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A New Hybrid Modified particle swarm optimization / Bacterial Foraging Algorithm technique for solving Optimal Location and Sizing of Shunt Capacitors

Mehdi mirzaee[1], Ali Abaspour[2],Sabet Sadegzadeh[3], Mehdi BaShirpour[3]*
[1]Ph.D Electrical Power Engineering, Department of Electrical Engineering, Horand Center*
Technical and Vocational Training Organization
East Azarbaijan , Horand, Iran

[2]B.S Electrical Power Engineering, Head of Department, Department of Electrical Engineering, Horand Center
Technical and Vocational Training Organization
East Azarbaijan , Horand, Iran

[3]B.S Electrical Power Engineering, Electrician trainee, Department of Electrical Engineering, Horand Center
Technical and Vocational Training Organization
East Azarbaijan , Horand, Iran

Email Group (mirzaeymehdi@yahoo.com)

Abstract— ***In this paper, Self-Adaptive Hybrid Modified Particle Swarm optimization (SAHMPSO) with time varying acceleration coefficients and Bacteria Foraging Algorithm (BFA) method is introduced to solve Optimal Location and Size of Capacitor (OLSC) problem in radial distribution networks. To arrive to SAHMPSO/BFA method, two developments have been employed on control parameters of mutation and crossover operators. To expand this study, three load conditions have been considered, i.e., constant, varying and effective loads. Objective function is introduced for the load conditions. The annual cost is objective function of OLSC problem, in addition to this cost, CPU time, voltage profile, active power loss and total installed capacitor banks and their related costs have been used for performance indexes. To confirm the ability of each improvements of SAHMPSO/BFA algorithm, the improvements are studied both in separate and simultaneous conditions. To verify the effectiveness of the proposed method, it is tested on IEEE 10 bus and 34 bus radial distribution networks and compared with other approaches.***

Keywords- Annual cost; swarm optimization algorithm; Bacterial Foraging algorithm; optimal capacitor allocation; Radial distribution networks.

1. Introduction

Majority of loads in power systems use reactive power. In a power system, active power in several MWs is only generated by synchronous generators, while reactive power is produced not only by synchronous generator but also is injected by the other devices such as: Static VAr Compensator (SVC), Synchronous Condenser (SC), and Capacitor. Among these equipments, capacitor has the slowest and stepped speed response while installation and operating costs of capacitor are considerably lower than the other reactive power sources. Despite technical limits of capacitors, a capacitor could be a better option to generate reactive power at least for the economic advantages. The Optimal Location and Size of Capacitor (OSLC) problem has been solved by many techniques. In this paper, these techniques have been categorized in three classes; numerical and mathematical methods, heuristic and artificial intelligence techniques.

In [1-3], a set of numerical programming approaches have been proposed. To solve OLSC problem a computational method were suggested in [1], in first step of this method the candidate buses for capacitor installation, optimal size and proper type of capacitors (fixed or switching) are selected. Khodr and et al. carried out similar work in [2]. Jabr has proposed a two stage technique to minimize OLSC problem in the presence of fixed and switching capacitors [3]. In first and second stages, OLSC problem is formulated as a conic program and a mixed integer linear program (MILP) based on minimizing the L1-norm, respectively.

The heuristic methods are in the other category of methods which have been suggested for solving OLSC problem in [4-5]. The proposed technique in [4] uses the solution from the mathematical model after relaxing the integrality of the discrete variables to elect candidate buses for installation capacitor banks. Da Silva et al. have proposed a technique by nonlinear mixed integer optimization to solve OLSC problem. For this, sigmoid function was used to determine capacitor location and then the problem is formulated using the primal-dual interior point method [5]. In addition to heuristic methods, meta-heuristic approaches have been proposed in [6-7]. Also, in [8], Memetic Algorithm (MA) was proposed to solve OLSC problem in large distribution networks. The MAs are population-based methods which can be taken as an extension of Genetic Algorithms (GAs).

The artificial intelligence is third category of approaches for solving OLSC problem. The most used artificial intelligences to solve OLSC problem are Evolutionary Algorithm (EA), Swarm Intelligence Algorithm (SIA), Neural Networks (NNs) and fuzzy sets. Also, in [9-11], GA or its improved branches were suggested to solve optimal capacitor placement. Main problem of GA is low convergence velocity, which authors of [12] have claimed that this problem is declined by methods based on the reduction of the search space of GAs or based on micro-GAs. Abu-Elanien and Salama in [13] have suggested Discrete Wavelet Transform (DWT) integrated with a feed-forward artificial neural network (FFANN) for PQ improvement and solving OLSC problem, in simultaneous manner. Main problems of NNs are: network training is very difficult, obtained solutions' accuracy is strongly depend on the size of training set, and finally predicting the future performance of the network (by popularity) is not possible.

Particle Swarm Optimization (PSO) is the most famous member of SIA. In [14], similar to [13], this work was performed using PSO. Hybrid PSO (HPSO) has been used to solve OLSC problem in unbalanced distribution in the presence of harmonics in [15]. This PSO obtained by combining PSO and radial distribution power flow algorithm. Main disadvantages of PSO are: high possibility of lying on local optimum point, especially in problems with large size and dimensions. Ant colony is another approach among SIA used by Chang for reconfiguration, capacitor placement and for loss reduction. Theoretical discussion of ant colony is difficult and is time consuming for convergence.

Fuzzy is free of problem structure and can be combined with other algorithms, then, in [16-17], fuzzy set has been composed with ant colony, Immune Algorithm (IA) and GA, respectively. Creating membership function of fuzzy sets is difficult and in most cases is not viable. Intelligent methods are frequent techniques that can search not only local optimal solutions but also a global optimal solution depending on problem domain and execution time limit. The old optimization methods have the advantage of searching the solution space more thoroughly. The major difficulty is their sensitivity to the choice of parameters.

On the other hand, Bacteria Foraging Algorithm (BFA) which is introduced by Passino as a tool of optimization is a strong algorithm. In this paper, to overcome the problems of the previous techniques, the Self-Adaptive Hybrid MPSO/BFA is proposed to solve proposed problem in power system. It is also seen that some simple adaptive feature incorporated in the main algorithm makes its convergence even faster. Different studies have been conducted and variety of methods has been proposed for optimal placement and parameter setting of

OLSC with different objective functions in the literature. The rest of this section introduces some of the previous studies in this field and also discusses the contributions of the present work that cover the blind spots of the former studies.

In this paper, a SAHMPSO/BFA is used to solve OLSC problem. The proposed method is obtained by applying two improvements on mutation to original PSO algorithm. Main goal of these improvements is self-adapting of two important control parameters of mutation and crossover operators. The fitness is a function of annual cost which is presented for two scenarios; constant and varying load conditions. The system load has been modeled in three patterns; constant, varying and effective patterns. Furthermore, in case studies, voltage profile and power loss and its related cost and total installed capacitor banks and its corresponding cost and CPU time have been used for comparison criteria. To shows the effect of each improvement, the results of these improvements have been presented separately and compared with SAHMPSO/BFA. Simulations have been implemented on IEEE 10-bus and 34-bus radial distribution networks.

2. Optimal Location and Sizing of Capacitor Problem

The optimal location and sizing of capacitor problem has been formulated with different goals. In majority studies, main target of capacitor installation is minimizing annual cost. In this paper, OLSC problem has been formulated as function of annual cost. In this study, to model different load conditions, three load patterns used; constant, varying and effective load.

2.1. Constant Load

In this load pattern, it is assumed that load of system is constant. This condition is the simplest pattern. First term of objective function is capacity of installed capacitor banks multiplied by corresponding cost. The second term is total power loss of network multiplied by related cost.

$$Min\left[\left(\sum_{i=1}^{NC} C_{oper}\times Q_{Ci}\right)+C_{Ploss}\times\sum_{i=1}^{NB-1}P_{Loss}\right] \qquad (1)$$

where, C_{oper} and C_{PLoss} are costs of power loss, in \$/kW/year, and operation of each capacitor bank, in \$/kVAr, respectively. Q_{Ci} and P_{Loss} are capacity of capacitor bank, in kVAr, and the total active power loss of network, in kW, respectively. NC and NB are the total the number of capacitors and bus, respectively.

2.2. Varying Load

The second load pattern is varying load. In this load condition, the load of network changes in duration year. For this, several load levels and related durations are defined. The difference between objective function of constant and varying load pattern is the second term of objective function. In varying load, to apply duration of each load level, energy loss is inserted in objective function.

$$Min\left[\left(\sum_{i=1}^{NC} C_{oper}\times Q_{Ci}\right)+\sum_{h=1}^{NLL}C_{Eloss}\sum_{i=1}^{NB-1}\left(P_{Loss,T_h}\times T_h\right)\right] \qquad (2)$$

where, $P_{Loss,Tk}$ and C_{Eloss} are power loss of any load level, in kW, and cost per energy loss, in \$/kWh/year. T_h is the duration of hth load level. NLL is yearly total number of load levels.

2.3. Effective load

The load levels of varying load condition has an effective level which its value is calculated by Eq.(3) and applied in Eq.(1),

$$S_{Eff\,(i)} = \sum_{i=1}^{NLL} \frac{T_i \times S_i}{\sum_{i=1}^{NLL} T_i} \tag{3}$$

where, T_i and S_i are duration of the ith load level, in hour, and the ith load level, in pu. Several constrains should be considered to solve OLSC which are visible in [18].

3. Hybrid PSO and BFA algorithm

3.1. Classic PSO

Classic PSO (CPSO) is one of the optimization techniques and a kind of evolutionary computation technique which is launched by the Aberhart Rasel. The method has been found to be robust in solving problems featuring nonlinearity and non-differentiability, multiple optima, and high dimensionality through adaptation, which is derived from the social-psychological theory. The features of the method are as follows:

- *The method is developed from research on swarm such as fish schooling and bird flocking.*
- *It is based on a simple concept. Therefore, the computation time is short and requires few memories.*
- *It was originally developed for nonlinear optimization problems with continuous variables. It is easily expanded to treat a problem with discrete variables.*

CPSO is basically improved through simulation of bird flocking in two-dimension space. The position of each agent is defined by XY axis position and also the velocity is expressed by VX (the velocity of X axis) and VY (the velocity of Y axis). Modification of the agent position is notified by the position and velocity information . Bird flocking optimizes a certain objective function. Each agent knows its best value so far (p_{best}) and its XY position. This information is comparison of personal experiences of each agent. Moreover, each agent knows the best amount so far in the group (g_{best}) among p_{best}. This information is comparison of knowledge of how the other agents around them have performed. Namely, each agent tries to update its position using the following information:

- *The current positions (x, y),*
- *The current velocities (VX, VY),*
- *The distance between the current position and pbest*
- *The distance between the current position and gbest*

This modification can be represented by the concept of velocity and the place of particle. Velocity of each agent can be modified by the following equation:

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{4}$$

$$V_i(t+1) = \omega v_i(t) + c_1 r_1(t)[pbest_i(t) - x_i(t)] + c_2 r_2(t)[leader_i(t) - x_i(t)] \tag{5}$$

Where,

- *x_i: position of agent i at iteration k*
- *v_i: velocity of agent i at iteration k*
- *w: inertia weighting*
- *$c_{1,2}$: tilt coefficient*
- *$r_{1,2}$: rand random number between 0 and 1*
- *leader: archive of unconquerable particles*
- *$pbest_i$: pbest of agent i*
- *gbest: gbest of the group*

Convergence of the PSO strongly depended on w, c1 and c2. While c1,2 are between 1.5 till 2, however the best choice to these factors is 2.05. Also, $0 \le w < 1$; this value is really an important factor to the system convergence and it is better that this factor is defined dynamically. It should be between 0.2 and 0.9 and should decrease *linear through evolution process of population. Being extra value of w at first, provides appropriate answers and small value of that help the algorithm to convergence at the end.*

3.2. PSO with Time-Varying Inertia Weight

The PSOTVIW method is capable of locating a good solution at a significantly faster rate, when compared with other meta-heuristic techniques; its ability to fine tune the optimum solution is comparatively weak, mainly due to the lack of diversity at the end of the search. Also, in PSO, problem-based tuning of parameters is a key factor to find the optimum solution accurately and efficiently. The main concept of PSOTVIW is similar to CPSO in which the Eqs. (4), (5) are used. However, for PSOTVIW the velocity update equation is modified by the constriction factor C and the inertia weight w is linearly decreasing as iteration grows.

$$V_i(t+1) = C\{\omega v_i(t) + c_1 r_1(t)[pbest_i(t) - x_i(t)] + c_2 r_2(t)[leader_i(t) - x_i(t)]\} \quad (6)$$

$$\omega = (\omega_{\max} - \omega_{\min}).\frac{(k_{\max} - k)}{k_{\max}} + \omega_{\min} \quad (7)$$

$$C = \frac{2}{\left|2 - \phi - \sqrt{\phi^2 - 4\phi}\right|}, where\ 4.1 \le \phi \le 4.2 \quad (8)$$

3.3. PSO with Time-Varying Acceleration Coefficients (PSO-TVAC)

Consequently, PSO-TVAC is extended from the PSO-TVIW. All coefficients including inertia weight and acceleration coefficients are varied with iterations. The equation of PSO-TVAC for velocity updating can be expressed as:

$$V_i(t+1) = C\{\omega v_i(t) + ((c_{1f} - c_{1i})\frac{k}{k_{\max}} + c_{1i}).r_1(t)[pbest_i(t) - x_i(t)] + ((c_{2f} - c_{2i})\frac{k}{k_{\max}} + c_{2i}).r_2(t)[leader_i(t) - x_i(t)]\} \quad (9)$$

3.4. Bacteria Foraging Algorithm

Bacteria Foraging Algorithm (BFA) is one of the new optimization techniques which is based on the assumption that animals search for nutrients which maximizes their energy intake (E) per unit time (T) spent for foraging. The E.coli bacterium is probably the best understood Micro Organism. Generally the bacteria move for a longer distance in a friendly environment.

3.5. Chemo-tactic Behavior of Escherichia Coli

We consider the foraging behavior of E. coli, which is a common type of bacteria. Its behavior and movement comes from a set of six rigid spinning (100–200 r.p.s) flagella, each driven as a biological motor. The E. coli bacterium alternates through running and tumbling. Running speed is 10–25 body lengths per second, however they can't swim straight. The bacterium sometimes tumbles after a tumble or tumbles after a run. This alternation between the two modes will move the bacterium, and this enables it to "search" for nutrients. If $\theta^i(j,k,l)$ represent the position of the each member in the population of S bacterial at the jth chemotactic step, and k_{th} reproduction step, and l_{th} elimination, the movement of bacterium may be presented by:

$$\theta^i(j+1,k,l) = \theta^i(j,k,l) + C(i)\phi(j) \quad (10)$$

Where, C(i)(i = 1,2,..., S) is the size of the step taken in the random direction specified by the tumble. φ(j) is the random direction of movement after a tumble and J(i, j, k, l) is the fitness, which also denote the cost at the location of the i_{th} bacterium $\theta^i(j, k, l) \in R^n$. Also if at $\theta^i(j + 1, k, l)$ the cost J(i, j + 1, k, l) is better (lower) than at $\theta^i(j, k, l)$, then another step of size C(i) in this same direction will be taken. Otherwise, bacteria will tumble via taking another step of size C(i) in random direction φ(j) in order to seek better nutrient environment [19].

3.6. Swarming

An interesting group behavior has been observed for several motile species of bacteria including E.coli and S. typhimurium [8].To achieve the function to model the cell-to-cell signaling with an attractant and a repellant. The E.coli swarming mathematical equation can be represented by:

$$J_{cc}(\theta, P(j,k,l)) = \sum_{i=1}^{S} J_{cc}^{i}(\theta, \theta^{i}(j,k,l)) \qquad (11)$$
$$= \sum_{i=1}^{S}\left[-d_{attract}\exp(-\omega_{attract}\sum_{m=1}^{p}(\theta_m-\theta_m^i)^2)\right] + \sum_{i=1}^{S}\left[-h_{repellant}\exp(-\omega_{repellant}\sum_{m=1}^{p}(\theta_m-\theta_m^i)^2)\right]$$

The $J_{cc}(\theta, P(j,k,l))$ is the additional cost function added to the actual objective function (for minimization) to present a time varying objective function. The additional cost function $J_{cc}(\theta, P(j,k,l))$ for each bacterium θ is composed of S terms $J_{cc}^{i}(\theta, \theta^{i}(j,k,l))$ measuring attracting and repelling effects between two bacteria θ and θ^i , illustrated in the next two lines of (12), respectively. In the original version of BF proposed by Passino [8], the parameters of $d_{attract}$, $\omega_{attract}$, $h_{repelent}$ and $\omega_{repelent}$ are set as follows:

$$\omega_{attract}=0.2,\ \omega_{repelent}=10,\ d_{attract}=h_{repelent} \qquad (12)$$

Considering the above parameters, each bacterium will try to move toward other bacteria to decrease the additional cost function $J_{cc}(\theta, P(j,k,l))$, but not too close to them, which is called swarming effect enhancing the local search capability of BFA. More details about (14) can be found in [8].

S = total number of bacteria
p = number of parameters to be optimized which are present in each bacterium
$\theta= [\theta_{1,} \theta_{2,\dots,} \theta_p]^T$ is a point in the p-dimensional search domain
$d_{attract}$ = depth of the attractant released by the cell
$w_{attract}$ = measure of the width of the attractant signal
hrepellant=dattract = height of the repellant effect
wrepellant = measure of the width of the repellant

3.7. Reproduction

According to the rules of evolution, individual will reproduce themselves in appropriate conditions in a certain way. For bacterial, a reproduction step takes place after all chemotactic steps.

$$J_{health}^{i} = \sum_{j=1}^{N_c+1} J(i,j,k,l) \qquad (13)$$

Where, J^i_{health} = health of bacterium i.

For keep a constant population size, bacteria with the highest J_{health} values die. The remaining bacteria are allowed to split into two bacteria in the same place. Actually, in the reproduction loop only the poor individuals, which are unlikely to represent promising areas of the solution space, are filtered out and replaced by good solutions. In other words, the reproduction loop prevents wasting the search ability of BFA for searching non-promising areas of the solution space and thus the algorithm can concentrate on the promising areas of the solution space and search these areas with high accuracy and resolution. This characteristic leads to high local search ability of BFA. Moreover, different search paths are devised for the bacteria generated from the same individual in the next iterations of the loop, due to the chemotaxis operators, such as tumble and swim. In other words, the bacteria generated from the same individual will only be the same at the birth place, but will proceed in different directions and search the solution space through different paths. Consequently, the reproduction loop will not deteriorate the search diversity of BFA but can effectively enhance its search efficiency by filtering out poor individuals of the population and concentrating on the promising areas of the solution space [20].

3.8. Elimination-Dispersal

In evolutionary process, elimination and dispersal events can occur such that bacteria in a region are killed or a group is dispersed into a new part of the environment due to some influence. They have the effect of possibly destroying chemotactic progress, but they also have the effect of assisting in chemotaxis, since dispersal may place bacteria near good food sources. From the evolutionary point of view, elimination and dispersal was used to guarantees diversity of individuals and to strengthen the ability of global optimization. In this technique to keeping the number of bacteria in the population constant, if a bacterium is eliminated, simply disperse one to a random location on the optimization domain.

3.9. Hybrid PSOTVAC-BFA

The main goal of the proposed hybrid PSOTVAC/BFA is to find the minimum of the function presented in equation (2). Actually, PSOTVAC is characterized as a simple, easy to implement and computationally efficient method, which is flexible with high global exploration ability. However, the local search ability of this algorithm is not as high as its global search ability and premature convergence may be occurred for the algorithm. In the opposite, the BFA algorithm via its adaptive reproduction and chemotaxis loop can effectively search promising areas of the solution space with high resolution enhancing the local search capability of PSOTVAC. However, there are some drawbacks in BFA in terms of its complexity and possibility to be locked up by a local solution. The proposed PSOTVAC can overcome these problems. Therefore, the algorithms have been combined such that each algorithm covers the deficiencies of the other one. The obtained hybrid method is designated as the hybrid PSOTVAC/BFA. The steps for executing the proposed hybrid method are:

STEP 1: *Execute PSOTVAC as described.*

STEP2: *Transport the solution obtained from the PSOTVAC to the BFA as an initial solution. The other initial individuals of the BFA are generated randomly within the allowable ranges.*

STEP3: *Execute BFA as described.*

STEP4: *Step 2 is run in the inverse direction such that the solution obtained by the BFA is transferred to the PSOTVAC and the initial population of the PSOTVAC is constructed.*

STEP5: *Repeat steps 1-4 until the termination criterion is satisfied. Here, the termination criterion is set as the maximum number of iterations of the cycle 1-4.*

4. Self Adaptive Hybrid Modified PSO/BFA

In many studies, better solutions have been extracted from original PSO algorithm by applying improvements on simple PSO. In general, applied improvements on original PSO have two categories; adaptive approaches and structure change. Main problem of Evolutionary Algorithms (EAs) is proper value allocation for control parameters. The PSOTVAC has three control parameters: C_{1f}, C_{2f} and population. In adaptive approach these parameters are selected dynamically and not by trial and error technique. The SAMPSO/BFA has two improvement steps. These improvements are applied on two control parameters; i.e. C_{1f} and C_{2f}. The capability and reliability of SAMPSO/BFA is confirmed by test on 21 test function [20-21].

4.1 SAMPSO/BFA-i: Self-adapting C_{1f}

In second step of original PSO, C_{1f} is multiplied by the difference of two selected vectors. Value of C_{1f} is selected from range [0, 1], randomly. The more the value of C_{1f} is lower (close to zero), the larger is the effect of the first selected vector and the lesser is the search space. But if C_{1f} was large (close to 1), search space was larger. If the search space is too large maybe the algorithm go away from the global optimum solution and if it is too small the mutation step is useless. The C_{1f} is defined in range [0,1]. While, in practical issue, to reach the optimal point it varies from 0.4 to 1 [21]. Thus, in Eq. (5) a novel approach is proposed for C_{1f},

$$\alpha_{HBMO\,i}^{G+1} = \begin{cases} C_{1f\,\min} + rand_2[0,1] \times C_{1f\,\max} & if \quad rand_2 < \tau_1 \\ C_{1f\,i}^{\;G} & otherwise \end{cases} \tag{14}$$

where, $C_{1f\ min}$ and $C_{1f\ max}$ are lower and upper limits of C_{1f}. To obtain optimal value, C_{1fmin} and C_{1fmax} are adjusted on 0.4 and 1.0, respectively. The selection criteria between a new value for C_{1f} and old value of C_{1f} are τ_1. If τ_1 was lower than a random value in range [0,1], a new value is generated by first scenario of Eq. (5), otherwise value of C_{1f} is maintained fixed for next case without any changes.

5. *SAMPSO/BFA-ii: Self-adapting C_{2f}*

The C_{2f} is main control parameter. This parameter is selected in range [0, 1] by operator. For the next step, C_{2f} determines which vectors of initial or mutation is selected. In original PSO, the C_{2f} is selected experimentally or by trial and error method. In SAMPSO/BFA, C_{2f} is generated by :

$$C_{2f\,i}^{\;G+1} = \begin{cases} rand_3[0,1] & if \quad rand_3 < \tau_2 \\ C_{2f\,i}^{\;G} & otherwise \end{cases} \qquad (15)$$

The role of τ_2 is same of role τ_1 in SAMPSO/BFA -i.

5.1. Adjustment for OLSC problem

In this paper, SAMPSO/BFA method has been proposed to solve optimal capacitor placement. The algorithm has two improvement phases; in first and second phases, novel equations for C_{1f} and C_{2f} has been used, respectively.

The solution of OLSC problem using SAMPSO/BFA algorithm, at first the size of population, generation, buses, capacitor type, values for base voltage and power, consumed active and reactive powers and lines impedance are applied. By load flow program, voltage profile and power loss of test system have been extracted. Then SAMPSO/BFA algorithm is initialized by Eq. (5) and objective function (OF) is computed based on initial values. After, mutation and crossover operators are applied on initial population based on Eqs. (5)-(8). Load flow is recomputed and OF is calculated again by new values. The selection operator selects best solution between two obtained OFs (after initialization and crossover). In this paper, termination criterion is ending the number of iteration, and then this algorithm is repeated until the maximum number of iteration is reached. Flowchart of OLSC problem solution by SAMPSO/BFA algorithm has been illustrated in Fig. 1.

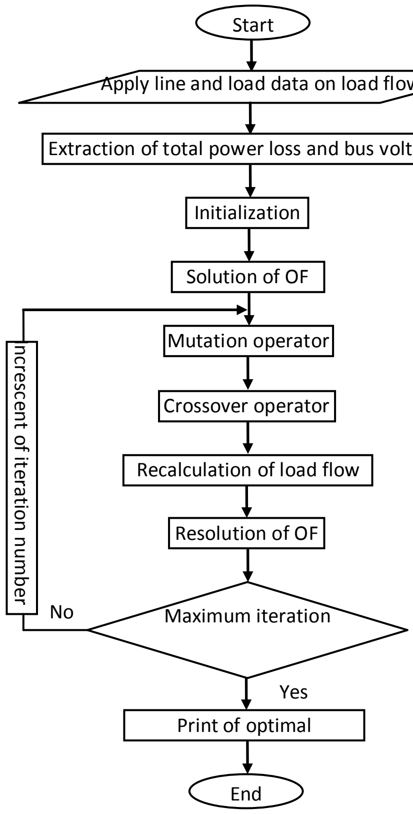

***Fig.1** Flowchart of OLSC problem solution by SAMPSO/BFA algorithm*

5.2. Case Study

In this section, to confirm robustness of SAMPSO/BFA in solving OLSC problem, three load patterns are tested on two test systems. The constant load is applied on IEEE 10-bus, and both varying and effective loads are applied on IEEE 34-bus standard radial network. A backward-forward load flow approach used in this paper is same as in [22]. Cost per power loss and cost per energy loss are 168 \$/kW/year and 0.06 \$/kWh/year, respectively [23]. τ_1 *and* τ_2 *are equal to 0.1 [20]. The capacity and related cost of capacitor banks have been presented in [23].*

The SAMPSO/BFA has two improvement steps. To show the capability of each improvement steps, simulations are carried out for each step separately. Then, SAMPSO/BFA-i and SAMPSO/BFA-ii show first and second improvements (Eq.(14) and Eq.(15)), respectively. It should be noted again that SAMPSO/BFA is composed of SAMPSO/BFA-i and SAMPSO/BFA-ii. To compare different methods, seven parameters have been introduced which are: annual cost, in \$, total installed capacitor bank, in kVAr, CPU time, in sec, power loss, in kW, and their related costs, in \$, minimum voltage, in pu, and annual cost, in \$.

5.3. Constant load

The constant load is applied on IEEE 10-bus standard radial network. Topology of IEEE 10-bus has been illustrated in Fig. 2 [23]. Table 1 shows results of OSLC problem in IEEE 10-bus radial network with constant load. In this table, results of various SAMPSO/BFA algorithms have been compared with results of hybrid method which is created by compositing fuzzy and genetic algorithm [19]. Methods 1, 2, 3, 4 and 5 are without capacitor, hybrid, SAMPSO/BFA-i, SAMPSO/BFA-ii and SAMPSO/BFA, respectively.

***Table 1**. Results of capacitor placement on 10-bus with constant load*

Meth	CPU Time	Power Loss	Min.Volt	Cost
				Loss+Cap.=Annual
1	-	783.8	0.8375	0+131675=131675
2	-	681.28	0.9001	1865+114455=116320
3	26.450	675.43	0.9001	1932+113472=115404
4	22.442	675.37	0.9002	1930+113462=115393
5	20.289	675.36	0.9002	1930+113460=115393

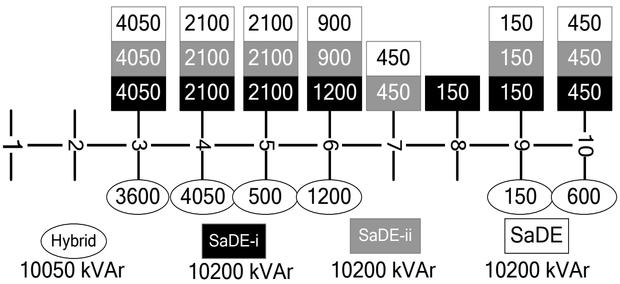

Fig.2 IEEE 10-bus distribution network

Table 2. Results of capacitor placement on 34-bus with varying load

method		CPU Time	Power Loss	Min. Volt.	Cost(\$)
					Loss+ Cap.= Annual
W/O Cap.	1	-	221.72	0.9492	13303+0=13303
	2	-	139.16	0.9609	56443+0=56443
	3	-	52.855	0.9783	3171+0=3171
Hybrid	1	-	160.5	0.9486	9630+611=10241
	2	-	101.18	0.9593	41041+497=41538
	3	-	39.276	0.9749	2357+320=2677
SAMPSO/BFA-i	1	4.387	160.49	0.9501	9629+511=10140
	2	56.439	100.05	0.9608	40580+692=41272
	3	53.645	39.229	0.9753	2354+246=2600
SAMPSO/BFA-ii	1	59.427	158.93	0.9499	9536+962=10498
	2	55.825	99.885	0.9606	40513+1005=41518
	3	54.449	39.233	0.9746	2354+525=2879

SAMPSO/BFA	*1*	*53.639*	*160.11*	*0.9502*	*9607+524=10131*
	2	*55.905*	*100.04*	*0.9609*	*40576+692=41268*
	3	*53.957*	*39.3*	*0.9753*	*2358+246=2604*

By considering results of Table 1, SAMPSO/BFA algorithm has the best solution. The CPU time for SAMPSO/BFA is the minimum among SAMPSO/BFA family and is less 6.1613 and 2.1529 sec respect to the related parameter of SAMPSO/BFA-i and SAMPSO/BFA-ii algorithms, respectively. The active power of SAMPSO/BFA is less than hybrid, SAMPSO/BFA-i, and SAMPSO/BFA-ii methods; the differences are 5.92, 0.07 and 0.01 kW, respectively. The minimum voltage of hybrid and SAMPSO/BFA-i approaches are close to each other and also less than minimum voltage of SAMPSO/BFA and SAMPSO/BFA-ii algorithms. The power loss cost of SAMPSO/BFA algorithm is less than hybrid, SAMPSO/BFA-i and SAMPSO/BFA-ii algorithms; the related amounts are 995, 12, and 2 in $, respectively. The annual cost of SAMPSO/BFA is equal to SAMPSO/BFA-ii, the values are 972 and 11 $ less than hybrid and SAMPSO/BFA-i algorithms, respectively. Fig. 3 shows optimal location/size of installed capacitor banks in IEEE 10-bus radial network. In this figure, presented values for capacitor banks is in term of kVAr.
The presented optimal location/size of SAMPSO/BFA and SAMPSO/BFA-ii algorithms are same and in most cases similar to SAMPSO/BFA-i algorithm. The number of capacitor banks of hybrid method is less than the number of capacitor banks of each SAMPSO/BFA family.

5.4. Varying Load

In practical cases, the network load is changing daily. To study varying load, three load levels are defined; i.e. 1st load level with 1.0 pu load for duration 1000 h, 2nd load level with 0.8 pu load for duration 6780 h and 3rd load level with 0.5 pu for 1000 h. The IEEE 34-bus radial distribution network is test case of varying load condition (see Fig. 3) [23]. The results of varying load simulation have been listed in Table 2. In all cases, the best solution has been bolded, while the worst are crossed with a line.
According to results of Tables 2, the minimum voltage of SAMPSO/BFA approach, in all load levels, are best solution. For power loss and its related cost and total installed capacitor banks and its related cost, SAMPSO/BFA-ii and SAMPSO/BFA-i algorithms give relatively better options, while annual cost of SAMPSO/BFA -ii technique is the worst solution. In first level, CPU time of SAMPSO/BFA algorithm is minimum amount among SAMPSO/BFA family and this value is less for 10.7442 and 5.7873 sec less than SAMPSO/BFA -i and SAMPSO/BFA-ii techniques, respectively. SAMPSO/BFA-i algorithm presents best solution for capacitor banks cost. From viewpoint of annual cost SAMPSO/BFA -ii is the worst case among SAMPSO/BFA family. In first and second load levels, SAMPSO/BFA presents best solution. Proposed optimal location/size of installed capacitor banks by SAMPSO/BFA family and hybrid method have been presented in Fig.3.
In all load levels, the number of capacitor banks proposed by SAMPSO/BFA-ii algorithm is more than other approaches. In first load level, the number of capacitor banks proposed by SAMPSO/BFA and SAMPSO/BFA-i is equal to each other, and is 1 and 5 capacitor banks less than hybrid and SAMPSO/BFA -ii algorithms, respectively. In 2nd load level, the number of installed capacitor banks of SAMPSO/BFA -ii algorithm is 3 banks more than related parameter of SAMPSO/BFA -i and SAIHBM techniques. In third load level, this deference is same for second load level.

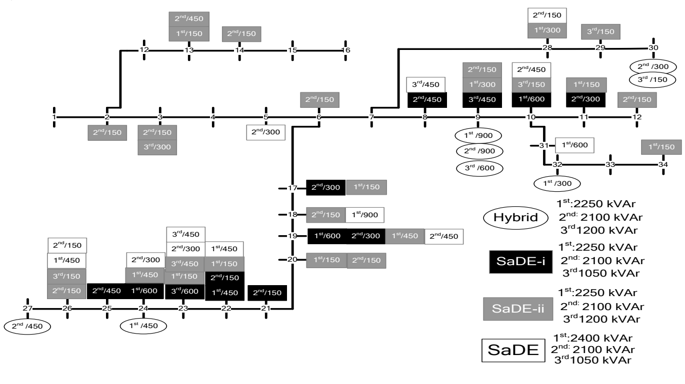

Fig.3 *Location and size of installed capacitors on 34-bus with Varying load*

5.5. Effective Load

The varying load has an effective level which is calculated by Eq. (3). For the introduced three load levels, effective load level is equal to 0.78858 pu. Tables 3 and Fig.4 show solution results of OLSC problem for effective load and their optimal location/size of installed capacitor banks of in IEEE 34-bus radial distribution network, respectively. Methods 1, 2, 3 and 4 are hybrid, SAMPSO/BFA-i, SAMPSO/BFA-ii and SAMPSO/BFA approaches, respectively.

Table 3. Results of capacitor placement on 34-bus with effective load

Meth.	CPU Time	Power Loss	Min.Volt	Cost
				Loss+Cap.=Annual
1	-	105.08	0.96015	17653+474=18127
2	51.570	97.304	0.96131	16347+729=17076
3	52.105	96.91	0.96142	16281+991=17272
4	53.173	97.271	0.96103	16341+627=16969

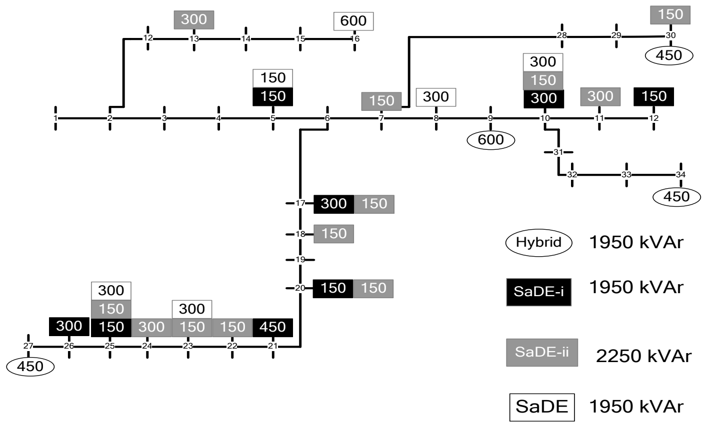

Fig.4 Compression of location/size of installed capacitor on 34-bus with effective load

By considering results of Table 3, it is obvious that the power loss of SAMPSO/BFA -ii has the least value, and is 8.16, 0.389, and 0.356 kW less than hybrid, SAMPSO/BFA -i, as well as SAMPSO/BFA, respectively. The least CPU time of effective load is obtained by SAMPSO/BFA-i algorithm; CPU time of SAMPSO/BFA-i algorithm is 0.5348 and 1.6033 second less than those of SAMPSO/BFA and SAMPSO/BFA algorithms, respectively.

The minimum voltage of SAMPSO/BFA-ii and SAMPSO/BFA are the most and least minimum voltages among SAMPSO/BFA family. The SAMPSO/BFA-ii algorithm presents optimal power loss cost being 1372, 66, and 60 $ less than hybrid, SAMPSO/BFA-i, and SAMPSO/BFA approaches, respectively. The total cost of SAMPSO/BFA algorithm is optimal value among four methods and is 1158, 107, and 303 $ less than annual cost of hybrid, SAMPSO/BFA-i, and SAMPSO/BFA-ii, respectively.

5.6. Comparison

In this part, to analyze performance of these three approaches to solve OLSC problem, two criteria are used. First criterion is the number of best or worst solution for each technique among solutions. The criterion shows reliability of any approach, the more the number of best solution, the more is the reliability of methods. The number of best/worst for SAMPSO/BFA family has been illustrated in Fig.5. Results of SAMPSO/BFA family are better than hybrid method; this fact confirms capability of SAMPSO/BFA family to solve OFLSC problem. Thus, in Fig.6, the obtained results by hybrid technique have been ignored.

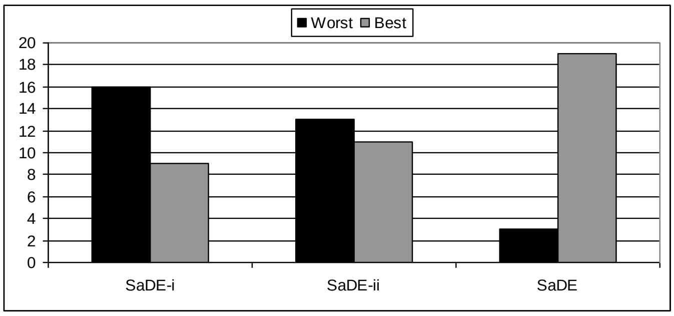

Fig.5 *The number of best/worst solution of SAMPSO/BFA family*

Focusing on Fig.6 reveals that SAMPSO/BFA -ii, and SAMPSO/BFA-i algorithms have better solution. The SAMPSO/BFA is the best option among these four algorithms; this algorithm has the minimum value in worst solution, and the maximum value for best solutions. Among SAMPSO/BFA family, SAMPSO/BFA-i technique is the worst option.

The other criterion is error percentage of base value respect to computed value. The base value of minimum voltage and power loss are 1 pu and 2000 kW, respectively. Fig.6 shows error percentage of minimum voltage of constant and varying as well as effective loads.

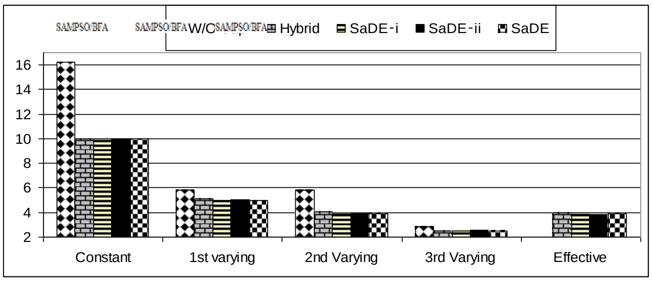

Fig.6 Error percentage of minimum voltage

Regarding results of Fig.6, for minimum voltages, SAMPSO/BFA algorithm reaches better solution in most cases; this algorithm except effective load level has optimal value. The SAMPSO/BFA -ii algorithm has better solution among four approaches only in constant load and effective load level. In this case, SAMPSO/BFA-i has the worst solution among SAMPSO/BFA family and only in 3rd level of varying load presents optimal value which is equal to related parameter of SAMPSO/BFA algorithm. In constant load, minimum voltage error percentage of SAMPSO/BFA -ii is equal to corresponding parameter of SAMPSO/BFA which both is 0.011 and 0.013 less than hybrid and SAMPSO/BFA -i algorithms, respectively. In first level of varying load, the error percentage of SAMPSO/BFA is 0.159, 0.004 and 0.029 less than related values of hybrid, SAMPSO/BFA-i, SAMPSO/BFA techniques, respectively. In level 2, these reduction values are 0.159, 0.006 and 0.028. In third load level, minimum voltage error percentage of SAMPSO/BFA -i and SAMPSO/BFA algorithms is equal and is 0.037 and 0.064 less than hybrid and SAMPSO/BFA -ii techniques, respectively. Finally, in effective load level, error percentage of minimum voltage of SAMPSO/BFA -ii is 0.127, 0.011, and 0.039 less than error percentage of hybrid, SAMPSO/BFA -i, SAMPSO/BFA approaches, respectively.

After computation of minimum voltage error percentage, error percentage of power loss is computed by the approach which was used for minimum voltage. The base value of power is 2 MW. Fig.7 shows error percentage of power loss for three load conditions.

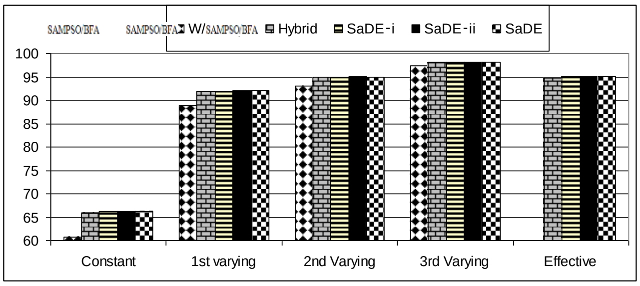

Fig.7 Error percentage of power loss

It should be mentioned that, in this case, the more the power loss error percentage, the better is the solution. Among five cases, the SAMPSO/BFA-ii algorithm in most cases presents better solution. In error percentage of power loss similar to error percentage of minimum voltage, SAMPSO/BFA is the worst option among SAMPSO/BFA family with only one best solution.

The error percentage of SAMPSO/BFA, in constant load, is 0.292, 0.0035, and 0.0005 more than hybrid, SAMPSO/BFA-i, and SAMPSO/BFA -ii algorithms, respectively. In first level of varying load, SAMPSO/BFA-ii approach presents the best value which its value is 0.0835, 0.0780 and 0.059 more than hybrid, SAMPSO/BFA -i, and SAMPSO/BFA algorithms, respectively. These increments in level 2 are 0.0658, 0.0083 and 0.0078. The SAMPSO/BFA -i algorithm in 3rd level of varying and effective loads has best value. In 3rd level of varying load, the difference between error percentage of SAMPSO/BFA -ii and three other algorithms; i.e. hybrid, SAMPSO/BFA -ii and SAMPSO/BFA techniques are 0.0024, 0.0002 and 0.0036, respectively. Finally, in effective load level, SAMPSO/BFA-ii algorithm has maximum power loss error percentage and its value is 0.4083, 0.0195 and 0.0178 more than hybrid, SAMPSO/BFA-i, SAMPSO/BFA algorithms, respectively.

5.7. Discussion

In this study, to solve optimal capacitor allocation in radial distribution network a novel algorithm based on simple HBMO algorithm has been proposed. The proposed algorithm, SAMPSO/BFA, has two improvement steps: self-adapting C_{1f} and C_{2f} called SAMPSO/BFA-i and SAMPSO/BFA -ii, respectively. From results of simulation and comparison, followings have been extracted:

Remark i) *In addition to capacity of installed capacitor banks, dispatch manner of capacitor banks has considerably effects on cost. This fact has been extracted by comparing cost of capacitor among SAMPSO/BFA family, in level 2 of varying load between SAMPSO/BFA-i and hybrid, in level 3 of varying load between hybrid and SAMPSO/BFA-ii. Thus less installed capacitor always does not result in lower cost.*

Remark ii) *The numbers of buses have impact on CPU time more than total demand of network. In varying load, demand of 1st load level is twice of 3rd load level demand while CPU time changes only about 20%. This fact could be derived by comparing between 10-bus and 34-bus radial networks. The number of buses are one of initial matrix dimension, then the more the number of buses, the lower is convergence velocity.*

Remark iii) *Form the view point of voltage profile improvement, SAMPSO/BFA-ii is better than SAMPSO/BFA-i algorithm. The SAMPSO/BFA-i has the worst solution in SAMPSO/BFA family. This fact confirms that among control parameters of DE algorithm; crossover rate has the maximum impact on voltage profile. Then self-adapting α_{HBMO} helps to extract better solution from algorithm respect to adjust a constant value for C_{1f} in original HBMO. The better results of SAMPSO/BFA -ii is compared to SAMPSO/BFA illustrates that self-adapting C_{2f} does not affect remarkably on voltage profile.*

Remark iv) *The capability of SAMPSO/BFA-i algorithm is confirmed in less installed capacitor banks presented by this algorithm. In constant load, total installed capacitor banks of SAMPSO/BFA family is equal, in effective load this parameter of SAMPSO/BFA and SAMPSO/BFA-i algorithms are 300 kVAr less than SAMPSO/BFA-ii algorithm. Unlike SAMPSO/BFA-i, SAMPSO/BFA-ii in the most cases has largest installed capacity; the total installed capacitor banks in second and third level of varying load and effective load confirm this extraction. Thus, C_{1f} improvement reduces installed capacitor banks more than C_{2f} improvement.*

6. Conclusion

In this work, an improved HBMO algorithm, named SAMPSO/BFA, was used to solve OLSC problem. The proposed algorithm was obtained by self-adapting control parameter of mutation and crossover operators; i.e. C_{1f} and C_{2f}, respectively. Three loads conditions, constant and varying as well as effective, were tested on 10-bus and 34-bus radial distribution networks. Fitness is function of annual cost, in addition to cost, six other parameters used for comparison were installed capacitor banks and related cost, CPU time, minimum voltage, active power loss and related cost. To compare results, the number of best/worst solutions and error percentage of minimum voltage and power loss were used.

From simulation results of case studies it can be claimed that: In general, self-adapting C_{1f} is more effective than self-adapting C_{2f}, latter has better solution for the number of installed capacitor banks and related cost. Sum of these two improvements has better overlapping and give an optimal solution. Cost of total installed capacitor banks is less than 10% of annual cost, remaining cost (90%) is power loss cost. Therefore, it is better to focus on power loss reduction. Load decline has less impact on the speed of algorithm running, and decreasing the load amount only 20% decrease the speed of algorithm running. In addition to capacitor banks amount, the number of installed capacitor banks also have remarkable impact on cost.

References

[1] Khodr H. M., Vale Z. A., Ramos C. Optimal cost-benefit for the location of capacitors in radial distribution systems, IEEE Transaction on Power Delivery, vol.; 24, no. 2.pp.787 796. 2009

[2] Khodr H.M., Olsina F.G., De Oliveira-De Jesus P.M., Yusta J.M. Maximum savings approach for location and sizing of capacitors in distribution systems, Electric Power Systems Research, vol. 78 .no.7 .pp. 1192-1203, 2008.

[3] Jabr R.A. Optimal placement of capacitors in a radial network using conic and mixed integer linear programming, Electric Power Systems Research,.vol.78 .no.6 .pp. 941 948, 2008.

[4] Hagh, M. T. and Ghadimi, N. (2014), Multisignal histogram-based islanding detection using neuro-fuzzy algorithm. Complexity. doi: 10.1002/cplx.21556.

[5] Da Silva I. Ch., Carneiro S., De Oliveira E. J., de Souza Costa J., JRezende Pereira. L. A Heuristic constructive algorithm for capacitor placement on distribution systems, IEEE Transaction on Power Systems vol.23 .no.4, pp.1619 1626, 2008.

[6] Ghadimi, N. (2014), An adaptive neuro-fuzzy inference system for islanding detection in wind turbine as distributed generation. Complexity. doi: 10.1002/cplx.21537.

[7] Noruzi, A., Banki, T., Abedinia, O. and Ghadimi, N. (2014), A new method for probabilistic assessments in power systems, combining monte carlo and stochastic-algebraic methods. Complexity. doi: 10.1002/cplx.21582.

[8] Mendes A., Fran-ca P.M., Lyra C., Pissarra C., Cavellucci C. Capacitor placement in large-sized radial distribution Networks, IEE Proc.-Gener. Transm. Distrib., vol. 152 .no.4, pp. 496 502, 2005.

[9] Sundhararajan S., Pahwa A. Optimal selection of capacitor for radial distribution systems using a genetic algorithm, IEEE Transactions on Power Systems, vol. 9 .no.3, pp.1499 15071994.

[10] Morsali, R., Mohammadi, M., Maleksaeedi, I. and Ghadimi, N. (2014), A new multiobjective procedure for solving nonconvex environmental/economic power dispatch. Complexity. doi: 10.1002/cplx.21505.

[11] Taher S. A., Hasani M., Karimian A. A novel method for optimal capacitor placement and sizing in distribution systems with nonlinear loads and DG using GA, Commun Nonlinear Sci Numer Simulat, vol.16.pp.851 862, 2011.

[12] Carpinelli G., Proto D., Noce C., Russo A., Varilone P. Optimal allocation of capacitors in unbalanced multi-converter distribution systems, A comparison of some fast techniques based on genetic algorithms, Electric Power Systems Research, vol. 80.pp.642 650, 2010.

[13] Abu-Elanien A. E. B., Salama M. M. A. A wavelet-ANN technique for locating switched capacitors in distribution systems, IEEE Transaction on Power Delivery, vol. 24 .no.1, pp.400 409, 2009.

[14] Taher S. A., Hasani M., Karimian A. A new method for optimal location and sizing of capacitors in distorted distribution networks using PSO algorithm, Simulation Modelling Practice and Theory, vol. 19 .no.2, pp. 662-672, 2011.

[15] Ghadimi, N. (2014), A new hybrid algorithm based on optimal fuzzy controller in multimachine power system. Complexity. doi: 10.1002/cplx.21544.

[16] Gasbaoui B., Chaker A., Laoufi A., Abderrahmani, A., Alloaoua B. Optimal placement and sizing of capacitor banks using fuzzy-ant approach in electrical distribution systems, Leonardo Electronic Journal of Practices and Technologies, vol. 16.pp.75-88, 2010.

[17] Chang G. W., Chang W.Ch., Chuang Ch.Sh., Shih D.Y. Fuzzy logic and immune-based algorithm for placement and sizing of shunt capacitor banks in a distorted power network, IEEE Transaction on power delivery, vol. 26 .no.4, pp.2145 2153, 2011.

[18] Seifi A., Hesamzadeh M.R. A hybrid optimization approach for distribution capacitor allocation considering varying load conditions, Electrical Power and Energy Systems, vol. 31 .no.10, pp.589 595, 2009.

[19] Passino K.M., "Biomimicry of Bacterial foraging for Distributed Optimization", University Press, Princeton, New Jersey, 2001.

[20] Passino K. M., "Biomimicry of bacterial foraging for distributed optimization and control," IEEE Control Syst. Mag., vol. 22, no. 3, pp. 52–67, June 2002.

[21] El-Zonkoly A. M., Khalil A. A. and Ahmied N. M., "Optimal tuning of lead-lag and fuzzy logic power system stabilizers using particle swarm optimizatio", Expert System with Applications, vol. 10, pp: 1-10, 2008.

[22] Teng J.H. A direct approach for distribution system load flow solutions, IEEE Transactions on Power Delivery, vol. 18 .no.3, pp.882 887, 2003.