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Full Length Research Paper

Reactive power optimization with artificial bee colony algorithm

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Reactive power optimization (RPO) is an important issue for providing the secure and economic run of the power systems. The importance of reactive power planning on economic profit and secure running has been increasing, because of the increasing fuel costs and investment funds. It is also quite important for an electric operator to provide voltage in a specified range for the customers. As such, RPO provides voltage control in power systems. Furthermore, it is used for decreasing active power loss and making better power coefficents. In this study, multi-objective RPO was used considering voltage deviations of buses, active power losses and reactive power generator costs. In this study, a new metaheuristic optimization method, which is an artificial bee colony (ABC), was used for the optimization. However, ABC was applied on ten bus system and the results were compared with the improving strength pareto evolutionary algorithm. It was observed that the system runs more effectively and economically with the results found with ABC.

Key words: Artificial bee colony, reactive power optimization, active power loss.

INTRODUCTION

Reactive power optimization (RPO) is an important optimizaton process in terms of voltage stability, voltage quality and active power loss. The main object function in RPO is the total active power loss function, but in later years, systems were analyzed in terms of reactive supply costs and voltage profile.

Since voltage profile minimizes the deviations between the nominal and bus voltages, the reactive power transferred from the bus will decrease and the lines current will also decrease. As such, these provide supplements for the decrement of active power loss. The effects of the reactive power supplies connected to buses are quite important on reduction of active power loss. However, due to the installation, some extra equipment and devices costs like disjoncteur needs to be be addressed from a different perspective. Based on this, cost functions are used in RPO, leading to a multi-objective function. This function is a non linear function having a lot of variables and constraints. Firstly, this problem was solved with classical methods such as linear, non-linear, quadratic and dynamic programming. Since the problems have a lot of variables, constraints, different local minimiums and the possibility of getting trapped in the local minimum, the metaheuristic methods are preferred as the solution to these problems.

In previous years, metaheuristic methods such as simulated annealing, ant colony optimization, genetic algorithm, plant growth simulation algorithm, particle swarm optimization, sequential quadratic programming algorithm, as well as artificial immune system, give more satisfied results in finding global optimum points. So nonlinear problems having multi variables and constraints like RPO have been solved generally with heuristic methods.

Deep and Shahidehpour used decomposition approach in considering RPO linearly. As such, they divided the bus systems into 16 and 30 bus systems for

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decomposition approach.

However, they divided the 16 bus system into two different systems having 7 and 9 buses. By this way, they decreased the complexity and used the classical method (Deep and Shahidehpour, 1990). Jwo et al. (1995) solved RPO with simulated annealing by combining the compensator and the active power loss of the system, and as such, they controlled the system in terms of voltage deviations, while Putman et al. (1999) solved the problem with a simplex method. Zhu et al. (1998) solved RPO with neural network using analytical hierarchical process. They analysed the RPO in terms of voltage quality and active power loss. Grudinin (1998) used successive quadratic programming method and bi-level programming method (a method that traces object function and controls variable value continuously). They applied their study on IEEE-30 bus system and other 278 bus system. Yoshida and Fukuyama (1999) analysed voltage security with particle swarm optimization (PSO). In the direction of this object, they used RPO at 14 and 112 bus systems. However, Liu et al. (2000) realized a hybrit study with genetic algorithm (GA), simulated annealing (SA) and tabu search (TS). Deng et al. (2002) minimized the active power demanded in 24 h with algorithmic combined approach, wherein the data belonging to the previous day represents the next day's variable values. Khiat et al. (2003) analysed West Algerian transmission system in terms of RPO. In their study, they used a hybrid system for both heuristic and numerical methods. Mantawy and Al-Ghamdi (2003) used particle swarm optimization as their new RPO method introduced by them. As such, they applied their methods on IEEE-6 bus system. Lin et al. (2003) analysed RGO considering voltage stability and they applied 14 bus system. They used non-linear programming in their studies. Wei et al. (2003) expressed that GA could get trapped by local minimums, so this can be solved with big crossover and mutation rates, but they stated that this method may slow the steps of the solution. So they solved RPO using a method called immune genetic algorithm. Chuanwen and Bompardb (2005) represented a hybrid method using chaotic particle swarm optimization and linear interior methods.

They stated that particle swarm optimization started the search process in a big solution space so it is a drawback for the solution time. So they used a method that narrowed the initial solution space. They applied their algorithm to IEEE-30 bus system and compared their results with PSO both graphically and numerically. Durairaj and Kannan (2005) made RPO with improved genetic algorithm. They tried to minimize voltage stability, voltage quality, active power loss and total cost in the objective function. As such, they applied their algorithm IEEE-30 and 57 bus systems. Abido and Bakhashwain (2006) analysed RPO using a multiobjective evolutionary algorithm. They used the best active power loss and the best voltage deviation, and tried to minimize these two different objectives. Li et al. (2006) used adaptive particle swarm optimization algorithm for RPO. They applied their algorithm IEEE-30 bus system and compared the results with genetic algorithm and particle swarm algorithm. Lenin and Mohan (2006) used ant colony algorithm for RPO. They applied ACO IEEE-30, 57 and 191 bus systems and compared the results with GA and adaptive GA. Abbasy et al. (2007) used differential evolution algorithm for the multiobjective optimization. They, especially, focused on cost function and used the reactive power production cost functions of the generator and compensator. Chettih et al. (2008) applied the particle swarm method to the West Algerian network. They compared the results before and after using the method. Xiangzheng (2007) solved IEEE-6 bus system with immune algorithms and compared the results with GA. Lu and Ma (2008) used direct neural dynamic programming. They applied their algorithm IEEE-6 bus system and compared the results with GA. Zhang et al. (2008) analysed the system for active power loss and voltage profile and used the application of oriented search algorithm. Lirui et al. (2008) optimized the reactive power using dual population ant colony optimization. They stated that one population ant colony could get trapped by the local minimal, so they started to attain more optimum solution using dual population. In order to present the efficiency of their algo-rithm which is more than one population algorithm, they used RPO problem. Zhang et al. (2008) minimized the active power loss of a 30-bus system using self-adaptive differential evolution algorithm. Lin et al. (2008) made voltage and active power loss control using improved tabu search algorithm. Firstly, they optimized active power loss in their algorithm and saved the best ten solutions, therby giving the maximum voltage range. They gathered these results using fuzzy set and obtained a single objective function and searched for optimal values with this function. Wei et al. (2008) searched optimal solutions for IEEE-30, 57 and 118 bus systems using bacterial chemotaxis method, whereas Wang et al. (2008) used plant growth simulation algorithm for RPO. Jikeng et al. (2008) applied adaptive immune algorithm for the solution of RPO and they applied their algorithm, IEEE 14 and 118 bus systems, and compared the results with GA. Varadarajan and Swarup (2008) used differential evolutionary algorithm for the minimization of the active power loss at IEEE 14, 30, 57 and 118 bus system. Li et al. (2009) made dynamic optimal reactive power dispatch based on parallel particle swarm optimization algorithm.

They gathered the active power loss with transformator and compensator cost functions as a single object function. They applied their algorithms 5 different IEEE bus systems and compared the results with PSO. Aribia and Abdallah (2007) studied multiobjective optimization for reactive dispatch and they minimized the active power loss, voltage deviation and VAR source cost separately.

In this study, ABC, being a new heuristic method is used for the multiobjective reactive power optimization. Karaboga introduced this algorithm as artificial bee colony into the literature in 2005. This algorithm runs based on some behaviour of bees, while bees collect nectar from the nectar sources. Generally, nonlinear function optimization is realized with ABC.

MULTIOBJECTIVE REACTIVE POWER OPTIMIZATION

The importance of reactive power management increases gradually, in the direction of increasing reactive power demand. Voltage is very important in power management; as it must be high enough to support loads and must be low enough not to cause any fault of equipment. Hence, voltage must be controlled from each point and must be supported. This can be realized to a large extent by controlling reactive power consumption and sources.

The controllable devices such as generator, sencron capacitor, reactor and FACTS devices are used for decreasing the loss and increasing the voltage control (capacity) in RPO. At the same time, these devices consist of constraints for the optimization problem.

In this study, there are three object function optimization called multiobjective RPO. These functions are: active power loss, voltage profile of load buses and cost function of reactive power sources.

Active power loss

Among the most important issues of power system, system loss is the most important. Active power loss (P_{loss}) is a serious economic loss among these losses, so it is needed to minimize the active power loss. Active power loss object function is given in Equation 1 (Deep and Shahidehpour, 1990; Li et al., 2009).

$$\min f_Q = \sum_{k\in N_E} P_{loss} = \sum_{k\in N_E} g_k (V_i^2 + V_j^2 - 2V_i V_j \cos\theta_{ij}) \quad (1)$$

N_E is the number of transmission lines, g_k is the conductance of the line connecting i and j bus, V_i is the voltage value of i th bus, V_j is the voltage value of jth bus, θ_{ij} is phase angle of the voltage value between i and j bus and P_{loss} is total active power loss in Equation 1.

Voltage profile

The other object function is related to the minimization of the voltage oscilations between bus voltage and nominal voltage. The first usage of the object for this object function is the relation of reactive power transmission to the bus voltage level, in that the load bus voltage values, close to the nominal values, provide the diminution of the reactive power value transmitted to the load bus. The dimunition of the reactive power value causes the dimunition of the line current. Active power loss is presented with I^2R. So the dimunition of the line current causes the dimunition of active power loss in the voltage profile. The second usage of the object for this object function is to stabilize the load bus voltage to a nominal value at the event of the unforeseen sudden voltage unstability scenarios. The average voltage deviation of the load bus can be minimized using Equation 2 (Abido and Bakhaswain, 2006; Zhang et al., 2008).

$$V_{dev} = \frac{\sum_{i\in N_{PQ}} |V_i - V_{ref}|}{N_{PQ}} \quad (2)$$

where $\mathbf{V_{dev}}$ is voltage deviation, $\mathbf{N_{PQ}}$ is load bus number, $\mathbf{V_i}$ is load bus voltage and $\mathbf{V_{ref}}$ is load bus reference (nominal) voltage value.

Reactive power source cost

Another object function to be minimized in RPO is the cost function of reactive power sources connected to the system. The cost of reactive power sources consist of the installation and purchasing costs. The cost of installation and extra equipment cost includes switching and disjoncteur costs. The object function is presented in Equation 3 with the combination of reactive power sources costs (Durairaj and Kannan, 2005; Li et al., 2009).

$$I_c = \sum_{i\in Nc} e_i + C_{ci}|Q_{ci}| \quad (3)$$

where e_i is the cost of the establishment and the equipment added to ith bus, C_{ci} is the cost of MVAr produced by Var sources connected to ith and Q_{ci} is the per-unit value of reactive power transferred from the Var source connected to the ith bus. However, Q_{ci} is the absolute value because FACTS devices can be run inductively or capacitively, considering the needs of the system.

Constraints of the problem

In order to attain practical variable values, there must be working conditions constraints in RPO. If the constraints are not used in RPO, the variables take the values that are harmful to the system. Both generator voltages and reactive power sources have value ranges. As such, active and reactive power equations are used for the equality constraint at the minimization of active power loss.

The equality constraints of the problem

The equality constraints at RPO are represented with active and reactive power equations known as power flow equations. The equilibrium of active and reactive power can not be omitted. There must be equilibrium between the produced and demanded power. The power equations are given in Equations 4 and 5.

$$P_{Gi} - P_{Di} - V_i \sum_{J=1}^{NB} V_j [G_{ij} \cos(\delta_i - \delta_j) + B_{ij} \sin(\delta_i - \delta_j)] = 0 \quad (4)$$

i$\in N_B$

$$Q_{Gi} - Q_{Di} - V_i \sum_{J=1}^{NB} V_j [G_{ij} \sin(\delta_i - \delta_j) + B_{ij} \cos(\delta_i - \delta_j)] = 0 \quad (5)$$

i$\in N_{PQ}$

where N_B represents the number of bus, P_G and Q_G represent respectively the active and reactive power of the generator, P_D and Q_D represent respectively demanded active and reactive powers, G_{ij} and B_{ij} represent the conductance and susceptance value of the line between the ith and jth bus and δ_i and δ_j represent bus voltage angle.

Inequality constraints

Inequality constraints consist of control variable constraints and bus voltage values at RPO. The control values of the system are the transformator scale range, reactive power transferred to the system by reactive power source and the voltage of the generators.

Bus voltages are confined into specified range, related to the equipment specialities. Accepted bus voltages changed to the bus nominal values.

$$V_{i\min} \le V_i \le V_{i\max} \quad (6)$$

$$Q_{Gi\min} \le Q_G \le Q_{Gi\max} \quad (7)$$

$$Q_{Ci\min} \le Q_C \le Q_{Ci\max} \quad (8)$$

where $i \in NB$, $i \in N_G$, $i \in N_C$ and N_G, N_B, N_T ve N_C are the number of generator bus, the number of total bus, the number of transformator and the number of capacitor, respectively.

If the limitation conditions are not obtained for the RPO inequality constraints, the variable values are assigned the limitation values. Specifically, at the optimization process of the variables, in order not to exceed the limitation values, the variable taking the value below the lower limit is assigned to the lower limit value, while the variable taking the value above the upper limit is assigned to the upper limit value.

$$V_{i,\lim} \quad V_i \ge V_{i\max} \quad \Rightarrow V_i = V_{i\max},$$

$$V_i \le V_{i\min} \quad \Rightarrow V_i = V_{i\min}$$

$$Q_{i,\lim} \quad Q_i \ge Q_{i\max} \quad \Rightarrow Q_i = Q_{i\max},$$

$$Q_i \le Q_{i\min} \quad \Rightarrow Q_i = Q_{i\min} \quad (9)$$

Artificial bee colony algorithm

Artificial bee colony algorithm is introduced to the literature in 2005 by Dervis Karaboga. ABC algorithm was developed by watching the behaviors of the real bees, while they were searching for the nectar resources and sharing the amount of the resources with the other bees.

Creating data flows around the beehive by roaming is a behavior of bees that comprises the basics of the swarm intelligence. There are three kinds of bees namely: employed, onlooker and scouts. Each species plays a different role in the optimization process. Employed bees stay above the nectar source and keep the neighboring sources in memory. Onlooker bees take that information from employed bees and make a resource choice to collect the nectar. Also, the scouts are responsible for

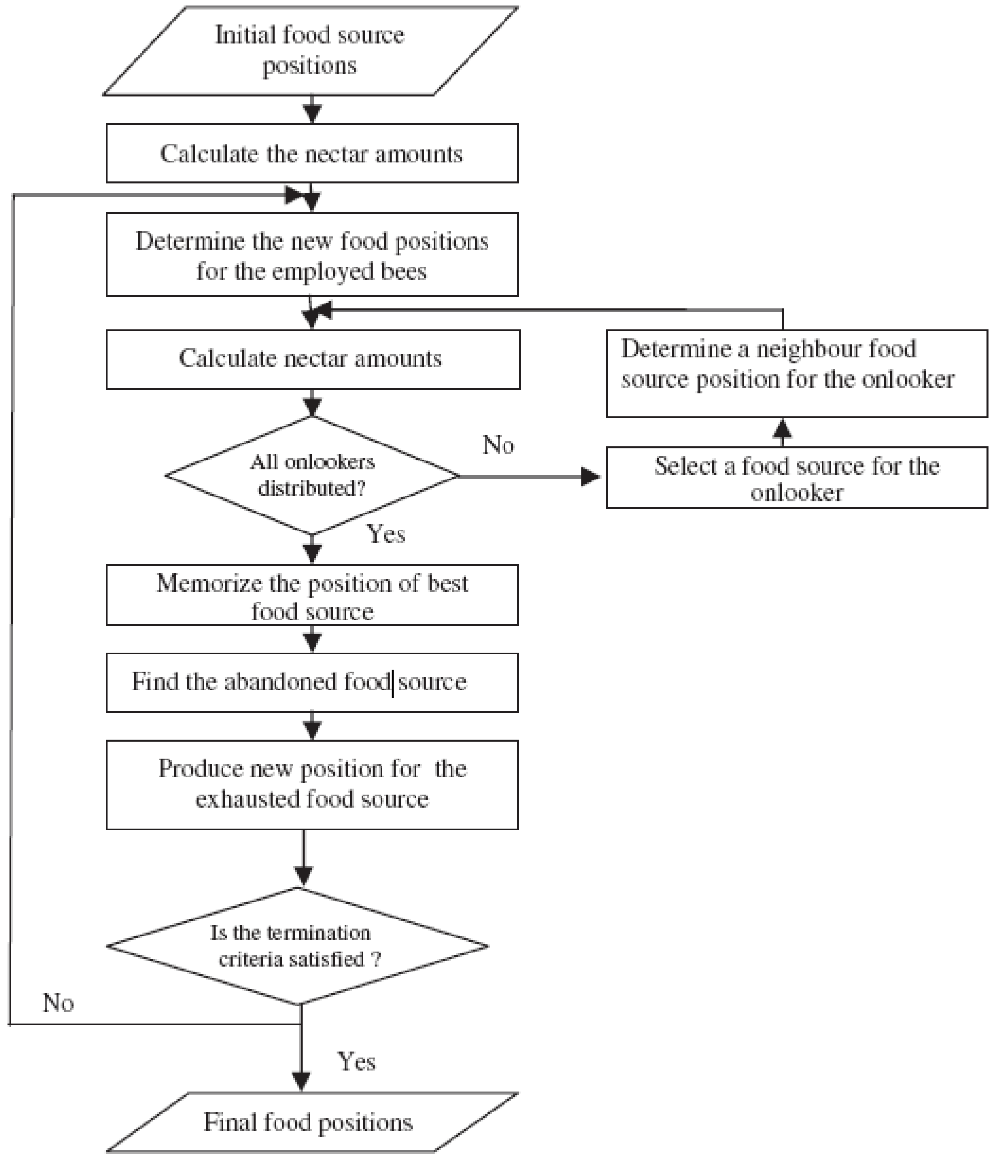

Figure 1. Flowchart of the ABC algorithm (Karaboga and Basturk, 2007).

calculated. In the second step, onlooker bees make a resource choice in accordance with the information they took from finding new nectar resources. The algorithm consists of three steps. In the first step, employed bees are sent to scamper for resources and the nectar amount here is the employed bees and the nectar amount is calculated. Lastly, in the third step, one of the employed bees is nominated randomly as a scout bee and it is sent to the sources to find new sources (Arabia and Abdallah, 2007; Karaboga and Basturk, 2007, 2008; Karaboua, 2009; Kang et al., 2009; Quan and Shi, 2008; Bao and Zeng, 2009; Sıngh 2009; Kumar et al., 2009). Half of the bees in the colony are appointed as employed and the rest half as onlooker bees in the algorithm. Therefore, the number of employed bees is equal to the number of nectar sources (Karaboga and Basturk, 2007). The food sources in the algorithm refer to the possible solutions of the problem to be optimized. The nectar amount belonging to a source means the quality value which is said by that source (Figure 1).

In the first step of the algorithm, random solutions are produced in the specified range of the variables $x_i (i = 1,......,S)$. Secondly, each employed bee discovers new sources whose amounts are equal to the half of the total sources. Equation 10 is used to find a new source.

$$vij = xij + \varphi ij(xij - xkj) \quad (10)$$

In Equation 10, k is equal to (int(rand*S)+1) and j is equal to 1,…..D. After creating vi, they compared x_i solutions and the best one was used as the source. In the third step, onlooker bees chose a food source with the possibility given in Equation 11.

$$P_i = \frac{fit_i}{\sum_{j=1}^{SN} fitj} \quad (11)$$

There are scout bees, responsible for random researches, in each colony. These bees do not use any pre knowledge while they are searching for nectar sources, and as such, their research was randomly done completely (Karaboga and Basturk, 2007, 2008; Karaboga, 2009; Kang et al., 2009; Quan and Shi, 2008; Bao and Zeng, 2009; Sıngh, 2009; Kumar et al., 2009; Omkar and Senthılnath, 2009; Venkata and Pawar, 2010; Pawar et al., 2008; Akay and Karaboga, 2009). The scout bees are selected among the employed bees. This selection is realized with respect to the limit parameter. If a solution that represents a source is not realized with certain number of trials, then this source is abandoned. The bee of that source goes to find new source as a scout bee. The number of comings and goings to a source is determined by the 'limit' parameter. Finding a new source of a scout bee is given in Equation 12.

$$xij = xj^{\min} + (xj^{\max} - xj^{\min}) * rand \quad (12)$$

In ABC, the employed and the onlooker bees serve in the exploitation process and the scouts serve in the exploration. The bees work for the maximization of the energy function E/T, showing the amount of the foods that are brought to the nest. The maximization of the objective function is $F(\theta_i)$, while $\theta_i \in R^p$ is done in the maximization problem. θ_i is the position of the ith source, while $F(\theta_i)$ is the nectar amount in this source and it is proportional with $E(\theta_i)$. $P(c) = \{\theta_i(c) | i = 1,2,...,S\}$ is the population of the sources including the positions of all the sources. Choosing a source of onlooker bees depends on the value of $F(\theta)$. The more nectar amount of a source means more possibility that the source would be chosen. That is, the possibility of choosing a nectar source in the position θ_i is:

$$P_i = \frac{F(\theta_i)}{\sum_{k=1}^{S} F(\theta_k)} \quad (13)$$

After the onlooker bee watches the dance of the employed bees and chooses the source with the equality (13), it specifies a neighboring source and takes its nectar. The position information of the chosen neighbor is calculated by:

(c+1)= θ_i (c)± $\phi(c)$

As such, $\phi(c)$ is calculated by taking the difference of some of the parts of θ_i (c) and θ_k (c), where k different from i, are randomly produced indices of a solution in the population. If the nectar amount of θ_i(c+1), F (θ_i (c+1)), is greater than the nectar amount in the position θ_i (c), then the bee goes to its beehive and shares this information with the other bees and keeps θ_i (c+1) in the mind as a new position. Otherwise, it goes on keeping θ_i (c) in mind. If the nectar source of the position θ_i is not realized by the number of 'limit' parameter, then the source in the position θ_i is abandoned and the bee of that source becomes scout bee. As such, the scout bee makes random researches and finds a new source and the new found source is assigned to θ_i. The algorithm continues up to the desired cycle number, and the sources having the best nectar in mind represent the possible values of the variables. The obtained nectar amount represents the solution of the object function.

The sample problem solution with ABC

The function given in Equation 1 is taken as a sample problem. The number of variables is assigned to 5, while the iteration number of the algorithm is assigned to 10. The focus should be on ensuring that the size of the colony is twice the number of the variables, because half of the colony will be assigned as employed bees and the number of the employed bees must be equal to the number of the variable. At the first step of the algorithm, the colony is created randomly. This colony is given in Table 1. As seen in Table 1, half of the colony represents the employed bees and the other half of the colony represents the onlooker. After creating the initial

Table 1. The initial colony created randomly.

Employed bees					Onlooker beees				
1.121	1.145	1.118	1.106	1.144	1.117	1.140	1.101	1.110	1.139
1.058	1.071	1.060	1.019	1.061	0.922	1.072	1.008	0.993	1.078
1.071	0.988	1.080	0.924	0.996	1.042	1.063	1.102	1.096	0.957
0.014	0.038	0.020	0.005	0.049	0.015	0.041	0.010	0.017	0.022
0.022	0.029	0.008	0.048	0.034	0.026	0.006	0.008	0.029	0.018

Table 2. The change of information in mind according to cycles.

9th cycle					10th cycle				
1.121	1.132	1.118	1.106	1.117	1.124	1.132	1.118	1.106	1.117
1.057	1.061	1.059	1.019	1.061	1.057	1.027	1.059	1.019	1.061
1.071	0.988	1.028	0.924	0.992	1.071	0.988	1.028	0.924	0.992
0.022	0.050	0.049	0	0.050	0.022	0.050	0.049	0	0.006
0.014	0.046	0.045	0.048	0.034	0.014	0.046	0.045	0.048	0.034

Table 3. The exchange of nectar resource in each cycle.

Cycle 1	Cycle 2	Cycle 3	Cycle 4	Cycle 5	Cycle 6	Cycle 7	Cycle 8	Cycle 9	Cycle 10
14.227	13.927	13.927	13.927	13.870	13.844	13.824	13.726	13.726	13.726

colony, employed bees nectars are replaced keeping their minds on the amount of the nectar in each nectar resources. Employed bees transfer the amount of nectars and the position information to the onlooker bees in each cycle. When the employed bee finds a new nectar resource having more amount of nectar, it replaces the new resource amount in mind. The information change in the employed bee mind is presented for the 9th and 10th cycles in Table 2. It is seen that the position information change of the nectar resources belong to the 2nd and 5th bee mind, in Table 2.

Since those two bees meet the criteria for nectar resources, having more nectar in the 10th cycle, they changed the position informations in their minds. The positions of the nectar resources represent the variables of the problem. After completing the maximum cycle, nectar amounts are calculated for the resources, knowing their positions. The calculated nectar amount represents the result of the problems' object function value. Since the sample problem is a minimization problem, the calculated value represents the best minimum value. The change in the amount of nectar according to the cycles is given in Table 3. As seen in Table 3, the result belonging to the 10th cycle is the best result and is calculated with the values of the first bee.

The employed bees transfer nectar amount of the sources to the onlooker bees, which they visited before. The neighbouring nectars of the current positions are selected based on Equation 14 by the onlooker bees. The employed bees have gone to the limit parameter piece of neighbor and have looked to their nectar amounts to find better nectar around the determined source. If the new nectar amount is more than the nectar amount of the first source, then they forget the nectar amount of the first source and accept the new source as the center for the other cycle, and if a better solution is not found, one of the employed bees becomes scout and looks for the new source.

MULTI OBJECTIVE REACTIVE POWER OPTIMIZATION WITH ABC

The multiobjective RPO is realized on 10 bus IEEE test system with ABC. There are 5 generator bus and 5 load bus. The voltage of the generator and reactive power sources connected to the load buses represents the variables of the problem. The IEEE 10 bus test system is seen in Figure 2, while the information belonging to this system is given in Tables 4 and 5. The compensator cost values and reference voltages of the system's load bus are given in Table 6.

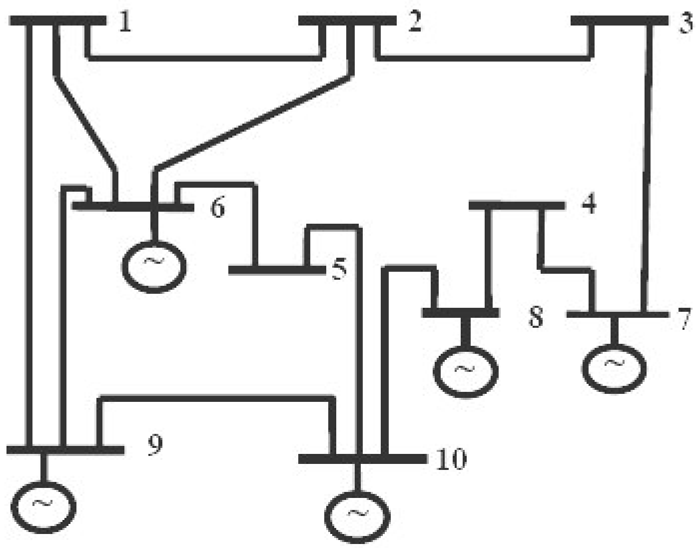

Figure 2. IEEE 10 bus test system.

Table 4. IEEE 10 test system line data.

Line number	Connection	Impedance
1	1-2	0.02+j0.08
2	1-6	0.06+j0.24
3	1-9	0.04+j0.16
4	2-3	0.06+j0.24
5	2-6	0.06+j0.24
6	3-7	0.06+j0.24
7	4-7	0.04+j0.16
8	4-8	0.06+j0.24
9	5-6	0.04+j0.16
10	5-10	0.06+j0.24
11	6-9	0.01+j0.04
12	8-10	0.04+j0.16
13	9-10	0.08+j0.32

Table 5. IEEE 10 test system bus data.

Bus	Type	Active power(pu)	Reactive power (pu)	Voltage (pu)
1	P-Q	0.20	0.097	-
2	P-Q	0.30	0.145	-
3	P-Q	0.20	0.097	-
4	P-Q	0.30	0.145	-
5	P-Q	0.20	0.097	-
6	P-V	0.30	0.145	1.00
7	P-V	0.15	0.0726	1.00
8	P-V	0.20	0.097	1.00
9	P-V	0.20	0.097	1.00
10	Oscilation	0.20	0.097	1.05

Table 6. Equipment, reactive power production cost and voltage reference values.

Bus	$e_i C_{ci}$($)	C_{ci}($/MVAr)	V_i^{ref} (pu)
1	1771.59	5314.8	1
2	1771.59	5314.8	1
3	1771.59	5314.8	1
4	1771.59	5314.8	1
5	1771.59	5314.8	1

Table 7. RPO results with ABC algorithm.

Active power loss (P_{loss})	123.66 MW
Voltage deviation (V_{dev})	0.00278 (pu)
Reactive power cost (I_c)	8918.44 ($)

Number of bus	V_i(pu)	Q_i(pu)
1	0.9164	0.1456
2	0.9709	0.0983
3	0.9006	0.0489
4	0.9635	0.1672
5	0.9058	0.1080

Table 8. The ABC and SPEA2 results.

	ABC	$SPEA2_1$	$SPEA2_2$	$SPEA2_3$
P_{loss} MW	123.66	129.6	124.7	125.9
V_{dev}(pu)	0.00278	0.00324	0.000578	0.0000326
I_c($)	8918.44	9093.9	13435	13013

RESULTS

The system is solved for the minimization of objective functions given in Equations 1, 2 and 3. When the solution steps stated in the ABC algorithm are applied, the results obtained are given in Table 7.

In this study, RPO with ABC algorithm is applied in a power system. During this application, the reactive power optimization is applied in a manner that has rare application in the literature. Not only is there active power loss minimization, the reactive power cost and the quality of voltage transferred to the customers are also optimized. Aribia and Abdallah (2007) study was used in improving the strength pareto evolutionary algorithm (SPEA2). They used three different minimizations in their study. The ABC algorithm results are compared with these results in Table 8. As seen in Table 8, active power loss and cost function results taken from ABC are more optimal. At the minimization of the voltage deviations, the more optimum result is taken as the cost function. With these values, the active power loss can be reduced and the compensators can be run at a minimum cost.

REFERENCES

Abbasy A, Tabatabal I, Hosseini SH (2007). Optimal Reactive Power Dispatch in Electricity Markets Using A Multiagent-Based Differential Evolution Algorithm, *POWERENG 2007*, Setubal, Portugal.

Abido MA, Bakhashwain JM (2005). Optimal VAR dispatch using a multiobjective evolutionary algorithm. Elect. Power Energy Syst., 27: 13-20.

Akay B, Karaboga D (2009). Solving Integer Programming Problems by Using Artificial Bee Colony Algorithm, XI. Conferences on Advances in Artificial Intelligence by the Italian Association for Artificial Intelligence (AI*IA 2009), Reggio Emilia.

Arabia HB, Abdallah HH (2007). Multi Objectives Reactive Dispatch Optimization of an Electrical Network. Leonardo J. Sci., 10: 101-114.

Bao L, Zeng J (2009). Comparison and Analysis of the selection Mechanism in the Articial Bee Colony Algorithm, Ninth International Conference on Hybrid Intelligent Systems.

Chettih S, Khiat M, Chaker A (2008). Optimal distribution of the reactive power and voltages control in Algerian network using the genetic algorithm method. Inf. Technol., J. 7: 1170-1175.

Chuanwena J, Bompardb E (2005). A hybrid method of chaotic particle swarm optimization and linear interior for reactive power optimization. Math. Comput. Simulation, 68: 57-65.

Deep N Shahidehpour SM (1990). Linear reactive power optimization in a large power network using the decomposition approach. IEEE Trans. Power Syst., 5: 2.

Deng Y, Ren X, Zhao C, Zhao D (2002). Heuristic and Algorithmic Combined Approach for Reactive Power Optimization With Time-Varying Load Demand in Distribution Systems, IEEE Trans. Power Syst., 17: 4. Distrib., 145(1): 89-97.

Durairaj S, Kannan S (2005). Improved Genetic Algorithm Approach for Multi-Objective contingency constrained Reactive Power Planning, IEEE Indicon 2005 Conference, Chennai, India.

Grudinin N (1998). Reactive Power Optimization Using Successive Quadratic Programming Method. IEEE Trans. Power Syst., 13: 4.

Jikeng L, Xudong W, Weihong Z (2008). Reactive Power Optimization Based on Adaptive Immune Algorithm, Proceedings of the International MultiConference of Engineers and Computer Scientists II IMECS, Hong Kong.

Jwo WS, Liu CW, Liu CC, Hsiao YT (1995). Hybrid expert system and simulated annealing approach to optimal reactive power planning. IEE Proc.-Gen. Transm. Distrib., 142: 4.

Kang F, LI J, ve XU Q (2009). Structural inverseanalysis by hybrid simplex artificial bee colony algorithms. Comput. Struc., 87: 861-870.

Karaboga D, Bastürk B (2007). A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm. J. Global Optim., 39(3): 459-471.

Karaboga D, Bastürk B (2007). Artificial bee colony (ABC) optimization algorithm for solving constrained optimization problems, Foundations of Fuzzy Logic and Soft Computing 4529: 789-798, Springer-Verlag, Berlin.

Karaboga D, Bastürk B (2008). On the performance of artificial bee colony (ABC) algorithm, Appl. Soft Comput., 8(1): 687-697.

Karaboğa N (2009). A new design method based on artificial bee colony algorithm for digital IIR filters. J. Franklin Inst., 346: 328-348.

Khiat M, Chaker A, Exposito A, Ramo JL (2003). Reactive power optimization and voltage control in the Western Algerian transmission

system: a hybrid approach, Elect. Power Syst. Res., 64: 3-10.
Kumar SK, Tiwari MK, Babiceanu RF (2009). Minimisation of supply chain cost with embedded risk using computational intelligence approaches, Int. J. Prod. Res., pp. 1-23.
Lenin K, Mohan MR (2006). Ant Colony Search Algorithm for Optimal Reactive Power Optimization. Serbian J. Elect. Eng., 3(1): 77-88.
Li D, Gao L, Zhang J, Li Y (2006). Power System Reactive Power Optimization Based onAdaptive Particle Swarm Optimization Algorithm, Proceedings of the 6th World Congress on Intelligent Control and Automatio*n*, Dalian, China.
Li Y, Cao Y, Liu Z, Liu Y, Jiang Q (2009). Dynamic optimal reactive power dispatch based on parallel particle swarm optimization algorithm. Comput. Math. Appl., 57: 1835-1842.
Lin W, Li Y, Xu X, Li M (2008). Reactive Power Optimization in Area Power Grid Based on Improved Tabu Search Algorithm, *DRPT2008* Nanjing, China.
Lin X, David AK, Yu CW (2003). Reactive power optimisation with voltage stability consideration in power market systems, IEE Proc.- Gen. Transm. Distrib. 150: 3.
Lirui G, Limin H, Liguo Z, Weina L, Jie H (2008). Reactive Power Optimization for Distribution Systems Based on Dual Population Ant Colony Optimization, Proceedings of the 27th Chinese Control Conference, Kunming,Yunnan, China.
Liu M, Ma L, Zhang J (2000). GA/SA/TS Hybrid Algorithms for Reactive Power Optimization. Power Eng. Soc. Summer Meeting, IEEE, 1: 245-249.
Lu Z, Ma L (2008). Power System Reactive Power Optimization Based on Direct Neural Dynamic Programming, Proceedings of 2008 3rd International Conference on Intelligent System and Knowledge Engineering.
Mantawy AH, Al-Ghamdi MS (2003). A New Reactive Power Optimization Algorithm, Paper accepted for presentation at 2003 IEEE Bologna PowerTech Conference Bologna, Italy.
Omkar SN, Senthılnath J (2009). Artificial Bee Colony for Classification of Acoustic Emission Signal. Int. J. Aerospace Innov., 1(3): 129-143(15)
Pawar PJ, Rao RV, Davim JP (2008). Optimization of process parameters of milling process using Particle Swarm Optimization and Artificial Bee Colony algorithm, Advances in Mechanical Engineering (AME), Surat, India.
Putman RE, Huff FC, Pal JK (1999). Optimal Reactive Power Control for Industrial Power Networks. Ind. Appl., IEEE Trans., 35(3): 506-514.
Quan H, Shi X (2008). On the Analysis of Performance of the Improved Artificial Bee Colony Algorithm, Fourth International conference on Natural Computation. ICNC.
Sıngh A (2009). An artificial bee colony algotihm for the leaf-constrained minumum spanning tree problem. Appl. Soft Comput., 9: 625-631.
Varadarajan M, Swarup KS (2008). Differential evolutionary algorithm for optimal reactive power dispatch. Elect. Power Energy Syst., 30: 435-441.
Venkata RR, Pawar PJ (2010). Parameter optimization of a multi-pass milling process using non-traditional optimization algorithms. Appl. Soft Comput. J., 10(2): 445-456.
Wang C, Cheng HZ, Yao LZ (2008). Reactive Power Optimization by Plant Growth Simulation Algorithm, DRPT2008 Nanjing, China.
Wei H, Chunli X, Jianhua Z, Shannag H (2003). Study of Reactive Power Optimization Based on Immune Genetic Algorithm. Transm. Distrib. Conf. Exposition, 1: 186 – 190.
Wei H, Cong Z, Jingyan Y, Jianhua Z, Zifa L, Zhilian W, Dongli P (2008). Using Bacterial Chemotaxis Method for Reactive Power Optimization, Transmission and Distribution Conference and Exposition.
Xıangzheng X (2007). Research on Reactive Power Optimizing Control Based on Immune Algorithms, The Eighth International Conference on Electronic Measurement and Instruments.
Yoshida H, Fukuyama Y (1999). A Particle Swarm Optimization for Reactive Power and Voltage Control in Electric Power Systems Considering Voltage Security Assessment, The 1999 IEEE Systems, Man, and Cybernetics Conference (SMC'99) Tokyo International Forum, Tokyo, Japan.
Zhang X, Chen W, Dai C (2008). Application of Oriented Search Algorithm in Reactive Power Optimization of Power System, DRPT2008 Nanjing, China.
Zhang X, Chen W, Dai C, Guo A (2008). Self-adaptive Differential Evolution Algorithm for Reactive Power Optimization, Fourth International Conference on Natural Computation.
Zhu JZ, Chang CS, Yan W, Xu GY (1998). Reactive power optimisation using an analytic hierarchical process and a nonlinear optimisation neural network approach, IEE Proc., Gener. Transm.