Optimal Placement of Power Factor Correction Capacitors Using a Discrete Teaching Learning Based Optimization

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Abstract: - Energy saving is one of the major concerns of the utility engineers. One problem leading to excessive power consumption is the system bad power factor. A low power factor implies a rise in the current drawn from the transformers which leads to an excessive electricity bill and serious problems on the transformer loading. To deal with this problem, many techniques have been proposed. These include the reactive power compensation and the placement of corrective capacitor banks. This paper contrasts two techniques to place capacitors in a distribution system. The first uses the Teaching Learning Based Optimization (TLBO) to solve the optimal capacitor placement problem in electric distribution systems. The second uses ETAP software and its integrated tool of optimally placing power factor correction capacitors. To demonstrate the efficacy and compare these methods, they were applied to conventional bus systems and simulation results of the two methods are illustrated.

Key-Words: - Power factor correction, Teaching Learning based Optimization, method, optimization, capacitor placement, energy saving, energy management, smart grids.

1 Introduction

Electric distribution systems are becoming large and complex causing the reactive currents to produce losses reaching up to 20% the total power generated [1]. Reduction of losses is more economical than increasing generation. Practically, losses can be reduced by connecting capacitors in shunt to locally supply a considerable portion of the reactive power demanded by the consumers and thereby reducing the reactive component of branch currents [2]. The advantages with the addition of shunt capacitors banks are to improve the power factor, feeder voltage profile, power loss reduction and increases available capacity of feeders. These advantages depend on the location, size, type and number of the capacitors as well as on their control settings.

Conventionally, there are two strategies to deal with the problem of capacitor placement for reactive power compensation. Either a bank of capacitors is placed at each power system bus or simply placing a bank of capacitors at the mains to enhance the overall system power factor. The effectiveness of either strategy depends on the criticality of the system. Indeed, the first strategy is not economically wise but allows the control of the individual reactive powers at each bus. The second strategy is cheap but no control on the individual bus reactive power levels is possible.

To compromise between the two philosophies, a question would rise: how can capacitors be selectively placed and controlled under some loading conditions. This means that the capacitor placement problem transforms to an optimization problem and should be formulated with some desired objective function (such as loss minimization) and various technical constraints (e.g. the limits of voltage levels and power flow) [3]. The adequate solution techniques should be applied to simultaneously determine the optimal number, location, type, size and control settings at different load levels of the capacitors to be installed [4-5]. Because capacitor sizes and locations are discrete variables, the capacitor placement problem has a combinatorial nature. The problem is a binary decision making problem with discrete steps of standard bank size of capacitors.

Different optimization techniques and algorithms have been proposed in literature [6]. Analytical methods based on impractical assumptions like constant conduction size, uniform loading, non discrete capacitor sizes, equal capacitor sizes and constant capacitor locations have been used. Earlier works on capacitor placement are mainly developed in [7]. The cost of capacitors and the changes at the node voltages were neglected.

Later, a voltage independent reactive current model was formulated and solved in [8-10] where the fixed and switched capacitors were placed to optimize the net monetary savings associated with the reduction of power and energy losses. In [11], a voltage dependent methodology for shunt capacitor compensation of primary distribution feeders was proposed. The author of [12] proposed analytical method to optimize number, location and size of capacitors. The authors in [13-14] formulated equivalent normalized feeders which considered feeder sections of different conductor sizes and non- uniformly distributed loads.

In [15], Duran used discrete capacitors for a feeder with many sections of different wire sizes and concentrated loads and proposed a dynamic programming solution method. The authors in [16] considered load growth as well as system capacity release and voltage rise at light load conditions and used a local optimization technique called the method of local variables by treating capacitor sizes as discrete variables. Baran and Wu in [17] determined the optimal size of capacitors placed on the nodes of a radial distribution system and minimize the power losses for a given load by nonlinear programming using decomposition technique. Integer quadratic programming was used in [18] to coordinate the optimal operation of capacitors and regulators in a distribution system. Khodr in [19] proposed a mixed integer programming for the optimal location and sizing of static and switched shunt capacitors in radial distribution systems. In [20], the authors combined capacitor placement and voltage regulator problems for a general distribution system and proposed a decoupled solution methodology.

The works based on heuristic algorithms have been reported but are not guaranteed to be optimal. Salam et.al. in [21] presented a heuristic strategy with varying load to reduce system losses by identifying sensitive nodes at which capacitors should be placed. In [22], Haque proposed a method of minimizing the loss associated with the reactive component of branch currents by placing optimal capacitors at proper locations. Hamada et al. in [23] introduced a new strategy for capacitor allocation handling the reduction in the section losses by adding a new voltage violation constraint. Genetic programming has been used to deal wth the optimal placement of capacitors. In [24], the authors used genetic algorithm for obtaining the optimum values of shunt capacitor bank. In [25], the authors proposed an optimization method using genetic algorithm to determine the optimal selection of capacitors. An improved adaptive genetic algorithm (IAGA) is developed in [26] to optimize capacitor switching, and a simplified branch exchange algorithm is developed to find the optimal network structure for each genetic instance at each iteration of capacitor optimization algorithm. Jalilzadeh et al.in [27] proposed a genetic algorithm as search method to determine optimum value of injected reactive power while considering the effects of loads harmonic component on network.

A two-stage artificial neural network has been used to control the capacitors installed on a distribution system for a non-uniform load profile in [28]. Gu et.al. in [29] controlled both capacitor banks and voltage regulators using artificial neural network. Chiang et al. in [30] used the optimization techniques based on simulated annealing (SA) to search the global optimum solution to the capacitor placement problem. In [31], Prakash and Sydulu presented a novel approach that determines the optimal location and size of capacitors on radial distribution systems to improve voltage profile and reduce the active power loss.

Bouri et al. in [32] presented an ant colony approach optimization to shunt capacitor placement on distribution systems under capacitor switching constraints. In [33], a method employing the ant colony search algorithm (ACSA) is proposed to solve the capacitor placement problems. De Lacerda and Medeiros, [34] minimized the total active losses in electrical distribution systems by means of optimal capacitor bank placement.

Recently, the teaching learning based optimization (TLBO) technique proposed in [35-38] and has been used successfully in a number of N-P optimization problems. The TLBO described in the previous references does not have a binary version that is able to optimize binary problems. A binary teaching learning based optimization (BTLBO) based method for solving the capacitor optimal size and placement is proposed here. Various examples (different bus systems) and simulation results of the applied technique are shown and discussed.

2 Problem Formulation

The majority of power systems operate at a lagging power factor due to inductive loads and delivery but excessive power systems are inductive in nature and require additional reactive power flow from the power grid. The excessive reactive power demands

result in reduced system capacity, increased losses and decreased voltages as well as higher operating costs.
The main constraints for capacitor placement are: To ensure that all voltage magnitudes of load (PQ) buses should be within the limits andto ensure that power factor (PF) should be greater than a threshold. It may be a maximum power factor limit.
Shunt capacitor banks may be used to compensate VAR requirement but their size, location and cost are important issues that need to be optimized during the design phase. The optimal capacitor placement (OCP) module provided by ETAP is an ideal solution to weigh all these factors. The OCP module allows you to place capacitor for voltage support and power factor correction while minimizing total cost.
Clicking the optimal placement icon launches the OCP calculation. First, all required data must have been entered into the device and study case pages prior to running an optimal capacitor placement calculations, otherwise, an error report will list the problems encountered.
To be able to compare the results, the optimization problem to be solved using the BTLBO has to be similar to the one handled in ETAP. Two main objective functions are used:

2.1 Loss reduction

The problem is defined as:

Minimize $L_t = \sum_{i=1}^{n} L_i$

Where:
L_t: the total losses.
n: is the number of lines.
L_i: is the active losses in line i.

$$L_i = \frac{R_i(\sum P_i^2 + \sum Q_i^2)}{V_i^2} \tag{1}$$

Where:
R_i = resistance of the line i.
Σ P²,i = the square of active power summation of the downstream system from node i (W).
Σ Q²,i = the square of reactive power summation of the downstream System from node i (VAr).
Vi = voltage at node i (Volts).

2.2 Cost reduction

The formal definition of our problem is as follows:
Given two sets, c ("capacitors") and L ("buses locations"), of equal size, together with a weight function w : P × P → R and a distance function d : L × L → R. Find the bijection f: P → L ("assignment") such that the cost function:

$$\sum_{a,b\in P} w(a,b) \times d(f(a), f(b)) \tag{2}$$

is minimized , the losses are decreased and the power factor is enhanced. The function W will be the flow (the voltage between capacitors).

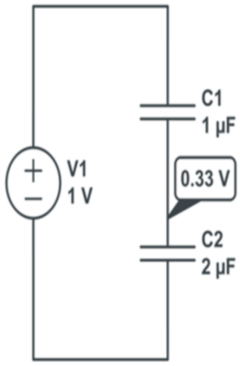


Fig. 1 Illustration of the potential between two capacitors

The voltage in the middle point will be:

$$V_X = \frac{C_1}{C_1 + C_2} V_1 \tag{3}$$

3 The Teaching Learning Based Optimization

3.1 Mechanism of TLBO

Most of the metaheuristic methods are inspired from nature i.e. they mimic the behavior of nature. For example in Genetic Algorithm inspired from Darwin’s theory, the fittest is the one who survive, Particle swarm is inspired from the movement of a flock of bird, a school of fish, or a swarm of bees that are looking for food, Artificial Bee Colony (ABC) simulates the intelligent forging of honey bee swarm, Ant colony shows how ants search for food and how to find an optimal way to it,…etc. The improper tuning of algorithm specific parameters either increases the computational effort or yields the local optimal solution. Considering these facts, Rao et al. in [35-38] recently introduced the Teaching-Learning Based Optimization (TLBO) algorithm which does not require any specific parameters. In this way, TLBO obtain global solutions for continuous nonlinear functions with less computational efforts and high consistency.
TLBO is a teaching-learning process inspired algorithm based on the effect of influence of a teacher on the output of learners in a class. Teacher and learners are the two vital components of the

algorithm and describes two basic modes of the learning, through teacher (known as teacher phase) and interacting with the other learners (known as learner phase). The output in TLBO algorithm is considered in terms of results or grades of the learners which depend on the quality of teacher. So, teacher is usually considered as a highly learned person who trains learners so that they can have better results in terms of their marks or grades. Moreover, learners also learn from the interaction among themselves which also helps in improving their results.

TLBO is population based method. In this optimization algorithm, a group of learners is considered as population and different design variables are considered as different subjects offered to the learners and learners' result is analogous to the 'fitness' value of the optimization problem. In the entire population the best solution is considered as the teacher. The working of TLBO is divided into two parts, 'Teacher phase' and 'Learner phase'. Working of both the phases is explained below.

Teacher phase: in this phase the best student is chosen from the population (the class) according to the fitness function and set as a teacher. Since the teacher is the highest learned person in the class, he puts effort to disseminate knowledge among students so that he tries to bring the mean level of the class up to his level, the new mean of the class depends on two things:

- The ability of the teacher i.e. his method in teaching is good or bad and this is represented by a factor t_f called "teaching factor", it can be 1 or 2 (those values are concluded from experiments).
- The ability of the student to receive and understand concepts from his teacher.

Learner phase: as known, when a student does not understand his teacher or he wants to have more knowledge, he will interact with one of their fellow students. If he finds his friend better than himself he will learn from him otherwise he will not.

3.2 Implementation of TLBO Algorithm for optimization

TLBO can be implemented in five steps:

Step1: formulate the optimization problem, the objective function and the side constraints:

Minimize (objective function)

$y = f(x_1, x_2, \dots, x_{n-1}, x_n)$

such that: $x_j^{min} \le x_j \le x_j^{max}$

Where j=1, 2, 3,……,D those are the side constraint which specify the limit of each design variable i.e. the maximum and minimum level in each course of any student.

The variables $x_1, x_2, \dots, x_{n-1}, x_n$ represent the level of student **X** in each course so x_1 is the level of **X** in the first course.

Decide how many student you will use or the population size, also the number of generation. Here a minimization problem is considered; the maximization is similar.

Step 2: initialization: suggest a population (that will be developed to reach the final solution) or students randomly according to the following equation:

$$x^1_{(i,j)} = x_j^{\min} + rand(i,j) \times (x_j^{\max} - x_j^{\min}) \quad (4)$$

i: refer to student number, so this is the ith student, *i*=1, 2, …,P

j: refer to the course number, $x_{(i,j)}$ is the level of the ith student at the jth course, *j*=1, 2,…,D

The small number 1 refer to the generation number, it's the first generation.

After manipulating the above equation $P \times D$ times, a $P \times D$ matrix which represents the population is obtained:

$$population^1 = \begin{bmatrix} x^1_{(1,1)} & \cdots & x^1_{(1,D)} \\ x^1_{(2,1)} & \ddots & x^1_{(2,D)} \\ \vdots & \ddots & \vdots \\ x^1_{(P,1)} & \cdots\theta & x^1_{(P,D)} \end{bmatrix} \quad (5)$$

So $X_1^1 = (x^1_{(1,1)}, \quad x^1_{(1,2)}, \dots, x^1_{(1,D)})$ is student number 1 in the first generation.

Choose the teacher: the best student is the one which has the minimum fitness function.

Step 3: teacher phase

Calculate the mean in each column in the population matrix:

$$mean^g = \begin{bmatrix} mean(x^g_{(1,1)}, x^g_{(2,1)}, \dots, x^g_{(P,1)}) \\ mean(x^g_{(1,2)}, x^g_{(2,2)}, \dots, x^g_{(P,2)}) \\ \vdots \\ \vdots \\ mean(x^g_{(1,D-1)}, x^g_{(2,D-1)}, \dots, x^g_{(P,D)}) \\ mean(x^g_{(1,D)}, x^g_{(2,D)}, \dots, x^g_{(P,D)}) \end{bmatrix} \quad (6)$$

Mathematically, how the best student teaches the others:

$$X_{i,new} = X_i + (X_{teacher} - t_f \times mean)$$

t_f is the teaching factor, it can be 0 or 1.

A comparison between the new student $X_{i,new}$ and the old one X_i should be made, if $X_{i,new}$ is better than X_i, replace the old by the new one otherwise keep the old one.

$$if\ f(X_{i,new}) < f(X_i) \text{ then } X_i = X_{i,new}$$

$$else \text{ do nothing; } i = 1...P$$

Step 4: learner phase

This phase shows the interaction between students. For each student i we pick another student j randomly and compare their level (fitness function), the first student i will learn from the second j (get close to him) if he is better than him otherwise he will go far from him, according to the formula:

$$X^g_{i,new} = \begin{cases} X_i + rand^g_i \times (X^g_j - X^g_i) & \text{if } f(X^g_i) < f(X^g_j) \\ X_i + rand^g_i \times (X^g_i - X^g_j) & \text{if } f(X^g_i) \geq f(X^g_j) \end{cases}$$

After completing the process for all the population, the fittest student is set as teacher.

Step 5: if $g \neq numberofgeneration$ go to step 3 else stop.

3.3 The discrete TLBO (DTLBO) algorithm

The capacitor placement is a combinatorial (discrete) problem where the capacitances can take discrete values and their locations are discrete, too. The TLBO does not have a discrete version since it is a new method. The difficulty is how to change the equations to be valid for vectors of discrete numbers. In the coming algorithm, the proposed changes on the TLBO explained in the previous section with emphasis on the capacitor placement problem are presented:

Step 0: define the optimization problem, the objective function:

Minimize (objective function) $y = f(x_1, x_2, \dots, x_{n-1}, x_n)$ such that: $x_1, x_2, \dots, x_{n-1}, x_n$ can take only discrete values that are the capacitor values and their locations. The solution vector is made up of two parts: the capacitances and the locations in a respective manner. Decide how many students will be used or the population size, elite size and the number of generation. This is generally done based on trial and error or by benchmarking to other techniques such as Genetic algorithms or Particle Swarm Optimization

Step 1: initialization: generate a population or students randomly. Choose the teacher: the best student is the one which has the minimum fitness function.

Step 2: teacher phase

As in the real-valued version, each student tries to be look like his teacher. So, he makes his design variables as those of the teacher. The student copies some components of teacher (capacitances and locations) and replaces his components by those copied ones. The number of copied components depends on the ability of teacher and the student. This is represented by one random number *h* that is set between 0 and D. The corresponding formula is:

$$h = randi(D, 1) \qquad (9)$$

This number determines how many courses that student *i* will learn from his teacher.

The location of those courses in the teacher vector can be specified according to the equation below:

$$Course = randi(h, [1, h]) \qquad (10)$$

These randomly selected courses are now ready to be transmitted from teacher to student:

$$\begin{aligned} &X_{i,new} = X_i \\ &X_{i,new}(course) = X_{teacher}(course) \\ &if\ f(X_{i,new}) < f(X_i) \text{ then } X_i = X_{i,new} \text{ else do nothing} \end{aligned} \qquad (11)$$

Executing (11) may produce duplicate solutions, therefore an additional step is needed.

Step 3: remove duplicate solutions by mutation on randomly selected dimensions. This is similar to the genetic algorithm mutation operator where some locations and capacitances are altered if the generated random number exceeds some preset value.

Step 4: learner phase

The interaction between students will be as follows: choose for a student i another one j, if j is better than i then i will learn from j by trying to change components that are different from those of j, in order to be like him; otherwise he will change some components that are similar to those of j. This can be done as follows:

$For\ i = 1{:}P\ do$

Choose another student j and record where they are similar and where they are different in a vector

$q = [q_1\ q_2\ \dots\ q_D]$ such that $q_k = 1\ if\ x^g_{i,k} = x^g_{j,k}$ else $q_k = 0;\ \ k = 1, \dots, D$

The vector $h = randi(D, 1)$ specifies how many courses will student i learn from j if he is better than him or change them in other case.

The vector $course = randi(h, [1, h])$ specifies the location of courses which will be learnt or changed.

Now the learning process can be implemented:

$X_{i,new} = X_i$ The new student is the old with some modifications.

$$\begin{aligned} &if\ f(X^g_i) < f(X^g_j) \text{ then } X_{i,new}(course) = X_j(course) \times not(q(course)) \\ &else\ if\ f(X^g_i) \geq f(X^g_j) \text{ then } X_{i,new}(course) = not(X_j(course)) \times q(course) \end{aligned} \qquad (12)$$

(12) Indicates that some components where i and j differs will be copied from j (the highest learned one between the two) to i otherwise (j is worse than i) some of similar component in i will be changed within the discrete range. Now, check if the new student is better than the old:

$$if\ f(X_{i,new}) < f(X_i) \text{ then } X_i = X_{i,new} \text{ else do nothing} \quad (13)$$

After completing the process for all the population, a new teacher will be determined.

Step 5:-Remove duplicate solutions.

-replace bad solutions by elite solutions and again remove duplicate solutions.

Step 6: if $g \neq number\ of\ generation$ go to *step 2 else stop.*

4 Simulation results and discussion

4.1 Using ETAP software

The IEEE 14-bus system (Fig. 2) is implemented on ETAP and the following parameters are chosen:

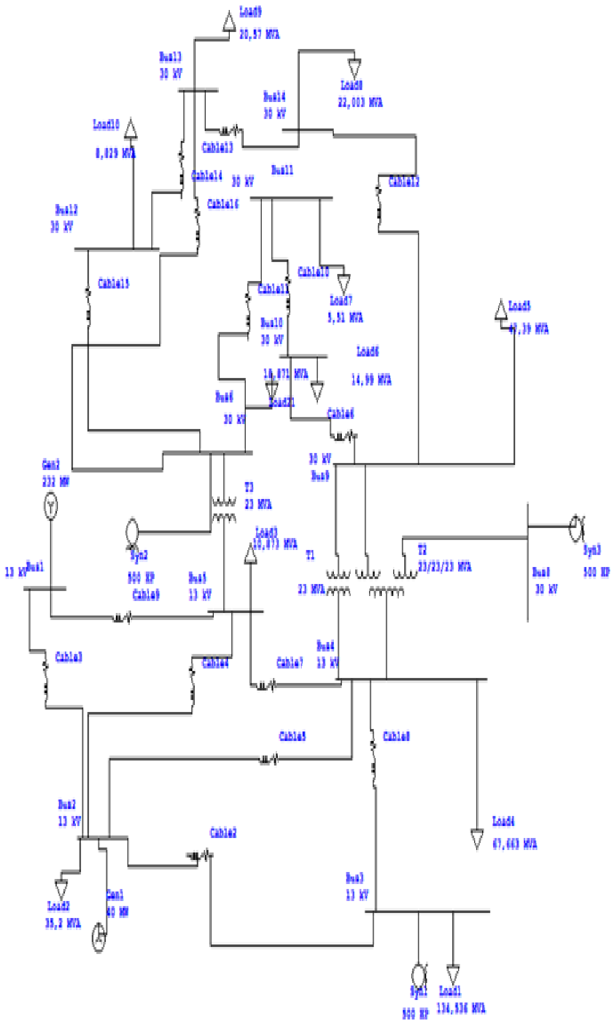


Fig.2 The IEEE 14-bus system

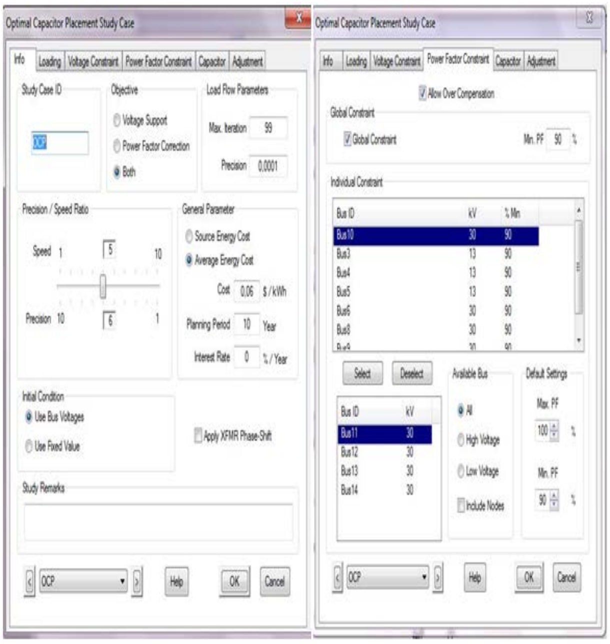


Fig. 3 study case parameters of the OCP of IEEE 14-bus system

Notice that the power factor is selected to be at least 90 %. After we move to select the chosen busses to place the capacitors in (the candidate buses) and specify the characteristics of these capacitors (max voltage, bank size and their cost).

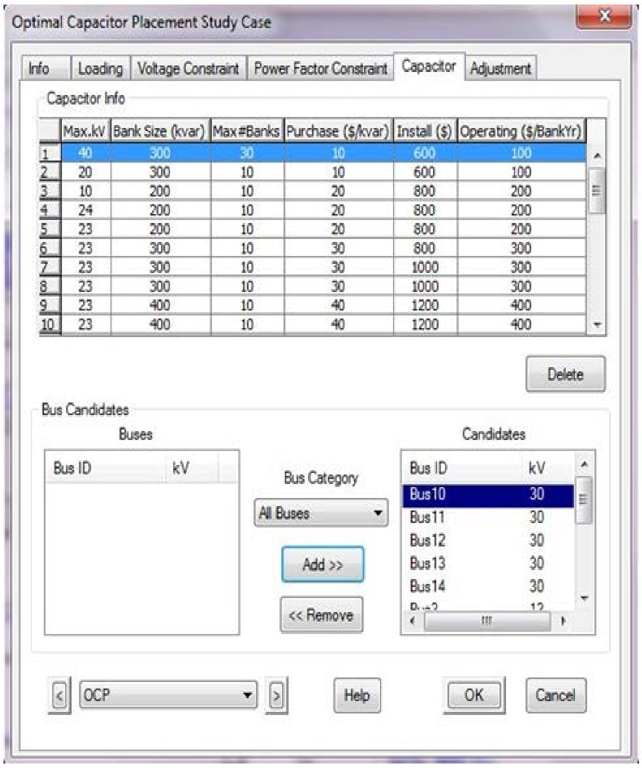
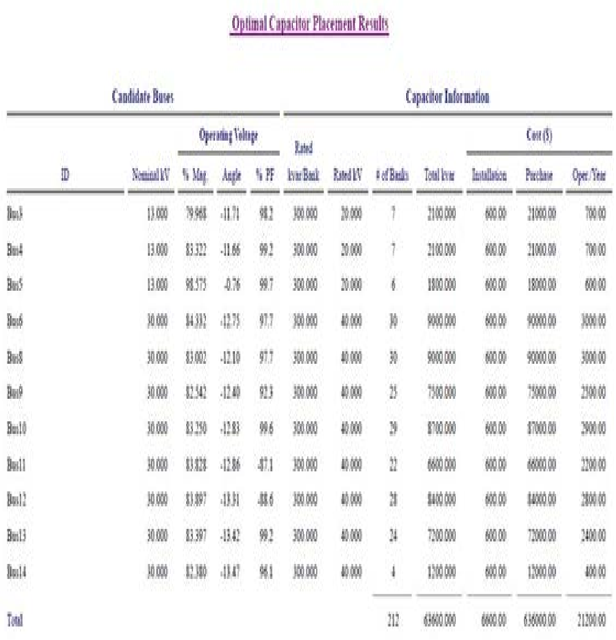


Fig. 4 capacitors parameters and bus candidates of the OCP of IEEE 14-bus system

Results

When the optimal capacitor placement tool is executed, the following results are obtained:



Optimal Capacitor Placement Results

Candidate Buses					Capacitor Information						
		Operating Voltage			Rated				Cost ($)		
ID	Nominal kV	% Mag.	Angle	% PF	kvar/Bank	Rated kV	# of Banks	Total kvar	Installation	Purchase	Oper./Year
Bus3	13.000	79.968	-11.71	98.2	300.000	20.000	7	2100.000	600.00	21000.00	700.00
Bus4	13.000	83.322	-11.66	99.2	300.000	20.000	7	2100.000	600.00	21000.00	700.00
Bus5	13.000	98.575	-0.76	99.7	300.000	20.000	6	1800.000	600.00	18000.00	600.00
Bus6	30.000	84.332	-12.75	97.7	300.000	40.000	30	9000.000	600.00	90000.00	3000.00
Bus8	30.000	83.002	-12.10	97.7	300.000	40.000	30	9000.000	600.00	90000.00	3000.00
Bus9	30.000	82.542	-12.40	92.3	300.000	40.000	25	7500.000	600.00	75000.00	2500.00
Bus10	30.000	83.250	-12.83	99.6	300.000	40.000	29	8700.000	600.00	87000.00	2900.00
Bus11	30.000	83.828	-12.86	-87.1	300.000	40.000	22	6600.000	600.00	66000.00	2200.00
Bus12	30.000	83.897	-13.31	-88.6	300.000	40.000	28	8400.000	600.00	84000.00	2800.00
Bus13	30.000	83.397	-13.42	99.2	300.000	40.000	24	7200.000	600.00	72000.00	2400.00
Bus14	30.000	82.380	-13.47	96.1	300.000	40.000	4	1200.000	600.00	12000.00	400.00
Total							212	63600.000	6600.00	636000.00	21200.00

Fig. 5 the optimal capacitor placement results of IEEE 14-bus system

The OCP method installed 3 more capacitor banks at 13 kV buses and 8 more capacitor banks at 30 kV buses. Due to the additional capacitors, OCP results show $63600 more one-time purchase cost, and $21200 more operating cost each year; however a system loss reduction is achieved.

4.2 TLBO-based placement

As for the DTLBO algorithm, the following system parameters are set out. These are taken from the IEEE standards.

4.2.1 Bus locations:

These are represented by these two vector matrices:
x= [67 80 62 34 54 22 36 90 95 15 40 23 75 46];
y= [9 81 9 43 89 55 63 42 58 95 64 51 52 58];
Bus 1, For example, has coordinates that are x=67 and y=9

4.2.2 The voltage between any two capacitors:

This information is summarized in table 1:

Table 1 the flow between capacitors in 14-bus system

	C1	C2	C3	C4	C5	C6
C1	0	6	6	3	5	5
C2	6	0	6	4	-10	3
C3	6	6	0	4	5	8
C4	3	4	4	0	4	4
C5	5	-10	5	4	0	3
C6	5	3	8	4	3	0

4.2.3 The optimal capacitor placement

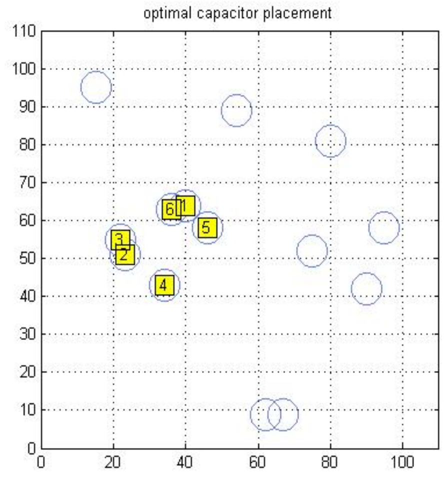


Fig. 6 the optimal capacitor placement of a 14-bus system

Figure 6 shows the ideal placement of the used capacitors performed by DTLBO algorithm for obtaining the best solution. In all cases simulated, the solution was found with 500 iterations. The figure shows the positioning of capacitors C3, C2, C4, C6, C1 and C5 on buses 6, 12,4,7,11,14 respectively. It should be noted that the cost values tend to converge after around 42 iterations to a best cost = 778.1096.

4.3 Comparison of the results

The results presented in Figures 5 and 6 seem different. They are similar indeed. The ETAP tool provides more specifications of the problem to be set up. The DTLBO problem, on the other hand, is difficult to specify as the more constraints and values are mentioned, the slower the convergence is besides the issue of not guaranteeing the convergence. To cure this problem, we have attempted to set as much as possible the same specifications. It turns out that the results in both cases are similar for the same IEEE-bus system. In fact, six capacitors re needed to be placed to reach a power factor within a value 0.9 as specified in both methods. The only difference lies in the fact that in the DTLBO, the set of candidate buses has to be chosen carefully as some choices might lead results that are impractical to be implemented in real life. It should be noted that a extensive work using larger IEEE bus systems has been conducted. Yet, the tough task was to model them in ETAP and the execution time of the DTLBO.

5 Conclusion

In this paper, a Teaching Learning Based Optimization approach has been used to determine optimal placement of capacitors. The state of art TLBO algorithm cannot handle the discrete nature of the problem at hand. We have proposed a modification on the TLBO mechanism such that it can handle the discrete values of both the capacitor values and their locations.

The placement using ETAP or DTLBO produced the following outcomes:

- Optimum value of the capacitor required is determined.
- The algorithm finds out the proper location of the capacitor.
- The results are encouraging with reference to the improvement in power factor and voltage, thereby increasing the feeder capacity.
- Maximum benefits are obtained by selecting the optimum size of the capacitor and by locating the capacitors as near the inductive reactance kVAR loads as possible.

The results presented here can be improved by considering the power factor correction using renewable energy systems. The idea is to exploit the power electronics tools such as the three phase PWM inverter available within the grid connected renewable energy system to compensate for the reactive power available in the grid. Another strategy is to minimize or completely compensate the harmonics so that the total harmonic distortion is reduced and hence the power factor is improved.

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