($/h)	802.62	802.376	**80.305**
Losses (MW)	-	9.459	9.467
CPU time (sec)	51.4	23.07	20.03
Population	20	18	20
Iteration	50	160	50

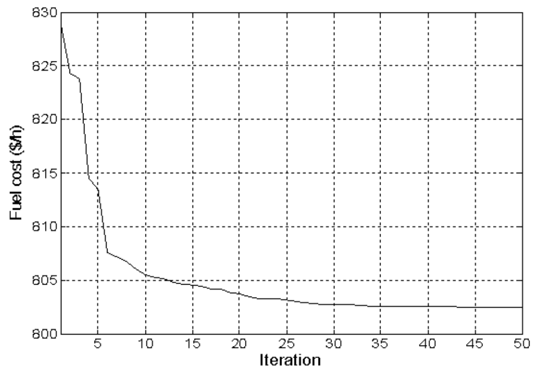

Fig.3: *Convergence fuel cost of BA-OPF*

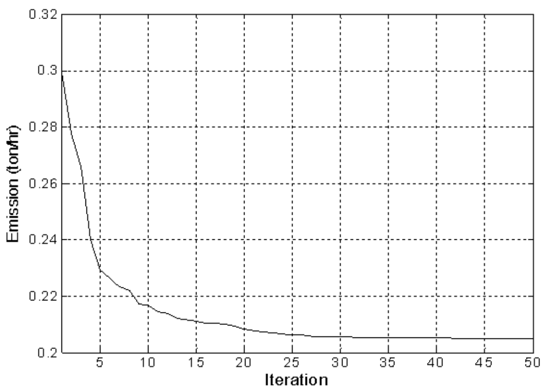

Fig.4: *Convergence Emission of BA-OPF*

5.2 Results of Multiobjective Optimization using Proposed MOBA

In this study, the proposed MOBA technique has been developed in order to make it suitable for solving nonlinear constraints optimization problem. A procedure checks the feasibility of the candidate solution in all stage of the search process. This ensures the feasibility of the non-dominated solution.

The parameter of MOBA with following setup: population $n_s = 40$, number of m site = 7, number of bees around $m - e$ site = 5 , number of elite site $e = 1$, number of bees around elite site = 10 , patch size = 0.1 , maximum iteration = 50. The parameters of MOBA were shown in Table 2. The maximum size of the Pareto-optimal set was selected as 50 solutions.

To demonstrate the effectiveness of the proposed MOBA technique, 30 different optimization runs have been carried out in MOBA. The best solution is shown in Table 5. It is quite evident that the propose MOBA gives good results. For different optimization runs with 50 non-dominated solutions per run, the total 1500 non-dominated solutions can be obtained by MOBA. The FCM are employed for reducing non-dominated solution in each run to 25 non-dominated solutions. The minimum fuel cost and emission from best solution using MOBA are compared with single objective of BA-OPF as shown in Table 5.

Table 5: *Results of the comparison based on the modified modeling*

Variable	Best Compromise	Minimum Fuel Cost	Minimum Emission
P_{G1}(MW)	11.749	173.1535	63.7720
P_{G2}(MW)	56.1260	49.2461	69.5016
P_{G3}(MW)	29.0751	21.0882	49.8207
P_{G4}(MW)	32.9166	25.3907	34.8865
P_{G5}(MW)	25.8106	11.8151	29.8560
P_{G6}(MW)	33.9545	12.0775	39.8835
V_{G1}(p.u.)	1.0365	1.0497	1.0317
V_{G2}(p.u.)	0.9781	1.0167	0.9702
V_{G5}(p.u.)	1.0365	1.0121	1.0099
V_{G8}(p.u.)	1.0460	1.0352	1.0099
V_{G11}(p.u.)	1.0692	1.0219	1.0368
V_{G13}(p.u.)	1.5096	1.0303	0.9611
T_{11}	0.9327	0.9990	0.9898
T_{12}	1.0026	0.9686	1.0140
T_{15}	1.0426	0.9983	1.0915
T_{36}	1.0454	0.9688	0.9075
Fuel cost ($/h)	**846.3703**	**802.954**	948.709
Emission (ton/h)	**0.2690**	0.3556	**0.2054**
Losses (MW)	6.2422	9.3829	4.3304
CPU time (sec)	**35.82**		
Minimum solution of single objective			
Fuel cost ($/h)	-	**802.305**	944.172
Emission (ton/h)	-	0.364	**0.2049**

The comparison result shows that fuel and emission costs of MOBA are nearly the same as those of BA solving single objective OPF problem (BA-OPF). Figure 5 shows Pareto-optimal fronts of the best solution, which have been searched by proposed MOBA. It can be seen that the non-dominated solutions obtained by proposed MOBA span over the entire Pareto-optimal fronts. Figure 6 and 7 show convergence of fuel cost and emission, which have been searched by proposed MOBA.

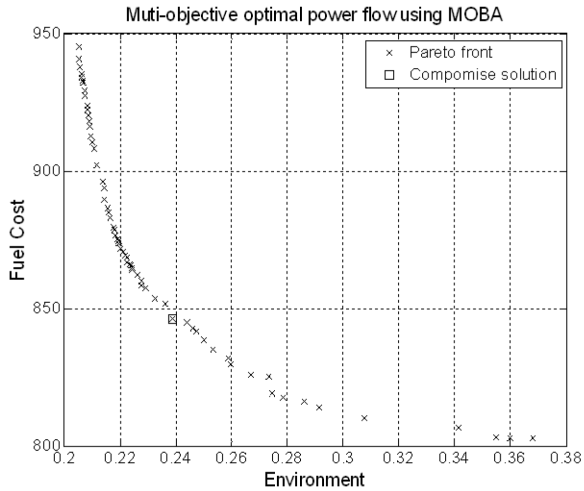

Fig.5: *Pareto-optimal fronts of the proposed MOBA*

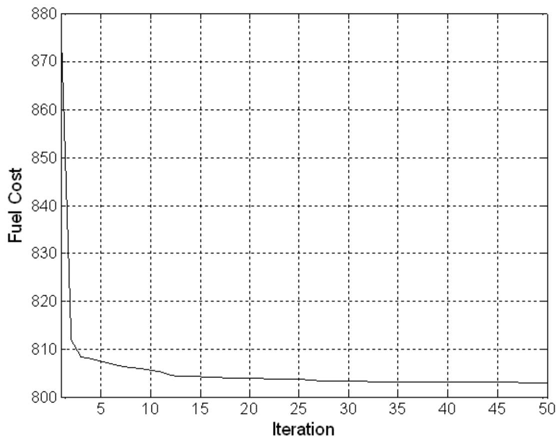

Fig.6: *Convergence fuel cost of proposed MOBA*

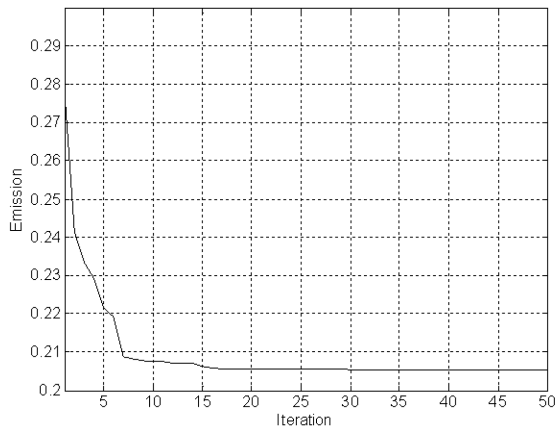

Fig.7: *Convergence emission of proposed MOBA*

6. CONCLUSION

The paper has employed a multiobjective bees algorithm (MOBA) to solve the MOOPF problem with many constraints in IEEE 30-bus system. A clustering technique is implemented to provide the operator with manageable Pareto-optimal set. The results show that the proposed approach is efficient and high quality for solving MOOPF problem, which multiple Pareto-optimal solutions can be found in a single run. In addition, the non-dominated solutions are well-distributed and have satisfactory diversity characteristics. In the future, efforts will be made to incorporate with more objective functions to the problem structure, which will be attempted by the proposed methodology.

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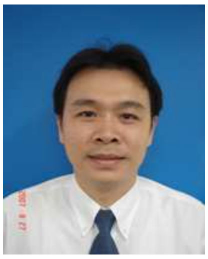

Sumeth Anantasate is presently studying PhD of electrical engineering at Thammasat University.He was born in Bangkok, Thailand, in 1971. He received his B. Eng and M.Eng degree in electrical engineering from University of Kasetsat in 2001. His working experience is spent over 16 years in the oil & gas engineering. He is currently working towards a PhD at Thammasat University on the reliability improvement and optimization of distributed generation (DG) in the power system networks. He is author of several papers published on international journals or presented in various international conferences. He is a student member of IEEE. He has been invited to be expert at the Technip Engineering, Ltd. (Oil & Gas International Engineering Company). His research activity is focus on electrical power system, energy management system, system reliability improvement, network planning and optimization, and distributed generation. The research is being carried out at the electrical power system department of Thammasat University.

Woraratana Pattaraprakorn is presently assistant profrossor, chemical engineering at Thammasat University. She was born in Bangkok, Thailand, in 1972. She received her B.Sci. and M.Eng degree in chemical technology and chemical engineering from Chulalongkorn University in 1994 and 1996, respectively and D.Eng. in chemical engineering from Tokyo Institute of Technology in 2005. She worked as environmental officer at Pollution Control Department, Ministry of Science, Technology and Environment during 1996-1998. She has spent over 10 years in department of chemical engineering, faculty of engineering, Thammasat University. She is author of several papers published on international journals or presented in various international conferences. Her research focuses on renewable energy utilization, waste utilization and energy management system. The research is being carried out at faculty of engineering, Thammasat University.

Pornrapeepat Bhasaputra is presently head of electrical and computer engineering department at Thammasat University. He was born in Bangkok, Thailand, in 1975. He received his B. Eng degree (First Class Honors) in electrical engineering from Thammasat University in 1996, M.Eng and D.Eng degree in electrical power system management from Asian Institute of Technology in 2001 and 2007, respectively. His working experience is spent over 10 years in electrical power system, energy conservation and energy management. He is author of several papers published on international journals or presented in various international conferences. His research activity focuses on power system operation, management and control, optimization application in power system and industrial, FACTS application in power system, electricity supply industrial reform and deregulation, power system stability and energy management and energy conservation. The research is being carried out at faculty of engineering, Thammasat University.