Loss Minimization Using Optimal Power Flow Based on Swarm Intelligences

Numphetch Sinsuphun[1], **Uthen Leeton**[2], **Umaporn Kwannetr**[3], **Dusit Uthitsunthorn**[4], and **Thanatchai Kulworawanichpong**[5], Non-members

ABSTRACT

This paper describes optimal power flow based on swarm intelligences in which the power transmission loss function is used as the problem objective. Although most of optimal power flow problems involve the total production cost of the entire power system, in some cases some different objective may be chosen. In this paper, to minimize the overall power transmission losses, four decision variables are participated. They are i) power generated from generating plants, ii) specified voltage magnitude at control substations, iii) tap position of tapchanging transformers and iv) reactive power injection from reactive power compensators. Swarm intelligences are wellknown and widely accepted as potential intelligent search methods for solving such a problem. In this paper, Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC) and Differential Evolution (DE) are employed to solve optimal power flow problems. A 6-bus and 30-bus IEEE power systems are used for test. As a result, all swarm intelligences search algorithms can solve optimal power flow problems efficiently. The artificial bee colony and the differential evolution provide results better than other swarm intelligent techniques.

Keywords: Optimal Power Flow, Power Loss Minimization, Genetic Algorithm, Particle Swarm Optimization, Artificial Bee Colony, Differential Evolution

1. INTRODUCTION

Optimal power flow is one of nonlinear constrained and occasionally combinatorial optimization problems of power systems. The various algorithms for solving such problems can be found in the literature. The optimal power flow problem has been developed continually since its introduction by Carpentier in 1962 [1]. It is useful to determine the goals of optimal power flow problems. The primary goal of a generic optimal power flow is to minimize the total production cost of the entire system to serve the load demand for a particular power system while maintaining the security of the system operation. The production costs of electrical power systems may depend on the situation, but in general they normally mean to the cost of generating power at each generating unit of power plants. This operation is subjected to keep each component in the power system within its desired operation range at steadystate. This will include maximum and minimum outputs for generators, maximum MVA flows of power transmission lines and transformers, as well as system bus voltages within specified ranges.

It has taken over decades to develop efficient algorithms for its solution because it is a very large, nonlinear mathematical programming problem. Many different mathematical approaches have been applied for seeking its solution. The methods discussed in the literature use one of the following five methods [2]. They are i) lambda iteration method as found in economic dispatch problem solving, ii) gradient method, iii) Newtons method, iv) linear programming and v) interior point method. Apart from analytical approaches, there also exist intelligent search methods.

Intelligent search methods (e.g. simulated annealing [3], genetic algorithm [4], evolutionary programming [5], particle swarm optimization [6]-[9], etc) have been recently released for the optimal power flow problem. The genetic algorithm (GA) based solution methods are found to be most suitable because of their ability of simultaneous multidimensional search for optimal solutions. They are wellknown and widely used at the beginning period of solving the optimal power flow problems based on intelligent search methods. However, in recently year, The ABC [10] is applied to solve optimal power flow. For economic dispatch problem, the results show that the ABC approach is able to obtain higher quality solutions efficiently and faster computational time than the conventional approaches. Also, DE [11] is applied to IEEE 30-bus test system for solving optimal power flow. The results reported are proficiency of methodology over other techniques and the DE solution give faster convergence than other existing techniques.

This paper proposes an application of swarm intelligences to solve optimal power flow problems. The

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[1,2,3,4,5] The authors are with Power System Research Unit, School of Electrical Engineering, Institute of Engineering, Suranaree University of Technology, Nakhon Ratchasima, Thailand 30000, E-mail: phetchty@hotmail.com, Uthen.leeton@gmail.com and Thanatchai@gmail.com

controllable system quantities are generator MW, controlled voltage magnitude, reactive power injection from reactive power sources and transformer tap setting. The objective used herein is to minimize the overall power transmission losses by optimizing the control variables within their limits. Therefore, no violation on other quantities (e.g. MVA flow of transmission lines, load bus voltage magnitude, generator MVAR) occurs in normal system operating conditions. A six-bus [12] and IEEE 30-bus test system are employed for test. The results obtained from various swarm intelligent techniques are compared.

This paper organizes a total of five sections. Next section, Section two, illustrates optimal power flow problems with corresponding mathematical expressions of its objective and various practical constraints. Section three gives the brief of four swarm intelligences (GA, PSO, ABC and DE) for comparative purposes. It also provides the algorithm procedure, described step-by-step. Section four is the simulation results and discussion. Conclusion remark is in Section five.

2. OPTIMAL POWER FLOW PROBLEMS

2.1 Problem Formulation

The optimal power flow problem is a nonlinear optimization problem. It consists of a nonlinear objective function defined with nonlinear constraints. The optimal power flow problem requires the solution of nonlinear equations, describing optimal and/or secure operation of power systems. The general optimal power flow problem can be expressed as a constrained optimization problem as follows.

Minimize $f(x)$
Subject to $g(x) = 0$, equality constraints
$h(x) \leq 0$,inequality constraints

By converting both equality and inequality constraints into penalty terms and therefore added to form the penalty function as described in (1) and (2).

$$P(x) = f(x) + \Omega(x) \tag{1}$$

$$\Omega(x) = \rho\{g^2(x) + [\max(0, h(x))]^2\} \tag{2}$$

Where $P(x)$ is the penalty function
$\Omega(x)$ is the penalty term
ρ is the penalty factor

By using a concept of the penalty method [13], the constrained optimization problem is transformed into an unconstrained optimization problem in which the penalty function as described above is minimized.

2.2 Objective Function

Although most of optimal power flow problems involve the total production cost of the entire power system, in some cases some different objective may be chosen. In this paper, the power transmission loss function is set as the objective function. The power transmission loss can be expressed as given in (3).

$$F_{loss} = \sum_{i=1}^{N_L} g_{i,j}\left\{V_i^2 + V_j^2 - 2V_iV_j\cos(\delta_i - \delta_j)\right\} \tag{3}$$

Where: V_i is the voltage magnitude at bus i
V_j is the voltage magnitude at bus j
$g_{i,j}$ is the conductance of line $i - j$
δ_i is the voltage angle at bus i
δ_j is the voltage angle at bus j
N_L is the total number of transmission lines
F_{loss} is the power loss function

2.3 System Constraints

The controllable system quantities are generator MW, controlled voltage magnitude, reactive power injection from reactive power sources and transformer tapping. The objective use herein is to minimize the power transmission loss function by optimizing the control variables within their limits. Therefore, no violation on other quantities (e.g. MVA flow of transmission lines, load bus voltage magnitude, generator MVAR) occurs in normal system operating conditions. These are system constraints to be formed as equality and inequality constraints as shown below.

1) Equality constraint: Power flow equations

$$P_{G,i} - P_{D,i} - \sum_{j=1}^{N_B} |V_i||V_j||Y_{i,j}|\cos(\theta_{i,j} - \delta_i + \delta_j) = 0 \tag{4}$$

$$Q_{G,i} - Q_{D,i} - \sum_{j=1}^{N_B} |V_i||V_j||Y_{i,j}|\sin(\theta_{i,j} - \delta_i + \delta_j) = 0 \tag{5}$$

Where: P_{Gi} is the real power generation at bus i
Q_{Gi} is the reactive power generation at bus i
P_{Di} is the real power demand at bus i
Q_{Di} is the reactive power demand at bus i
N_B is the total number of buses
$\theta_{i,j}$ is the angle of bus admittance element i, j
$Y_{i,j}$ is the magnitude of bus admittance element i, j

2) Inequality constraint: Variable limitations

$$V_i^{min} \leq V_i \leq V_i^{max} \tag{6}$$

$$T_i^{min} \leq T_i \leq T_i^{max} \tag{7}$$

$$Q_{comp,i}^{min} \leq Q_{comp,i} \leq Q_{comp,i}^{max} \tag{8}$$

$$P_{G,i}^{min} \leq P_{G,i} \leq P_{G,i}^{max} \quad (9)$$

Where: V_i^{min}, V_i^{max} are upper and lower limits of voltage magnitude at bus i
T_i^{min}, T_i^{max} are upper and lower limits of tap position of transformer i
$Q_{comp,i}^{min}, Q_{comp,i}^{max}$ are upper and lower limits of reactive power source i
$P_{G,i}^{min}, P_{G,i}^{max}$ are upper and lower limits of power generated by generator i

The penalty function can be formulated as follows.

$$P(x) = F_{loss} + \Omega_P + \Omega_Q + \Omega_C + \Omega_T + \Omega_V + \Omega_G \quad (10)$$

Where:

$$\Omega_P = \rho \sum_{i=1}^{N_B} \left\{ P_{G,i} - P_{D,i} - \sum_{j=1}^{N_B} |V_i \| V_j \| V_y| \cos(\theta_{i,j} - \delta_i + \delta_j) \right\}^2 \quad (11)$$

$$\Omega_Q = \rho \sum_{i=1}^{N_B} \left\{ Q_{G,i} - Q_{D,i} - \sum_{j=1}^{N_B} |V_i \| V_j \| V_y| \sin(\theta_{i,j} - \delta_i + \delta_j) \right\}^2 \quad (12)$$

$$\Omega_C = \rho \sum_{i=1}^{N_C} \left\{ max(0, Q_{comp,i} - Q_{comp,i}^{max}) \right\}^2 + \rho \sum_{i=1}^{N_C} \left\{ max(0, Q_{comp,i}^{min} - Q_{comp,i}) \right\}^2 \quad (13)$$

$$\Omega_T = \rho \sum_{i=1}^{N_r} \left\{ max(0, T_i - T_i^{max}) \right\}^2 + \rho \sum_{i=1}^{N_r} \left\{ max(0, T_i^{min} - T_i) \right\}^2 \quad (14)$$

$$\Omega_V = \rho \sum_{i=1}^{N_B} \left\{ max(0, V_i - V_i^{max}) \right\}^2 + \rho \sum_{i=1}^{N_B} \left\{ max(0, V_i^{min} - V_i) \right\}^2 \quad (15)$$

$$\Omega_G = \rho \sum_{i=1}^{N_G} \left\{ max(0, P_{G,i} - P_{G,i}^{max}) \right\}^2 + \rho \sum_{i=1}^{N_G} \left\{ max(0, P_{G,i}^{min} - P_{G,i}) \right\}^2 \quad (16)$$

N_G is the total number of generators
N_C is the total number of reactive power sources
N_T is the total number of transformers

3. SWARM INTELLIGENT SEARCH METHODS

3.1 Genetic Algorithm (GA)

There exist many different approaches to adjust the control parameters. The GA is well-known [14] there exist a hundred of works employing the GA technique to optimize the system objective in various forms. The GA is a stochastic search technique that leads a set of population in solution space evolved using the principles of genetic evolution and natural selection, called genetic operators e.g. crossover, mutation, etc. With successive updating new generation, a set of updated solutions gradually converges to the real solution. Because the GA is very popular and widely used in most research areas where an intelligent search technique is applied, it can be summarized briefly as shown in the flowchart in figure 1 [15].

In this paper, the GA is selected to build up an algorithm to solve optimal power flow problems (all generation from available generating units). To reduce programming complication, the Genetic Algorithm (GADS TOOLBOX in MATLAB [16]) is employed to generate a set of initial random parameters. With the searching process, the parameters are adjusted to give the best result.

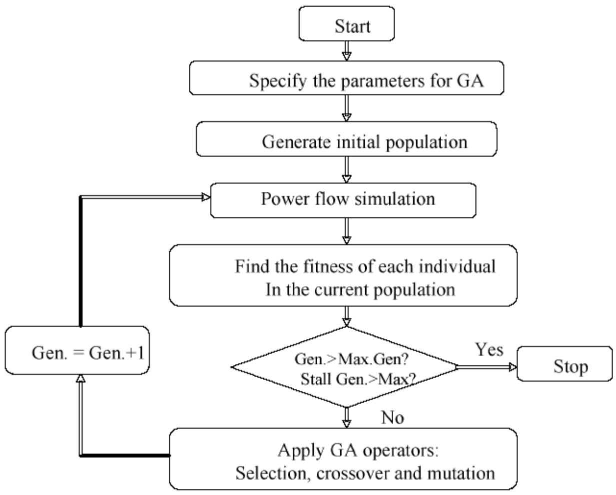

Fig.1: *Flowchart of the GA procedure*

3.2 Particle Swarm Optimization (PSO)

Kennedy and Eberhart developed a particle swarm optimization algorithm based on the behavior of individuals (i.e., particles or agents) of a swarm [17]. Its roots are in zoologists modeling of the movement of individuals (i.e., fish, birds, and insects) within a group. It has been noticed that members of the group seem to share information among them to lead to increased efficiency of the group. The particle swarm optimization algorithm searches in parallel using a group of individuals similar to other AI-based heuristic optimization techniques. Each individual corresponds to a candidate solution to the problem. Individuals in a swarm approach to the optimum through its present velocity, previous experience, and the experience of its neighbors. In a physical n-dimensional search space, the position and velocity of individual i are represented as the velocity vectors. Using these information individual i and its updated velocity can be modified under the following equations in the particle swarm optimization algorithm. The procedure of the particle swarm optimization can be summarized in the flow diagram of figure 2.

$$x_i^{k+1} = x_i^{(k)} + v_i^{(k+1)} \quad (17)$$

$$v_1^{k+1} = v_i^k + \alpha_i \left(x_i^{lbest} - x_i^{(k)} \right) + \beta_i \left(x_i^{gbest} - x_i^{(k)} \right) \quad (18)$$

Where

$x_i^{(k)}$ is the individual i at iteration k

$v_i^{(k)}$ is the updated velocity of individual i at iteration k

α_{i,β_i} are uniformly random numbers between [0,1]

x_i^{lbest} is the individual best of individual i

x^{gbest} is the global best of the swarm

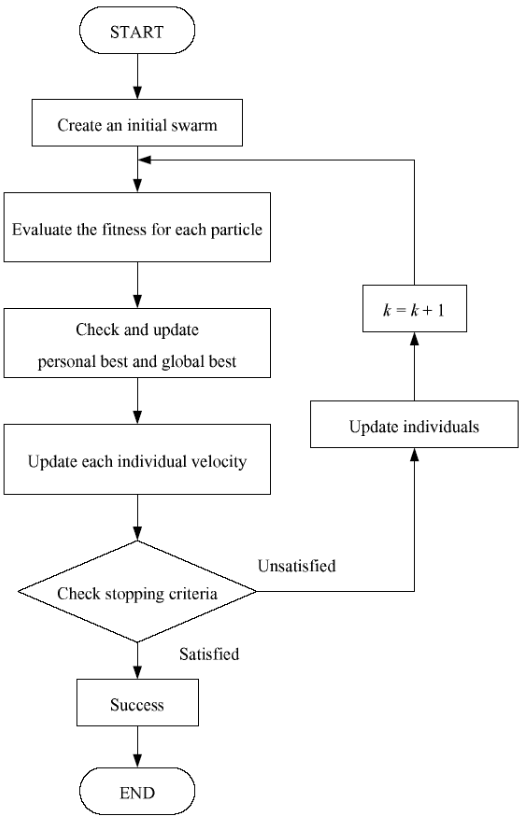

Fig.2: *Flowchart of the PSO procedure*

3.3 Artificial Bee Colony (ABC)

Artificial bees colony [18-20] was proposed by Karaboga for solving numerical optimization problems. It simulates the intelligent behavior of honey bee swarms. In artificial bees algorithm, the colony of artificial bees contains three groups of bees: employed bees, and unemployed bees: onlookers and scouts. First half of the colony consists of employed artificial bees and the second half constitutes the artificial onlookers. The employed bee whose food source has been exhausted becomes a scout bee. The position of a food source represents a possible solution to the optimization problem and the nectar amount of a food source corresponds to the quality or fitness of the associated solution. The number of the employed bees is equal to the number of food sources, each of which also represents a site, being exploited at the moment or to the number of solutions in the population. In artificial bees algorithm, the steps given below are repeated until a stopping criteria is satisfied.

1) Initial phase

Initial population of artificial bee swarms is created randomly by the following formula.

$$x_{ij} = x_{min,j} + rand(0,1) \times (x_{max,j} - x_{min,j}) \quad (19)$$

2) Employed bees phase

Each employed bee determines a food source representing a site. Each employed bee shares its food source information with onlookers waiting in the hive and then each onlooker selects a food source site depending on the information taken from employed bees. To simulate the information sharing by employed bees in the dance area, probability values are calculated for the solutions by means of their fitness values using the following equation.

$$P_j = \frac{f_{iti}}{\sum_{j=1}^{SN} f_{iti}} \quad (20)$$

$$f_{iti} = \begin{cases} \frac{1}{1+f_i} & , f_i \geq 0 \\ 1 + |f_i| & , f_i < 0 \end{cases} \quad (21)$$

The fitness values might be calculated using the above definition as expressed in (21).

3) Onlooker bees phase

Onlookers are placed onto the food source sites by using a fitness based selection technique, for example roulette wheel selection method.

4) Scout bees phase

Every bee swarm has scouts that are the swarms explorers. The explorers do not have any guidance while looking for food. In case of artificial bees, the artificial scouts might have the fast discovery of the group of feasible solutions. In the searching algorithm, the artificial employed bee whose food source nectar has been exhausted or the profitability of the food source drops under a certain threshold level is selected and classified as the artificial scout. The classification is controlled by “abandonment criteria” or “limit”. If a solution representing a food source position is not improved until a predetermined number of trials, then that solution is abandoned by its employed bee and the employed bee becomes a scout. The procedure of the artificial bees algorithm can be summarized in the flow diagram of figure 3.

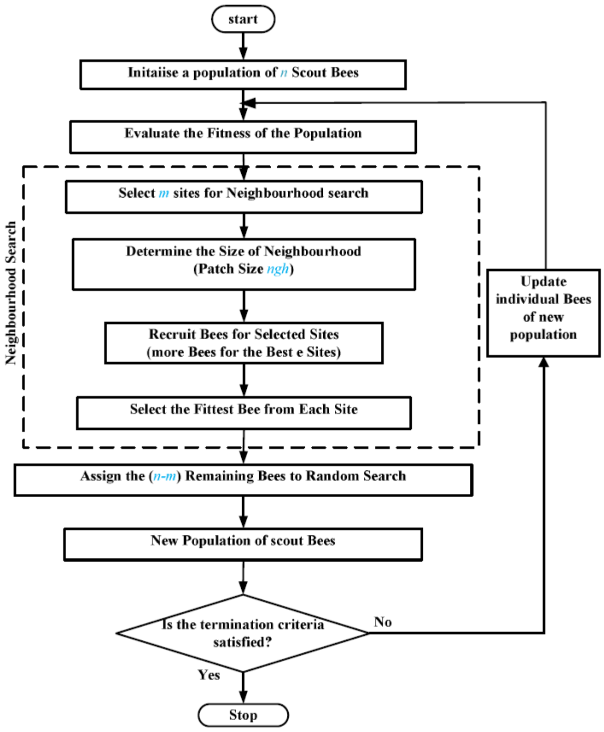

Fig.3: *Flowchart of the artificial beecolony*

3.4 Differential Evolution (DE)

Differential Evolution (DE) [21-22] is a recently developed evolutionary computation technique. DE is an extremely powerful yet simple evolutionary algorithm that improves a population of individuals over several generations through the operators of mutation, crossover and selection for global optimization introduced by Price and Storn. Differential evolution presents great convergence characteristics and requires few control parameters which remain fixed throughout the optimization process and need minimum tuning. DE differs from other EA in the mutation and recombination phase. Unlike stochastic techniques such as genetic algorithm and evolutionary strategy where perturbation occurs in accordance with a random quantity, DE uses weighted differences between solution vectors to perturb the population. It has a minimum number of EA control parameters, which can be efficiently tuned.

DE uses a population P of size N_P, composed of floating point encoded individuals that evolve over G generations to reach an optimal solution. Each individual X_i is a vector that contains as many parameters as the problem decision variables D. The population size N_P is an algorithm control parameter selected by the user which remains constant throughout the optimization process.

$$P^G = [X_1^G, \dots, X_{N_p}^G] \tag{22}$$

$$X_i^G = [X_{1,i}^G, \dots, X_{D,i}^G]^T, i = 1, \dots, N_p \tag{23}$$

The optimization process in Differential Evolution is carried out by three basic genetic operations: Mutation, Crossover and Selection. The algorithm starts by creating an initial population of Np vectors. Random values are assigned to each decision parameter in every vector according to:

$$X_{j,i}^0 = X_j^{min} + \eta(X_j^{max} - X_j^{min}) \tag{24}$$

Where:

X_j^{min} and X_j^{max} are the lower and upper bounds of the $\mathrm{j^{th}}$ decision parameter.

η_i is a uniformly distributed random number within [0,1] generated a new for each value of j

$X_{j,i}^0$ is the $\mathrm{j^{th}}$ parameter of the $\mathrm{i^{th}}$ individual of the initial population

The mutation operator creates mutant vectors $X_i^{'}$ by perturbing a randomly selected vector ($\mathrm{X_a}$) with difference of two other randomly selected vectors ($\mathrm{X_b}$ and $\mathrm{X_c}$)

$$X_i^G = X_a^G + F(X_b^G - X_c^G), i = 1, \dots, N_p \tag{25}$$

Where:

X_a, X_b, X_c are randomly chosen vectors $\in \{1, \dots, N_p\}$ and a $\neq$ b $\neq$ c $\neq$ i.

X_a, X_b, X_c are selected anew for each parent vector. The scaling constant (F) is an algorithm control parameter used to adjust the perturbation size in the mutation operator and improve algorithm convergence. The crossover operation generates trial vectors ($X_i^{''}$) by mixing the parameters of the mutant vectors ($X_i^{'}$) with the target vectors (Xi) according to a selected probability distribution.

$$X_{j,i}^{''G} = \begin{cases} X_{j,i}^{'G}, if\ \eta_i^{'} \leq C_R \\ X_{j,i}^{'G}, otherwise \end{cases} \tag{26}$$

The crossover constant CR is an algorithm parameter that controls the diversity of the population and aids the algorithm to escape from local optima. The new generation population is obtained by selection operator that chooses between the trial vectors and their predecessors (target vectors) those individuals that present a better fitness or are more optimal according to

$$X_i^{G+1} = \begin{cases} X_i''^{G}, f(X_i''^{G}) \leq f(X_i^G), i = 1, \ldots, N_p \\ X_i^G, otherwise \end{cases} \tag{27}$$

This optimization process is repeated for several generations, allowing individuals to improve their fitness as they explore the solution space in search for optimal values.

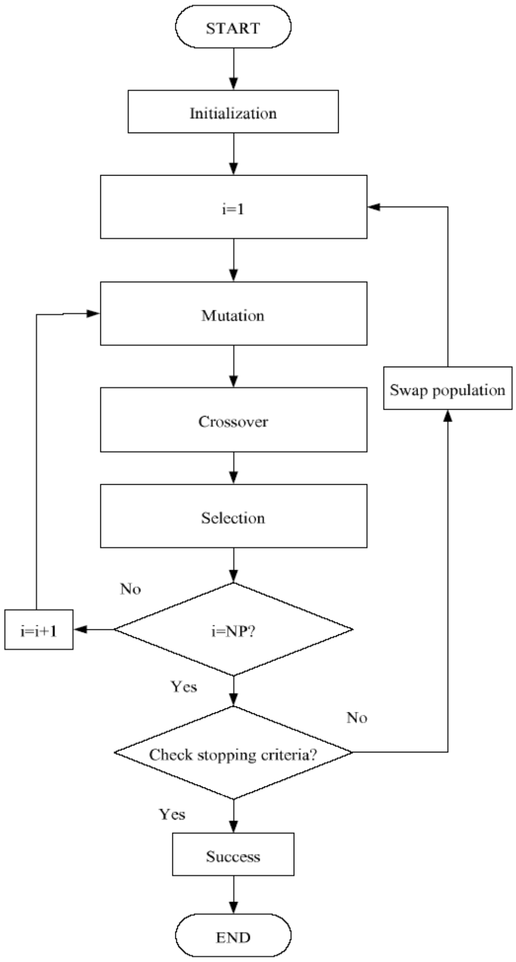

Fig.4: *Flowchart of the differential evolution algorithm*

DE has three essential control parameters: the scaling factor (F), the crossover constant (CR) and the population size (NP). The scaling factor is a value in the range (0, 2] that controls the amount of perturbation in the mutation process. The crossover constant is a value in the range [0, 1] that controls the diversity of the population. The population size determines the number of individuals in the population and provides the algorithm enough diversity to search the solution space. The procedure of the differential evolution algorithm can be summarized in the flow diagram as shown in figure 4.

4. SIMULATION RESULTS

To verify the effectiveness and performance of the swarm intelligent optimization, 6-bus and IEEE 30-bus test power systems were used for test. Information of the 6-bus test system was given in [12]. The simulations were performed using MATLAB software [16]. The test was carried out by solving the optimal power flow problem of the power loss objective. Variable limits given in Table 1 were used as system constraints. For comparison purposes, genetic algorithm, particle swarm optimization, artificial bees algorithm and differential evolution were applied to solve the test system with various cases. Each method was challenged by solving given optimal power flow problems of 30 trials randomly. Minimum, average, maximum and standard deviation of the 30 trial solutions for the 6-bus test system obtained by each method were evaluated and shown in Table 2. Table 3 showed the comparison of CPU time spent by each approach. The optimal control variables obtained by each method were shown in Tables 4 7. All test cases were simulated by using the same computer which was an Intel®, Core 2 Duo, 2.4 GHz, 3.0 GB RAM.

Table 1: *Variable limit used for optimal power flow for the 6-bus test system*

Variable	Limit	
	Min.	Max
V1 - V6 (p.u.)	0.90	1.1
T1,T2 (p.u.)	0.90	1.1
Q1, Q2(Mvar)	0	50
PG1 (MW)	25	80
PG2 (MW)	25	80

Table 2: *OPF solutions obtained by using GA, PSO ABC and DE for the 6-bus test system*

Method	Power transmission loss (MW)			
	Minimum	Average	Maximum	Deviation
GA	6.7747	6.9705	7.5292	0.1521
PSO	6.7486	6.8425	7.1517	0.0759
ABA	6.7361	6.7361	6.7364	0.0001
DE	6.7361	6.7361	6.7368	0.0001

Table 3: *Computational time to obtain optimal solutions by GA, PSO, ABC and DE for the 6-bus system*

Method	Computational Time (s)			
	Minimum	Average	Maximum	Deviation
GA	6.91	8.05	9.79	0.7
PSO	17.93	136.11	516.49	93.20
ABA	7.40	7.52	7.74	0.0597
DE	3.07	3.10	3.22	0.0286

The results showed that the ABC and the DE optimal methods gave the best power flow solution when compared with those obtained by the GA and the PSO. For the 6-bus test system, the average power loss solutions were 6.9705 MW, 6.8425MW, 6.7361 and 6.7361MW for the GA, PSO, ABC and DE methods, respectively. However, when considering the minimum power loss, the ABC and DE were the two methods that can find the least loss function of 6.7361 MW. The standard deviation of the solutions obtained by the GA, PSO, ABC and DE were 0.1521, 0.0759, 0.0001 and 0.0001 respectively. The CPU times spent by each method to find the optimal solution showed that the DE consumed the least computational time effort. In addition, the DE method gave the least power transmission loss and spent the least computational time to reach the best solution. As a result, the power loss of the entire system can be improved with 65% reduction.

The voltage profile of the base case before improvement was set to be lower than the specified range. After adjust the control variables to their optimal values the system voltage profile can be resumed to the operating value within the specified range as shown in figure 5. Table 8 showed the parameter setting of each method used for conducting the test. Also, figure 8 gave the convergence characteristic of the solutions obtained by using these methods.

Table 4: *Optimal solution by the PSO for the 6-bus system*

Control Variables		Bus	Computational Time(s)				Optimal
			Mean	S.D.	Max.	Min.	
Generator (p.u.)	V1	6	1.1	0	1.1	1.1	1.1
	V2	5	1.09	0.02	1.1	1.03	1.0975
	PG2	5	27.9	1.6	32	25	27.3814
Reactive Power (Mvar)	Q1	4	29.7	6	47.1	16.9	24.1667
	Q2	1	38.6	5.7	47.9	23.7	43.1091
Transformer Tap (p.u.)	T1	3-4	0.98	0.03	1.06	0.91	0.994
	T2	1-2	1.02	0.03	1.07	0.97	1.0294
Computational Time (s)			136.11	93.2	516.49	17.93	131.9952
Power Transmission Loss (MW)			6.84	0.08	7.15	6.75	6.7486
Power Loss Saving(%)			65.13	-	63.55	65.61	65.61

Table 5: *Optimal solution by the GA for the 6-bus system*

Control Variables		Bus	Computational Time(s)				Optimal
			Mean	S.D.	Max.	Min.	
Generator (p.u.)	V1	6	1.09	0.01	1.10	1.06	1.0994
	V2	5	1.09	0.01	1.10	1.05	1.1000
	PG2	5	29.1	3.4	42.9	25.0	25.4363
Reactive Power (Mvar)	Q1	4	28.1	4.7	38.9	15.9	24.0278
	Q2	1	42.5	3.5	48.7	29.7	41.9286
Transformer Tap (p.u.)	T1	3-4	0.99	0.02	1.04	0.94	1.0044
	T2	1-2	1.03	0.02	1.08	0.96	1.0598
Computational Time (s)			8.05	0.70	9.79	6.91	7.1468
Power Transmission Loss (MW)			6.97	0.15	7.53	6.77	6.7747
Power Loss Saving(%)			64.48	-	61.63	65.48	65.48

Table 6: *Optimal solution by the ABC for the 6-bus system*

Control Variables		Bus	Computational Time(s)				Optimal
			Mean	S.D.	Max.	Min.	
Generator (p.u.)	V1	6	1.1	0	1.1	1.1	1.1
	V2	5	1.1	0	1.1	1.1	1.1
	PG2	5	27.5	0.0481	27.72	27.46	27.5
Reactive Power (Mvar)	Q1	4	27.17	0.1356	27.65	26.84	27.21
	Q2	1	43.07	0.1397	43.28	42.53	43.06
Transformer Tap (p.u.)	T1	3-4	0.9965	0.0002	0.9969	0.9959	1.0351
	T2	1-2	1.0351	0.0003	1.0356	1.0337	0.9963
Computational Time (s)			7.52	0.0597	7.74	7.40	7.49
Power Transmission Loss (MW)			6.7361	1.91	6.7364	6.7361	6.7361
Power Loss Saving(%)			65.67	-	65.67	65.67	65.67

Table 7: *Optimal solution by the DE for the 6-bus system*

Control Variables		Bus	Computational Time(s)				Optimal
			Mean	S.D.	Max.	Min.	
Generator (p.u.)	V1	6	1.1	0	1.1	1.1	1.1
	V2	5	1.1	0	1.1	1.1	1.1
	PG2	5	27.49	0.0167	27.51	27.43	27.48
Reactive Power (Mvar)	Q1	4	27.15	0.069	27.3	26.87	27.18
	Q2	1	43.11	0.1212	43.71	42	43.12
Transformer Tap (p.u.)	T1	3-4	0.9965	0.0001	0.9972	0.9963	0.9966
	T2	1-2	1.0352	0.0003	1.0355	1.0338	1.0352
Computational Time (s)			3.1	0.0286	3.22	3.07	3.12
Power Transmission Loss (MW)			6.7361	0.0001	6.7368	6.7361	6.7361
Power Loss Saving(%)			65.67	-	65.67	65.67	65.67

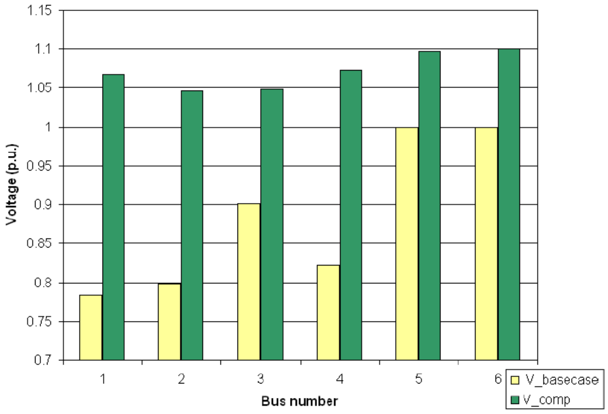

Fig.5: *Voltage profiles for the 6-bus test system*

Table 8: *Variable limit used for optimal power flow for the 6-bus test system*

Parameter	GA	PSO	ABC	DE
Population size(N_P)	30	30	30	30
Maximum iteration	200	200	200	200
Crossover Probability	0.85	-	-	0.895
Mutation Probability	0.0058	-	-	-
Maximum error	1×10^{-6}	1×10^{-6}	1×10^{-6}	1×10^{-6}

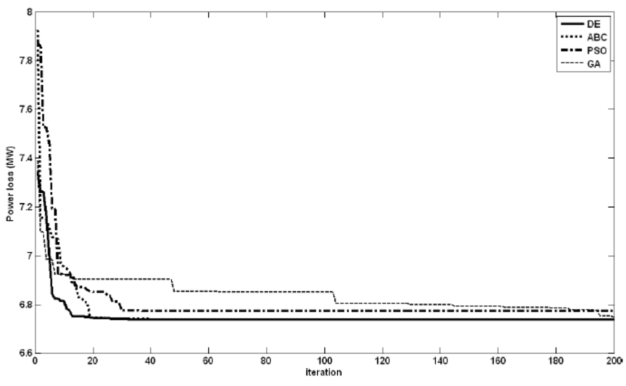

Fig.6: *Convergence characteristics of each method for the 6-bus test system*

The second test system to verify the effectiveness and performance of the swarm intelligences was the standard IEEE 30-bus test power system. The test was carried out by solving the optimal power flow problem of the power loss objective with variable limits used as system constraints given in Table 9. For comparison purposes, genetic algorithm, particle swarm optimization, artificial bee colony and differential evolution were applied to solve the test case of this test system. Each method was challenged by solving a given optimal power flow problem of 30 trials. Minimum, average, maximum and standard deviation of the 30 trial solutions for the 30-bus system obtained by each method were evaluated and shown in Table 10. Table 11 showed the comparison of CPU time spent by each approach. The optimal control variables obtained by each method were shown in Tables 12 15. All test cases were simulated by using the same computer which explained previously.

Table 9: *Variable limit used for optimal power flow for the 30-bus test system*

Variable	Limits	
	Min.	Max.
V1 to V30 (p.u.)	0.9	1.1
T1 to T7 (p.u.)	0.9	1.1
Q1 to Q4 (Mvar)	0	50
Q1 to Q4 (Mvar)	15	80

Table 10: *OPF solutions obtained by using GA, PSO, ABC and DE for the 30-bus test system*

Method	Power transmission losses (MW)			
	Minimum	Average	Maximum	Deviation
GA	10.90	15.95	31.32	5.83
PSO	13.55	17.72	22.66	2.39
ABC	11.74	15.74	19.34	2.08
DE	10.44	10.51	11.16	0.14

Table 11: *Computational time to obtain optimal solutions by GA, PSO, ABC and DE for the 30-bus system*

Method	Power transmission losses (MW)			
	Minimum	Average	Maximum	Deviation
GA	100.67	531.63	732.33	192.67
PSO	691.40	2335.84	4066.20	914.01
ABC	174.70	974.60	2366.30	542.20
DE	205.68	206.89	207.30	0.2786

The results showed that the DE-based optimal power flow method gave the best result when compared with those obtained by the GA, PSO and ABC. For the IEEE 30-bus test system, the average power loss solutions were 15.95 MW, 17.72 MW, 15.74 and 10.51 MW for the GA, PSO,ABA and DE, respectively. However, when considering the minimum power loss, the DE was the method that can find the

Table 12: *Optimal solution by the GA for the 30-bus system*

Control Variables		Bus	Statistic				
			Mean	S.D.	Min.	Max.	Optimal
Generator (pu)	V25	25	1.03	0.03	0.95	1.07	1.0565
	V26	26	1.07	0.04	0.91	1.10	1.0862
	V27	27	1.02	0.04	0.91	1.09	1.0475
	V28	28	1.07	0.04	0.93	1.10	1.0993
	V29	29	1.05	0.05	0.91	1.09	1.0914
	V30	30	1.06	0.05	0.91	1.10	1.0979
	PG25	25	36.2	15.0	15.4	75.1	39.5686
	PG26	26	20.2	7.1	15.1	36.7	15.2307
	PG27	27	41.8	15.6	17.8	73.6	28.5806
	PG28	28	61.2	17.5	19.5	80.0	77.741
	PG29	29	20.6	6.9	15.0	37.4	15.3489
Reactive Power (Mvar)	Q1	2	26.0	9.0	20.1	55.8	22.1001
	Q2	6	33.9	9.0	20.6	54.4	39.4685
	Q3	10	28.5	7.6	20.2	52.9	26.3212
	Q4	18	25.0	7.4	20.0	50.1	20.0381
Transformer Tap (p.u.)	T1	4-12	0.99	0.04	0.93	1.09	0.9865
	T2	6-9	0.96	0.05	0.91	1.07	0.9983
	T3	6-10	0.99	0.06	0.90	1.09	0.9443
	T4	9-11	0.97	0.05	0.90	1.07	0.9479
	T5	9-10	0.95	0.05	0.90	1.09	0.9067
	T6	12-13	0.98	0.05	0.91	1.10	0.908
	T7	28-27	1.07	0.04	0.92	1.10	1.0992
Computational Time (s)			531.63	192.67	100.67	732.33	644.91
Power Transmission loss (MW)			15.95	5.83	10.90	31.32	10.90
Real Power saving (%)			60.94	-	73.30	23.27	73.30

Table 13: *Optimal solution by the PSO for the30-bus system*

Control Variables		Bus	Statistic				
			Mean	S.D.	Min.	Max.	Optimal
Generator (pu)	V25	25	1.02	0.04	1.00	1.10	1.0597
	V26	26	1.03	0.05	1.00	1.10	1.0891
	V27	27	1.00	0.04	0.90	1.10	1.0596
	V28	28	1.03	0.05	1.00	1.10	1.0593
	V29	29	1.02	0.05	0.90	1.10	1.0794
	V30	30	1.03	0.05	1.00	1.10	1.0993
	PG25	25	38.1	13.9	16.2	71.6	25.0614
	PG26	26	19.8	4.3	15.0	29.6	16.0168
	PG27	27	41.5	15.1	18.6	73.3	43.028
	PG28	28	63.0	15.6	20.4	79.1	75.2901
	PG29	29	19.8	5.1	15.0	29.9	18.6751
Reactive Power (Mvar)	Q1	2	38.3	10.0	20.2	52.1	39.2182
	Q2	6	40.7	10.0	22.3	55.2	43.3492
	Q3	10	37.7	10.3	20.4	57.4	49.7789
	Q4	18	34.7	9.8	20.5	54.9	32.4971
Transformer Tap (p.u.)	T1	4-12	1.01	0.04	0.94	1.10	0.9729
	T2	6-9	1.00	0.05	0.90	1.08	1.0272
	T3	6-10	1.00	0.05	0.90	1.09	0.9042
	T4	9-11	1.00	0.05	0.90	1.10	1.0143
	T5	9-10	0.98	0.05	0.91	1.10	1.0121
	T6	12-13	1.00	0.05	0.92	1.10	1.0204
	T7	28-27	1.03	0.05	0.92	1.10	1.0629
Computational Time (s)			2335.8	914.01	691.40	4066.20	4066.20
Power Transmission loss (MW)			17.12	2.39	13.55	22.66	13.55
Real Power saving (%)			58.06	-	66.81	44.48	66.81

Table 14: *Optimal solution obtained by the ABC for the30- bus system*

Control Variables		Bus	Statistic				
			Mean	S.D.	Min.	Max.	Optimal
Generator (pu)	V25	25	1.0341	0.0285	0.9749	1.0781	1.0522
	V26	26	1.0833	0.02124	1.0326	1.1	1.0775
	V27	27	1.0254	0.02899	0.9689	1.0675	1.0557
	V28	28	1.0736	0.04591	0.9337	1.1	1.1
	V29	29	1.0723	0.03316	0.985	1.1	1.0967
	V30	30	1.0759	0.0265	1.015	1.1	1.1
	PG25	25	36.070	15.8274	15	77.85	23.34
	PG26	26	22.6	4.9974	15	33.68	17.52
	PG27	27	41.6	15.5716	16.89	72.315	49.86
	PG28	28	54.20	18.601	26.44	80.00	69.69
	PG29	29	26.62	7.82234	15	39.13	16.93
Reactive Power (Mvar)	Q1	2	12.74	11.4446	2.2485	48.05	6.5982
	Q2	6	40.94	13.7958	0	50	50
	Q3	10	22.25	13.4554	0	48.52	20.61
	Q4	18	22.89	8.93215	1.5897	44.15	18.8
Transformer Tap (p.u.)	T1	4-12	0.9934	0.04706	0.9188	1.1	0.9817
	T2	6-9	0.9832	0.05316	0.9	1.1	0.9773
	T3	6-10	0.9677	0.05069	0.9	1.1	0.9203
	T4	9-11	1.0120	0.07139	0.9	1.1	1.0618
	T5	9-10	0.9454	0.03876	0.9	1.0313	0.9725
	T6	12-13	1.0381	0.08142	0.9	1.1	1.1
	T7	28-27	1.0926	0.0235	0.9995	1.1	1.1
Computational Time (s)			974.6	542.203	174.7	2366.3	1042.6
Power Transmission loss (MW)			15.738	2.08755	11.74	19.345	11.740
Real Power saving (%)			61.44	-	71.23	52.65	71.23

least power loss function of 10.44 MW. The standard deviation of the solutions obtained by the GA, PSO, ABC and DE were 5.83, 2.39, 2.08 and 0.14 respectively. The CPU times spent by each method to find the optimal solution showed that the DE consumed the least computational time effort. In addition, the DE method gave the least power transmission loss and spent the least computational time to reach the best solution. As a result, the power loss of the entire system can be improved with 60-70% reduction.

The voltage profile of the base case before improvement was set to be lower than the specified range. After adjust the control variables to their optimal values the system voltage profile can be resumed to the operating value within the specified range as shown in figure 9. Table 16 showed the parameter setting of each method used for conducting the test. Also, figure 10 gave the convergence characteristics of the solutions obtained by using these methods.

Table 15: *Optimal solution by the DE for the30-bus system*

Control Variables		Bus	Statistic				
			Mean	S.D.	Min.	Max.	Optimal
Generator (pu)	V25	25	1.073803	0.001601	1.0712	1.0801	1.0739
	V26	26	1.099803	0.000548	1.0975	1.1	1.1
	V27	27	1.06865	0.001273	1.0644	1.071	1.0689
	V28	28	1.099983	3.79E-05	1.0999	1.1	1.1
	V29	29	1.09954	0.001044	1.0947	1.1	1.1
	V30	30	1.099883	0.00034	1.0984	1.1	1.1
	PG25	25	35.61541	3.062004	33.4197	51.315	34.9661
	PG26	26	15.00397	0.005512	15	15.0232	15
	PG27	27	30.55335	3.019784	15.0045	32.8194	31.1405
	PG28	28	79.99145	0.021448	79.8825	80	79.9981
	PG29	29	15.00401	0.007645	15	15.0332	15.0001
Reactive Power (Mvar)	Q1	2	7.862173	8.710024	0	49.9982	5.8186
	Q2	6	43.46954	11.83968	0.005	49.9999	49.975
	Q3	10	29.02644	14.9968	0	49.9996	26.9423
	Q4	18	18.82517	0.800328	17.3027	21.4009	18.9169
Transformer Tap (p.u.)	T1	4-12	0.99989	0.003185	0.9888	1.0077	1
	T2	6-9	0.983317	0.049532	0.9	1.0528	0.9693
	T3	6-10	1.031557	0.084306	0.9	1.1	1.0992
	T4	9-11	0.937193	0.035572	0.9	0.9985	0.9
	T5	9-10	0.917743	0.01972	0.9	0.9481	0.9036
	T6	12-13	0.98559	0.06828	0.9	1.0842	0.9
	T7	28-27	1.093153	0.036485	0.9	1.1	1.1
Computational Time (s)			206.8961	0.278618	205.6863	207.3049	206.8236
Power Transmission loss (MW)			10.51208	0.147691	10.4449	11.1629	10.4449
Real Power saving (%)			73.99286657	-	74.15907966	72.38273132	74.15907

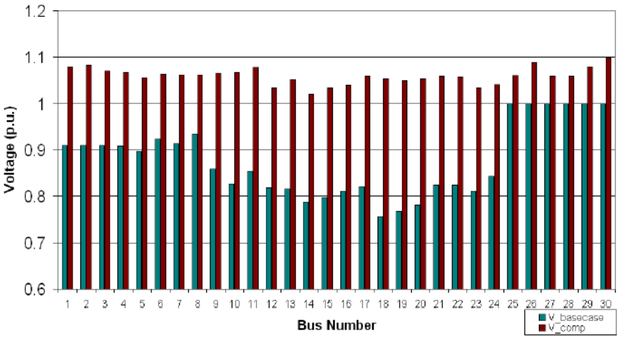

Fig. 7: *Voltage profiles for the 30-bus test system*

Table 16: *Parameter setting of each method for the 30-bus*

Algorithm	GA	PSO	ABC	DE
Population size(N_P)	30	30	30	30
Maximum iteration	500	500	500	500
Crossover Probability	0.85	-	-	0.895
Mutation Probability	0.0053	-	-	-
Maximum error	1×10^{-6}	1×10^{-6}	1×10^{-6}	1×10^{-6}

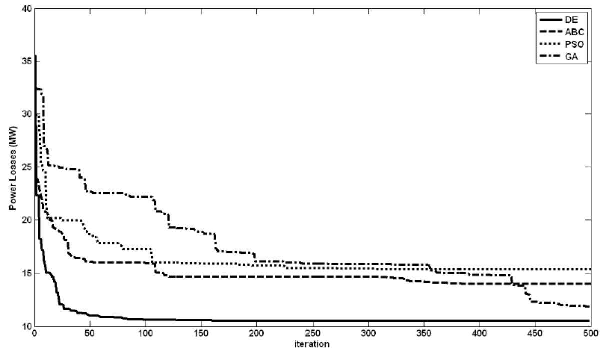

Fig. 8: *Convergence characteristics of each method for the 30-bus test system*

5. CONCLUSION

Solution methods for solving optimal power flow problems with the power transmission loss objective are described in this paper. Some efficient search methods in forms of swarm intelligences (e.g. genetic algorithm, particle swarm optimization, artificial bee algorithm and differential evolution) were employed. A 6-bus test system and the standard IEEE 30-bus power system were used for benchmarking. The results showed that a set of optimal solutions with respect to the power transmission loss objective can be efficiently solved by using the swarm intelligences As a result, the DE and ABC methods showed satisfactory performances of finding the optimal power flow solutions. In these two test systems, the power loss can be minimized and the power losses of the entire network can be improved by 65% power loss reduction.

References

[1] M.R AlRashidi and M.E El-Hawary, "Hybrid Particle Swarm Optimization Approach for Solving the Discrete OPF Problem Considering the Valve Loading Effects," *IEEE Transactions on Power Systems*, Issue 4, Vol. 22, pp.2030 2038, 2007.

[2] B. Zhao, C.X. Guo and Y.J. Cao, "Improved particle swam optimization algorithm for OPF problems," *IEEE-PES Power Systems Conference and Exposition*, Vol. 1, pp.233 - 238, 10-13 October 2004.

[3] C.A Roa-Sepulveda and B.J. Pavez-Lazo, "A solution to the optimal power flow using simulated

annealing," *Power Tech Proceedings 2001*, Vol. 2, pp. 5, 10-13 September 2001.

[4] R.N. Banu and D. Devaraj, "Optimal Power Flow for Steady state security enhancement using Genetic Algorithm with FACTS devices," *3^{rd} International Conference on Industrial and Information Systems*, pp. 1 6, 8-10 December 2008.

[5] L.L. Lai and J.T. Ma, "Power flow control in FACTS using evolutionary programming," *IEEE International Conference on Evolutionary Computation*, pp. 10, 29 November-1 December 1995.

[6] C. Gonggui and Y. Junjjie, "A new particle Swarm Optimization Solution to Optimal reactive power Flow Problem," *Asia-Pacific Power and Energy Engineering Conference*, pp.1 4, 27-31 March 2009.

[7] L. Weibing, L. Min and W. Xianjia, "An improved particle swarm optimization algorithm for optimal power flow," *IEEE 6^{th} International Power Electronics and Motion Control Conference 2009*, pp. 2448 2450, 17-20 May 2009.

[8] W. Cui-Ru, Y. He-Jin, H. Zhi-Qiang, Z. Jiang-Wei and S. Chen-Jun, "A modified particle swarm optimization algorithm and its application in optimal power flow problem," *International Conference on Machine Learning and Cybernetics 2005*, pp. 2885 2889, 18-21 August 2005.

[9] S. M. Kumari, G. Priyanka and M. Sydulu , "Comparison of Genetic Algorithms and Particle Swarm Optimization for Optimal Power Flow Including FACTS devices," *IEEE Power Tech 2007*, pp. 1105 - 1110, 1-5 July 2007.

[10] C. Chokpanyasuwant, S. Anantasate1, S. Pothiya ,W. Pattaraprakom and P. Bhasaputra1, "Honey Bee Colony Optimization to solve Economic Dispatch Problem with Generator Constraints," *ECTI-CON 2009*. 6th International Conference, Vol. 1, pp. 200 203, 2009.

[11] S. Anantasate, C.Chokpanyasuwan and P. Bhasaputra, "Optimal Power Flow by using Bees Algorithm," *ECTI Conference*, pp.459 463, 2010.

[12] U. Leeton, D. Uthitsunthorn, U. Kwannetr, N. Sinsuphun and T. Kulworawanichpong, "ower Loss Minimization Using Optimal Power Flow Based on Particle Swarm Optimization," *ECTI Conference*, pp.469 473, 2010.

[13] P. Dutta and A. K. Sinha, "Voltage Stability Constrained Multi-objective Optimal Power Flow using Particle Swarm Optimization," *1^{st} International Conference on Industrial and Information Systems*, pp. 161 166, 8-11 August 2006.

[14] Z. Haibo, Z. Lizi and M. Fanling, "Reactive power optimization based on genetic algorithm," *International Power Conference on Power System Technology*, pp.1448 1453, 18-21 August 1998.

[15] K. Somsai, A. Oonsivilai, A. Srikaew, and T. Kulworawanichpong, "Optimal PI controller design and simulation of a static var compensator using MATLABs SIMULINK," *The 7^{th} WSEAS International Conference on POWER SYSTEMS*, Beijing, China, pp. 30 35, September 2007.

[16] The MathWorks Inc., Genetic Algorithms and Direct Search TOOLBOX, CD-ROM Manual, 2004.

[17] J. Hazra1 and A. K. Sinha, "A Study on Real and Reactive Power Optimization using Particle Swarm Optimization," *International Conference on Industrial and Information Systems*, pp. 323 328, 9-11 August 2007.

[18] N.T. Linh and N.Q. Anh, "Application of artificial beecolony algorithm (ABC) for reconfiguring distribution network," *International Conference on Computer Modelling and Simulation*, pp. 102-106.

[19] N. Karaboga, "A new design method based on artificial bees colony algorithm for digital IRR filters," *Journal of the Franklin Institute*, Vol. 346, pp.328348, 2009.

[20] D. Karaboga and B. Busturk, "A powerful and efficient algorithm for numerical function optimization: artificial bee colony optimization," *Journal of Global Optimization*, VOl. 39, pp. 459- 471.

[21] S.P. Karthikeyan, K. Palanisamy, L.J. Varghese, I.J. Raglend, and D.P. Kothari, "Comparison of Intelligent Techniques to Solve Economic Load Dispatch Problem with Line Flow Constraints," *Advance Computing Conference, 2009. IACC 2009. IEEE International*, pp. 446452, 6-7 March 2009 .

[22] M. Varadarajan, K. S. Swarup, "Solving multiobjective optimal power flow using differential evolution," *Generation, Transmission & Distribution, IET*, Vol 2, pp. 720730, 2008.

Numphetch Sinsuphun is a Master Student of the School of Electrical Engineering, Institute of Engineering, Suranaree University of Technology, Nakhon Ratchasima, THAILAND. She received B.Eng. in Electrical Engineering from Suranaree University of Technology, Thailand (2008). Her fields of research interest include a power system analysis, application of harmony search in optimal power flow solution. She has joined the school since June 2009 and is a research assistant and a member in Power System Research Unit, Suranaree University of Technology.

Uthen Leeton is a Ph.D. Student of the School of Electrical Engineering, Institute of Engineering, Suranaree University of Technology, Nakhon Ratchasima, THAILAND. He received B.Eng. with first-class honour in Electrical Engineering from Suranaree University of Technology, Thailand (2007). His fields of research interest include a power system analysis, optimization and artificial intelligent techniques. He has joined the school since June 2009 and is a research assistant and a member in Power System Research Unit, Suranaree University of Technology.

Umaporn Kwannetr was born in Bansang, Thailand, on November 9, in 1986. She received the B.Eng. in Electrical Engineering, Suranaree University of Technology, Nakhon Ratchasima, Thailand Thailand, in 2009. Currently she is pursuing the master degree at the University of Nakhon Ratchasima, Thailand. Her interests include the application of artificial intelligence techniques to power system optimization problems.

Dusit Uthitsunthorn He received the Master of Electrical Engineering degree from King Mongkuts University of Technology North Bangkok (KMUTNB), Thailand in 2007. Currently he is a Ph.D. Student and a research assistant at Power System Research Unit, School of Electrical Engineering Institute of Engineering, Suranaree University of Technology, Nakhon Ratchasima, THAILAND. His research interest includes power system, power system intelligent protection and optimization technique.

Thanatchai Kulworawanichpong is an associate professor of the School of Electrical Engineering, Institute of Engineering, Suranaree University of Technology, Nakhon Ratchasima, THAILAND. He received B.Eng. with first-class honour in Electrical Engineering from Suranaree University of Technology, Thailand (1997), M.Eng. in Electrical Engineering from Chulalongkorn University, Thailand (1999), and Ph.D. in Electronic and Electrical Engineering from the University of Birmingham, United Kingdom (2003). His fields of research interest include a broad range of power systems, power electronic, electrical drives and control, optimization and artificial intelligent techniques. He has joined the school since June 1998 and is currently a leader in Power System Research, Suranaree University of Technology, to supervise and co-supervise over 15 postgraduate students.