Ant Colony Based Optimization Technique for Voltage Stability Control

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Abstract: - This paper presents Ant Colony Optimization (ACO) technique for optimal reactive power dispatch (ORPD) in order to improve voltage stability condition along with transmission loss and voltage profile monitoring. ACO is a new cooperative agent's approach, which is inspired by the observation of the behaviours of real ant colonies on the topics of ant trial formation and foraging method. The set of cooperating agents called "ant" cooperate to find the optimal point of reactive power dispatch. Comparative studies presented with respect to Evolutionary Programming (EP) and Artificial Immune System (AIS) had indicated the merit of the proposed technique. Tests were conducted on the IEEE Reliability Test System producing promising results as compared to EP and AIS. The capability of developed ACO in solving continuous optimization problems rather that only limited to graphical optimization problems has been revealed as the added value in the algorithm.

Key-Words: - Optimal Reactive Power Dispatch, Ant Colony Optimization, Evolutionary Programming, Artificial Immune System.

1 Introduction

The voltage instability has been found to be responsible for several major network collapses in many countries. This situation is normally due to the stressed condition as a result of the increase in reactive power load. The control strategies aim to avoid some of the symptoms that lead to voltage collapse such as heavily loaded situation, weakened by transmission outages, or subjected to reactive power shortages. It is associated to reactive power deficiencies, and it may result in uncontrollable system-wide voltage collapse, loss of loads and blackout [1].

The operating system loads need a significant amount of reactive power that has to be supplied and to maintain load bus voltages within their acceptable operating limits. Scheduling of reactive power in an optimum manner reduces circulating reactive power promoting better voltage profile which leads to appreciable real power saving on account of reduced system losses [2]. Past studies have reported several techniques for reducing voltage collapse occurrences. Among the possible techniques are optimal reactive power planning, installation of FACTS devices, capacitor placement, transformer tap setting and management of reactive power reserve.

The purpose of an optimal reactive power dispatch (ORPD) is mainly to improve the voltage profile in the power system and to minimize transmission losses. This can be achieved by using a number of control tools such as switching VAR sources, changing generator voltages and adjusting transformer settings [3]. The problem of reactive power dispatch was considered as a special case of optimal power flow (OPF) in which the control variables are those that present close relationship with reactive power flow. An alternative approach for the determination of ORPD is based on the used of optimization techniques. Several optimization techniques have been applied to the reactive power dispatch problem such as artificial neural network [3], genetic algorithm [4-5], evolutionary programming [6], artificial immune system [7] and particle swarm optimization [2].

ACO is multi-agent system in which the behaviour of each single agent, called artificial ant or ant is inspired by the behaviour of real ants [8]. ACO has been successfully employed to combinatorial optimization problems in power system such as unit commitment [9], optimal placement of capacitors in distribution systems [10], economic generator scheduling and load dispatch [11] and multi-state electrical power systems problems [12]. The feature of technique presentation is different from other method since it can be implemented easily; flexible for many different problem formulations and finally its capability in avoiding the occurrences of local optima for a given problem [13].

This paper presents ACO based optimization technique for voltage stability improvement in a power transmission system. Along with this, voltage profile, loss reduction, computation time and iteration numbers are the added criteria monitored in this study. Validation on the IEEE 30-bus Reliability Test System (RTS) indicated that ACO has outperformed the EP and AIS in all criteria, while its capability in solving continuous optimization problems rather than only graphical mode in nature has been revealed as added value in this study.

2 Ant Colony Optimization (ACO)

ACO algorithm is inspired by the behaviour of real ant colonies used to solve combinatorial optimization problem. The real ants lay down in some quantity an aromatic substance, known as pheromone, in their way to food source. The pheromone quantity depends on the length of the path and the quality of the discovered food source [14]. An ant chooses an exact path in connection with the intensity of the pheromone. The pheromone trail evaporates over time if no more pheromone is laid down. Other ants are attracted to follow the pheromone trail. Therefore, the path will be marked again and it will attract more ants to use the same path. The pheromone trail on paths leading to rich food sources closet to the nest will be more frequented and will therefore grow faster. In this way, the best solution has more intensive pheromone and higher probability to be chosen [14]. The described behaviour of real ant colonies can be used to solve combinatorial optimization problems in which artificial ants search the solution space by transiting from nodes to nodes. The artificial ants movement usually associated with their previous action that stored in the memory with a specific data structure [13]. The pheromone consistencies of all paths are updated only after the ant finished its tour from the first node to the last node. Every artificial ant has a constant amount of pheromone stored in it when the ant proceeds from the first node. The pheromone that has been stored will be evenly distributed on the path after artificial ants finished its tour. The amount of pheromone will be high if artificial ants finished its tour with a good path and vice versa. The pheromone of the routes progressively decreases by evaporation in order to avoid artificial ants stuck in local optima solution [13].

ACO algorithm has been used to solve combinatorial optimization problem involving initialization, state transition rule, fitness evaluation, local updating rule and global updating rule.

3 Optimal Reactive Power Dispatch

Conventionally, the purpose of optimal reactive power dispatch (ORPD) is to improve voltage stability condition and to minimize loss, which can be implemented separately. In this study, voltage stability improvement has been chosen as the objective function which utilized a voltage stability index as the fitness in the problem formulation.

3.1 Problem Formulation

Stress load condition will lead to voltage decay along with increase of transmission loss. This phenomenon can be alleviated by performing reactive power planning which involves optimization problems. In this study, the optimal reactive power dispatch was chosen as the reactive power planning technique in the attempt of alleviating voltage stability condition. A line-based voltage stability index termed as Fast Voltage Stability Index (*FVSI*) developed by I. Musirin and T. K. A. Rahman [15] based on the quadratic equation of voltage at the receiving end of a 2 bus system was adopted as the fitness function. Numerous line indices were computed at all lines in the system considering a particular loading condition. The mathematical equation for *FVSI* - 15] is given as follows:-

$$FVSI_{ij} = \frac{4Z_{ij}^{2}Q_{j}}{V_{i}^{2}X_{ij}} \tag{1}$$

where:

Z_{ij} = line impedance
X_{ij} = line reactance
V_i = voltage at the sending end
Q_j = reactive power at the receiving end

FVSI ranges from 0 at no load to 1.0 at stress condition which already experiencing instability condition.

3.2 Algorithm for ORPD using ACO

The general algorithm ACO has been described in Fig. 1, while this section translates the ACO operators for the implementation of ORPD. The process involves initialization, state transition rule, local updating rule, fitness evaluation and global updating rule.

Step 1: Initialization; during the initialization process n, m, t_{max}, d_{max}, β, ρ, α and q_0 are specified.

where:

n : no. of nodes
m : no. of ants
t_{max} : maximum iteration
d_{max} : maximum distance for every ants tour
β : parameter, which determines the relative importance of pheromone

versus distance ($\beta > 0$)

ρ : heuristically defined coefficient ($0 < \rho < 1$)

α : pheromone decay parameter ($0 < \alpha < 1$)

q_0 : parameter of the algorithm ($0 \leq q_0 \leq 1$)

τ_o : initial pheromone level

Every parameter requires to be set for limiting the search range in order to avoid large computation time.

d_{max} can be calculated using the following formula:

$$d_{\max} = \max\left[\sum_{i=1}^{n-1} d_i\right] \quad (2)$$

$$d_i = r - \max(u) \quad (3)$$

where:

r current node

u unvisited node

Step 2: Generate first node randomly; the first node will be selected by generating a random number according to a uniform distribution, ranging from 1 to n.

Step 3: Apply state transition rule; in this step the ant located at node r (current node) will choose the nodes s (next node) based on the following rule.

$$s = \begin{cases} \arg\max_{u\varepsilon J_{k(r)}} \{ [\tau(r,u)].[\eta(r,u)^{\beta}] \}, if\ q \leq q_0 \text{ (exp}loitation) \\ S,\ otherwise (biased \text{ exp}loration) \end{cases} \quad (4)$$

where:

q = random number uniformly distributed in [0…1]

S = random variable selected according to the probability distribution given in eq. (5)

The probability for an ant k at node r to choose the next node s, is calculated using the following equation.

$$P_k(r,s) = \begin{cases} \dfrac{[\tau(r,s)].[\eta(r,s)^{\beta}]}{\sum_{u\varepsilon J_{k(r)}} [\tau(r,u)].[\eta(r,u)^{\beta}]}, & if\ s\varepsilon J_{k(r)} \\ 0, & otherwise \end{cases} \quad (5)$$

τ : pheromone

$J_{k(r)}$: set of nodes that remain to be visited by ant k positioned on node (to make the solution feasible)

η : $1/\delta$, is the inverse of the distance $\delta(r,s)$.

Step 4: Apply local updating rule; while constructing a solution of reactive power dispatch search, ants visit edges and change their pheromone level by applying the local updating rule of eq. (6).

$$\tau(r,s) \longleftarrow (1-\rho)\,\tau(r,s) + \rho.\Delta\,\tau(r,s) \quad (6)$$

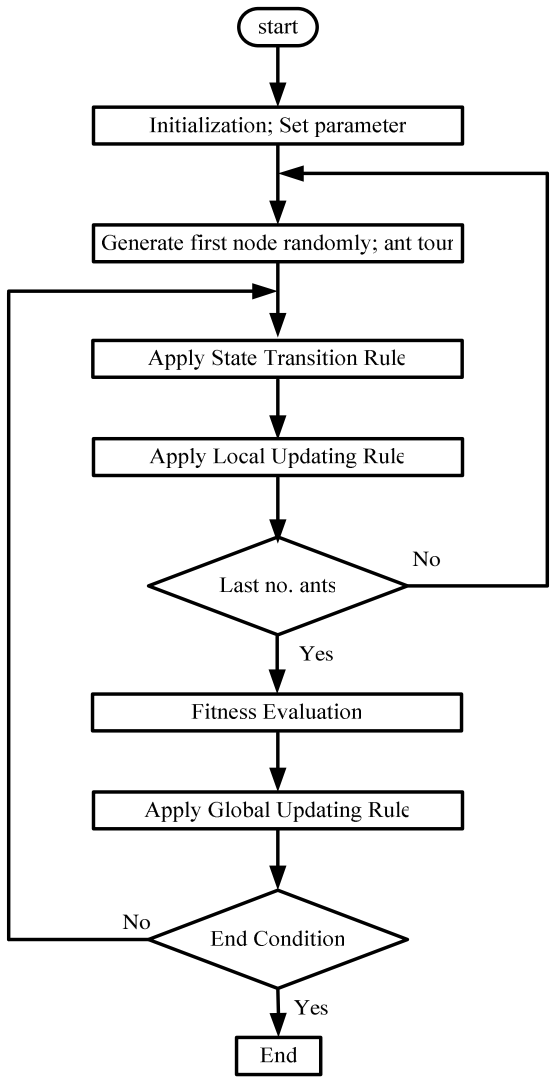

Fig. 1: Flow chart for Ant Colony Optimization

where: $\Delta\,\tau(r,s) = \tau_o$

Step 5: Fitness evaluation; it is performed after all ants have completed their tours. In this step, the control variable is computed using the following equation:-

$$x = \frac{d}{d_{\max}} \times x_{\max} \quad (7)$$

where:

d : distance for every ants tour

$x_{\max}$: maximum x

The values of x will be assigned for the reactive power at the generator buses. The fitness is computed by performing ac load flow program. This program is called repeatedly into the ACO main program for the whole process.

Step 6: Apply global updating rule; to simplify the problem, this step is applied to edges belonging to the best ant tour which give the best fitness among all ants. The pheromone level is updated by applying the global updating rule in eq. (8).

$$\tau(r,s) \longleftarrow (1-\alpha)\, \tau(r,s) + \alpha . \Delta\, \tau(r,s) \qquad (8)$$

where:

$$\Delta(r,s) = \begin{cases} (L_{gb})^{-1},\ if\ (r,s)\ \varepsilon\ global-best\ tour \\ 0,\ otherwise \end{cases} \qquad (9)$$

α is the pheromone decay parameter ($0 < \alpha < 1$)

L_{gb} is the length of the globally best tour from the beginning of the trial.

Step 7: End condition; the algorithms stop the iteration when a maximum number of iterations have been performed otherwise, repeat step 2. Every tour that was visited by ants should be evaluated. If a better path is discovered in the process, it will be kept for next reference. The best path selected between all iterations engages the optimal scheduling solution to the reactive power dispatch problem. The overall steps of the ACO algorithm can be represented in the flow chart of Fig. 1.

4 Results and discussion

The Ant Colony Optimization (ACO) engine was written in MATLAB used to perform optimal reactive power dispatch. IEEE 30-bus system was used as the test specimen, which has 6 generator buses and 25 load buses with 41 interconnected lines. The results of this study were consequently compared with other techniques such as EP and AIS. The comparison is made in terms of voltage stability improvement, total loss reduction, voltage profile and computation time.

4.1 Results of ORPD Performed Using Ant Colony Optimization

Table 1 tabulates the results for ORPD performed to the system considering voltage stability improvement as the objective function. In this study bus 29 was taken as the test bus considering several loading conditions. The impact of ORPD via ACO was investigated in terms of voltage profile, transmission loss and voltage stability improvement which was indicated by reduction in *FVSI* value.

From the table, the values of *FVSI* at maximum loading (Q_{d29} = 38 MVAr) at bus 29 identified by ACO technique is reduced from 0.9942 to 0.6716. It also reduced the total loss in the system from 32.74 MW to 10.28 MW and at the same time voltage profile is improved from 0.5313 p.u. to 0.7775 p.u.. The amount of reactive power that should be injected to generators 2, 5, 8, 11 and 13 are 14.10 MVAr, 20.51 MVAr, 44.62 MVAr, 9.23 MVAr and 16.62 MVAr as indicated in Table 1. The result for other loading conditions can be observed in the same table. Apparently at all loading conditions ACO has successfully improved the voltage stability condition indicated by reduction of *FVSI* values in post-RPD.

4.2 Results of ORPD Performed Using Evolutionary Programming

Table 2 tabulates the results for ORPD performed on the similar bus using Evolutionary EP. From the table it is observed that at Q_{d29} = 38 MVAr, *FVSI* value is reduced from 0.9942 to 0.7428. At the same time voltage profile is improved from 0.5313 p.u. to 0.7170 p.u., while

Table 1: Results for ORPD using ACO when bus 29

Loading Conditions (MVAr)	Analysis	*FVSI*	Total loss (MW)	Iter. no.	Comp Time (sec)	Q_{g2} MVAr	Q_{g5} MVAr	Q_{g8} MVAr	Q_{g11} MVAr	Q_{g13} MVAr	V_m (p.u.)
Q_{d29} = 10	pre-RPD	0.2111	18.12								0.9436
	post-RPD	0.1636	4.81	3	11.51	14.10	19.49	26.15	6.15	5.54	1.0318
Q_{d29} = 35	pre-RPD	0.7613	25.56								0.6733
	post-RPD	0.5899	9.03	3	9.03	19.23	21.54	38.46	10.46	15.38	0.8214
Q_{d29} = 38	pre-RPD	0.9942	32.78								0.5313
	post-RPD	0.6716	10.28	3	10.10	14.10	20.51	44.62	9.23	16.62	0.7775

Table 2: Results for ORPD using EP with bus 29 loaded

Loading Conditions (MVAr)	Analysis	*FVSI*	Total loss (MW)	Iter. no.	Comp Time (sec)	Q_{g2} MVAr	Q_{g5} MVAr	Q_{g8} MVAr	Q_{g11} MVAr	Q_{g13} MVAr	V_m (p.u.)
Q_{d29} = 10	pre-RPD	0.2111	18.12								0.9436
	post-RPD	0.1598	4.79	5	22.01	29.84	37.27	50.90	13.11	3.11	1.0321
Q_{d29} = 35	pre-RPD	0.7613	25.56								0.6733
	post-RPD	0.6343	9.34	5	26.14	34.26	27.49	56.14	9.82	12.94	0.7790
Q_{d29} = 38	pre-RPD	0.9942	32.78								0.5313
	post-RPD	0.7428	11.31	5	87.41	34.26	27.49	56.14	9.82	12.94	0.7170

the loss has been reduced from 32.78 MW to 11.31 MW. The amount of reactive power that should be injected to generators 2, 5, 8, 11 and 13 are 34.26 MVAr, 27.49 MVAr, 56.14 MVAr, 9.82 MVAr and 12.94 MVAr as indicated in Table 2. The results for other loading condition are indicated in the same table.

4.3 Results of ORPD Performed Using Artificial Immune System

Table 3 tabulates the results for ORPD performed using Artificial Immune System (AIS). From the table it is observed that at Q_{d29} = 38 MVAr, *FVSI* value is reduced from 0.9942 to 0.7433. At the same time voltage profile is improved from 0.5313 p.u. to 0.7165 p.u., while the loss has been reduced from 32.78 MW to 11.32 MW. The amount of reactive power that should be injected to generators 2, 5, 8, 11 and 13 are 34.18 MVAr, 27.45 MVAr, 56.08 MVAr, 9.79 MVAr and 12.91 MVAr as indicated in Table 3. The results for other loading condition are indicated in the same table.

4.4 Comparative Studies of ORPD Using ACO, EP and AIS

Results from Tables 1, 2 and 3 for Q_{d29} = 38 MVAr are extracted and retabulated in Table 4. From Table 4, it is observed that ACO outperformed EP and AIS in all criteria in terms of voltage stability improvement, loss minimization, voltage profile improvement and fast computation time. This reveals the superiority of ACO with respect to others.

Table 4: Results of Comparative Studies for ORPD

Criteria	pre-RPD	post-RPD		
		ACO	EP	AIS
FVSI	0.9942	0.6716	0.7428	0.7433
Total loss (MW)	32.78	10.28	11.31	11.32
Voltage (p.u.)	0.5313	0.7775	0.7170	0.7165
Comp. Time (sec)		10.10	87.41	525.02

The profiles for *FVSI*, bus voltage and loss in voltage stability improvement using ACO, EP and AIS are shown in Figure 2, 3 and 4. In Fig. 2, it is observed that ACO is better than EP and AIS since the *FVSI* profile is lower indicating better voltage stability improvement.

On the other hand, in Fig. 3 the bus voltage is higher with the implementation of ACO as compared to EP and AIS. This reveals the strength of ACO in improving voltage profile. Fig. 4 illustrates the loss profile with ORPD implemented using ACO, EP and AIS. From the figure, ACO managed to reduce the largest transmission loss as compared to EP and AIS. This has revealed the merit of ACO as compared to EP and AIS optimization techniques.

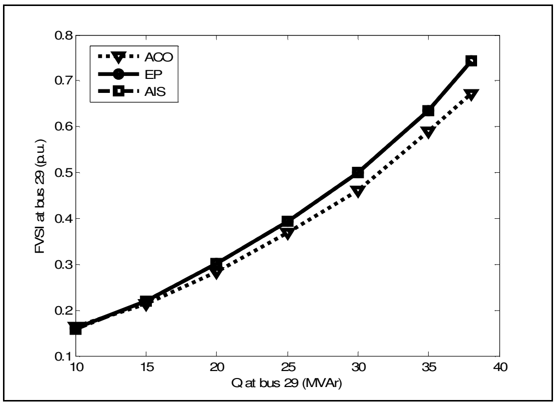

Fig. 2: FVSI profiles computed with load varies at bus 29

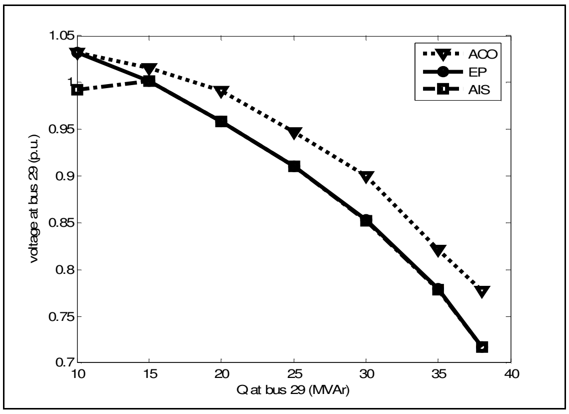

Fig. 3: Voltage profiles monitored with load varies at bus 29

5 Conclusion

Application of ACO in ORPD for voltage stability control was presented. Results from the study indicated that optimal reactive power dispatch using ACO has outperformed EP and AIS in terms of voltage profile, loss reduction,

Table 3: Results for ORPD using AIS with bus 29 loaded

Loading Conditions (MVAr)	Analysis	*FVSI*	Total loss (MW)	Iter. no.	Comp Time (sec)	Q_{g2} MVAr	Q_{g5} MVAr	Q_{g8} MVAr	Q_{g11} MVAr	Q_{g13} MVAr	V_m (p.u.)
Q_{d29} = 10	pre-RPD	0.2111	18.12								0.9436
	post-RPD	0.1587	4.67	3	321.29	25.56	28.61	26.22	7.98	5.35	0.9917
Q_{d29} = 35	pre-RPD	0.7613	25.56								0.6733
	post-RPD	0.6346	9.35	3	503.26	34.18	27.45	56.08	9.79	12.91	0.7787
Q_{d29} = 38	pre-RPD	0.9942	32.78								0.5313
	post-RPD	0.7433	11.32	3	525.02	34.18	27.45	56.08	9.79	12.91	0.7165

computation time and voltage stability improvement. The merit of ACO over EP and AIS can be highlighted in terms of its accuracy and least computation time. The original philosophy of using ACO in solving the discrete or graphical optimization problems has been enhanced into solving continuous problem as highlighted in this study. This study has also discovered that ACO technique is useful for solving more complex power system optimization problems.

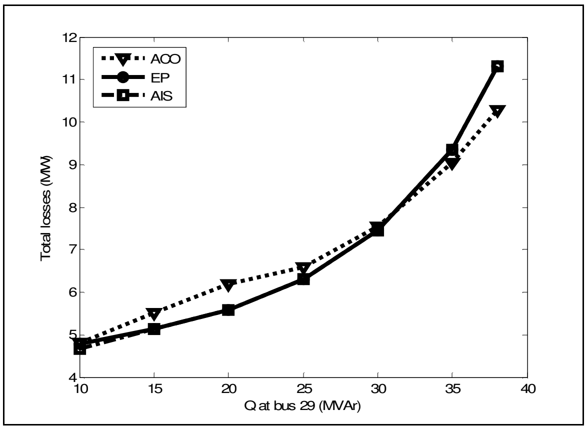

Fig. 4: Total loss profiles monitored with load varies at bus 29

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