http://dx.doi.org/10.5755/j01.eie.22.5.16340 ELEKTRONIKA IR ELEKTROTECHNIKA, ISSN 1392-1215, VOL. 22, NO. 5, 2016

A Comparison of Heuristic Methods for Optimum Power Flow Considering Valve Point Effect

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***Abstract*—Optimum Power Flow (OPF) is one of the key considerations for planning, generation control and management of electric utility. Hence it is of major importance to solve OPF with minimum cost within reasonable computing time. This paper presents solutions of OPF with Valve Point Effect (OPF-VPE) using Genetic Algorithm (GA), Differential Evolution (DE), Particle Swarm Optimization (PSO) and Artificial Bee Colony (ABC). When steam valve starts to open in a turbine it changes generation curve. The valve point effect is considered by adding sine component to the quadratic cost function for OPF-VPE. Also, penalty function is added for generator violations. The common parameters of algorithms such as population size and the iteration number are selected same values for the comparison of algorithms for solving OPF-VPE. Specific parameters are stated and used for each algorithm. The heuristic algorithms are examined on IEEE-30 bus system and convergence curves are demonstrated with the system results. Performances of each algorithm are discussed as regards optimizing fuel cost, iteration time and other system results.**

***Index Terms*—Optimum power flow; valve point effect; heuristic algorithms.**

I. INTRODUCTION

Growing worldwide population, industrialization and urbanization, will result in an increase in the energy demand. Numbers of generation units and transmission lines are increasing in order to meet the demand. System operators need some analysis tools for optimum and smooth operation of complicated systems. The Optimum Power Flow (OPF) is used as a significant tool for planning and operating of the power systems. Aim of OPF is optimum setting of control variables to minimize the generation cost by satisfying power flow equations and physical boundaries of operating system.

OPF has become vital issue for power system operation since its first introduction by Carpentier in 1962 [1]. Many different methods have been applied to solve OPF, which is a large scale, nonlinear, constrained optimization problem. Previously, OPF problems were solved with mathematic based traditional methods such as Gardient Method [2], Newton based Methods [3], Linear Programming [4], Quadratic Programming [5], Interior Point Method [6] and Nonlinear Programming [7].

Traditional methods have some disadvantages such as converge problem for large-scale systems, difficult adaptation to formulation changes, plenty of mathematical computations and excessive memory consumption [8]. Recently, heuristic methods have been widely used for solving OPF due to their properties like robustness, flexibility and converging global optimum.

Different heuristic methods such as Evolutionary Programming (EP) [9], Genetic Algorithm (GA) [10], Differential Evolution (DE) [8], Swarm based methods; Particle Swarm Optimization (PSO) [11], Ant Colony Optimization (ACO) [12] and Artificial Bee Colony (ABC) [13] are applied to OPF problems in the literature. Also artificial intelligence methods as Fuzzy Logic (FL) [14] and Artificial Neural Networks (ANN) [15] are employed to solve OPF problems.

Osman *et al*. [10] proposed a genetic algorithm based OPF solution. The OPF problem is described combination of the load flow and the economic dispatch problem. Sayah *et al.* [16] presented a DE based solution. Mutation process of the algorithm modified to improve the solution quality and convergence time. Quadratic cost function with sine component is used for each generating unit characteristic. In [17], fuel cost, emissions, stability and losses are considered as the objective functions and PSO is employed for solution. Ozturk *et al*. [18] applied ABC on 10-bus system for reactive power optimization and the results were compared with other evolutionary algorithms.

In this study, fuel cost is considered as an objective function and it is minimized using heuristic methods and considering system constraints. Valve point effect and a penalty function for generator active power violations are added to quadratic cost function in order to provide the more appropriate simulation of fuel cost. Optimum values of specific parameters of each algorithm are determined and OPF-VPE has been solved for IEEE-30 bus system. Finally, performance of GA, DE, PSO and ABC are compared with regarding to solution of OPF-VPE.

II. MATHEMATICAL FORMULATION OF OPF

OPF is defined as a tool which secures most convenient power flow between buses with minimum fuel cost considering physical limits. OPF is a kind of general constrained optimization problem. The objective function

Manuscript received 18 December, 2015; accepted 28 June, 2016.

$f(x)$ is the generating fuel cost; $g(x,u)$ is the equality constraints and $h(x,u)$ is the inequality constraints which represent physical and operation limits of the power system [8]

$$Min. f(x) \ subject \ to \ \begin{matrix} g(x,u)=0, \\ h(x,u)\le 0, \end{matrix} \quad (1)$$

x is the vector of state variables and described as

$$x=[P_{G1}, V_{LB1}...V_{LBTN}, Q_{G1}...Q_{GTN}, S_{TL1}...S_{TLTN}], \quad (2)$$

where P_{G1} is the slack bus real power, V_{LB} is the load bus voltages, Q_G is the reactive power outputs of generators, S_{TL} is the transmission line MVA loading, $LBTN$ is the load buses total numbers, GTN is the generators total numbers, $TLTN$ is the transmission lines total number. Hence, u which is the independent control variables vector can be defined as

$$u=[P_{G2}...P_{GTN}, V_{GB}], \quad (3)$$

where P_{GTN} is the real power of generators, V_{GB} is generator bus voltage.

The fuel cost curve characteristics of large units are highly nonlinear due to some system factors and multiple steam valves. Each valve creates a ripple when they start to open [19]. Therefore the generating fuel cost with the valve point effect is expressed as adding a sinusoid component to the cost function as follows

$$f(x)=\sum_{i=1}^{GTN}\left(a_i P_{Gi}^2+b_i P_{Gi}+c_i\right)+ + \left|d_i \sin\left(e_i\left(P_{Gi}^{\min}-P_{Gi}\right)\right)\right|+\sum_{i=1}^{GTN} w_i, \quad (4)$$

where a_i, b_i, c_i are cost coefficients of the ith generator. d_i, e_i describe valve point coefficient in cost function. w_i indicates the penalty function as follows

$$w_i=\begin{cases} s_i\left(P_i-P_i^{\max}\right)^2, \ if \quad P_i>P_i^{\max}, \\ s_i\left(P_i-P_i^{\min}\right)^2, \ if \quad P_i<P_i^{\min}. \end{cases} \quad (5)$$

Penalty function is implemented for the active power of generators. Amount of the violated active power is multiplied with a coefficient and calculated amount is added to fuel cost.

Equality constraints are typical power flow equations and described as follows:

$$P_{Gi}-P_{Di}-V_i\sum_{j=1}^{NB}V_j\left(G_{ij}\cos\theta_{ij}+B_{ij}\sin\theta_{ij}\right)=0, \quad (6)$$

$$Q_{Gi}-Q_{Di}-V_i\sum_{j=1}^{NB}V_j\left(G_{ij}\sin\theta_{ij}-B_{ij}\cos\theta_{ij}\right)=0, \quad (7)$$

where $i=1,2,3,...,NB$, P_{Gi} is real power output, P_{Di} is real power demand, Q_{Gi} is reactive power output, Q_{Di} is reactive power demand at the ith bus, B_{ij} is susceptance of the line, θ_{ij} voltage angle differences between ith and jth bus, NB is the total number of buses. Inequality constraints consist of the system operating conditions and physical limits.

Active power, reactive power and voltage output of ith generator as follows:

$$\begin{cases} P_{Gi}^{\min}\le P_{Gi}\le P_{Gi}^{\max}, \\ Q_{Gi}^{\min}\le Q_{Gi}\le Q_{Gi}^{\max}, \\ V_i^{\min}\le V_i\le V_i^{\max}, \end{cases} \quad (8)$$

where $i=1,...,NG$. MVA capacity of the transmission line between bus i and j as follows

$$S_{ij}\le S_{ij}^{\max}, \quad (9)$$

where $i=1,...,NTL$. The limits of transformer tap settings are given as follows

$$T_i^{\min}\le T_i\le T_i^{\max}, \quad (10)$$

where $i=1,...,NG$.

III. HEURISTIC METHODS AND OPF APPLICATIONS

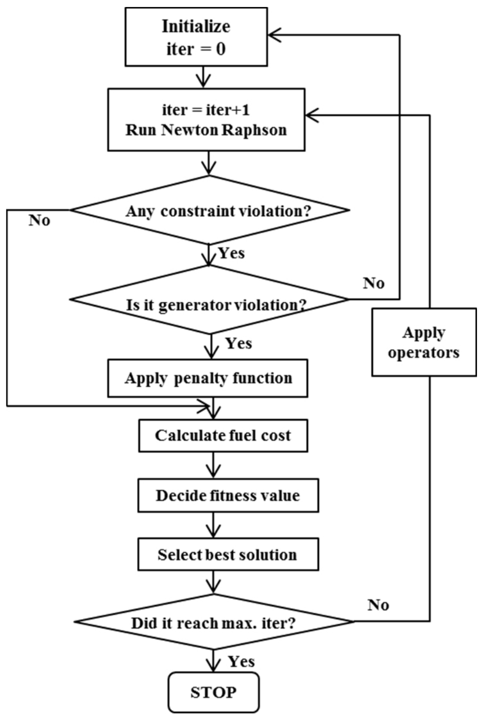

Fig. 1. Flowchart of OPF-VPE solution with heuristic methods.

In this paper, evolutionary based methods such as GA and DE, swarm based heuristic methods such as PSO and ABC are employed to solve complex OPF-VPE problems.

General steps of OPF-VPE with optimization algorithms are shown in Fig. 1.

Firstly, the algorithm is initialized with random values and power flow solution is applied for those values. Next, it is checked if the constraints violated. If generator violation arises, penalty function is applied. Otherwise the algorithm reinitializes with different random values. Unless violation occurs, fuel costs are calculated for next step. Then, fitness values are decided to determine quality value of candidate solution and best solution is selected. After that, the operators, which are specific for each optimization algorithm, are applied in order to create better solutions for next iteration. Finally, the algorithm is ended when maximum iteration number is reached.

A. Genetic Algorithms

GA was initially introduced by Holland as a means of studying adaptive behaviors [20]. GA creates a new population using gene of individuals belong to previous population. The individuals which have the best fitness degree are selected and new individuals are generated.

At first, GA encodes the individuals which will create the solution set. Then, algorithm is initialized with random solution. Three main operators are used in GA process; reproduction, crossover and mutation. In a routine cycle of GA chromosome string is selected from previous generation for reproduction. Selected string is transferred to next generation according to fitness degree of individual. Reproduction continues until next generation is constituted. Reproduction works with crossover operator which is gene changing between chromosomes. Main purpose of crossover is getting best features of parents and obtaining more quality offspring. Mutation is arbitrary changing independently in genes of a chromosome. After applied genetic operators, selection process is applied and the current population is replaced with the new population. If stopping criteria is satisfied algorithm is ended.

B. Differential Evolution

DE is introduced as a population based heuristic optimization method by Price [21]. Mutation, cross over and selection processes are applied to each chromosome to create a new individual. If the individual presents a better solution, it is transferred to next generation. Unless, former individual is used for next generation.

Initialization: Number of population (NP) must be more than three. To generate a new chromosome three chromosomes are needed except for existing one. Number of Population NP and D dimensional jth component of the ith population members $(x_{i,j})$ is generated

$$x_{i,j}(0) = x_j^{\min} + rand(0,1)\left(x_j^{\max} - x_j^{\min}\right). \quad (11)$$

Mutation: Three different chromosomes are selected $(r1, r2, r3)$. The difference of two chromosomes is scaled with scaling factor (F) and added to the third one. By this way jth component of each vector is obtained and donor vector $(v_{i,j}(t))$ is created.

$$v_{i,j}(t+1) = x_{r1,j}(t) + F\left(x_{r2,j}(t) - x_{r3,j}(t)\right). \quad (12)$$

Cross Over: The trial vector $U_i(t)$ is obtained from mixing current vector $X_i(t)$ and donor vector $V_i(t)$ with probability Crossover Rate (CR)

$$u_{i,j}(t) = \begin{cases} v_{i,j}(t), & \text{if } rand\,[0,1] \le CR \;\; j = j_{rand}, \\ x_{i,j}(t), & \text{otherwise.} \end{cases} \quad (13)$$

Selection: Most fitness chromosome is transferred to the next generation regarding to comparison of $X_i(t)$ and trial vector $U_i(t)$

$$X_i(t+1) = \begin{cases} U_i(t), & \text{if } f(U_i(t)) \le f(X_i(t)), \\ X_i(t), & \text{otherwise.} \end{cases} \quad (14)$$

Mutation, cross over and selection continue until reaching optimum solution.

The procedure of DE implementation has a similar procedure of GA for solving OPF. The selection and mutation processes of DE are different from those of GA.

C. Particle Swarm Optimization

Particle Swarm Optimization which is developed by Kennedy and Eberhart in 1995 [22], is the simulation of coveys. Food searching of birds in the space is similar to searching solution for a problem. Each individual solution is called a particle in searching space; it corresponds to a bird in the swarm. When a particle moves, it sends it's coordinates to the function to define fitness value. By the way distance of particle to the food is decided. Each particle is defined by D dimensional vector and D indicates number of the control variables. Main important elements are the position and the velocity of the particle.

Position of the ith particle is expressed as

$$x_i = (x_{i1}, x_{i2}, ..., x_{iD}). \quad (15)$$

Velocity of the ith particle is expressed as

$$v_i = (v_{i1}, v_{i2}, ..., v_{iD}). \quad (16)$$

PSO is initialized with a population which is formed by random generated individuals and best solutions are searched by updating position of the particle for each iteration. Position and velocity of the particle are updated by best previous solution, $pbest = (p_{i1}, p_{i2}, ..., p_{iD})$ and $gbest$ is best global solution in the memory.

Updating velocity of the ith particle is expressed as

$$v_t^{(t+1)} = wv_i^{(t+1)} + c_1 r_1\left(pbest_i - x_i^{(t)}\right) + \\ + c_1 r_1\left(gbest - x_i^{(t)}\right), \quad (17)$$

where t number of current generation, $r1, r2$; uniform random value in the range [0, 1], w ; inertia weight factor, $c1, c2$; acceleration constant of $pbest_i$ and $gbest_i$.

Updating position of ith particle is found summing its previous position and current velocity as follows

$$x_i^{t+1} = x_i^t + v_i^{t+1}. \tag{18}$$

Optimal solution is found after competition among the particles.

D. Artificial Bee Colony

ABC algorithm was proposed for solving optimization problems by Karaboga [23]. Bees do job sharing without central authority in a colony. There are three main groups in a bee colony; employed bees, onlookers and scouts. Employed bees go to explored food sources in advance and they bring nectar to the hive. Employed bees share the quality of information of food source with the onlooker bees in the hive. After getting information onlooker bees select a food source considering their nectar quality. When an onlooker bee find a food source it turns into employed bee. It is assumed that total number of employed bees equal to total food sources number. Then scout bees are scattered randomly to find new food sources. When the employed bees finish their food source totally, they become scout bees.

Each food source is a D dimensional vector. D is number of control variables. Each individual food source offers a candidate solution. Process of ABC is described as follows:

Initialization: It's the stage of random generated food sources. Starting value is achieved between lower and upper limits

$$x_{i,j} = x_j^{\min} + rand(0,1)\left(x_j^{\max} - x_j^{\min}\right). \tag{19}$$

Producing new food sources: Employed bees determine new sources according to principle of neighborhood. Quality food sources' neighbors are chosen as new sources. v_i represents new food source

$$v_{i,j} = x_{i,j} + \phi_{i,j}\left(x_{i,j} - x_{k,j}\right). \tag{20}$$

Defining the quality of new source: A new fitness value is assigned for v_i and greedy selection is applied. f_i is error value of ith solution, used for determining quality of the source. New and old food sources are compared and best one is held in memory

$$fitness_i = \begin{cases} 1/\left(1+f_i\right), & f_i \geq 0, \\ 1+abs\left(f_i\right), & f_i < 0. \end{cases} \tag{21}$$

Determining the new source: The source with the higher nectar quality is more probable to be determined as defined in (22)

$$p_i = \frac{fitness_i}{\sum_{i=1}^{SN} fitness_i}. \tag{22}$$

This process continues until stopping criteria satisfied.

IV. SIMULATION RESULTS

In this paper, GA, DE, PSO and ABC are applied to IEEE-30 bus system for solving OPF-VPE. IEEE-30 bus system total load = 283.4 MW, 126.2 MVAR. The sine component is added to the quadratic function in order to simulate valve point effect in OPF problem as in (4). Also, penalty factor is added for active power violation of generators. The algorithms are initialized randomly to decide independent control variables in their limits. Then depended state variables are assigned by Newton-Raphson power flow. Solution is improved using specified process of each algorithm at every iteration. If the constraints are satisfied, process of the algorithm continues with next step, unless process is terminated and the algorithm is initialized again.

Common control parameters of the algorithms are population size and the iteration numbers. Specified values of common parameters; Population Size = 20, Iteration Number = 100. The characteristic parameters of each algorithm are chosen as follows [24], [25]:

GA Parameters: Selection function is roulette, Crossover function is scatted, mutation function is constraint dependent and crossover fraction = 0.8

DE Parameters: Scaling Factor (F) = 0.6, Crossover Rate (CR) = 0.4

PSO Parameters: Inertia weight factor (w) = 0.5, Acceleration Constants $(c1, c2)$ = [1.2, 1.5].

ABC Parameters: Limit = 100. Limit is threshold value which indicates colony size and iteration number.

As generator outputs, line losses, fuel cost and iteration times are presented in Table I, fuel cost curve is shown in Fig. 2. ABC converges to 931.08 (\$/h) in 34.18 s as seen in Table I. It spends maximum computational time and value of fuel cost. PSO converges to 930.24 (\$/h) in 33.29 s. GA has a good converges performance in this case. Fuel cost is 921.57 (\$/h) and iteration time is 30.46 s.

TABLE I. OPF-VPE SOLUTION USING GA, PSO, DE AND ABC.

	GA	PSO	DE	ABC
P_{G1} (MW)	197.957	185.352	199.440	199.617
P_{G2} (MW)	35.428	40.917	39.569	20.060
P_{G3} (MW)	20.078	20.712	20.062	22.890
P_{G4} (MW)	18.137	20.106	15.454	19.559
P_{G5} (MW)	11.899	12.915	9.135	10.849
P_{G6} (MW)	10.539	13.233	10.655	20.601
Total (MW)	294.038	293.235	294.315	293.576
Line Loss (MW)	10.68	9.835	10.990	10.176
Fuel Cost (\$/h)	921.570	930.240	918.169	931.087
Iter. Time (sec.)	30.46	33.29	31.29	34.18

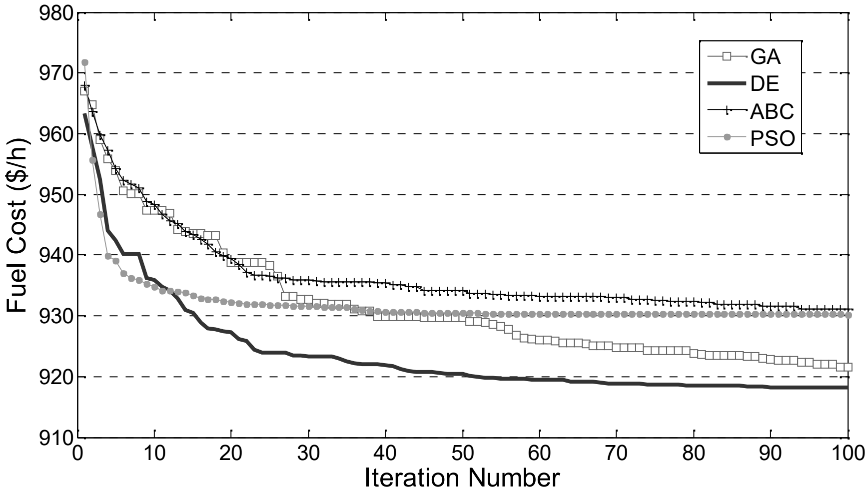

Fig. 2. Convergence curves of GA, PSO, DE and ABC for OPF-VPE.

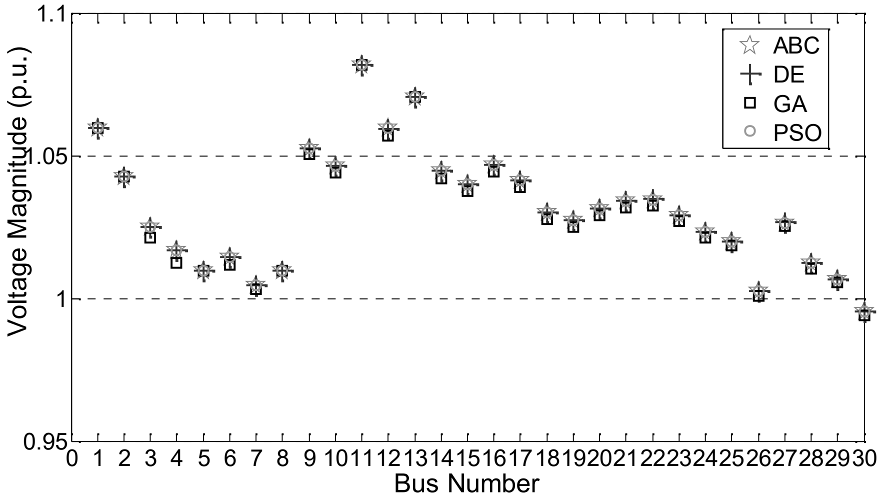

Fig. 3. Voltage profile of the IEEE-30 bus system for OPF-VPE.

As demonstrated Fig. 2, Initialization values of each algorithms vary between 960 ($/h) and 975 ($/h). DE is the only algorithm which produces the fuel cost under 920 ($/h). Furthermore it has a fast iteration time with 31.29 s.

Transmission line losses are 10.68 (MW), 9.83 (MW), 10.99 (MW) and 10.17 (MW) using GA, PSO, DE and ABC, respectively. Transmission losses are inversely proportional with fuel costs for GA, PSO and DE. However ABC has a high transmission loss contrary to expectations.

While GA, DE and ABC continue to converge PSO reached the optimum value around fortieth iteration. However, the converged value does not present better solution than GA and DE at the end of 100 iterations.

As shown in Fig. 3, voltage profiles of the system are almost same with each other after simulating each algorithm. Voltage level of any buses is not lower than 0.95 p. u.

V. Conclusions

In this paper, Genetic Algorithms, Differential Evolution, Particle Swarm Optimization and Artificial Bee Colony are employed for solving Optimum Power Flow considering valve point effect. Simulation results demonstrate that DE and GA are the most effective algorithms for solving OPF-VPE problem. Whereas GA has the fastest iteration time, DE has the minimum fuel cost result. Although these algorithms have the best simulation results from objective function which is fuel cost point of view, they have high line losses rate. Fuel cost results of PSO and ABC are not as good as evolutionary based methods. Also they spend much more time for reaching 100 iterations. Although PSO has the high initialization value, it reaches its optimum solution at early number of iteration. But it is not guarantee the best solution. Finally, DE is the most cost effective algorithm with good iteration times. That is to say, population based algorithms, DE and GA, are more cost effective than swarm based algorithms, PSO and ABC, in a solution of OPF where valve point effect is considered.

Appendix A

TABLE AI. COEFFICIENTS OF THE GENERATION UNITS FOR IEEE-30 BUS SYSTEM CONSIDERING VALVE POINT EFFECT.

No	$P_{Gi}^{\min}$	$P_{Gi}^{\max}$	Coefficients				
			a	b	c	d	e
1	50	200	0.00160	2	150	50	0.063
2	20	80	0.01	2.5	25	40	0.098
3	15	50	0.0625	1	0	0	0
5	10	35	0.0083	3.25	0	0	0
8	10	40	0.025	3	0	0	0
13	12	40	0.025	3	0	0	0

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