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CAPACITOR PLACEMENT USING FUZZY AND PARTICLE SWARM OPTIMIZATION METHOD FOR MAXIMUM ANNUAL SAVINGS

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ABSTRACT

This paper presents a fuzzy and Particle Swarm Optimization (PSO) method for the placement of capacitors on the primary feeders of the radial distribution systems to reduce the power losses and to improve the voltage profile. A two-stage methodology is used for the optimal capacitor placement problem. In the first stage, fuzzy approach is used to find the optimal capacitor locations and in the second stage, Particle Swarm Optimization method is used to find the sizes of the capacitors. The sizes of the capacitors corresponding to maximum annual savings are determined by considering the cost of the capacitors. The proposed method is tested on 15-bus, 34-bus and 69-bus test systems and the results are presented.

Keywords: capacitor placement, fuzzy, PSO, method, savings.

1. INTRODUCTION

Shunt capacitors are very commonly used on the primary feeders of a radial distribution system to reduce the power losses and to improve the voltage profile of the system. The objective of the capacitor placement problem is to determine the location and size of the capacitor so that the annual savings are maximized. Even though considerable amount of research work was done in the area of optimal capacitor placement [1]-[11], there is still a need to develop more suitable and effective methods for the optimal capacitor placement.

Although some of these methods to solve capacitor allocation problem are efficient, their efficacy relies entirely on the goodness of the data used. Fuzzy logic provides a remedy for any lack of uncertainty in the data. Fuzzy logic has the advantage of including heuristics and representing engineering judgments into the capacitor allocation optimization process. Furthermore, the solutions obtained from a fuzzy algorithm can be quickly assessed to determine their feasibility in being implemented in the distribution system.

H. Ng *et al.,* [9] proposed the capacitor placement problem by using fuzzy approximate reasoning. In the first stage, the method proposed by H. Ng *et al.,* [9] is adopted to determine the optimal capacitor locations using fuzzy logic.

The global optimization method is most useful in saving the cost. In that sense, meta-heuristic methods are very attractive for distribution system operation and planning. Particle Swarm optimization (PSO) method is one of the popular meta-heuristic methods in all the engineering fields.

In the second stage, a Particle Swarm Optimization (PSO) method is proposed to find the sizes of the capacitors. The capacitor placement problem is modeled with the objective function, which maximizes the annual savings.

The proposed method is tested on 15-bus, 34-bus, and 69-bus test systems and the results are presented.

2. TOTAL REAL POWER LOSS IN A DISTRIBUTION SYSTEM

The total I^2R loss (P_L) in a distribution system having *n* number of branches is given by:

$$P_L = \sum_{i=1}^{n} I_i^2 \, Ri \tag{1}$$

Here I_i is the magnitude of the branch current and R_i is the resistance of the i^{th} branch respectively. The branch current can be obtained from the load flow solution. The branch current has two components, active component (I_a) and reactive component (I_r). The loss associated with the active and reactive components of branch currents can be written as:

$$P_{La} = \sum_{i=1}^{n} I_{ai}^2 \, Ri \tag{2}$$

$$P_{Lr} = \sum_{i=1}^{n} I_{ri}^2 \, Ri \tag{3}$$

Note that for a given configuration of a single-source radial network, the loss P_{La} associated with the active component of branch currents cannot be minimized because all active power must be supplied by the source at the root bus. However, supplying part of the reactive power demand locally can minimize the loss P_{Lr} associated with the reactive component of branch currents. This paper presents a method that minimizes the loss due to the reactive component of the branch current by optimally placing the capacitors and thereby reduces the total loss in the distribution system.

3. IDENTIFICATION OF OPTIMAL CAPACITOR LOCATIONS USING FUZZY APPROACH

This paper presents a fuzzy approach to determine suitable locations for capacitor placement. Two objectives are considered while designing a fuzzy logic for identifying the optimal capacitor locations. The two objectives are: (i) to minimize the real power loss and (ii)

ARPN Journal of Engineering and Applied Sciences

to maintain the voltage within the permissible limits. Voltages and power loss indices of distribution system nodes are modeled by fuzzy membership functions. A fuzzy inference system (FIS) containing a set of rules is then used to determine the capacitor placement suitability of each node in the distribution system. Capacitors can be placed on the nodes with the highest suitability.

For the capacitor placement problem, approximate reasoning is employed in the following manner: when losses and voltage levels of a distribution system are studied, an experienced planning engineer can choose locations for capacitor installations, which are probably highly suitable. For example, it is intuitive that a section in a distribution system with high losses and low voltage is highly ideal for placement of capacitors. Whereas a low loss section with good voltage is not ideal for capacitor placement. A set of fuzzy rules has been used to determine suitable capacitor locations in a distribution system.

In the first step, load flow solution for the original system is required to obtain the real and reactive power losses. Again, load flow solutions are required to obtain the power loss reduction by compensating the total reactive load at every node of the distribution system. The loss reductions are then, linearly normalized into a [0, 1] range with the largest loss reduction having a value of 1 and the smallest one having a value of 0. Power Loss Index value for n^{th} node can be obtained using equation 4.

$$PLI_{(n)} = \frac{(Lossreduction_{(n)} - Lossreduction_{(\min)})}{(Lossreduction_{(\max)} - Lossreduction_{(\min)})} \tag{4}$$

These power loss reduction indices along with the p.u. nodal voltages are the inputs to the Fuzzy Inference System (FIS), which determines the node more suitable for capacitor installation. In this present work, Fuzzy Logic Toolbox in MATLAB7 is used for finding the capacitor suitability index.

3.1. Building systems with the fuzzy logic toolbox

Although it is possible to use the Fuzzy Logic Toolbox by working strictly from the command line, it is easier to build the system using graphical user interface. There are five primary GUI tools for building, editing, and observing fuzzy inference systems (FIS) in the Fuzzy Logic Toolbox: the Fuzzy Inference System or FIS Editor, the Membership Function Editor, the Rule Editor, the Rule Viewer, and the Surface Viewer.

Type **fuzzy** in the command window to invoke the basic FIS Editor

In the FIS Editor, go to **File** and select either of the following.

New Mamdani FIS: to open a new Mamdani-style system with no variables and no rules called Untitled
New Sugeno FIS: to open a new Sugeno-style system with no variables and no rules called Untitled.
New Mamdani FIS is selected for this present work.
Five pop-up menus (default) are selected to change the functionality of the following five basic steps in the fuzzy implication process:

For **And method:** min is selected

For **Or method:** max is selected

For **Implication method:** min is selected

For **Aggregation method:** max is selected

For **Defuzzification method:** Centroid method is selected.

The FIS Editor handles the high level issues for the system namely the number of input and output variables used and their names. In this paper, two input and one output variables are selected. Input variable-1 is power loss index (PLI) and Input variable-2 is the per unit nodal voltage (V). Output variable is capacitor suitability index (CSI). Power Loss Index range varies from 0 to 1, P.U. nodal voltage range varies from 0.9 to 1.1 and Capacitor suitability index range varies from 0 to 1.

The Membership Function Editor is used to define the shapes of all the membership functions associated with each variable. In this present work, five membership functions are selected for PLI. They are **L, LM, M, HM and H**. All the five membership functions are triangular as shown in Figure-1. Five membership functions are selected for Voltage. They are **L, LN, N, HN and H**. These membership functions are trapezoidal and triangular as shown in Figure-2. Five membership functions are selected for CSI. They are **L, LM, M, HM and H**. These five membership functions are also triangular as shown in Figure-3.

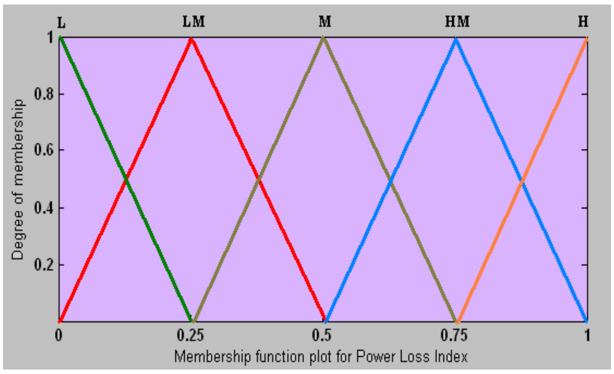

Figure-1. Membership function plot for Power Loss Index (PLI).

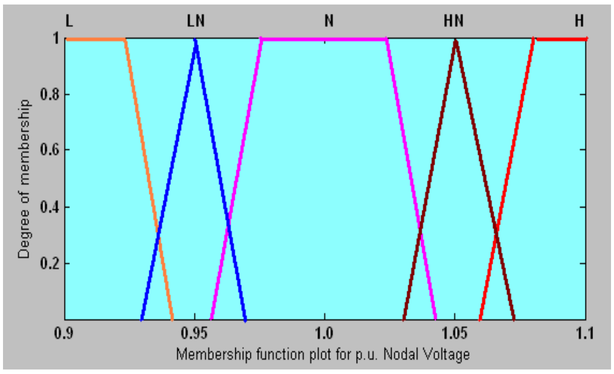

Figure-2. Membership function plot for p.u. nodal voltage.

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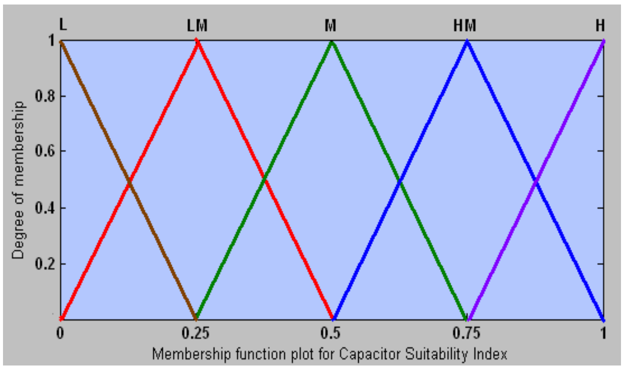

Figure-3. Membership function plot for Capacitor Suitability Index (C.S.I.)

The Rule Editor is for editing the list of rules that defines the behavior of the system. Constructing rules using the graphical Rule Editor interface is fairly self-evident. Based on the descriptions of the input and output variables defined with the FIS Editor, the Rule Editor allows us to construct the rule statements automatically, by clicking on and selecting one item in each input variable box, one item in each output box and one connection item. Choosing none as one of the variable qualities will exclude that variable from a given rule. Choosing not under any variable name will negate the associated quality. Rules may be changed, deleted or added, by clicking on the appropriate button.

For the capacitor allocation problem, rules are defined to determine the suitability of a node for capacitor installation. Such rules are expressed in the following form:

IF premise (antecedent), THEN conclusion (consequent). For determining the suitability of capacitor placement at a particular node, a set of multiple-antecedent fuzzy rules has been established. The inputs to the rules are the voltage and power loss indices and the output is the suitability of capacitor placement. The rules are summarized in the fuzzy decision matrix in Table-1. The consequents of the rules are in the yellow shaded part of the matrix.
In the present work 25 rules are constructed.
For Example:

If **PLI** is **H** and **Voltage** is **L** then **CSI** is **H**.

If **PLI** is **M** and **Voltage** is **N** then **CSI** is **LM**.

If **PLI** is **H** and **Voltage** is **H** then **CSI** is **LM**.

The Rule Viewer is a MATLAB-based display of the fuzzy inference diagram. Used as a diagnostic, it can show which rules are active, or how individual membership function shapes are influencing the results. Surface Viewer can display how one of the outputs depends on any one or two of the inputs - that is, it generates and plots an output surface map of the system.

Finally, to save the current file uses the commands **Export to workspace** and **Export to disk.** By calling this file in the main program, the CSI values corresponding to each bus can be obtained. Thereby, we can find the nodes suitable for capacitor installation.

Table-1. Decision matrix for determining the optimal capacitor locations.

AND		Voltage				
		LL	LN	NN	HN	HH
PLI	L	LM	LM	L	L	L
	LM	M	LM	LM	L	L
	M	HM	M	LM	L	L
	HM	HM	HM	M	LM	L
	H	H	HM	M	LM	LM

4. PARTICLE SWARM OPTIMIZATION METHOD

4.1. Introduction

Particle swarm optimization (PSO) method is a population based evolutionary computation technique developed by Dr. Eberhart and Dr. Kennedy in 1995, inspired by social behavior of bird flocking or fish schooling. The particle swarm concept originated as a simulation of simplified social system, and has been found to be robust in solving continuous linear and nonlinear optimization problems. The PSO technique can generate high-quality solutions within shorter calculation time and have more stable convergence characteristic than other stochastic methods. PSO-based approach is considered as the one of the most powerful methods for resolving the non-smooth global optimization problems. It has been found that the PSO quickly finds the high-quality optimal solution for many power system optimization problems.
PSO shares many similarities with evolutionary computation technique such as Genetic Algorithms. Both algorithms start with a group of a randomly generated population and both have fitness values to evaluate the population. Both update the population and search for the optimum with random techniques. However, PSO does not have genetic operators like crossover and mutation. Particles update themselves with the internal velocity. They also have memory, which is important to the algorithm. Compared with genetic algorithms, the information sharing mechanism in PSO is significantly different. In genetic algorithms, chromosomes share information with each other. So the whole population moves like a one group towards an optimal area. In PSO, only gbest gives out the information to others. It is a one -way information sharing mechanism. The evolution only looks for the best solution.

4.2. Particle swarm optimization

PSO technique traces its evolution to the emergent motion of a flock of birds searching for food. It uses a number of particles that constitute a swarm. Each particle traverses the search space looking for the global minimum. In a PSO system, particles fly around in a multidimensional search space. During flight, each particle adjusts its position according to its own experience and the experience of neighboring particles, making use of the best position encountered by itself and its neighbors. The swarm direction of a particle is defined by the set of particles neighboring to the particle and its history experience.

Let x and v denote a particle coordinates (position) and its corresponding flight speed (velocity) in a search space, respectively. The best previous position of a particle is recorded and represented as pbest. The index of the best particle among all the particles in the group is represented as gbest. Each particle knows the best value so far (pbest) and best value in the group (gbest). The particle tries to modify its position using the current velocity and the distance from pbest and ***gbest.***

The modified velocity and position of each particle can be calculated using the following formulas [10]:

$$v_i^{k+1} = K[w* v_i^k + c_1*rand_1*(pbest_i - x_i) + c_2*rand_2*(gbest_i - x_i)] \quad (5)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (6)$$

Where K is constriction factor
v_i^k = velocity of particle i in k^{th} iteration
w = inertia weight parameter
c_1, c_2 = weight factors
$rand_1$, $rand_2$ = random number between 0 and 1
x_i^k = position of particle i in k^{th} iteration

Suitable selection of inertia weight w provides a balance between global and local explorations. In general, the inertia weight w is set according to the following equation:

$$w = w_{max} - ((w_{max} - w_{min})* t / T) \quad (7)$$

Where w is an adjustable parameter between w_{max} and w_{min}

t = current iteration number

T = maximum number of iterations

In the iterative process, the particle velocity is limited by some maximum value v_i^{max}. The parameter v_i^{max} determines the resolution or fitness, with which regions are to be searched between the present position and the target position. This limit enhances the local exploration of the problem space and it realistically simulates the incremental changes of human learning. If v_i^{max} is too high, particles might fly past good solutions. If v_i^{max} is too small, particles may not explore sufficiently beyond local solutions. In many experiences with PSO, v_i^{max} was often set at 10%–20% of the dynamic range of the variable on each dimension.

4.3. Algorithm to find the capacitor sizes using PSO method

After identifying the n number of candidate locations using fuzzy approach, the capacitor sizes in all these n candidate locations are obtained by using the Particle swarm optimization method (PSOM).

Step 1: Initially [nop x n] number of particles are generated randomly within the limits, where nop is the population size and n is the number of capacitors. Each row represents one possible solution to the optimal capacitor-sizing problem.

Step 2: Similarly [nop x n] number of initial velocities are generated randomly between the limits ($-v_i^{max}$) and ($+v_i^{max}$). Iteration count is set to one.

Step 3: By placing all the n capacitors of each particle at the respective candidate locations and load flow analysis is performed to find the total real power loss P_L. The same procedure is repeated for the nop number of particles to find the total real power losses. Fitness value corresponding to each particle is evaluated using the equation (8) for maximum annual savings.

Fitness function for maximum savings (considering the capacitor cost) is given by:

$$F_A = K_P. \Delta P + K_E. \Delta E - K_C. Q_C \quad (8)$$

Where S is the savings in \$/year,
K_P is a factor to convert peak power losses to dollars,
K_E is a factor to convert energy losses to dollars,
K_C is the cost of capacitors in dollars,
ΔP is the reduction in peak power losses,
ΔE is the reduction in energy losses, and
Q_C is the size of the capacitor in kVAr.

The capacitor sizes corresponding to maximum savings are required. For any one particle, the negative F_A value indicates that savings are negative and F_A is fixed at F_A (minimum) and capacitor sizes corresponding to that particle are fixed at Q_C (minimum).

Step 4: pbest values for all the particles are obtained from the fitness values and the best value among all the pbest values (gbest) is identified.

Step 5: Maximum fitness and average fitness values are calculated. Error is calculated using the equation (9).

Error = (maximum fitness - average fitness) (9)
If this error is less than a specified tolerance then go to step 10.

Step 6: New velocities for all the particles are calculated using equation (10) in the range of ($-v_i^{max}$) and ($+ v_i^{max}$).

$$v_{i,j}^{k+1} = K* [w* v_{i,j}^k + c_1*rand_1*(p^{pbest}_{i,j} - p_{i,j}) + c_2*rand_2*(p^{gbest}_{1,j} - p_{i,j})] \quad (10)$$

Where K is constriction factor
$V_{i,j}^k$ = velocity of particle i,j in k^{th} iteration
w = inertia weight parameter
c_1, c_2 = weight factors
$rand_1$, $rand_2$ = random number between 0 and 1

$p_{i,j}^{k}$ =particle *i,j* in k^{th} iteration
$p^{pbest}{}_{i,j}$ =pbest particle *i,j* in k^{th} iteration
$p^{gbest}{}_{1,j}$ =gbest particle *1,j* in k^{th} iteration

Step 7: The position of each particle is updated using equation (11).

$$p_{i,j}^{k+1} = p_{i,j}^{k} + v_i^{k+1} \tag{11}$$

Step 8: New fitness values are calculated for the new positions of all the particles. If the new fitness value for any particle is better than previous pbest value then pbest value for that particle is set to present fitness value. Similarly gbest value is identified from the latest pbest values.

Step 9: The iteration count is incremented and if iteration count is not reached maximum then go to step 3.

Step 10: gbest particle gives the optimal capacitor sizes in *n* candidate locations and the results are printed.

5. RESULTS

Fuzzy approach is used to find the optimal capacitor locations and PSO method is used to find the optimal capacitor sizes for maximum annual savings. Convergence criterion of PSO method is error must be less than 0.000000001 dollars.

The data shown below is used for finding the optimal capacitor sizes:

nop = 30, T = 1000, C_1 = 2.05, C_2 = 2.05, w_{max} = 0.9 and w_{min} = 0.4.

5.1. Results of 15-bus system

The proposed algorithm is applied to 15-bus system [12]. Optimal capacitor locations are identified based on the C.S.I. values. For this 15-bus system, five optimal locations are identified. Capacitor sizes in the five optimal locations, total real power losses before and after compensation are shown in Table-2.

Table-2. Results of 15-bus system.

Bus No.	**Capacitor size in kVAr**
4	274
6	193
7	143
11	267
15	143
Total kVAr	1020
Total power loss in kW (before)	61.7944
Total power loss in kW (after)	30.5522
Savings in dollars	$ 16,007.2322

5.2. Results of 34-bus system

The proposed algorithm is applied to 34-bus system [7]. Optimal capacitor locations are identified based on the C.S.I. values. For this 34-bus system, seven optimal locations are identified. Capacitor sizes in the seven optimal locations, total real power losses before and after compensation are shown in Table-3.

Table-3. Results of 34-bus system.

Bus No.	**Capacitor size in kVAr**
20	683
21	145
22	144
23	143
24	143
25	143
26	228
Total kVAr	1629
Total power loss in kW (before)	221.7235
Total power loss in kW (after)	168.9548
Savings in dollars	$ 27,505.5511

5.3. Results of 69-bus system

The proposed algorithm is applied to 69-bus system [4]. Optimal capacitor locations are identified based on the C.S.I. values. For this 69-bus system, two optimal locations are identified. Capacitor sizes in the two optimal locations, total real power losses before and after compensation are shown in Table-4.

Table-4. Results of 69-bus system.

Bus No.	**Capacitor size in kVAr**
61	1029
64	207
Total kVAr	1236
Total power loss in kW (before)	225.0044
Total power loss in kW (after)	152.0541
Savings in dollars	$ 43,105.2581

The results show that $16,007 annual savings for 15-bus system, $27,505 for 34-bus system and $43,10532.58% for 69-bus system is possible as shown in Tables-2, 3 and 4 respectively and bus voltages are also improved substantially.

6. CONCLUSIONS

In this paper, a two-stage methodology of finding the optimal locations and sizes of shunt capacitors for reactive power compensation of radial distribution systems is presented. Fuzzy approach is proposed to find the optimal capacitor locations and PSO method is proposed to find the optimal capacitor sizes.

Based on the simulation results, the following conclusions are drawn:

By installing shunt capacitors at all the potential locations, the total real power loss of the system has been reduced significantly and at same time annual savings are increased and bus voltages are improved substantially.

The proposed fuzzy approach is capable of determining the optimal capacitor locations based on the C.S.I. values.

The proposed PSO method iteratively searches the optimal capacitor sizes for the maximum annual savings.

The coding of PSO method is simple because the PSO method has no evolution operators such as cross over and mutation, which appears in GA method.

REFERENCES

[1] Duran H. 1968. Optimum number, location and size of shunt capacitors in radial distribution feeders: A dynamic programming approach. IEEE Transactions on Power Apparatus and Systems. 87(9): 1769-1774.

[2] Bae Y.G. 1978. Analytical method of capacitor allocation on distribution primary feeders. IEEE Transactions on Power Apparatus and Systems. PAS-97(4): 1232-1238.

[3] Grainger J.J and S.H. Lee. 1981. Optimum size and location of shunt capacitors for reduction of losses on distribution feeders. IEEE Transactions on Power Apparatus and Systems. PAS- 100(3): 1105-1118.

[4] Baran M.E. and Wu F.F. 1989. Optimal capacitor placement on radial distribution systems. IEEE Transactions on Power Delivery, vol.4, no-1, pp. 725-734, January

[5] Baran M.E. and Wu F.F. 1989. Optimal sizing of capacitors placed on a radial distribution system. IEEE Transactions on Power Delivery. 4(1): 735-743.

[6] Sundhararajan S. and Pahwa A. 1994. Optimal selection of capacitors for radial distribution systems using a genetic algorithm. IEEE Transactions on Power Systems. 1.9(3): 1499-1507.

[7] Chis M., Salama M.M.A. and Jayaram S. 1997. Capacitor placement in distribution systems using heuristic search strategies. IEE proceedings on Generation, Transmission and Distribution. 144(3): 225-230.

[8] Haque M.H. 1999. Capacitor placement in radial distribution systems for loss reduction. IEE Proceedings on Generation, Transmission and Distribution. 146(5): 501-505.

[9] Ng H.N., Salama M.M.A. and Chikhani A.Y. 2000. Capacitor allocation by approximate reasoning: fuzzy capacitor placement. IEEE Transactions on Power Delivery. 15(1): 393 – 398.

[10] Prakash K. and Sydulu M. 2007. Particle swarm optimization based capacitor placement on radial distribution systems. IEEE Power Engineering Society general meeting 2007. pp. 1-5.

[11] AlHajri M.F., AiRashidi M.R. and El-Hawary M.E. 2007. A novel discrete particle swarm optimization algorithm for optimal capacitor placement and sizing. IEEE Conference 2007. pp. 1286-1289.

[12] Das D., Kothari D.P. and Kalam A. 1995. Simple and efficient method for load flow solution of radial distribution networks", Electrical Power and Energy Systems. 17(5): 335-346,