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An Interactive Best-Compromise Approach for Capacitor Placement and Sizing in Distribution Feeder by Using Particle Swarm Optimization

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Abstract: - A new formulation of bi-objective optimization for the general capacitor placement and sizing problem is presented. The objectives include energy loss reduction, investment cost minimization, and maximum voltage deviation improvement. The operating and expansion constraints of the system are considered for practical needed. Also, both fixed and switched types of capacitors are included. A particle swarm optimization aided interactive best-compromise method for solving general bi-objective optimization problems is then proposed. It can provide a flexible solution as dictated by the decision makers of the utilities. To demonstrate the effectiveness of the proposed method, comparative study is conducted on an actual feeder with rather encouraging results.

Key-Words: - Capacitor placement, sizing problem, Bi-objective programming, Distribution feeder, Interactive best-compromise, Particle Swarm Optimization.

1. Introduction

Capacitors have been widely employed in radial distribution systems for reactive power compensation to achieve energy loss reduction and voltage regulation. The benefits greatly depend on how the capacitors are installed in the system. This kind of problem is termed the general capacitor placement and sizing problem. It consists of determining the locations, types (fixed or switched) and sizes of capacitors to be installed in the system such that the economic profits and quality conditions of the system are improved considering the load, operating, and expansion constraints.

Most previous studies [1-9] formulated the problem with a single objective. Generally, cost is employed as the objective function and the other possible objectives, such as voltage deviation and system capacity, are treated as constraints. However, the competition between utilities is more extremely after the deregulation of power system. Power quality plays an important role for the loyalty of customers. It is necessary for utilities to take not only the economy but also the quality into consideration. Therefore, a new bi-objective formulation combined with particle swarm optimization (PSO) for the above problems is presented. In bi-objective problems, the objectives are usually non-commensurable and conflict with each other. Hence, any improvement of one objective may be reached only by the reduction of another. The interactive best-compromise (IBC) method proposed in this paper is a powerful tool, which can provide a flexible best-compromise solution for capacitor placement and sizing problem by following the intention of decision makers (DMs). Two important objectives are included, one is the economic operation, and the other is the maximum voltage deviation of the system. The load, operating and expansion constraints of the system are considered. Also, the fixed and switched types of capacitors are included for increased realism.

2. Problem Description and Formulation

In this section, a new bi-objective formulation of the capacitor placement and sizing problem is proposed. It aims to simultaneously optimize each objective, while satisfying the equality and inequality constraints given below:

2.1 Operating Constraints

The voltage magnitude at each bus of each load period has to lie in a permissible range. The current on each branch must stay within its capacity limits for security reasons. Also, the number of capacitors mounted on the buses should be below the total number of installed capacitors. These constraints are expressed as follows.

$$V_i^{\min} \le V_i^k \le V_i^{\max} \quad , i = 1 \sim N_b \quad , k = 1 \sim N_p \tag{1}$$

$$I_i^k \le I_i^{\max} \quad , i = 1 \sim N_l \quad , k = 1 \sim N_p \tag{2}$$

$$N_{c,i}^k \le [N_{f,i} + N_{s,i}] \quad , i = 1 \sim N_b \quad , k = 1 \sim N_p \tag{3}$$

where:

V_i^k : voltage magnitude at bus i of period k,

$V_i^{\max}$: maximum allowable voltage of bus i,

$V_i^{\min}$: minimum allowable voltage of bus i,

$I_i^{\max}$: maximum allowable current of feeder section i,

N_b : number of buses,

N_p : number of different load periods for yearly load duration curve,

N_l : number of branches,

$N_{c,i}^k$: number of capacitor banks mounted on bus i of period k,

$N_{f,i}$: number of fixed type capacitors installed at bus i,

$N_{s,i}$: number of switched type capacitors installed at bus i.

2.2 Expansion Constraints

The number of capacitors installed at each bus should be limited due to some practical concerns. For example, it is impossible to install more capacitors if there is not enough space in the buses. These constraints are stated below.

$$[N_{f,i} + N_{s,i}] \leq N_{c,i}^{\max} \qquad , i = 1 \sim N_b \tag{4}$$

where:

$N_{c,i}^{\max}$: upper limit of installed capacitors at bus i.

2.3 Objective Functions

The objective functions considered in the study are:

1) Economic Objective Function: The economic objective function employed is:

$$\begin{aligned} E(\overline{S}) = &\sum_{i=1}^{N_b} [C_{I,i} \times u(N_{f,i} + N_{s,i}) + C_f N_{f,i} + C_s N_{s,i}] / Y \\ &+ C_e \sum_{k=1}^{N_p} [T_i P_{loss}^k (\overline{S})] \end{aligned} \tag{5}$$

where:

$E(\overline{S})$: annual cost of system under $\overline{S}$ configuration,

C_e : energy cost per kWh,

$C_{I,i}$: installation cost at bus i,

C_f : fixed type capacitor cost per bank,

C_s : switched type capacitor cost per bank,

T_i : time duration of the ith load period,

P_{loss}^k : total power loss of load period k,

Y : average lifetime of capacitors,

$u(.)$: unit step function.

In the right hand side of (5), the first term represents the annual cost of capacitor placement, with two components: fixed installment cost and purchase cost. Generally, fixed type capacitors serve as the base compensation and they are cheaper than switched type capacitors that are used for additional compensation in different load periods. The second term represents the total annual cost of energy loss, where the energy loss is obtained by summing up the power losses for each load period multiplied by the duration of the load period. In fact, capacitors are grouped into banks of standard discrete capacities. Therefore, capacitor sizes are represented as discrete variables to meet the real situation.

2) Quality Objective Function: This objective is concerned with the voltage deviation of the system. Voltage deviation at bus i of period k is defined as:

$$VD_i^k = \left| V_i^{ideal} - V_i^k \right| \qquad , i = 1 \sim N_b \, , k = 1 \sim N_p \tag{6}$$

where:

V_i^{ideal} : ideal specific voltage at bus i.

Voltage deviation is important for both the utilities and customers. The more voltage deviation a system has, the shorter the lifetime and the less efficient the operation of any equipment mounted onto the system. Moreover, voltage collapse may arise due to the voltage deviation of some fixed power equipment such as synchronous machines. Hence, voltage deviation in a system represents the quality of the power that the utilities supply to their customers. Electricity quality and economic conditions of its supply are somewhat non-commensurable. To avoid customers' dissatisfaction and to maintain the stability of systems, it is beneficial to tackle the voltage deviation problem as an objective function instead of a constraint. In this paper, we attempt to minimize the maximum term of the voltage deviation of all buses and periods as shown below:

$$Q(\overline{S}) = \max_{i \in N_b , k \in N_p} VD_i^k = \max_{i \in N_b , k \in N_p} \left| V_i^{ideal} - V_i^k \right| \tag{7}$$

2.4 Overall Problem

In compact notation, the general capacitor placement and sizing problem can be formulated as a non-differentiable bi-objective problem with constraints optimization as below.

$$\min \begin{cases} E(\overline{S}) \\ Q(\overline{S}) \end{cases}$$

s.t.

$$Eqs. (1) \sim (4) \tag{8}$$

3. The IBC Method

In (8), if $Q(\overline{S})$ is multiplied by a weight W and added to $E(\overline{S})$ as a single objective function, a problem will arise: the weight value W is very difficult to determine because both $E(\overline{S})$ and $Q(\overline{S})$ are important for utilities and also vary in units. A better way to work with bi-objective problems is to provide a flexible best-compromise solution between the objective functions automatically. The IBC method presented here is based on this concept and derivative in the following steps.

3.1 Step 1

In (8), ignore the objective function $Q(\overline{S})$ and solve the single objective optimization problem expressed below by a PSO that will be described in the next section.

$$\begin{aligned}&\min\ E(\overline{S})\\ &\text{s.t.}\\ &Eqs.(1)\ \sim\ (4)\end{aligned} \tag{9}$$

The solution of (9) is $\overline{S}_E$, that is:

$$\begin{cases}E(\overline{S}_E)=E_{ideal}\\ Q(\overline{S}_E)=Q_{nonideal}\end{cases}$$

Due to its conflicting character, this single objective optimization problem can provide the best solution of $E(\overline{S})$, denoted E_{ideal}, but worst solution of $Q(\overline{S})$, denoted $Q_{nonideal}$. The subscript ideal denotes the desired goal value and nonideal denotes the worst value. A similar step process for another objective function $Q(\overline{S})$ is shown below.

$$\begin{aligned}&\min\ Q(\overline{S})\\ &\text{s.t.}\\ &Eqs.(1)\ \sim\ (4)\end{aligned} \tag{10}$$

The solution of (10) is $\overline{S}_Q$ and the values Q_{ideal} and $E_{nonideal}$ are found. Note that $\overline{S}_E$ and $\overline{S}_Q$ represent the two extreme solutions.

$$\begin{cases}E(\overline{S}_Q)=E_{nonideal}\\ Q(\overline{S}_Q)=Q_{ideal}\end{cases}$$

3.2 Step 2

The new single objective optimization problem is solved as below.

$$\min\ T(\overline{S})=\frac{E(\overline{S})-E_{ideal}}{E_{nonideal}-E_{ideal}}+\frac{Q(\overline{S})-Q_{ideal}}{Q_{nonideal}-Q_{ideal}}$$

s.t.

$$\begin{cases}Eqs.(1)\ \sim\ (4)\\ E_{ideal}\le E(\overline{S})\le E_{nonideal}\\ Q_{ideal}\le Q(\overline{S})\le Q_{nonideal}\end{cases} \tag{11}$$

Again, the PSO is employed and the solution of (11) is $\overline{S}_i$:

$$\begin{cases}E(\overline{S}_i)=E_i\\ Q(\overline{S}_i)=Q_i\end{cases}$$

The "decision region" is defined as the area between ideal and nonideal values of both E and Q. The (E_{ideal}, Q_{ideal}) is the inaccessible best solution for the system. It can be treated as the goal during the search. Also, ($E_{nonideal}$, $Q_{nonideal}$) is the hypothetical worst solution of the search process. The first and second terms in the right hand side of (11) represent the normalized distance between $E(\overline{S})$ and E_{ideal}, and between $Q(\overline{S})$ and Q_{ideal} respectively. Two additional constraints are added to ensure that the searching process will occur within the decision region. Minimization of the objective function $T(\overline{S})$ means to find a best-compromise solution $\overline{S}_i$ that must lie within the decision region and can be a best investment solution.

3.3 Step 3

The solution $\overline{S}_i$ from step 2 is a best-compromise answer, but it may be unsuited due to the policy of utilities. To choose not only a best-compromise but also a solution which is desirable for the utilities, the solution $\overline{S}_i$ should be judged by the DMs of the utilities. If $\overline{S}_i$ is not acceptable, one of the objective functions ($E(\overline{S})$, $Q(\overline{S})$) should be chosen to be the compromised term. For example, if the DMs think that the cost of $\overline{S}_i$ is above the budget of the utilities and the voltage deviation of the system can be further degraded to save money, then $Q(\overline{S})$ can be chosen as the compromised term and the parameters should be changed as below:

$$\begin{cases}E_{nonideal}=E_i\\ Q_{ideal}=Q_i\end{cases} \tag{12}$$

Conversely, if the DMs decide that the voltage deviation of $\overline{S}_i$ should be improved by spending more money, then $E(\overline{S})$ should be chosen as the compromised term and the parameters should be changed as shown below.

$$\begin{cases}E_{ideal}=E_i\\ Q_{nonideal}=Q_i\end{cases} \tag{13}$$

In (12) or (13), the decision region is modified toward the region of interest indicated by DMs according to the policy of the utilities. The parameters Dis_E and Dis_Q shown below represent the decision region by detailed values. They also show the maximum improvement or degradation that the next search can attain.

$$\begin{cases}Dis\_E=E_{nonideal}-E_{ideal}\\ Dis\_Q=Q_{nonideal}-Q_{ideal}\end{cases} \tag{14}$$

They are very important references for DMs to use in deciding whether further searching is valuable or not. If the DMs determine to search in this decision region then the process should go back to step 2, otherwise the $\overline{S}_i$ will be the answer. The process should be executed continuously until a satisfactory solution is found.

4. Implementation of the Particle Swarm Optimization method

Conceptually, (9,10,11) belong to the class of problems known as combinatorial optimization with constraints. Possible combinations grow dramatically as the number of switches increases. It is computationally intractable to deal with this problem by exhaustive search that every possible binary combination is traversed. Recently, the use of the global optimization technique called PSO [10], to solve real world problems have aroused researchers' interest due to its flexibility and efficiency. Limitations regarding the form of the objective function employed and the continuity of variables used for the classical greedy search technique can be completely eliminated. Owing to these attractive properties, PSO is used as the tool for solving (9,10,11) in this paper.

4.1 Brief Review of the Particle Swarm

Particle swarm optimization (PSO), first introduced by Kennedy and Eberhart, is one of the modern heuristic algorithms. It was developed through simulation of a simplified social system, and has been found to be robust in solving continuous nonlinear optimization problems [10-11]. The PSO technique can generate a high-quality solution within shorter calculation time and stable convergence characteristic than other stochastic methods [12-14]. Much research is still in progress for proving the potential of the PSO in solving complex power system operation problems. Researchers including Yoshida et al. have presented a PSO for reactive power and voltage control considering voltage security assessment. The feasibility of their method is compared with the reactive tabu system and enumeration method on practical power system, and has shown promising results [15]. Naka et al. have presented the use of a hybrid PSO method for solving efficiently the practical distribution state estimation problem [16].

Searching procedures by PSO based on the above concept can be described as follows: a flock of individuals optimizes a certain objective function. Each individual knows its best value $Pbest$ so far and its position. Moreover, each individual knows the best value in the group $Gbest$ among $Pbest$, namely the best value so far of the group. The modified velocity of each individual can be calculated using the current velocity and the distance from $Pbest$ and $Gbest$ as shown below:

$$\begin{aligned} v_i^{k+1} = \omega v_i^k &+ c_1 Rand() \times (Pbest_i^k - s_i^k) \\ &+ c_2 Rand() \times (Gbest^k - s_i^k) \end{aligned} \tag{15}$$

$$s_i^{k+1} = \begin{cases} s_i^k + v_i^{k+1} & \text{if } s_{i,\min} \le s_i^k + v_i^{k+1} \le s_{i,\max} \\ s_{i,\min} & \text{if } s_i^k + v_i^{k+1} < s_{i,\min} \\ s_{i,\max} & \text{if } s_i^k + v_i^{k+1} > s_{i,\max} \end{cases} \tag{16}$$

where:

- v_i^k : current velocity of individual i at iteration k,
- v_i^{k+1} : modified velocity of individual i at iteration k+1,
- $Rand()$: random number between 0 and 1,
- s_i^k : current position of individual i at iteration k,
- $Pbest_i^k$: $Pbest$ of individual i until iteration k,
- $Gbest^k$: $Gbest$ of the group until iteration k,
- ω : weight function for velocity of individual ,
- c_i : weight coefficients for each term,
- $s_{i,\max}$: the maximum boundary of allowable searching space,
- $s_{i,\min}$: the minimum boundary of allowable searching space.

The constants c_1 and c_2 represent the weighting of the stochastic acceleration terms that pull each individual toward the $Pbest$ and $Gbest$ positions. Low values allow individual to roam far from the target regions before being tugged back. On the other hand, high values result in abrupt movement toward target regions. Hence, the acceleration constants c_1 and c_2 were often set to be 2.0 according to simulation experiences. Suitable selection of inertia weight ω in (17) provides a balance between global and local explorations, thus requiring less iteration on average to find a sufficiently optimal solution. As originally developed ω often decreases linearly from about 0.9 to 0.4 during a run. In general, the inertia weight ω is set according to the following equation:

$$\omega = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{Iter_{\max}} \times Iter \tag{17}$$

where:

- $\omega_{\max}$: initial weight,
- $\omega_{\min}$: final weight,
- $Iter_{\max}$: maximum number of iterations
- $Iter$: current number of iterations.

The search mechanism of the PSO using the modified velocity and position of individual based on (15) and (16) is illustrated in Fig.1.

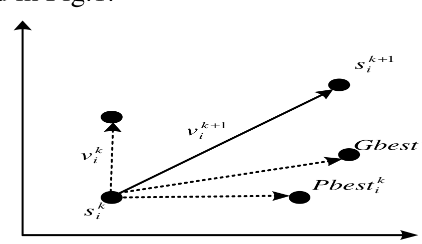

Fig. 1. The searching scheme of the PSO

4.2 Representation of Individual String

Implementation of a problem in the PSO framework starts from the parameter encoding, i.e., the representation of the problem. In this study, integer representation is chosen for each particle. The individual string structure is represented in Fig. 2. The parameter $N_{c,i}^{k}$ describes the number of capacitor banks mounted on bus i of period k, as defined previously. The value of each chromosomes' position should be limited so that they are not violating the expansion constraints $N_{c,i}^{\max}$. The value of each particle should be limited to 6 so that they are feasible solution. In the initial process, a random number from 1 to 6 will be generated to create the first positions of each individual.

$N_{c,1}^{1}$	$N_{c,2}^{1}$	....	N_{c,N_b-1}^{1}	N_{c,N_b}^{1}
$N_{c,1}^{2}$	$N_{c,2}^{2}$	....	N_{c,N_b-1}^{2}	N_{c,N_b}^{2}
. .	. .	....	. .	. .
$N_{c,1}^{N_p}$	$N_{c,2}^{N_p}$	....	$N_{c,N_b-1}^{N_p}$	$N_{c,N_b}^{N_p}$

Fig. 2. The individual string structure.

4.3 Evaluation Function

Implementation of an optimization problem in PSO is realized within the evolutionary process of an evaluation function. The function adopted is given below.

$$Evaluation = \frac{1}{1 + (Penalty \times Obj)} \tag{18}$$

where:

Obj : the objective function,

$Penalty$: a penalty term. If any constraint is violated then the penalty will be set to 1.5, otherwise 1 is instead.

4.4 Parameter Selection and Convergence Criterion

If one of the following conditions is met, the PSO process is considered converged.

(i). After 50 consecutive iterations, the best solution does not change.

(ii). The total iterations exceed the upper limit of 10000.

5. Test Study

To illustrate the performance of the proposed solution methodology, consider a practical 12-bus, 11.4 kV distribution feeder, as shown in Fig. 2, that is a portion of the Taiwan Power Company's distribution system. The parameters that are the average values according to the real conditions in Taiwan are shown in Table 1 and each bank of capacitors is 300 kVar. The satisfaction rates for each objective are defined in (18). It represents the level of satisfaction within the attainable search region for each objective.

$$\begin{aligned} \textit{Satisfaction Rate of } \mathrm{O}_1 &= SA_{O1} \\ &= (\max O_1 - O_1)/(\max O_1 - \min O_1) \end{aligned} \tag{18}$$

The test results are summarized in Table 2, where the symbols F (fixed), or S (switched), represent the capacitor type, and H (heavy), N (normal), L (light), indicate the various load levels. The digits before the capacitor type and load level indicate the number of capacitors installed and the number mounted during different load levels, respectively. The second column represents the performance of the system before the capacitors were installed. Obviously, the voltage constraint is violated and the compensating capacitors are needed. The third and fourth columns each correspond to a single objective programming that minimizes voltage deviation and cost respectively. Columns five to seven show the results of the proposed bi-objective solution procedures that consider both cost and voltage deviation. In fourth column, to achieve the minimum cost, the minimum voltage is only 0.920, which is almost on the feasible margin (0.92~1.05). The fifth column represents the first result of the proposed algorithm. Comparing the fifth column and the fourth column, it is obvious that SA_E has degraded slightly from 100% to 82.95% but SA_Q has greatly improved from 0% to 75.11%. Generally, it is beneficial to perform such an investment.

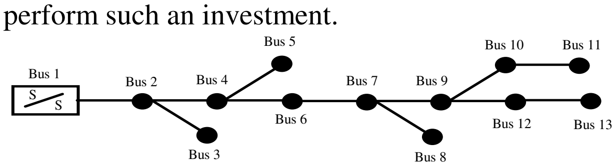

Fig.2. The schematic of the 12-bus distribution test system.

Table 1. Parameters for the study system.

V_i^{ideal}	C_e	$C_{I,i}$	C_f	C_s	$V_i^{\min}$	$V_i^{\max}$	$N_{c,i}^{\max}$	Y
1 p.u.	1.8NT/ kWh	387278 NT	43362 NT/bank	66241 NT/bank	0.92 p.u.	1.05 p.u.	6	7 years

The suitability of result 1 should be judged by the DMs of electricity utilities. If the DMs think that result 1 is not suitable for the policy of the utilities, then further compromise can be made according to the directions dictated by DMs. Unlike other approaches that indicate many unknown parameters such as weight values for further search, the DMs only have to choose one of the objectives (cost or voltage deviation) as the compromised term and then the proposed method can find a best-compromise and desirable solution for the bi-objective problem. Assume the DMs think that the power quality of result 1 should be further improved and decide to spend more money to reduce the voltage deviation of the system. The parameter of $Q_{nonideal}$ in result 1 is then changed, because further improvement of voltage deviation is needed. Similarly, the E_{ideal} is also changed, because further compromise will be made on the cost. Note that the decision region is changed simultaneously with the ideal and nonideal values of both E and Q such that it shifts toward the region of interest as indicated by DMs.

The values Dis_E and Dis_Q can help the DMs to understand the maximum improvement that a further step can achieve. If the DMs think that the maximum improvement in the desired term is too small to make further searching worthwhile, then they can stop the process. Assuming that the further step is allowed by the DMs, result 2 shows the consecutive result. Again, it is a flexible best-compromise solution within the decision region.

The same procedure can be repeated again as shown in result 3. Gradually, the decision region will become smaller and focused on the intention of the DMs.

Table 2. Numerical results.

	Original	Single objective		Bi-objective programming		
	system	Min Q	Min E	Result 1	Result 2	Result 3
$E(\overline{S})$ (NT/year)	6209146	6284417	3934274	4335098	5137890	4595468
$Q(\overline{S})$ (V)	1520	13	913	237	67	138
$\min V_i^k$ (p.u.)	0.867	0.999	0.920	0.979	0.994	0.988
SA_E (%)	------------	0	100	82.95	48.79	71.87
SA_Q (%)	------------	100	0	75.11	94.00	86.11
Satisfy ?	------------	------------	No	No	No	Yes
Compromised term ?	------------	------------	$E(\overline{S})$	$E(\overline{S})$	$Q(\overline{S})$	------------
E_{ideal}	------------	------------	3934274	4335098	4335098	------------
$E_{nonideal}$	------------	------------	6284417	6284417	5137890	------------
Q_{ideal}	------------	------------	13	13	67	------------
$Q_{nonideal}$	------------	------------	913	237	237	------------
Dis_E	------------	------------	2350143	1949319	802792	------------
Dis_Q	------------	------------	900	224	170	------------
Continue ?	------------	------------	Yes	Yes	Yes	------------
Bus 1	None	2F, 2S 4H, 3N, 2L	None	None	None	None
Bus 2	None	1F, 2S 3H, 1N, 1L	None	None	None	None
Bus 3	None	1F, 0S 1H, 1N, 1L	None	None	None	None
Bus 4	None	1F, 0S 1H, 1N, 1L	None	None	None	None
Bus 5	None	1F, 0S 1H, 1N, 1L	None	0F, 5S 5H, 0N, 0L	3F, 0S 3H, 3N, 3L	None
Bus 6	None	1F, 4S 5H, 1N, 1L	3F, 1S 4H, 3N, 3L	None	3F, 0S 2H, 0N, 3L	None
Bus 7	None	2F, 4S 6H, 2N, 3L	None	3F, 3S 6H, 4N, 3L	0F, 5S 4H, 5N, 0L	0F, 6S 6H, 4N, 0L
Bus 8	None	1F, 2S 1H, 3N, 1L	None	None	0F, 4S 4H, 0N, 0L	None
Bus 9	None	2F, 4S 2H, 6N, 4L	0F, 5S 5H, 4N, 0L	0F, 4S 4H, 1N, 0L	0F, 5S 5H, 1N, 0L	3F, 2S 5H, 3N, 3L
Bus 10	None	1F, 5S 6H, 1N, 1L	None	3F, 3S 6H, 3N, 3L	4F, 0S 4H, 4N, 4L	2F, 4S 6H, 2N, 3L
Bus 11	None	2F, 3S 5H, 3N, 2L	5F, 0S 5H, 5N, 5L	None	0F, 4S 4H, 0N, 1L	0F, 6S 6H, 1N, 0L
Bus 12	None	2F, 3S 5H, 3N, 2L	None	5F, 1S 6H, 6N, 5L	5F, 1S 5H, 6N, 5L	5F, 1S 5H, 6N, 5L

6. Conclusion

A new bi-objective formulation for the general capacitor placement and sizing problem has been successfully applied. The objectives include both concerns of economics and quality. To get a more realistic solution, the load, operating, and expansion constraints of the system, together with the fixed and switched types of capacitors are considered. The IBC method for solving general bi-objective optimization problems has been presented and tested on a real system. The results show that the proposed methodology can find a flexible best-compromise solution to be dictated by the DMs of the utilities.

7. Acknowledgment

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