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HYBRID EVOLUTIONARY–HEURISTIC ALGORITHM FOR CAPACITOR BANKS ALLOCATION

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The issue of optimal allocation of capacitor banks concerning power losses minimization in distribution networks are considered in this paper. This optimization problem has been recently tackled by application of contemporary soft computing methods such as: genetic algorithms, neural networks, fuzzy logic, simulated annealing, ant colony methods, and hybrid methods. An evolutionaryheuristic method has been proposed for optimal capacitor allocation in radial distribution networks. An evolutionary method based on genetic algorithm is developed. The proposed method has a reduced number of parameters compared to the usual genetic algorithm. A heuristic stage is used for improving the optimal solution given by the evolutionary stage. A new cost-voltage node index is used in the heuristic stage in order to improve the quality of solution. The efficiency of the proposed two-stage method has been tested on different test networks. The quality of solution has been verified by comparison tests with other methods on the same test networks. The proposed method has given significantly better solutions for time dependent load in the 69-bus network than found in references.

K e y w o r d s: capacitor allocation, radial distribution network, evolutionary method, heuristic method, optimization

1 INTRODUCTION

The installation of shunt capacitor banks in radial distribution networks is widely used for improvement of network voltage profile and decrease of real power losses in network lines. Decrease of real power losses produces economical benefit for a distributor. Low values of node voltage in a network can cause certain problems in network operation. A trade-off between the cost of capacitor banks installation and the benefit induced from decrease of losses represents an optimization problem. The solution to the optimization problem is the optimal allocation of capacitor banks in distribution networks. The optimal capacitor allocation determines the size of capacitors to be installed in certain nodes with the aim of minimizing active power losses with minimal capacitor costs. The optimization problem is very difficult to solve. The difficulty arises from characteristics of the optimization problem. Both capacitor sizes and capacitor locations are discrete values. Capacitor banks are installed in certain locations in a distribution network such as substation, load points or line poles. The optimization problem has a discrete character because its variables are discrete. Additionally, calculation of power flows, power losses and node voltages in a network is done by numerical mathematical methods. Discrete variables and the numerical calculation make the optimization problem very complex and difficult to solve. Furthermore, it is necessary to satisfy certain network operating conditions. These conditions are usually voltage limits at network nodes and current limits of network lines. Other conditions can also be used. To sum up, the optimization problem can be defined as nonlinear constrained optimization problem with discrete variables and non-derivable objective function. Considerable effort has been put into solving the optimization problem in current literature. In [1] and [2], a review of optimal capacitor placement methods sorted by methods and authors is given. Different soft computing methods such as: genetic algorithms simulated annealing, artificial neural networks, fuzzy based logic, heuristics based methods, and tabu search algorithms are widely used for recent solution of the optimization problem. Some applications of these methods can be found: in [3] for heuristic strategies, in [4–9] for genetic algorithms, in [10] for tabu search algorithms, in [11] for fuzzy logic. Additionally, synergy of usually two of these methods is often used to develop hybrid methods. So, in [12–14] combination of genetic algorithms and fuzzy logic, in [15] combination of heuristic and tabu search algorithms and in [16] combination of fuzzy and simulated annealing algorithms can be found. Definition of procedures inside a given method and determination of parameter values inside the procedures are main problems in the application of these methods. Basic shortcoming of application of these methods to the given optimization problem is high impact of parameter values, such as crossover and mutation probabilities for GA, on the quality of the solution. Therefore there appears the impossibility of definition of common parameter values for all topologies and all designs in the application of these methods to distribution network. The proposed evolutionary-heuristic method is a trial to overcome this main and general drawback found in application of referenced methods.

In this paper, a new hybrid method based on an evolutionary method and a heuristic approach is presented. The method consists of a two-stage algorithm for optimal capacitor banks allocation. The first algorithm stage is the evolutionary method based on adjustment of a simple genetic algorithm to the capacitor allocation problem.

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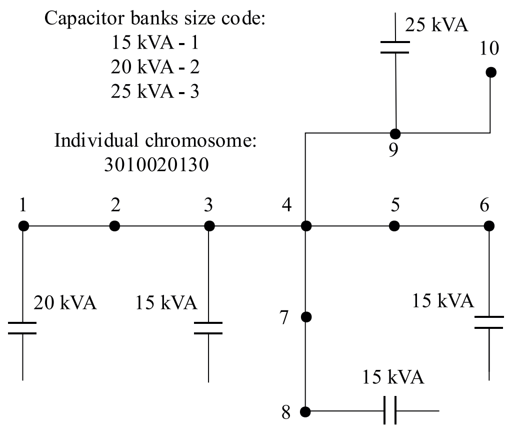

Fig. 1. An example of node numeration, capacitor size coding and design of individual unit chromosome

The second algorithm stage uses the problem solution from the first stage as well as a node index to improve the solution to the problem. The new cost-voltage node index is presented here. In the paper, a traditional objective function which considers both decrease of active power loss and capacitor banks cost is used. The solutions obtained by the proposed method have been compared to solutions found in existing references on the same test type networks.

2 TRADITIONAL OBJECTIVE FUNCTION

The observed optimization problem represents minimization of the total network cost which consists of costs associated with power peak loss, energy loss and capacitor banks costs. The minimization problem can be mathematically formulated as

$$CNt(Q_C, L_C) = Pl(Q_C, L_C)Cp + El(Pl)Ce + Cct(Q_C, N_C) \to \min \tag{1}$$

$$\text{subject to } Vll \le V_i(Q_C, L_C) \le Vul \tag{2}$$

where: CNt is total network cost, Pl is real power loss, Cp is cost coefficient of peak power loss, El is energy loss, Ce is cost coefficient of energy loss, Cct is total capacitor banks cost, Vll is lower voltage limit, Vul is upper voltage limit, V_i is voltage at node i, Q_C is reactive power of capacitor banks, L_C is location of capacitor banks, N_C is number of capacitor banks. Q_C, L_C and N_C are variables of objective functions in (1) and (2). Decrease of the peak power loss increases the network capacity. Furthermore, decrease of the energy loss decreases the operational loss of the network. Both of them bring economical benefit from the installation of capacitor banks. However, the economical benefit decreases due to costs regarding all installed capacitor banks.

In this paper, we use different capacitor costs depending on the test network. Capacitor costs are given in section 5 for each test network. Moreover, cost coefficients are given in section 5.

3 EVOLUTIONARY METHOD STAGE

An evolutionary method is an iterative procedure where a population of solutions evolves by transferring beneficial population features in genetic code to the next generation. The evolutionary method is based on natural selection among population units and is usually derived from a genetic algorithm. The main goals in the development of this evolutionary method were both to find a solution as close as possible to that of the global optimum and to simplify the algorithm. The development of this evolutionary method is based on the adjustment of the genetic algorithm for optimal capacitor allocation given in [17]. It is performed by adjusting three elements of genetic algorithm: individual coding, reproduction and selection.

3.1 Individual coding

Individual coding is a procedure where variable values are assigned to a chromosome in the population unit. In the proposed algorithm, individual coding using an integer code, as presented in [5], [17] and [18], is used. This coding is different from the frequently used binary chromosome coding as in [4], [7, 8], [12] and [14]. There is also combined coding as shown in [6]. Coding which is used here is the simplest one. Sizes and locations of a capacitor are variables in the optimization problem.

The first step includes coding of the capacitor size. It is done in a very simple way so that each capacitor size is coded by an integer starting from 1 for the smallest capacitor size. Then, a unit chromosome structure is designed. The chromosome structure is designed so that a chromosome has a specific number of positions. These positions are chromosome genes.

Chromosome positions correspond to network nodes which represent possible places for the installation of capacitors. A very simple rule, which equalizes the numeration of chromosome position and node numeration, is used here. Consequently, the number of chromosome positions equals the number of network nodes except for the referent node. The next step is to assign values to each position in the chromosome, *ie* define the value of genes. It is done by using the following rule: if there is no capacitor at a network node, the value of the corresponding chromosome position is 0; if there is a capacitor at a network node, the value of the corresponding chromosome position is the code of capacitor size. The example of the described individual coding is shown in Fig. 1.

3.2 Reproduction in evolutionary method

Crossover and mutation genetic operators are used in genetic algorithm which can be seen in [5–8], [13] and [14]. In this evolutionary method, we developed one operator inherently including both processes, *ie* crossover and mutation. The basis for its development is the representation of solution space of the optimization problem.

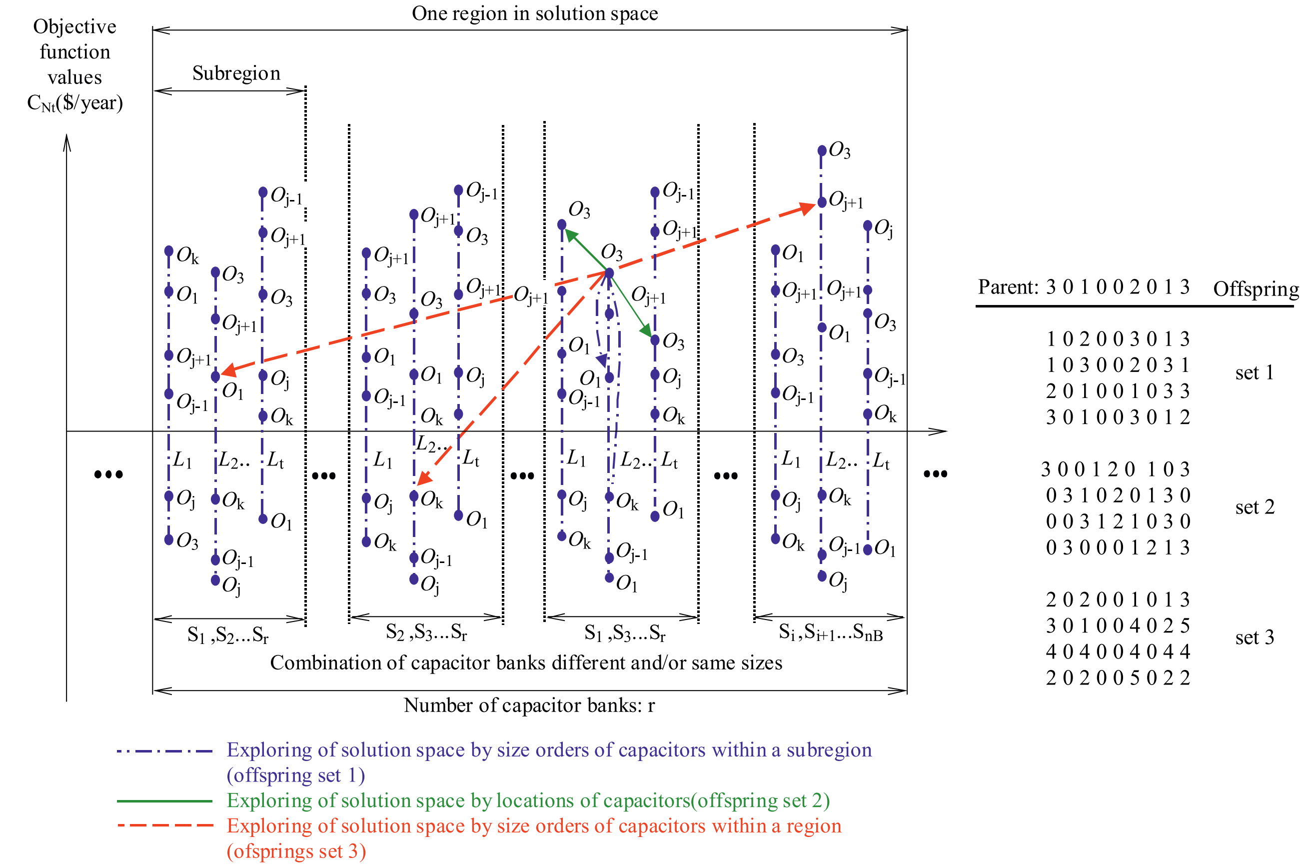

Fig. 2. Exploration of the solution space by the reproduction operator, given in right to the graph

Beside this, the idea of development of such reproduction operator emanates from parthenogenetic reproduction of descendents in nature. Parthenogenetic reproduction is inherent in nature mainly for simpler organisms with shorter DNA chains. Using parthenogenetic reproduction by producing descendents from one parent corresponds to the proposed way of unit coding and to the observed problem because of the short chromosome of the coded unit. A two-dimensional representation of the solution space is developed. This representation is done in the following way: combinations of capacitor locations are marked on the horizontal axis, in contrast to the objective function values which are marked on the vertical axis. Furthermore, for each combination of capacitor locations there are more combinations of capacitor sizes. Now, a corresponding value of the objective function is joined to a pair of one combination of capacitor location, as well as to one combination of capacitor sizes. This procedure can be presented as shown in Fig. 2. It is important to mention here, that the combination of capacitor sizes depends on both capacitor sizes alone and on the order of capacitor sizes in combination. The same set of capacitor sizes has more capacitor orders related to network nodes. The solution space, shown in Fig. 2, is divided into regions corresponding to the number of capacitors, as well as into subregions corresponding to the set of capacitor sizes. The idea about the reproduction operator, which follows from Fig. 2, is that important genetic materials of chromosomes are combinations of capacitor locations and sizes. If a chromosome is fit (value of the objective function is low) its fitness is partly defined by combination of locations and partly by combination of capacitor sizes. Therefore, we propose a reproduction operator which transfers information either about capacitor locations or capacitor sizes from the parent individual to its offspring.

We developed a reproduction operator which produces three sets of offspring individuals from a parent individual. The reproduction operator produces the first offspring set by transferring information about capacitor locations and sizes from the parent individual to the offspring. The order of capacitors is randomly chosen. These offspring individuals have the same capacitor locations and sizes as their parent individuals, but different order of capacitors.

The second set of offspring individuals is produced by transferring information about sizes and order of capacitors from the parent to its offspring. Capacitor locations are chosen at random. This set of offspring individuals has the same sizes and orders of capacitors as their parent, however, different capacitor locations. The algorithm explores one subregion in the solution space by using offspring individuals defined in these two offspring sets.

The offspring in the third set are made by transferring information about capacitors locations from the parent individual to the offspring. Capacitor sizes and order of capacitors are randomly chosen. These offspring individuals have the same capacitor locations as their parent. Capacitor sizes and order of sizes are different. The third offspring set extends the search to more subregions within a region in the solution space. Figure 2 shows the exploration of the solution space by the proposed reproduction operator given in the right. Some information about the offspring chromosomes is transferred from the parent and some are randomized using the proposed reproduction operator. The reproduction operator has both crossover and mutation function. Moreover, the reproduction operator ensures transfer of important information, as well as entry of new genes in a population. The advantage of the proposed reproduction operator with respect to reproduction in genetic algorithms is that this method requires no parameters: crossover probability and mutation probability. Note that the proposed reproduction operator needs only one parent in comparison with the parent population (two parent or more) used in genetic algorithm.

Selection of parent individuals is an important procedure in genetic algorithm. Only one parent is suggested to be selected in this evolutionary method. This is possible because the reproduction operator transfers data about locations, sizes and order of capacitor sizes from the parent to one part of offspring randomizing this data at the same time for other parts of offspring.

The reproduction operator ensures genetic diversity even with only one parent also ensuring that the evolutionary method does not get "stuck" in the local optimum. The proposed selection simplifies the method additionally. This selection also ensures elitism in evolutionary method.

The first parent in the evolutionary method is randomly chosen at the method start-up.

3.3 Other elements of evolutionary method

Coding type, selection criteria and method of generating offspring have great effect on the quality of the solution. Apart from these elements, the way of producing new population of individuals in the subsequent generation, stopping criteria as well as the number of individuals in the population influence the solution quality. The way of producing a new generation is very simple here. The new generation is simply generated by adding the parent to its offspring. The maximum number of generations is chosen for stopping criteria. The number of generations and individuals in a population are experimentally defined.

3.4 Defining individual fitness in evolutionary method

It is clear that an individual is better fitted if the value of objective function, according to (1), is smaller for that individual. Besides, the individual needs to satisfy constraint (2). In genetic algorithm, a constraint optimization problem is replaced by a series of unconstrained problems using the penalty method [19] and defining the penalty function [4]. By testing the evolutionary method for different networks, it has been noticed that for some networks certain individuals have a low objective value (1) but do not satisfy the voltage constraint (2). On the other hand, some individuals satisfy the voltage constraint but have a considerable higher objective value. In order to carry out more detailed research into capacitor allocations, which significantly reduce active power loss, execution of evolutionary method without voltage constraints is proposed. It means that the evolutionary method provides capacitor allocation, which has a low objective value, in the process of which it either satisfies or does not satisfy the voltage constraint. The voltage constraint is considered in the heuristic stage of the method.

4 HEURISTIC BASED STAGE

Heuristic stage is developed to improve the quality of solution provided by the evolutionary method. Capacitor allocation obtained by the evolutionary method is the first allocation (start allocation) in the heuristic stage. The idea is to analyze whether capacitors can be installed in some nodes with the aim of decreasing the objective function value with respect to the objective function value for the start allocation. If installations that decrease the objective function value exist, a new allocation will be made. The process is in iterative progress until there are capacitor installations which decrease the objective function value. The allocation defined in each iteration is the start allocation in the subsequent iteration. At this stage, it is necessary to define a criterion for choosing a new capacitor installation. We developed a simple criterion based on the following idea. Two cases are considered. The first case when capacitor allocation satisfies the voltage constrains and the second case when it does not satisfy the voltage constrains. If the solution satisfies the voltage constraint, it is logical to consider the decreasing objective function value only. However, an analysis of those capacitor installations, which result in a large decrease of the function value and small decrease of the minimum node voltage at the same time, is proposed. During that process, only those capacitor installations where the voltage stays within permissible limits are taken into account. Furthermore, it has been noticed that the method gets "stuck" in a local optimum if only the decrease of the objective function is observed. However, by using the proposed procedure, the algorithm gives better solutions.

If the solution does not satisfy the voltage constraint, we suggest observing those capacitor installations which simultaneously cause large decrease or small increase of the function value, as well as considerable change of extreme node voltage (decrease or increase depending whether the voltage is above or below the limit value). In this case, not only capacitor installations which decrease the function value are taken into account, but also installations which increase the function value. Furthermore, if there are no capacitor installations decreasing the

Table 1. Results for 10-bus, 23-bus and 34-bus test networks where the algorithm is executed 5 times

		Uncompensated network	Compensated network I	II	III	IV	V
10-bus network	Allocation of capacitors (node-kvar)		2-3900; 3-1800; 4-2400; 5-1200; 8-450; 9-300	2-3900; 3-1800; 4-2400; 5-1200; 7-150; 8-150; 9-450	2-4050; 3-1200; 4-2850; 5-1200; 8-450; 9-300	2-3900; 3-1200; 4-3150; 5-900; 7-450; 9-450	2-4050; 3-1200; 4-2850; 5-1200; 8-450; 9-300
	Real loss (kW)	783.777	676.160	675.891	676.765	677.126	676.765
	Loss cost ($)	131,674.60	113,594.80	113,549.61	113,696.57	113,757.23	113,696.57
	Capacitor cost ($)	0	1,877.25	1,922.25	1,873.35	1,920.45	1,873.35
	Network cost ($)	131,674.6	115,472.05	115,471.86	115,569.92	115,677.68	115,569.92
	Min. V (pu)	0.83750	0.90008	0.90018	0.90027	0.90016	0.90027
23-bus network	Allocation of capacitors (node-kvar)		4-450; 8-600; 17-900	7-900; 16-900	5-600; 9-450; 17-900	6-600; 11-600; 17-600	7-900; 17-900
	Real loss (kW)	157.146	94.787	95.322	94.839	94.895	95.327
	Loss cost ($)	26,400.47	15,924.22	16,014.15	15,932.95	15,942.41	16,014.86
	Capacitor cost ($)	0	410.55	329.40	410.55	396.00	329.40
	Network cost ($)	26,400.47	16,334.77	16,343.55	16,343.50	16,338.41	16,344.26
	Min. V (pu)	0.89339	0.95732	0.95474	0.95880	0.95405	0.95549
34-bus network	Allocation of capacitors (node-kvar)		4-600; 8-600; 18-900; 24-600	7-900; 18-600; 23-900; 32-150	7-900; 11-150; 20-900; 24-450	9-450; 16-600; 20-600; 25-600; 27-300	5-900; 9-600; 19-300; 21-300; 24-600
	Real loss (kW)	221.724	159.830	160.558	160.595	159.256	159.148
	Loss cost ($)	37,249.55	26,851.52	26,973.74	26,979.93	26,755.06	26,736.89
	Capacitor cost ($)	0	560.70	536.40	518.25	614.85	638.70
	Network cost ($)	37,249.55	27,412.22	27,510.14	27,498.18	27,369.91	27,375.59
	Min. V (pu)	0.94169	0.95028	0.95062	0.95006	0.95067	0.95059

Table 2. Comparison of results for 10-bus, 23-bus and 34-bus test networks

		Literature [3]	[11]	[14]	[16]	Proposed algorithm
10-bus netw.	Loss reduction (kW)	76.000	97.800	96.907	107.340	107.886
	Cost reduction($)	12,012.00	14,580.00	14,399.00	16,130.00	16,202.74
23-bus netw.	Loss reduction (kW)	61.450	–	–	62.200	62.359
	Cost reduction($)	9,992.90	–	–	10,038.00	10,065.70
34-bus netw.	Loss reduction (kW)	61.800	–	–	62.610	62.468
	Cost reduction($)	9,842.00	–	–	9,850.00	9,879.64

function value, it is necessary to install capacitors which bring extreme voltage closer to voltage limits even if it results in the decrease of the objective function value. If the extreme voltage is higher than the upper voltage limit, only those installations which decrease the extreme voltage are considered. However, if the extreme voltage is lower than the lower voltage limit, only those installations which increase the extreme voltage are taken into consideration. The capacitor installation which simultaneously provides the largest decrease (or the smallest increase) of total costs and the largest increase of minimum voltage (or largest decrease of maximum voltage) will be found by this procedure. After extreme voltage has reached a value within limits, all subsequent iterations are performed as in the case where the capacitor allocation satisfies the voltage constraint. The aforementioned procedure is mathematically expressed by the following node cost-voltage index

$$NI_{i,j} = \frac{CNt_{j,k} - CNt_{k-1}}{\left(|Ve_{j,k} - Ve_{k-1}|/Ve_{k-1}\right)^t} \tag{3}$$

for each $i = 1,2,\dots,n$ and $j = 0,1,2,\dots,m$, where: n is the number of network nodes, m is the number of available capacitors ($j = 0$ means that there is no capacitor at a node i), k is the number of current iteration,

Ve is the extreme value (maximum or minimum) of node voltage, t is the exponent defined as $t = 1$ for capacitor allocation which does not satisfy the voltage constraint and $t = -1$ for capacitor allocation which satisfies the voltage constraint.

Notice that the negative value of node index (3) indicates that there is a decrease of total network cost defined by (1), while the positive index shows that there is an increase of total network cost between two consecutive iterations. Installation of a capacitor in a node is better if the node cost-voltage index is smaller.

The heuristic stage of the optimization method is executed as follows:

1) For a solution start from the evolutionary stage, calculate the node voltages and objective function value according to (1).
2) If extreme node voltage for the current capacitor allocation is within voltage limits go to step 8 and if above voltage limits go to step 3.
3) Set $t = 1$.
4) Calculate node cost-value index for the current capacitor allocation for every nodes for installation of each available capacitor and no installed capacitor with no change capacitors in others nodes.
5) If $t = -1$ and there is no node with a negative node index go to step 9, otherwise go to step 6.
6) In the node and for the capacitor for which the node index is the smallest install the capacitor and set this capacitor allocation as actual. Notice that if node index is the smallest for some node in case of removing capacitor from this node existing capacitor will be removed from the node.
7) If the extreme node voltage for the current capacitor allocation is within voltage limits go to step 8, otherwise return to step 3.
8) Set $t = -1$ and return to step 4.
9) Set the current capacitor allocation as the optimization problem solution and stop the method.

5 IMPLEMENTATION AND RESULTS ON TEST NETWORKS

In order to check the proposed method and solution quality, different distribution networks are analyzed in this section. The obtained results are compared to the results found in other references for the same test networks. Four different test networks from literature were implemented: three small-sized (10-bus, 23-bus, 34-bus system) and one middle-sized (69-bus system) test network. All networks were tested on the assumption that there exists a balanced three-phase system. The optimization problem was solved for time independent load and fixed capacitors for 10-bus, 23-bus and 34-bus networks. In the case of the 69-bus network, we considered time variable load levels and switched capacitors. All these assumptions were used since our results were compared to the results in current references for the same network conditions. Energy losses for the 10-bus, 23-bus and 34-bus system have been disregarded due to the fact that they were not taken account of in the compared references. In the case of the 69-bus network, power peak losses have not been considered for the same reason. The voltage constraint for all test networks, $0.9 \le V_i \le 1.1$, was used as specified in references. The computation of power flows was done using well known classical Newton-Raphson method. The method was implemented by writing a source code in MATHCAD software. Numeration of network nodes was done so that referent node (supply network node) was designated as 0 and other nodes were designated as $1, 2, 3, \ldots$ continuing along the main feeder, then along the laterals closest to the referent node *etc*.

We tested the method 5 times for each case to check the abilities of the method to provide sufficient quality solutions due to the stochastic character of the evolutionary stage. Moreover, it was also done to check the behavior of the heuristic stage for its different starting solutions.

5.1 Tests on the 10-bus network

The first test network is a 10-bus system with a 23 kV rated voltage and no laterals. The single line diagram and network data are given in [14] and [16]. The node numerations are the same as in [14]. We tested this network for load data given in [16] (it represents load case 1 from [14]). Available capacitor sizes and capacitor cost coefficients for this network are taken from [14]. The total capacitor cost (Cct in (1)) is obtained by multiplying the capacitor cost coefficient with the capacitor size for each node with a capacitor and by summing all nodes with installed capacitors. We used the largest capacitor size according to the rule that the maximum capacitor sizes should not exceed the total reactive load of a network. So, the largest capacitor size is 4050 kvar. The cost coefficient for power peak loss (Cp) as reported in [14] is used here, $CP = 168\,\$/(\text{kW-Year})$. Table 1. shows results for an uncompensated and a compensated network obtained by the proposed two-stage method. The best result is compared to results in [3], [11], [14], [16] shown in Table 2.

5.2 Tests on the 23-bus network

The rated voltage for the 23-bus network is 11 kV. This network has a main feeder with no laterals. Network data are given in [3] and [16]. The node numeration is the same as in [3] and [16]. Data for capacitor cost and cost coefficient for power peak loss are the same as for the 10-bus network. The largest capacitor in this case is 1650 kvar. The results are given in Table 1 which represent data for the uncompensated and compensated network. The solution obtained by the proposed method is compared to solutions from [3] and [16] in Table 2.

Table 3. Results for 69-bus network where the algorithm is executed 5 times

		Uncompensated network	Compensated network I	II	qIII	IV	V
Load level 0.5	Allocation of capacitors (node-kvar)		60-200; 63-100	60-200; 63-100	60-200; 64-100	60-200; 63-100	60-200; 63-100
	Real loss (kW)	51.582	40.204	40.204	40.248	40.204	40.204
	Loss cost ($)	6,189.86	4,824.52	4,824.52	4,829.81	4,824.52	4,824.52
	Min. V (pu)	0.95668	0.96158	0.96158	0.96185	0.96158	0.96158
Load level 1.0	Allocation of capacitors (node-kvar)		17-300; 60-1100; 64-100	17-300; 60-1100; 64-100	15-300; 60-1100; 64-100	11-100; 20-200; 58-100; 60-900; 63-100; 64-100	11-100; 21-200; 58-100; 60-900; 63-100; 64-100
	Real loss (kW)	224.895	146.579	146.579	146.652	146.266	146.269
	Loss cost ($)	70,976.84	46,260.23	46,260.23	46,283.27	46,161.68	46,162.40
	Min. V (pu)	0.90920	0.93050	0.93050	0.93050	0.93058	0.93058
Load level 1.6	Allocation of capacitors (node-kvar)		15-100; 21-200; 58-300; 60-1400; 63-900; 64-300	15-100; 17-100; 22-200; 56-100; 57-100; 60-1500; 63-900; 64-300	17-100; 20-100; 23-100; 52-100; 56-100; 60-1200; 62-800; 63-500; 64 -300	16-200; 23-100; 55-100; 56-200; 60-1600; 63-800; 64-300	15-100; 22-200; 55-100; 56-200; 58-100; 60-1400; 63-900; 64-300
	Real loss (kW)	652.217	439.787	437.761	439.309	437.407	437.496
	Loss cost ($)	58,699.49	39,580.87	39,389.47	39,537.83	39,366.66	39,374.61
	Min. V (pu)	0.84450	0.90000	0.90030	0.90004	0.90019	0.90026

5.3 Tests on the 34-bus network

The 34-bus network has a main feeder and 4 laterals. The system voltage is 11 kV. The system data are given in [11] and [16] and the single line diagram is given in [3] and [11]. Node numeration in the paper is in part different from numeration in [3], [11] and [16]. Numeration of the main feeder nodes is the same whereas numeration of lateral nodes correspond to numeration presented in [3], [11] and [16] as follows: nodes 12–15 correspond to nodes 2_1–2_4, nodes 16– 26 correspond to nodes 5_15_11, nodes 27–29 correspond to nodes 6_16_3 and nodes 30–33 correspond to nodes 9_19_4. Data for capacitor cost and cost coefficient for power peak loss are the same as for the 10-bus network. The largest capacitor is 2850 kvar. The results are given in Table 1 which show data for the uncompensated and compensated network. The solution obtained by the proposed method is compared to solutions from [3], [16] in Table 2.

5.4 Tests on the 69-bus network

This network has a main feeder and 7 laterals. The rated voltage is 12.66 kV. Network data are given in [13]. In this case, energy losses in the objective function have been considered while power peak losses have not been taken into account. Load levels and time duration of each load level are taken from [13]. The cost of energy losses is defined as

$$C_E = E_C \sum_{i=1}^{n} Tl_i \, Pl_i \tag{4}$$

where: $E_C = 0.06\,\$/\text{kWhr}$ [13] is the energy cost, Tl is the time duration of load level in hours, Pl_i is the active power loss for load level i. Now, the objective function is

$$C_{Nt} = E_C \sum_{i=1}^{n} Tl_i \, Pl_i + Cc \sum_{j=1}^{m} Qc_j \tag{5}$$

where: n is the number of load levels, Qc_j is the capacitor size at a node j, m is the number of nodes with installed capacitors for all load levels, $Cc = 3.0\,\$/\text{kvar}$ [13] is the purchase cost of the capacitor.

The maximum capacitor size for load levels 1.0 and 1.6 is 2000 kvar in accordance with the rule given in [13] which states that one bank is 100 kvar and the maximum number of banks in a node is 20. For the load level 0.5, the maximum capacitor size is 1300 kvar. Table 3 shows results for the uncompensated and compensated network for all three load levels. Table 4 shows the total results for the best combination of solutions of each load level. Control settings for capacitor switching depending on the load level are shown in Table 5. In Table 5, fixed capacitors are marked with (F) and switchable with (S). The solution obtained by the proposed method is compared to solutions from [13] in Table 6.

Table 4. Result for the best combination of solutions for 69-bus network

Total costs	Uncompensated network	Compensated network
Loss cost ($)	135,866.19	90,688.66
Capacitor cost ($)	0	10,200.00
Network cost ($)	135,866.19	100,888.66

Table 5. Control setting for 69-bus network

Capacitor location	Control setting (kvar) for load level 0.5	1.0	1.6	Capacitor size (kvar)
15	0	300	100	300 (S)
21	0	0	200	200 (S)
58	0	0	300	300 (S)
60	200	1100	1400	200 (F)+1200 (S)
63	100	0	900	900 (S)
64	0	100	300	300 (S)

Table 6. Comparison of results for 69-bus test network

Total costs	Literature [13]	Proposed algorithm
Loss cost ($)	95,727.00	90,688.66
Capacitor cost ($)	9,300.00	10,200.00
Network cost ($)	105,027.00	100,888.66
Cost reduction ($)	30,878.00	34,977.53

5.5 Result overview for test networks

Comparisons of results presented in Table 2 and Table 6. show that the two-stage method proposed in the present paper can find solutions very close to the best solutions which can be found in the present references. Solutions obtained by the proposed method are even better than those found in references. Solutions provided by each stage of the method separately have not been reported due to space limitation. However, it is interesting to mention that the evolutionary stage has given the final solution for the 23-bus network. In the case of the 10-bus and 34-bus networks, the heuristic stage has significantly improved the quality of solutions obtained by the evolutionary stage. Power losses for all three networks are very close to power losses reported in references. In order to achieve the better solution, the 10-bus network has one capacitor more installed than the number of capacitors suggested in references whereas the 23-bus and 34-bus networks have one capacitor less installed.

For time dependent load in the 69-bus network, the proposed method has also given better solutions than found in references. A comparison of the number of capacitors has not been made because in [13] only three capacitor locations have been chosen with the aim of reducing the search space.

The number of iterations and individuals in a population in the evolutionary method is as follows: the 10-bus network has 100 iterations and 100 individuals, the 23-bus network 20 and 100, 34-bus network 30 and 100 and 69-bus network 20 and 100.

6 CONCLUSIONS AND DISCUSSION

The proposed algorithm has been executed in two stages; first, using an evolutionary method and second, a heuristic method. This paper proposes the use of the evolutionary method without considering voltage constraints, which is not an usual practice. A new idea for searching the solution space has been developed in the evolutionary method. The main characteristic of the proposed evolutionary method is its simplicity and reduced number of parameters compared with genetic algorithm. By using the proposed reproduction tool based on the idea of parhenogenesys for the observed problem, an advantage is obtained compared with the reproduction tools used in classic and referenced literature. Classic reproduction mechanism produces descendents with crossover of chromosomes from two parents with the results of over-population of capacitor banks which is not usable while exploring the whole population set and approaching to the global optimum solution. Such descendants unnecessarily occupy population place and they have to be eliminated using additional actions. These shortcomings are completely eliminated with the proposed parthenogenetic reproduction operator, which contributes to the simplification of the proposed evolutionary method compared to crossover method. The benefit of parthenogenetic method over conventional GA crossover can be quantified for the observed problem. The quantification can be calculated with the ratio of the number of all combinations of capacitor banks obtained with classical crossover and the number of all combination of capacitor banks with the given number of capacitor. Thus for the case of network with 34 nodes exemplified in the work and with 6 capacitor banks this ratio equals to

$$R = \frac{\left(\sum_{i=0}^{M} \frac{(N/2)!}{((N/2)-i)!i!}\right)^2}{\sum_{j=0}^{M} \left(\frac{(N/2)!}{((N/2)-i)!i!} \frac{(N/2)!}{((N/2)-(M-j))!(M-j)!} \right)} = 352.65 \tag{6}$$

where N is the number of network nodes ($N = 34$) and M is the number of built-in capacitor banks ($M = 6$).

This means that the search is reduced to the 352.65-th part of the solution space for the case of proposed parthenogenetic reproduction operator compared to the conventional crossover operator. This ratio increases with the number of nodes in the network. The proposed method can be used beside the presented problem solution also for solving optimization problems of protection and load forecasting in power systems.

Beside this the developed parthenogenetic reproduction operator can be applied generally for evolution methods independent of the nature of problem for cases with restricted constrains.

The heuristic stage has obtained improved solutions in the first stage. The heuristic method is based upon a new sensitivity factor including changes in the objective function and voltage values. Characteristic of the heuristic method is that it significantly improves solutions obtained in the evolutionary method. Also, the proposed heuristic method is able to provide very close solutions for different start capacitor allocations.

Comparison of solutions in previous papers for the same test networks and same conditions has shown that the proposed method has given quality solutions for different networks.

Advantages of the proposed method are its simplicity and good quality of solutions.

In conclusion, the proposed simple two-stage method is acceptable for solving optimization problems of capacitor placement in radial distribution networks.

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