Leonardo Electronic Journal of Practices and Technologies
ISSN 1583-1078
Issue 16, January-June 2010
p. 75-88

Optimal Placement and Sizing of Capacitor Banks Using Fuzzy-Ant Approach in Electrical Distribution Systems

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Abstract

Among optimizations of reactive power are minimization of total active power losses and control of voltage in the real-time. This can be achieved by placing the optimal value of capacitor at proper locations in electrical distribution systems. The proposed methodology is an intelligent fuzzy-ant approach of critical buses detection for optimal placement and sizing of capacitor banks in electrical distribution systems the critical nodal is determiner using fuzzy controller and the sizing of capacitor banks is obtained based on ant colony system. Calls up to the ant colony system which are use for complexes combinatorial problem minimizes the cost function. Voltage constraints are considered. The proposed fuzzy-ant approach is has been evaluated on a 25 and 30 buses.

Keywords

Critical Nodal Detection; Capacitor Placement and Sizing; Fuzzy-Ant Approach; Ant Colony System; Power Flow.

Introduction

Power distribution from electric power plants to ultimate consumers is accomplished via the transmission sub transmission, and distribution lines. Studies have indicated that as much as 13% of total power generated is consumed as RI^2 losses at the distribution level. The RI^2 losses can be separated to active and reactive component of branch current, where the losses produced by reactive current can be reduced by the installation of shunt capacitors. Capacitors are widely used in distribution systems to reduce energy and peak demand losses, release the KVA capacities of distribution apparatus and to maintain a voltage profile within permissible limits. The objective of optimal capacitor placement problem is to determine the size, type, and location of capacitor banks to be installed on radial distribution feeders to achieve positive economic response. The economic benefits obtained from the loss reduction weighted against capacitors costs while keeping the operational and power quality constraints within required limits.

Fuzzy logic provides a remedy for any lack of uncertainty in the data. Furthermore fuzzy logic has the advantage of including heuristics and representing engineering judgments into the capacitor allocation optimization process.

The ACS is a meta-heuristic motivated by the behaviour observed in colonies of real ants for finding the shortest path from a food source to their nest. Ants can find the shortest path because they deposit pheromones on paths they visit and they follow paths with higher pheromone trails. In [2], the ACS was proposed to solve the travelling salesman problem (TSP) by generating successively shorter feasible tours using information accumulated in the form of a pheromone trail deposited on the edges of the TSP graph.

Many of the previous strategies for capacitor allocation in the literature are also limited for the application to planning, expansion or operation of distribution systems. Very few of these capacitor allocation techniques have the flexibility of being applicable to more than one of the above problems. Hence, this paper presents a fuzzy-ant approach to determine suitable locations for capacitor placement and the sizing of the capacitor. This approach has the versatility of being applied to the planning, expansion, and operation studies of distribution systems. The proposed method was tested on electrical distribution systems consisting of 25 buses distribution system.

Mathematical Formulation

The Principe of method is presented in Fig.1.

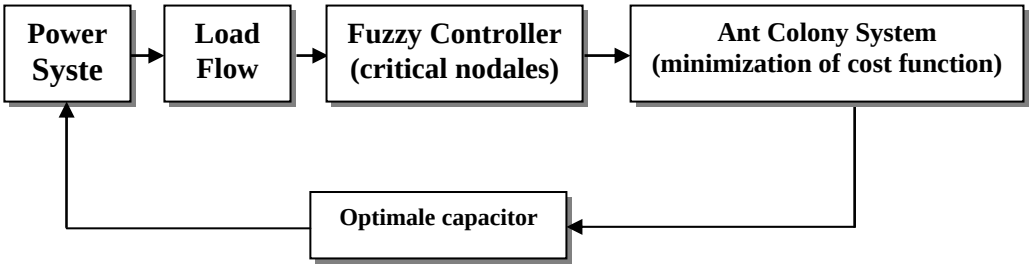

Figure 1. *Bloc of intelligent fuzzy-ant approach*

The objective function of placements to reduce the power loss and keep bus voltage within prescribed limits with minimum cost .The constraint are voltage limits .Following the above notation, the total annual cost function due to capacitor placement and power loss is written as [10]:

$$\textit{Minimize} \qquad \left\{ F = K_{PL} P_L + \sum_{j=1}^{N} K_{Cj} B_J \right\} \tag{1}$$

Constraint of voltage:

$$V_i^{min} \le V_i \le V_i^{max} \quad i = 2, 3, \ldots N \tag{2}$$

where: F = Total annual cost function [$], K_{PL} = Annual cost per unit of power losses [$/kW], P_L = Total active power loss [kW], K_{Cj} = Capacitor annual cost [cost/KVar], B_j = Shunt capacitor size placed at bus j [kVar], N = Number of buses, V_{min} = Minimum permissible rms voltage, V_{max} = Maximum permissible rms voltage.

Fuzzy Logic Controller

Fuzzy logic is expressed by means of the human language. Based on fuzzy logic, a fuzzy controller converts a linguistic control strategy into an automatic control strategy, and fuzzy rules are constructed by expert experience or knowledge database.

First, set the power loss index *PLI* and the voltage *V* to be the input variables of the fuzzy logic controller. The Capacitor suitable index *CSI* is the output variable of the fuzzy logic controller. The structure of fuzzy controller is shown in Fig. 2.

The linguistic variables are defined as {**L**, **LM**, **M**, **HM**, **H**}, where **L** means low, **LM** means low medium, **M** means medium **HM** means height medium and **H** means height. The membership functions of the fuzzy logic controller are shown in Fig. 3, Fig. 4 and Fig. 5. The fuzzy rules are summarized in Table 2. The surface of fuzzy controller is shown in Fig. 6. The type of fuzzy inference engine is Mamdani. The fuzzy inference mechanism in this study follows as:

$$\mu_B(u(t)) = \max_{j=1}^{m}\left[\mu_{A_1^j}(PLI),\mu_{A_2^j}(V),\mu_{B^j}(CSI)\right] \tag{4}$$

where $\mu_{A_1^j}(PLI)$ is the membership function of *PLI*, $\mu_{A_2^j}(V)$ is the membership function of *V*, $\mu_{B^j}(CSI)$ is the membership function of *SCI*, *j* is an index of every membership function of fuzzy set, *m* is the number of rules and is the inference result. Fuzzy output *CSI* can be calculated by the centre of gravity defuzzification as:

$$u(t) = \frac{\sum_{i=1}^{m} \mu_B(u_i(t)).u_i}{\sum_{i=1}^{m} \mu_B(u_i(t))} \tag{5}$$

where i = the output rule after inferring.

Fuzzy Based Capacitor Location

Node voltages and power loss indices are the inputs to fuzzy controller to determine the suitability of a node in the capacitor placement problem. The suitability of a node is chosen from the capacitor suitability index (*CSI*) at each node. The higher values of *CSI* are chosen as best locations for capacitor placement [1, 2, 3, 4, 5].

The power loss indices are calculated as:

$$PLI(i) = (L_R - L_{MAX})/(L_{MIN} - M_{MAXN}),\ i = 2, 3, \ldots, N \tag{6}$$

where: L_R : Loss reduction, L_{MIN} : Minimum reduction, L_{MAX} : Maximum reduction, N : Number of bus.

To determine the critical busses the voltage and power loss index at each node shall be calculated and are represented in fuzzy membership function. By using these voltages and *PLI*, rules are framed and are summarized in the fuzzy decision matrix as given in Table 1.

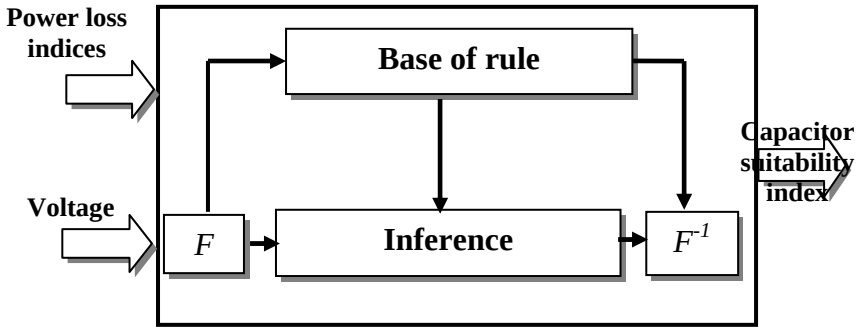

Figure 2. *Structure of Fuzzy Controller (where: F = Fuzziffication; F^{-1} = Defuzziffication)*

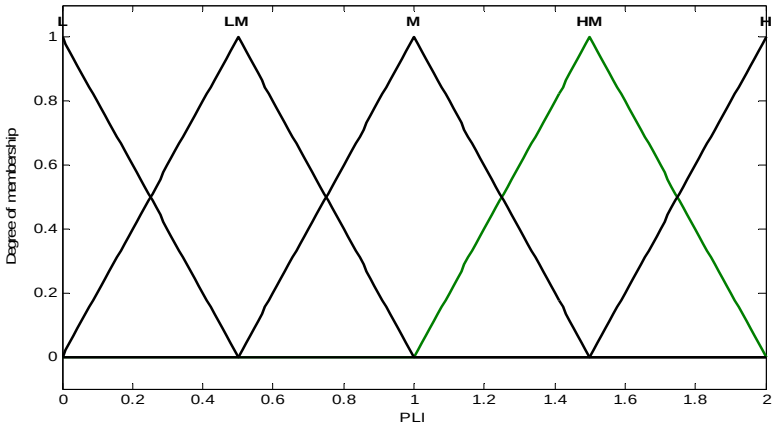

Figure 3. *Power loss indices membership*

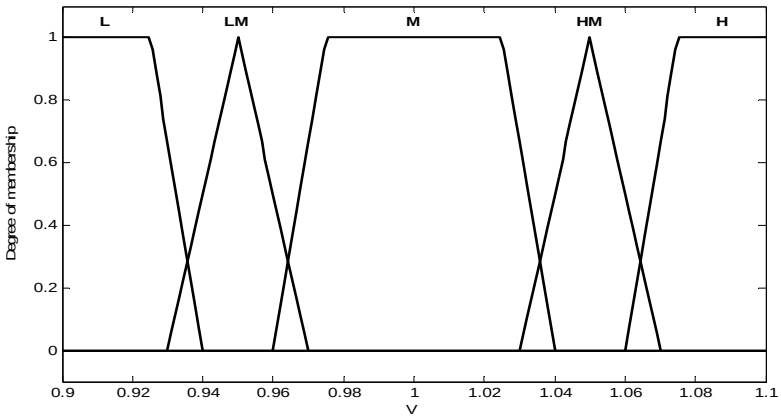

Figure 4. *Voltage membership functions*

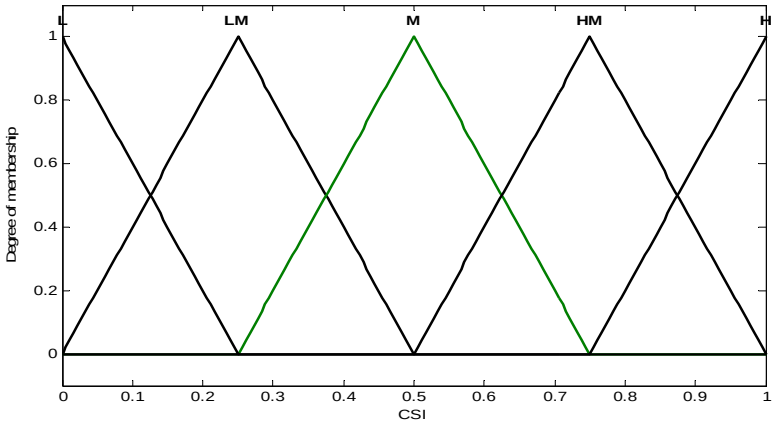

Figure 5. *Capacitor suitability index membership function*

Table 1. Decision matrix for determining suitable capacitor

CSI		*V*				
		L	**LM**	**M**	**HM**	**H**
PLI	**L**	**L**	**L**	**L**	**LM**	**LM**
	LM	**L**	**L**	**LM**	**LM**	**M**
	M	**L**	**L**	**LM**	**M**	**HM**
	HM	**L**	**LM**	**M**	**HM**	**HM**
	H	**LM**	**LM**	**M**	**HM**	**H**

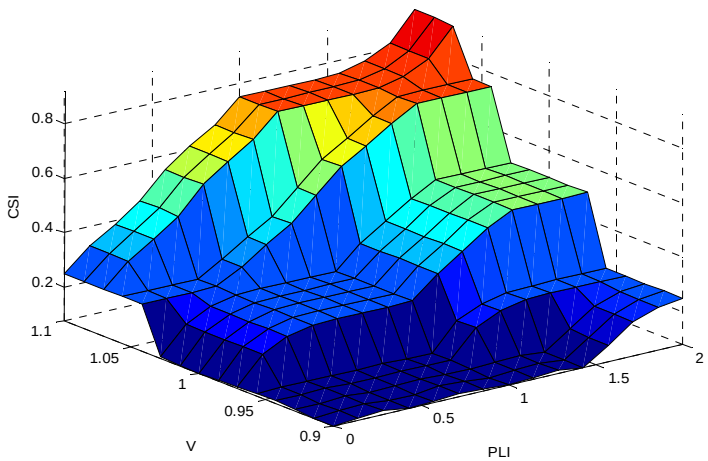

Figure 6. *View plot surface of fuzzy controller*

Algorithm for critical busses identification

Following algorithm explain the methodologies to identify critical busses, witches are more suitable for capacitor placement [6, 10].

Step1: Read line and load data of power system.

Step2: Calculate power flow Newton Raphson methods

Step3: Determine total active power loss.

Step4: By compensation the self –reactive power at each node and conduct the load flow to determinate the total active power losses in each case.

Step5: Calculate the power loss reduction and power flow loss indices.

Step6: The PLI and the per-unit voltage are the inputs to the fuzzy Controller.

Step7: The outputs of Fuzzy controller are deffuzzified. This gives the ranking of *CSI*. The nodes having the highest value of *CSI* are the most suitable for capacitor placement.

Step8: Stop.

Ant Colony System (ACS)

Overview

The ACO algorithms form a class of meta-heuristic to solve NP-hard combinatorial optimization problems. It has been introduced to solve the travelling salesman problem. The basic idea is to imitate the behavior of real ants foraging for food. In fact, the real ants can found the shortest path from a food source to their nest without visual cue. Indeed, they communicate, in a local and indirect way, through an aromatic essence called “pheromone”, deposed on the ground as they move about. Being very sensitive to this substance, an ant seeking food choose, in a randomly way, the path comprising a strong concentration of this substance. Thus, as more ants take the same path, more than ants will be attracted by this path. By analogy, in ACO algorithm, artificial ants build a solution by applying a probabilistic decision to choose a next destination. The generation of solutions is guided by pheromone trail and information related on the problem specification. Then, the ACO can be defined as an extension of traditional construction heuristics which have to adapt the pheromone quantity during the execution of the algorithm to take, into account, the experiment of research. We note that, in addition to the real ants characteristics, the artificial ants are equipped with a memory, are not completely blind, and the used time is discrete.

The Ant Colony System ACS is a particular approach of the ACO, proposed by [12-13] to solve the travelling salesman problem. In the ACS, a set of cooperation agents (ants), initially positioned at a starting point with a number of destination points, cooperate to find

routes according to some rules. In fact, each ant builds a feasible solution by applying a probabilistic function based on the pheromone trail and a heuristic function. While constructing its solution, an ant changes pheromone level of the selected edge by applying a local updating rule. Once all the ants have completed their solution, a global updating rule is performed [11-18].

Implementation of ant colony system based capacitor sizing

To apply the ant colony system (ACS) algorithm to a combinatorial optimization problem, is reside to represent the problem by a matrix $G = [n, r]$.

$$G = \begin{bmatrix} C_{11} & C_{12} & \dots & \dots & \dots & C_{1n} \\ C_{21} & C_{21} & \dots & \dots & \dots & C_{2n} \\ C_{31} & C_{31} & \dots & \dots & \dots & C_{3n} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ C_{m1} & C_{m2} & \dots & \dots & \dots & C_{nm} \end{bmatrix} \tag{4}$$

where: n = Number of capacitor size; r = Number of critical busses

An ant positioned on node *i* chooses the capacitor *j* by applying the rule given by:

$$j = \begin{cases} arg \quad max_{j \in L_{k(i)}}([\tau_{ij}]^{\alpha}[\eta_{ij}]^{\beta}) & if \quad q \le q_0 \\ J & otherwise \end{cases} \tag{5}$$

And *j* is a random variable selected according to the probability distribution given by:

$$j = \begin{cases} arg \quad P_{ij} = \dfrac{[\tau_{ij}]^{\alpha}[\eta_{ij}]^{\beta}}{\sum [\tau_{ij}]^{\alpha}[\eta_{ij}]^{\beta}} & if \quad j \in L_k(i) \\ J & otherwise \end{cases} \tag{6}$$

α and β are parameters that control the relative weight of the pheromone. $A\ C_i$ is the set of available Components or capacitors. While constructing its solution, an ant also modifies the amount of pheromone on the visited capacitor by applying the local updating rule: While building a solution of the problem, ants choose elements by visiting element on the matrix *G*, and change their pheromone level by applying the following local updating rule:

$$\tau_{ij}^{new} = (1-\rho)\tau_{ij}^{old} + \rho\tau_0 \tag{7}$$

where ρ is a coefficient such that $(1-\rho)$ represents the evaporation of trail and τ_0 represent the initial trail of pheromone. Once all ants have terminated their tour, the amount of pheromone on capacitor size is modified an Ant colony system in (by applying the global updating rule): Once all ants have built a complete system, pheromone trails are updated. Only the globally

best ant (i.e., the ant which constructed the best solution from the beginning of the trial) is allowed to deposit pheromone. A quantity of pheromone $\Delta\tau_{ij}$ is deposited on each capacitor size that the best ant has used. Therefore, the global updating rule is:

$$\tau_{ij}^{new} = (1-\rho)\tau_{ij}^{old} + \rho\Delta_{ij} \tag{8}$$

where $0 < \rho < 1$ is the pheromone decay parameter representing the evaporation of trail and $\Delta\tau_{ij}$ represent the lay of the pheromone in the Capacitor $C(i, j)$. Ants are guided, in building their tours, by both heuristic information (they prefer to choose "less expansive" element), and by pheromone information. Naturally, an element with a high amount of pheromone is a very desirable choice. The pheromone updating rules are designed so that they tend to give more pheromone to element which should be visited by ants.

Ant colony algorithm for size capacitor computing

The Ant colony system based capacitor sizing algorithm is given below:

Step1: Initializing pheromone an visibility each element of matrix *G*,

For $i = 1:n$
For $j = 1:r$
$\tau_{ij} = \tau_0$
$\eta_{ij} = 1/F$
End For
End For

Step2: In this phase each ant builds their tours. The tour of ant is stored in tabu list,

While $k \leq p$ (stopping criterion is no wet met)
For $l = i:m$
For $s = l:r$

- Choose the next element of matrix G according to formula (5) and formula (6),
- Stored in tabu list,
- For each chosen element local updating occurs and pheromone is updated using formula (7),

End For

- Evaluate the fitness for each combination according to the objective function (including penalty function). The fitness function includes the total cost investment F and the penalty functions .the penalty function used in implantation is quadratic .It act as a soft constraint .The constraint includes the bus voltage at each bus:
- Find the minimum (F_{best}) among m_1 cost functions,

End For

Step 3: In this phase global updating occurs and pheromone is updated,

- Update elements of matrix G belonging to F_{best} using formula. (8) and $\Delta\tau_{ij} = \frac{1}{F_{best}}$.

End While.

where: m = Number of ant; p = Number of maximum cycle.

Results and Discussion

The proposed method is illustrated with a system, consisting of 25 bus. The location for placement of capacitors is determined by fuzzy controller and the capacitor sizes are evaluated using ant colony system.

KPL was selected to be 168 $/kW, and voltage limits on the rms voltage were selected as V_{min} = 0.95 pu and V_{max} = 1.10 pu.

Fuzzy-Ant is applied for 25 buses electrical distribution systems the results of approach given above are shows at table 2.fu Ant colony system parameter setting are show in table 3.in Table we show that the active power losses are decrease for e 29.8913 at 23.2082 MW, decreasing 22.358% and the minimal voltage are improved to 0.9241 at 0.9639 pu.

Table 2. Results of Fuzzy-Ant approach for 25 buses

N° of critical buses	Value of capacitor [MVARS]	Active power loss [MW]		Minimal voltage [PU]	
		Before placement of optimal capacitor	After placement of optimal capacitor	Before placement of optimal capacitor	Before placement of optimal capacitor
7	9.00	29.8913	23.2082	0.9241	0.9636
8	5.00				
10	8.00				
11	5.00				
Optimal annual cost		1262226 $			

The different voltages of 25 bus electrical network given before ant colony system are illustrated in Fig. 7.

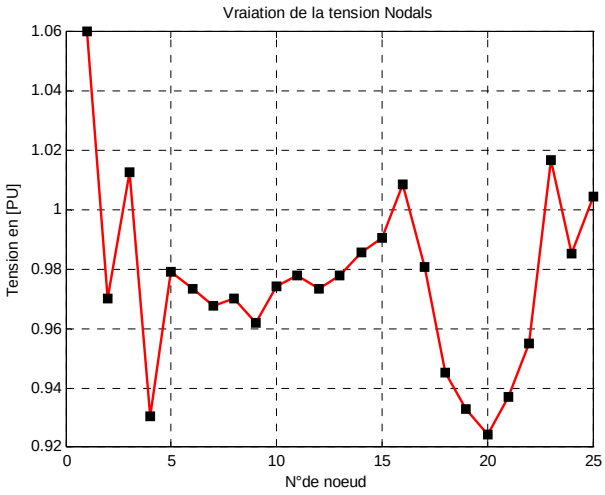

Figure 7. *Voltage before optimization*

The different voltages of 25 bus electrical network given after ant colony system are illustrated in Fig. 8. The 30 buses electrical network topology is presented in Fig. 9.

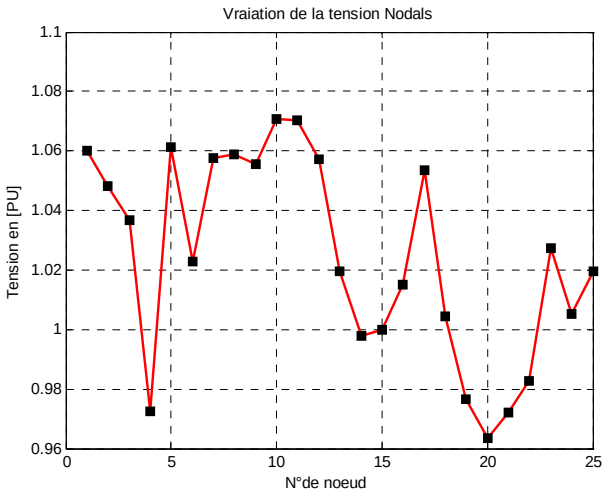

Figure 8. *Voltage before optimization*

Fuzzy-Ant is applied for 30 buses electrical distribution systems the results of approach given above are shows at table 3. Fu Ant colony system parameters setting are show in table 4. In Table we show that the active power losses are decrease for 9.457 at 6.645MW, decreasing 29.67 % and the minimal voltage are improved to 0.959at 0.968 pu.

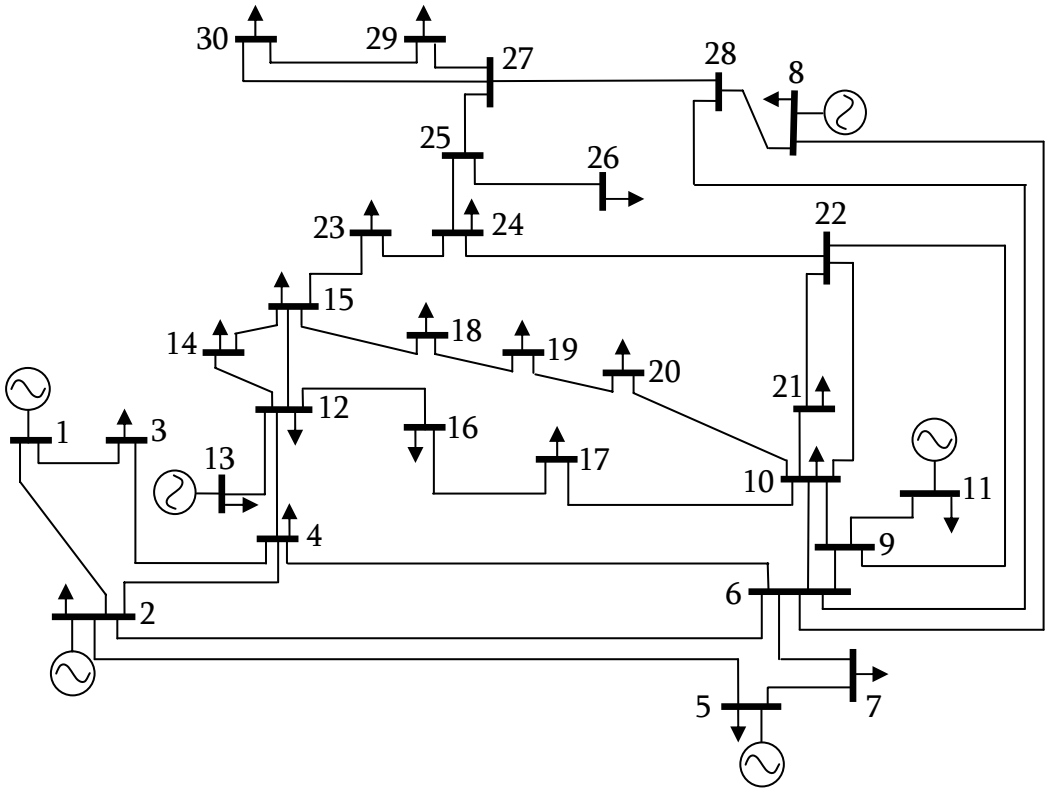

Figure 9. *The 30 buses electrical network*

Table 3. Results of Fuzzy-Ant approach for 30 buses

N° of critical buses	Value of capacitor [MVARS]	Active power loss [MW]		Minimal voltage [PU]	
		Before placement of optimal capacitor	After placement of optimal capacitor	Before placement of optimal capacitor	Before placement of optimal capacitor
7	4.00	9.457	6.645	0.959	0.968
12	2.00				
19	5.00				
26	2.00				
27	5.00				
Optimal annual cost		762226 $			

Table 4. Ant colony systems parameters

	Ant colony system parameter setting	Value
α	Alpha parameters that control the relative weight of the pheromone.	1
β	Beta parameters that control the relative weight of the pheromone.	5
τ_0	Initial pheromone trails.	0.1
ρ	Parameter of evaporation.	0.5
p	Number of maximum cycle.	100
m	Number of Ant.	10
η	Heuristic information.	$1/F$

Conclusions

This paper introduces an intelligent Fuzzy-Ant approach method to determinate a critical busses by fuzzy controller and ant colony system (ACS) for minimization a total cost investment for capacitor this combination reduce active power losses and improve the bus voltage .The main advantage of this approach is robustness of ant colony systems, over modern heuristic is flexibility, robustness of the complex combination problem, sure and fast convergence. As a study case the 25 buses system and 30 buses, the simulation results show that for medium-scale system an ant colony optimization method can give a best result.

Ant colony system parameter alpha, beta and visibility play an important role in the performance of ant colony system and some permutations and combinations of these parameters are to be tested to get the best performance.

References

1. Baran M.E., Wu F.F., *Optimal capacitor placement on radial distribution systems*, IEEE Trans. Power Delivery, 1989, 4, p.725-734.
2. Baran M.E., Wu F.F., *Optimal sizing of capacitors placed on radial distribution systems*, IEEE Trans. Power Delivery, 1989, 4, p.735-743.
3. Ponnavaiko M., Prakasa R.K.S., *Optimal choice of fixed and switched capacitors on radial distribution feeders by the method of local variations*, IEEE Trans. Power Apparatus and Systems, 1983, vol. 102, p.1607-1615.
4. Grainger J.J., Lee S.H., *Optimum size and location of shunt capacitors for reduction of losses on distribution feeders*, IEEE Trans. Power Apparatus and Systems, 1981, 100, p.1105-1118.
5. Das D., Novel *method for solving radial distribution networks*, IEE Proc. C, 1994, 141, p. 291-298.
6. Bouri S., Zeblah A., Ghoraf A., Hadjeri S., Hamdaoui H., *Ant colony optimization to shunt capacitor allocation in radial distribution systems*, Acta Electrotechnica et Informatica, 2005, 4(5), [online], Available at: http://www.aei.tuke.sk/pdf/2005-04/Bour.pdf.

7. Prasad P.V., Sivana S., Sreenivasulu N., *A fuzzy-genetic algorithm for optimal capacitor in radial distribution systems*, ARPN Journal of Engineering and Applied Sciences, 2007, 2(3), p. 28-32.
8. Parpinelli R., Lopez H.S., Freita A.A., *Data mining with ant colony optimization algorithm*, IEEE Transaction on Evolutionary Computation, 2002, 6(4), p. 321-332.
9. Semet Y., Lutton E., Collet P., *Ant Colony Optimization for e-learning Oberserving the emergence of pedagogic suggestions*. In IEEE Swarm Intelligence Symposium 2003.
10. Gabriel Estrada Soria Morelia, Mich., Febrero, *Metodología Técnico-económica de Localización de Capacitares en Sistemas de Distribución para la Reducción de Pérdidas Eléctricas*, thesis 2003.
11. Taillard E., *Ant systems*, Handbook of Applied Optimization, P. PARDALOS, M.G.C RESENDE.
12. Dorigo M., Gambardella M., *Ant Colony System: A Cooperative Learning Approach to the Travelling Salesman Problem*, IEEE Transactions on Evolutionary Computation, 1997, 1, p. 53-66.
13. Dorigo M., Gambardella L. M., *Ant colony system: a cooperative learning approach to the travelling salesman problem*, IEEE Transactions on Evolutionary Computation, 1997, 1(1), p. 53-66.
14. Dorigo M., Maniezzo V., Colorni A., *Ant system: optimization by a colony of cooperating agents*. IEEE Transactions on Systems, Man, and Cybernetics-Part B: Cybernetics, 1996, 26(1), p. 29-41.
15. Dorigo M., Gambardella L. M., Middendorf M., Stutzle T., *Guest editorial special section on ant colony optimization*. IEEE Transactions on Evolutionary Computation, 2002, 6(4), p. 317-319.
16. Gambardella L.M., Dorigo M., *Ant-Q: a reinforcement learning approach to the traveling salesman problem*, Proceedings of ML-95, Twelfth International Conference on Machine Learning, A. Prieditis and S. Russell (Eds.), Morgan Kaufmann, pp. 252-260, 1995.
17. Gambardella L.M., Dorigo M., *Solving Symmetric and Asymmetric TSPs by Ant Colonies*, Proceedings of the IEEE Conference on Evolutionary, 1996.
18. Zhang J., Hu X., Tan X., Zhong J. H., Huang Q., *Implementation of an Ant Colony Optimization technique for job shop scheduling problem*, Transactions of the Institute of Measurement and Control, 2006, 28, p. 93-108.