The Study of Ant Colony Optimization (ACO) Parameters for STATCOM Optimization

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Abstract-**Continuous demand in power transmission network caused by reactive power has been highlighted as the main factor in voltage depreciation and also increase of total transmission loss. Past studies have reported several possible techniques such as optimal reactive power dispatch, optimal capacitor placement; transformer tap setting and static VAR compensator are solutions for reducing voltage collapse occurrences. This paper presents Ant Colony Optimization (ACO) technique to improve voltage stability condition along with transmission loss and voltage profile monitoring using STATCOM. The purpose is to search for a solution for the best parameters of ACO that will improve the voltages and also to reduce the power losses in an electric power system. The proposed technique was tested using the standard IEEE 30-bus system and the capability of developed ACO in solving continuous optimization problems has been revealed as the added value in the algorithm.**

Keywords- Ant Colony Optimization; ACO parameters; Voltage Magnitude; Power Losses.

I. INTRODUCTION

Voltage stability is the ability of a power system to maintain suitable voltages level at all buses in the system when subjected to disturbance. Voltage instability is due to the deficiency of the voltage stability and results in progressive voltage decrease or increase. A power system is encountered a state of voltage instability when a disturbances causes a progressive and uncontrollable decline in voltage. In power system, transmission losses become a major aspect to be considered when it is needed to transmit electric energy over long distances or in the case of relatively low load density over a infinite area. The active power losses may amount to *20* to *30% of* total generation in some situations [1]. Losses in power systems can occur from the following mechanism; line and cable losses, transformer losses and machine losses. Thus, losses increase the operating cost of running a power system and determine how to operate various generating plants. In addition to that, thermal losses reduce the overall lifetime of the electrical equipments [1].

For voltage control, magnitude of the bus voltage is specified at a voltage controlled bus and it is observed that reactive power controls the bus voltage magnitudes. 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 [2]. 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 [3]. A power system controller must ensure that the power demand is satisfied and the voltage at each load bus is between a specified limit. The low voltages in the system would lead to system collapse. It is a fact that the voltage collapse occurs when the system load (P and/or Q) increases beyond a certain limit. Thus, controlling reactive power, Q, will result in maintaining a bus voltage magnitude, V, at specified level [1]. There are several methods of controlling reactive power on a bus and STATCOM [4] is one of them.

To determine the optimal values, optimization process will be required. Among the popular related optimization techniques are Genetic algorithms (GA), Simulated annealing (SA), Tabu search (TS)[5], Artificial immune system (AIS) and Particle swarm optimization (PSO) [6].

Ant Colony Optimization (ACO) technique is newly invented optimization technique to solve graphical optimization problem. It has been developed for combinatorial optimization problems [7]. ACO are multi-agent system in which the behavior of each single agent, called artificial ant or ant for short in the following, is inspired by the behavior of real ants [8]. ACO has been successfully employed to combinatorial optimization problems such as maximum loadability in voltage control study, loss minimization in distribution networks, unit commitment problem, multiobjective reactive power compensation, and complex multi-stage decision problem [9]. The feature of the presenting technique different from other method is that it can be implemented easily; flexible for many different problems' formulation and the most of all, it can escape the local of the given problem [10],[11],[12]. ACO has been widely used in many applications in solving power system optimization problems.

This paper presents the application of ACO technique to optimize the ACO parameters value in voltage control study. In this study, ACO engine was developed to implement the STATCOM optimization considering voltage magnitude and loss as the objective function. In realizing the effectiveness of the proposed technique, an IEEE Reliability Test System was used as the test specimen.

II. STATCOM OVERVIEW

A static compensator, simply known as STATCOM is essentially a voltage-sourced converter, as shown in Fig. 1. A current-source inverter can also be substituted. If the line voltage V is in phase with the converter output voltage V_0 and has the same magnitude so that $V\angle 0^0 = V_0\angle 0^0$, there can be no current flowing into or out of the compensator and no exchange of reactive power with the line [13]. If the converter voltage is now increased, the voltage difference between V and V_0 appears across the leakage reactance of the step-down transformer [13]. As a result, a leading current with respect to V is drawn and compensator behaves as a capacitor, generating VARs [13]. On the other hand, if $V > V_0$, then the compensator draws a lagging current, behaving as an inductor, and absorbs VARs. This compensator operates basically like a synchronous compensator where the excitation may be greater or less than the terminal voltage. This operation allows continuous control of reactive power, but a far higher speed, especially with a forced-commutated converter using GTOs, MCTs, or IGBTs. The main features of a STATCOM are:

1. Wide operating range providing full capacitive reactance even at a low voltage.
2. Lower rating than its conventional equivalent with SVC to achieve the same stability.
3. Increased transient rating and advanced capability to handle dynamic system disturbances.

If a dc storage device such as a superconducting coil arrangement replaces the capacitor, it would be possible to exchange both active and reactive power with the system. Under conditions of low demand, the superconducting coil can supply power, which can be released into the system under contingency conditions [13].

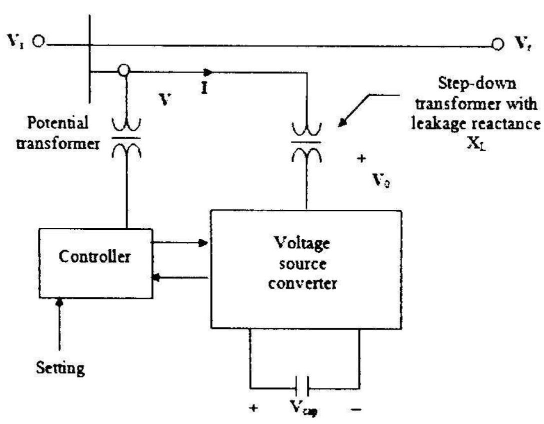

Fig. 1. General arrangement of STATCOM

III. FUNDAMENTAL IDEA OF ANT COLONY OPTIMIZATION

The original idea comes from observing the exploitation of food resources among ants, in which ants' individually limited cognitive abilities have collectively been able to find the shortest path between a food source and the nest [6]. In a series of experiments on a colony of ants with a choice between two unequal length paths leading to a source of food, biologists have observed that ants tended to use the shortest route [illegible]. A model explaining this behavior is as follows:

1. An ant (called "blitz") runs more or less at random around the colony;
2. If it discovers a food source, it returns more or less directly to the nest, leaving in its path a trail of pheromone;
3. These pheromones are attractive, nearby ants will be inclined to follow, more or less directly, the track;
4. Returning to the colony, these ants will strengthen the route;
5. If two routes are possible to reach the same food source, the shorter one will be, in the same time, traveled by more ants than the long route will
6. The short route will be increasingly enhanced, and therefore become more attractive;
7. The long route will eventually disappear, pheromones are volatile;
8. Eventually, all the ants have determined and therefore "chosen" the shortest route.

IV. THE ACO ALGORITHM

The general algorithm ACO has been described in Fig. 2, while this section translates the ACO operators for the implementation of STATCOM. The process involves initialization, state transition rule, local updating rule, fitness evaluation and global updating rule [3].

Step 1: Initialization

During the initialization process n, m, $tmax$, $dmax$, β, ρ, α, *and* q_0 are specified [3].

where:

n	: no. of nodes
m	: no. of ants
$tmax$	: maximum iteration
$dmax$	: 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 ($0 \le q_0 \le 1$)
τ_0	: initial pheromone level.

Every parameter requires to be set for limiting the search range in order to avoid large computation time [3].

dmax can be calculated using the following formula [3]:

$$dmax = \max\left[\sum_{i=1}^{n-1} di\right] \quad (1)$$

$$di = r - \max(u) \quad (2)$$

where:

r : current node

u : unvisited node

Step 2: Generate first node

The first node will be selected by generating a random number according to a uniform distribution, ranging from 1 to *n* [3].

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 [3].

$$s = \begin{cases} \arg\max_{u\varepsilon J_{k(r)}}\{[\tau(r,u)][\eta(r,u)^{\beta}]\}, if\ q \le q_0 (exploitation) \\ S, otherwise\ (biased\ exploration) \end{cases} \quad (3)$$

where:

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

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

S : random variable selected according to the probability distribution given in eq. (4)

The probability for an ant *k* at node *r* to choose the next node *s*, is calculated using the following equation [3].

$$P_k(r,s) = \begin{cases} \frac{[\tau(r,s)].[\eta(r,s)^{\beta}]}{\sum_{u\varepsilon J_{k(r)}}[\tau(r,s)].[\eta(r,s)^{\beta}]}, if\ s\varepsilon J_{k(r)} \\ 0, otherwise \end{cases} \quad (4)$$

where:

τ : pheromone

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

β : parameter, which determines the relative importance of pheromone versus distance ($\beta > 0$)

η : 1/δ, is the inverse of the distance δ(r,s)

In equation (3) and (4) the pheromone on path $\tau(r,s)$ is multiplied by the heuristic value $\eta(r,s)$ in order to determine the selection of paths which are shorter and have a greater amount of pheromones [1]. The parameter q_0 determines the relative importance of the exploitation versus exploration condition: an ant at node *r* (current node) has to choose a node *s* (next node) to travel. This is determined by the value of *q* randomly where ($0 < q < 1$) [1]. If ($q < q_0$) the best path will be determined based on equation (3), (i.e. in the exploitation mode). Conversely, if ($q \ge q_0$) the best path will be determined based on equation (4), (i.e. in the exploration mode) [1]. The process to determine the next node (*s*) starts by calculating the probability of choosing the next node using equation (4) [1]. After the calculation of probability, the value of *q* is then generated randomly [1]. If ($q < q_0$), node 4 was selected as next node (*s*) which has the highest probability (i.e. in the exploitation mode) [1]. On the other hand, if ($q \ge q_0$), the next node (*s*) will be selected randomly from the list of unvisited nodes (i.e. in the exploration mode) [1]

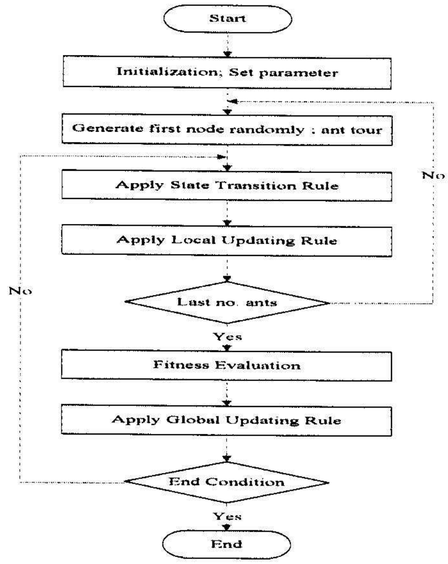

Fig. 2. Flow chart for Ant Colony Optimization

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 the equation below [3]:

$$\tau(r,s) \leftarrow (1-\rho)\,\tau(r,s) + \rho.\Delta\tau(r,s) \quad (5)$$

where:

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

$\Delta\tau(r,s) = \tau_0$

τ_0 : initial pheromone level.

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 [3]:-

$$x = \frac{d}{d_{max}} x\, x_{max} \quad (6)$$

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. This program is called repeatedly into the ACO main program for the whole process [3].

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 following equation [3]:

$$\tau(r,s) \leftarrow (1-\alpha)\,\tau(r,s) + \alpha.\Delta\tau(r,s) \qquad (7)$$

where:

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

α : the pheromone decay parameter (0 < α < 1)

L_{gb} : 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 or else, repeat step 2. Every tour that was visited by ants should be evaluated [3]. If a better path is discovered in the process, it will be kept for next location. The best path selected between all iterations engages the optimal scheduling solution to the reactive power dispatch problem [3].

V. RESULTS AND DISCUSSION

The main objectives of this project are to improve the voltage profile and hence minimize the power losses of the system when it was loaded with selected parameters of ACO and high loading conditions. As consequences of these conditions, the voltage profile will reduce and cause the system to be unstable. It will also increase the total losses of the system and may cause the possible system collapse.

In the beginning, the ACO parameters have to be specified during initialization process [1]. In order to get better result in the development of the ACO's program, every parameter must be selected carefully [1]. On other hand, every parameter requires to be set for limiting the search range in order to avoid large computation time [1]. Determination of the weakest bus in the system is required by evaluating the load flow program using the Newton Raphson for the base case or evaluates the Fast Voltage Stability Index (*FVSI*) [3] value for every line in the system (where *FVSI* value that close to *0.9* is indicates as the weakest bus in the system). The experiments have been conducted at bus-26; i.e bus-26 is the weakest bus for IEEE 30-bus RTS system.

TABLE I. RESULTS BEFORE (USING INITIAL PARAMETERS VALUE OF ACO) BY STATCOM IMPLEMENTATION AT (a) β=1, (b) β=2 AND (c) β=3

Load Qd (MVar)	α	ρ	q_0	Voltage magnitude (p.u)	Losses (MW)
30	0.1	0.1	0.1	0.9742	17.8823
60	0.1	0.1	0.1	0.9761	17.8262
90	0.1	0.1	0.1	0.8798	24.6446

(a)

Load Qd (MVar)	α	ρ	q_0	Voltage magnitude (p.u)	Losses (MW)
30	0.1	0.1	0.1	0.9719	17.9547
60	0.1	0.1	0.1	0.9771	17.8012
90	0.1	0.1	0.1	0.8813	23.4998

(b)

Load Qd (MVar)	α	ρ	q_0	Voltage magnitude (p.u)	Losses (MW)
30	0.1	0.1	0.1	0.9719	17.9547
60	0.1	0.1	0.1	0.9503	18.6512
90	0.1	0.1	0.1	0.8901	24.8448

(c)

The results of the simulation when bus-26 was loaded are presented in TABLE I, TABLE II and TABLE III. TABLE II shows the results for *β=1*, *β=2* and *β=3* using initial value of ACO parameters with respect to load variation. The results for voltage and total losses of TABLE II can be obtained by setting the initial value of ACO parameters that are using *α=0.1*, *ρ=0.1* and *q_0=0.1*. From that table it can be observed that the voltage magnitude is unstable with different *β* with respect to variation loading. It also noted that the higher the loading condition, the lower the transmission loss should be [4]. But what was happened is vice versa whereby increasing the load, the losses are also increased.

TABLE II. RESULTS AFTER (USING SELECTED ACO PARAMETERS) BY STATCOM IMPLEMENTATION AT (a) β=1, (b) β=2 AND (c) β=3

Load Qd (MVar)	α	ρ	q_0	Voltage magnitude (p.u)	Losses (MW)
30	0.4	0.4	0.5	0.9746	17.8686
60	0.9	0.5	0.1	0.9836	17.6635
90	0.6	0.9	0.1	0.9657	16.7567

(a)

Load Qd (MVar)	α	ρ	q_0	Voltage magnitude (p.u)	Losses (MW)
30	0.7	0.9	0.4	0.9824	17.7049
60	0.1	0.3	0.3	0.9844	17.6506
90	0.5	0.7	0.7	0.986	16.5772

(b)

Load Qd (MVar)	α	ρ	q_0	Voltage magnitude (p.u)	Losses (MW)
30	0.6	0.5	0.9	0.9893	17.5938
60	0.1	0.3	0.3	0.9936	17.573
90	0.4	0.8	0.5	0.9978	17.6115

(c)

The reduction in losses and increment of voltage magnitude at each loading condition at bus-26 are shown in

TABLE II after implementing the selected ACO parameters. It should be clear that with variation of loading, different settings of ACO parameters may result in much better performance of voltage magnitude and loss reduction.

TABLE III. RESULTS FOR BUS-26 IS LOADED WITH 90MVAR BEFORE AND AFTER IMPLEMENTATION OF ACO PARAMETERS (a) VOLTAGE MAGNITUDE AND (b) TOTAL LOSSES

Load Qd (MVar)	β	α	ρ	q_0	Voltage magnitude (p.u)		%
					Before	*After*	
90	1	0.6	0.9	0.1	0.8798	0.9657	9.760
	2	0.5	0.7	0.7	0.8813	0.9860	11.88
	3	0.4	0.8	0.5	0.8901	0.9978	12.10

(a)

Load Qd (MVar)	β	α	ρ	q_0	Losses (MW)		%
					Before	*After*	
90	1	0.6	0.9	0.1	24.6446	16.7567	32.00661
	2	0.5	0.7	0.7	23.4998	16.5772	29.45812
	3	0.4	0.8	0.5	24.8448	17.6115	29.11394

(b)

On the other hand, the voltage increase and reduction in losses before and after implementation of ACO parameters for bus-26 is loaded with Q_d=90MVar are tabulated in TABLE III (a) and TABLE III (b) respectively. In TABLE III (a), it is observed that the implementation of ACO parameters has increased the voltage profile in the system as value of β is increased. For instance, at $\beta=3$, Q_d = 90 MVar, the voltage is increased *12.10 %* that is from *0.8901 p.u* to *0.9978 p.u*. Loss value at each loading condition was also monitored. It is also observed that from TABLE III (b) at $\beta=3$, Q_d = 90 MVar, the percentage reduced of loss is *29.11394%*. When the reduced of losses are concern, $\beta=1$ has highest percentage loss that is *32.00661%*. It can be observed that the percentage reduction of losses are increased as the β is increased. Fortunately, $\beta=2$ performed more stability condition in term of voltage and reduce of losses and it tend to be applied in this ACO algorithm.

This is may be not the only combinations that can be calculated to obtain the improvement of the voltage and reduce the total losses but the combination of ACO parameters range may be vary each time it is executed because it depends on the best tour by ants during simulation. If the better tour is discovered, it will give better results for voltage and total losses [1]. In general, it can be found that, for a fixed number of ants which in this case used 5 ants, the algorithm tended to converge to the shortest path more often when α (pheromone decay parameter) was close to *1*. For example, at $\beta=1$, *Qd* = *90 MVar*, $\alpha=0.6$ is instinctively clear that large value of α tend to amplify the influence of initial random fluctuations. Means that, the majority of ants are initially selected the long path, and then the search of the whole colony is quickly biased toward it. This happens to lower extend when the value of α is close to *1*.

In the other hand, the pheromone evaporation rate ρ can be critical since it influenced on the convergence behavior of ACO. In particular, it can be observed $\rho=0.9$ from the result of $\beta=1$, that ACO often converged to suboptimal paths when evaporation was set to a value that was too high. The ACO tend to converge to the longer path rather than the shortest path. Furthermore, with the probability $q_0 = 0.1$, the ant makes the best possible move as indicate by the learned pheromone trails and the heuristic information in this case, the ant is exploiting the learned knowledge. Tuning the parameter q_0 allows modulation of the degree of exploration and the choice of whether to concentrate the search of the system around the best-so-far solution (the ants exploit the visited path) or to explore other tours.

Besides that, role in the balance of exploration and exploitation are important is that of the parameters α and β, which determine the relative influence of pheromone trail and heuristic information. Consider first the influence of parameter α. For $\alpha>0$, the larger the value of α, the stronger the exploitation of the search experience; for $\alpha=0$ the pheromone trails are not taken into account at all; and for $\alpha<0$ the most probable choices taken by the ants are those that are less attractive of pheromone trails. Hence varying α could be used to shift from exploration to exploitation and vice versa [8]. The parameter β determines the influence of the heuristic information in a similar way [8]. In fact, systematic variations of α and β could, similarly to what is done in the strategic oscillation approach [5], be part of a simple and useful strategy to balance exploration and exploitation [8].

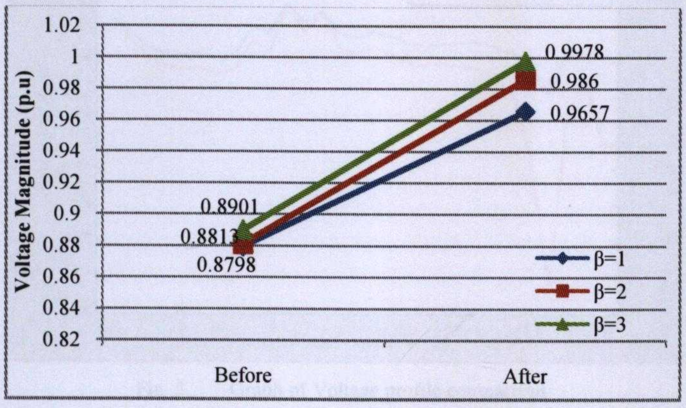

Fig. 3. Graph Voltage Magnitude (p.u) before and after ACO parameters implementation

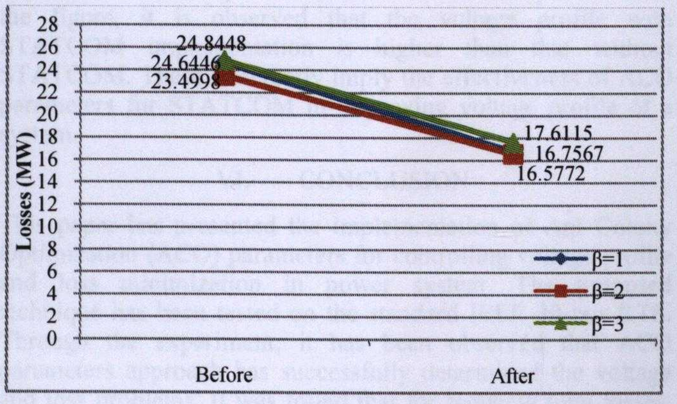

Fig. 4. Graph Losses (MW) before and after ACO parameters implementation

Fig. 3 illustrates the voltage magnitude before and after ACO parameters implementation with respect to β. From the figure, it is observed that the voltage magnitude with the selected ACO parameters implementation is higher than that before ACO implementation (using initial parameters value). These coherently imply the effectiveness of ACO parameters in improving voltage profile of a system. Meanwhile, Fig. 4 illustrates the total losses before and after ACO parameters implementation with respect to β. For total losses, it is observed that ACO technique can be implemented more effectively at $\beta=2$ and at high loading condition as shown in the figure. Different load bus will have different maximum loadability since it depends on the capacity of the load. For example from TABLE III (a) and (b), the maximum loading condition for bus-26 is *90 MVar*.

TABLE IV. RESULTS FOR THE EFFECT OF NUMBERS OF ANTS AND NODES TO (a) VOLTAGE MAGNITUDE (b) TOTAL LOSSES AND (c) COMPUTATION TIME

Nodes	Voltage Magnitude (p.u)				
	Ants				
	1	*4*	*5*	*10*	*15*
10	0.9917	0.9851	0.974	0.9731	0.9719
15	0.9247	0.9208	0.8961	0.9095	0.9354
20	0.9053	0.9452	0.9482	0.9513	0.9387

(a)

Nodes	Losses (MW)				
	Ants				
	1	*4*	*5*	*10*	*15*
10	17.579	17.641	17.886	17.915	17.954
15	20.436	20.779	22.784	21.347	19.583
20	21.776	18.939	18.764	18.605	19.347

(b)

Nodes	Computation time (sec)				
	Ants				
	1	*4*	*5*	*10*	*15*
10	2.526	3.323	3.917	6.822	9.722
15	4.978	7.048	7.484	15.18	25.406
20	9.647	60.99	56.21	104.2	151.9

(c)

TABLE IV tabulates the effect of number of ants and nodes to (a) voltage magnitude, (b) losses and (c) computation time for $\beta=2$, $Q_d=90MVar$,, $\alpha= 0.5$, $\rho=0.7$, $q_0=0.7$. For instance, TABLE IV tabulates the results for 1 ant, *4* ants, *5* ants, *10* ants and *15* ants. These processes were conducted for *10*, *15* and *20* nodes. Apparently at *10* nodes, the number of ants did really influence the results; the losses and computation times were increased with increased number of ants, however, the voltage magnitude is decreased as numbers of ants increased. Meanwhile, in TABLE IV (c) it is observed that the increasing number of ants and nodes did increased the computation time.

From TABLE IV (a) and IV (b) the highest voltage magnitude, $V_m = 0.9917\ p.u$ and the lowest loss reduction 17.579 *MW* are came from single ant with *10* nodes. But, in this case, although a single ant is capable of generating the solution, efficiency considerations suggest that the use of a colony of ants is often a desirable choice [8]. This is particularly true for geographically distributed problem, because the differential path length effect exploited by ants in the solution of these class problems can only arise in the existence of a colony of ants. On the other hand, in case of combinatorial optimization problems, the differential length effect is not exploited and the use of *m* ants, $m>1$, that build *r* solutions each (i.e, the ACO algorithm is run for *r* iterations) could be equivalent to the use of one ant that generates *m.r* solutions. Nevertheless, experimental evidence [8] suggests that, in the great majority of situations, ACO algorithms perform better when the number *m* of ants is set to a value $m>1$. For these case studied the experimental result of voltage magnitude and loss reduction has been revealed by *5* ants and *10* nodes. In general, the best value for *m* is a function of the particular ACO algorithm chosen as well as of the class of problems being attacked, and most of the times it must be set experimentally. Fortunately, ACO algorithm seems to be rather robust with respect to the actual number of ants used.

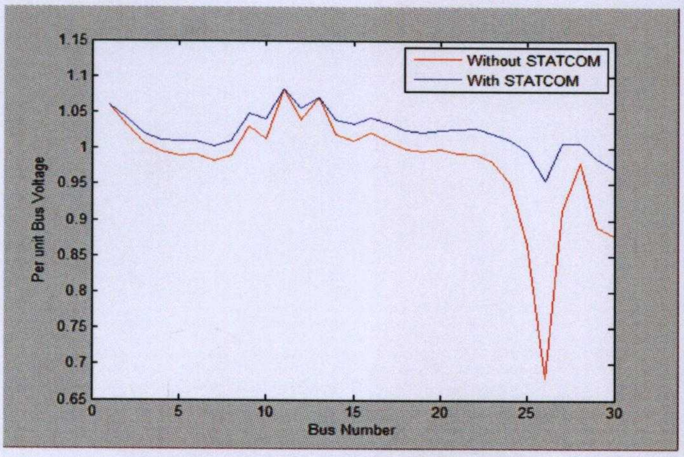

Fig. 5. Graph of Voltage profile comparison

Fig. 5 illustrates the voltage profile with and without STATCOM with respect to bus number of the system. From the figure, it is observed that the voltage profile with STATCOM implementation is higher than that without STATCOM. These coherently imply the effectiveness of ACO parameters for STATCOM in improving voltage profile of a system.

VI. CONCLUSION

This paper has presented the implementation of Ant Colony Optimization (ACO) parameters for controlling voltage profile and loss minimization in power system. The proposed technique has been tested on the standard IEEE 30-bus RTS. Through the experiment, it has been observed that ACO parameters approach has successfully determined the voltage and loss problems. It was found that for reducing total losses, ACO technique can be implemented more effectively at high loading condition. The effect of number of ants for various numbers of nodes in performing the optimization problems was also investigated that can be concluded as the larger the number of ants, the better convergence behavior of the algorithm, although it comes with longer computation times. Furthermore, the ACO parameters must be selected carefully since its capability towards the performance of the system. It can be concluded that $\beta=2$ (parameter, which determines the relative importance of pheromone versus distance) is selected based on its potential on voltage stabilization and reduction of loss and it has been applied in past studied involving ACO technique [4], [3], [1]. On the other hand, small number of ants and less number of nodes (in this studied used 5 ants and 10 nodes) which characterises the flow of ACO indicates that ACO is able to reduce computation burden in an optimization process. The implementation of STATCOM in solving the voltage profile and losses problems is the added value in ACO algorithm. The capability of the proposed technique in solving nongraphical optimization problem unlike the traditional ACO which solved graphical optimization problems has indicated new development in the ACO studies. Minor modification of the developed ACO algorithm or engine in this study could be the next step for solving more complex power system optimization problems.The dynamic ant colony algorithm is prompted and a series of simulating experiment shows that the method proposed in this paper is one of the effective algorithms for the purpose of the continuous function optimization.

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