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Optimal Switching Capacitor Placement Model for Unbalanced Loading Problem using Extreme Learning Machine

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Abstract-This paper deals with the design of unbalanced power loading problem in a power distributed systems and optimal switching capacitor placement based on Extreme Learning Machine. The recent studies reveal that the problem of optimal switching capacitors placement have been solved through various non-traditional optimization techniques, which are less accurate and time consuming. In this paper, we introduce Extreme Learning Machine (ELM) concept to design and implement an intelligent, automated ELM based switchable capacitor placement control unit. This control unit will periodically get the input from the feeders along with the other inputs called the power loss index and voltage. Based on the power flow (unbalanced) and other calculations, this control unit will automatically determine the candidate sites and size of the capacitors to activate switchable capacitors dynamically. For quick decision making, the centralized control unit requires less computational time to evolve the site and size of the capacitors and it is achieved through ELM, because its computational time is comparatively less than other methods. Finally, the results are compared using a standard 70-bus test system with other models, with respect to the capacitor placement on the networks, savings and the computational time. It is finally proved that the proposed model performs better than other models.

Keywords: Optimal Capacitor Placement, Fuzzy Logic, Artificial Neural Networks (ANN), Particle Swarm Optimization, Fuzzy Expert Systems, Optimal power flow.

I. INTRODUCTION

The design of fixed capacitor bank in a power distributed system is not applicable always because the determination of the instantaneous, peak, and average power factor vary greatly. Consequently, target power factor may be much different than the 'typical' power factor during peak or off-peak loading periods in a normal situation. In many of the situations, the power systems recorded the variable loading throughout the day, especially in commercial and industrial areas. These areas require peak loads during the day and considerably lower overnight, but in heavy industries loads are consistent during 'normal' operation but vary largely through various stages of the process. Because of this variability in loading, switched capacitors are often required to minimize power factor penalties, to regulate voltage, and to minimize system loading. Still, it is very difficult to beat the cost and simplicity of applying a fixed capacitor bank.

The main advantage of a switchable capacitor bank is that it automatically selects as much as required kVar capacitors at any point of time. Switched capacitor banks have an electronic controller that senses the system power factor (measuring system voltage within the capacitor bank and system current via an external CT or CTs) and regulates the number of steps or stages that are energized. The controller is programmed to raise the system power factor to a "target" power factor. LV capacitors often have more stages/steps than MV systems. MV switched capacitors require significant additional cost per switched stage because of the required switching devices (contactors) and physical space for the switching components. One method of achieving multiple step variability without having multiple switching devices is to use different size switching steps. For example, if the load varies greatly and 1500 kVar of MV capacitors is required; one can use 1 × 300 and 2 × 600 kVar stages. This would allow steps of 300, 600, 900, 1200, and 1500 kVar with three switching devices instead of five.

A high percentage of switched capacitor banks are switched with mechanical contactors. These contactors are relatively inexpensive and are simply used as a switch. The control algorithm switches steps in and out in order to maintain a set power factor. It does not switch in steps as soon as the power factor falls below a certain level nor does it switch out banks as soon as the power factor rises above a certain level.

The importance of control unit algorithm is to activate the respective capacitor with respect to the places and sizes depending on the input. The conventional control algorithm takes much time to decide the place and size and hence we require a very sophisticated control unit (Benemar Alencar de Souza etal. (2004), Ng et al., (2000), Gasbaoui,B., etal.(2010), Ivo Chaves da Silva, Jr., etal. (2008), Shirrang Karankikar, & Ashok Ghatol (2008), Srinivasa rao,R (2010)). Biswarup Das et al., (2001) proposed an ANN based optimal capacitor switching in a distributed system and proved that ANN performs 100 times better than the conventional method. A conventional particle swarm optimization proposed by Lee et al., (2008), found an optimal solution in an unbalanced loading distribution systems. Auchariyamet et al.,(2008) proposed an Adaptive Particle Swarm Technique to search for an optimal or near-optimal solution using unbalanced loading distribution systems with the presence of non-linearity loads.

This paper is organized as follows. The reactive compensation problem and its mathematical background are formulated in section II. Section III elucidates the proposed solution method with a brief explanation of ELM. In Section IV, the proposed method is evaluated using 70-bus test system and discussed with all system loads and finally the result is compared with other techniques. The conclusion is given in section-V.

II. MATHEMATICAL FORMULATION

The objective function of capacitor placements is to reduce the total energy losses and to maintain the bus voltage within the prescribed limits with minimum cost. The defined objective function has two parts, namely the cost of capacitor placement and the cost of total energy losses. The cost of capacitor placement includes the cost of capacitor, its installation and operational cost.

The objective function of the optimal capacitor placement is given below:

Minimize

$$F = K_{PL} P_L + \sum_{m=1}^{N} K_C(m)\, B(m) \tag{1}$$

subject to the constraints

$$V_{min}(i) \le V(i) \le V_{max}(i) \quad \text{for } i = 2, 3, 4, \ldots, N \tag{2}$$

where F = the total annual cost function defined in \$'s, K_{PL} = annual cost per unit of power losses (\$/kW) , P_L = total active power losses (kW), $K_C(m)$ = cost of capacitor placement (cost / kVAR), B(m) = shunt capacitor size placed at bus m (kVAR), N = total number of buses, $V_{min}(i)$ = minimum permissible rms voltage at bus i, and $V_{max}(i)$ = maximum permissible rms voltage at bus i.

Generally, the losses in the distribution line happen due to the following two factors. They are (i) Current flowing through the conductor, and (ii) The resistance in the line. The annual power losses can be estimated through the formula

$$P_L = 3\, I^2 . R . L . DF . LF .TPY \tag{3}$$

Where I = total current flowing through the line for single phase, R = resistance of the line, L = length of the line, DF = discounting factor, LF = load factor and TPY = total number of hours working per year.

Several researchers have developed the optimum sizes of the capacitor using various techniques like algebraic methods, linear programming, heuristic search, fuzzy expert systems, AI based techniques and so on. But in this paper, we have used the following optimization model for finding the size of the capacitor, and it is given below:

Maximize

$$S = K_P\, \Delta L_P + K_E \Delta L_E - K_C\, C \tag{4}$$

subject to the constraint

$$\Delta V \le \Delta V_{max} \tag{5}$$

where ΔL_P = the loss reduction in peak demand, ΔL_E = energy due to capacitor installation, K_P = cost of peak demand per kVAR, K_E = cost of energy per kVAR, K_c = cost of capacitor per kVAR, C is the size of the capacitor in kVAR, ΔV = the change in voltage due to capacitor installation, and ΔV_{max} = Maximum Voltage which cannot be exceeded.

III EXTREME LEARNING MACHINE (ELM)

The design of power flow problem in the distribution network is unbalanced system load and its load varies normally from 0% to 25% from time to time. To avoid various drawbacks of the fixed capacitor bank, we design an intelligent automated control system to determine the switchable and non switchable capacitor dynamically by using ELM.

The conventional methodology efficiently controls a static environment rather than a dynamic one with lots of errors in finding site, but ANN is addresses these problems to some extent and its performance is faster than the conventional method (Biswarup Das, & Pradeep Kumar Verma, (2001)). Generally, in the feedforward artificial neural network training scheme, all its weight vectors are tuned according to their actual input and output data sets, and it uses the optimized learning algorithm called back propagation / hybrid learning algorithms. Back propagation learning algorithm is used to optimize the neural network non-linearly and its learning algorithm depends on deepest-descent non-linear optimization technique. Back propagation learning algorithm is one of the most powerful feedforward neural network algorithms but at the same time, the notable drawbacks of these gradient descent based learning methods are generally slower due to improper learning steps and may converge to local minima. Again, it requires large number of epochs to obtain a better performance.

In this paper, we introduce ELM which is more effective in deciding the switchable capacitor very accurately with less computational time and is well suited for the dynamic environment. It is more efficient than ANN (Biswarup Das, & Pradeep Kumar Verma, 2001) and its performance analysis is given in table-3.

A. Introduction on ELM

In the recent past, Huang et al., (Huang,G.B., Zhu,Q.Y., Siew,C.K., Charatchandran,P., & Soundarajan,N., 2004; Huang,G.B., & Siew,C.K., 2004; Huang,G.B., & Siew,C.K., 2005) has proposed a new learning algorithm called the ELM and it is a single-hidden layered feedforward neural network (SLFNs). Hanang, G.B., et.al., (Huang,G.B., Zhu,Q.Y., Siew,C.K., Charatchandran,P., & Soundarajan,N., 2004) states that ELM may randomly choose and fix all the hidden node parameters and then analytically determine the output weights.

Once the weights of the SLFNs have been randomly assigned, and considered as a linear system, the output weights can be obtained analytically through a generalized inverse operation of the hidden layer output matrices. The activation function used in ELM is anyone of the non-linear activation functions used in neural network (sigmoid, hyperbolic function etc.,), radial basis function (Huang,G.B., & Siew,C.K., 2004; Huang,G.B., & Siew,C.K., 2005), complex activation function (Li,M.B., Huang,G.B., Saratchandran,P., & Sundarajan,N., 2005), and so on.

The proposed SLFN can have P hidden nodes and it can be approximated through the given N pairs of input / output values, namely, $(x_i, t_i) \in R^n$ x R^m with zero error, then we have

$$\sum_{i=1}^{P} \beta_i G(a_i, x_j, b_i) = t_j \quad \text{for } j = 1, 2, \ldots. P \tag{6}$$

where (a_i, b_i) is the parameter associated with i^{th} hidden node and β_I is the output weight linking the i^{th} hidden node to the output node. In this paper, we use non-linear activation function, called sigmoid function. That is,

$$(a_i, x_j, b_i) = \frac{1}{1+e^{-(-a_i \cdot x_j + b_i)}}.$$

Hence, equation (*) can be rewritten as

$$H\beta = T \tag{7}$$

Where#

$$H = \begin{bmatrix} G(a_1, x_1, b_1) & G(a_2, x_1, b_2) & \dots & G(a_P, x_1, b_P) \\ G(a_1, x_2, b_1) & G(a_2, x_2, b_2) & \dots & G(a_P, x_2, b_P) \\ & \vdots & & \\ G(a_1, x_N, b_1) & G(a_2, x_N, b_2) & \dots & G(a_P, x_N, b_P) \end{bmatrix} \tag{8}$$

$$\beta = [\beta_1^T, \beta_2^T, \dots, \beta_P^T]^T \text{ and, } T = [t_1^T, t_2^T, \dots, t_N^T]^T \tag{9}$$

While computing, $\hat{\beta} = H^{\#} T$ is used as the estimated value of β, where $H^{\#}$ is the Moore-Penrose (D.Serre, 2002) generalized inverse of the hidden layer output matrix H. The following is the formal ELM algorithm proposed by Huang et. al.,(Huang,G.B., Chen,L., & Siew,C.K., 2006).

B. ELM Algorithm

Given a training set of input / output values $(x_i, t_i) \in R^n \times R^m$, for i = 1, 2, …, N; the activation function $G(a_i, x_j, b_i) = \frac{1}{1+e^{-(a_i \cdot x_j + b_i)}}$ and the number of hidden nodes P.

Step (1): By using continuous sampling distribution, assign random hidden nodes by randomly generating parameters (a_i, b_i) for i = 1,2, …, N

Step (2): Compute the hidden layer output matrix H

Step (3): Compute the output weight $\hat{\beta}$, by using the relation $\hat{\beta} = H^{\#} T$

C. ELM Approach for Optimal Switching Capacitor Placement

The following is the procedure for finding the optimal switchable capacitor placement through automated centralized control unit.

1. The fuzzy variable, system load is linguistically divided into three types which are low, medium and high. The classification of the fuzzy linguistic rule is followed by the combination of both triangular and trapezoidal membership function as in fig.-1. In this paper, we assume that the variation of the system load is between 0% and 25%. The switchable capacitor patterns are derived from system load.

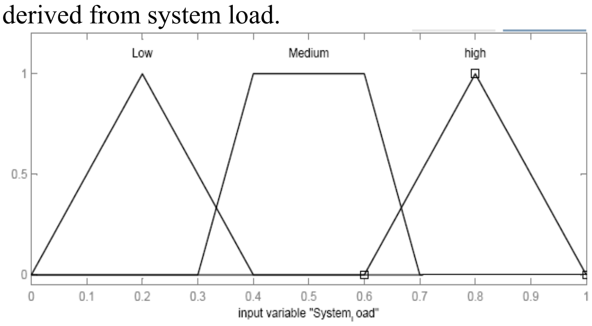

Fig.-1: Fuzzy Membership Function for input variable 'System Load'

2. The other two input variables are power loss index and the voltage. Again, initially the system load is normalized between 0 and 1 before feeding to ELM.
3. All the three input values are fed into ELM, which is available in the centralized control unit. The given ELM is a single layered feed forward network with three inputs and one output, called capacitor placement suitability. Then, ELM structure is to be trained with a set of training input / output data. The training data would be obtained from an optimal capacitor switching software package based on a conventional capacitor switching algorithm.
4. After training ELM, the control unit will find the optimal capacitor placement.
5. Once ELM is trained with sufficiently large number of training data set, the training will be stopped with error 1e-05.
6. Again, with the help of equations (4) & (5), it will also find the size of the capacitors.

Depending on the size of the capacitor evaluated by ELM algorithm, the control unit will activate the required amount of switchable capacitors to ON state and others to OFF state.

IV RESULTS AND DISCUSSION

The design of ELM-based optimal switching algorithm can be explained with a sample of 70-bus system and all its bus related data are given in (Gary Boone and Hsiao-Dong Chiang, 1993). The one-line diagram of the network is given in Fig.-2 and the data for this test system is given in Gary Boone and Hsiao-Dong Chiang, (Gary Boone and Hsiao-Dong Chiang, 1993). In the given 70-bus test system, there are 49 load points and in each point the real (kW) and reactive (kVar) loads are specified. Hence, there are 98 real and reactive loads available in the given test system. Depending on the load flow as defined in fig.-1, there are 31 locations identified to install capacitors with size of 200 kVar each. The identified locations are 7, 8, 9, 10, 11, 12, 13, 15, 17, 18, 19, 22, 25, 27, 28, 43, 45, 50, 51, 52, 55, 56, 60, 62, 63, 65, 66, 67, 68, 69, and 70. Thus, the designed ELM has 294 input nodes and 31 output nodes.

The power loss in the developed countries varies from 4% to 7% where as in the developing countries, this variation is between 20% to 51%, especially in India it is 31 % [18]. That is why, the role of automation is essential now-a-days for both static power load and unbalanced power load. The automation is required in static power load to maintain the voltage stability throughout the system. Again, Distribution Automation System (DAS) is beneficial in day-to-day operation and maintenance of distribution network. The other benefits of the distribution automation are: reduced technical and commercial losses, improved cash flow, lower electric service restoration time, reduction in equipment damage, better availability of system information, improved operational planning, remote load control and shedding, and enhanced power quality and reliability. Currently the scope of Power System Automation in India has been limited to SCADA system automation up to transmission level (Ahmed et al., 2010).

In countries like India, most of the times the load flow is varying drastically and hence fixed capacitor installation is not viable and hence we need to go for automation dynamically. Set up a centralized control unit and it will decide what are all the switchable capacitors, which will activate ON / OFF state with respect to the appropriate place? It is time now to design an effective, intelligent, soft computing technique based centralized control unit which will immediately decide the decision of the optimal place and sizable switchable capacitors with the help of ELM.

To train and test ELM, it is necessary to generate a sufficient number of input-output patterns in different loading conditions. The different loading conditions in the system are achieved by varying the kW and kVar loading the system within a certain range with respect to the base operating condition. For that purpose, derive a set of input-output patterns in different loading conditions and design a programming technique to simulate as many required as input-output data patterns for training and testing with respect to the different base operating conditions, namely, low, medium and high. The data set used for training is different from a data set used for testing.

For a thorough study of a system, we artificially fluctuate the system load on the basis of the random number generation. Then, we have to check how many instances per day the system load touches Low, medium and High. Then we have to find the **weight factor** of the system by using the formula,

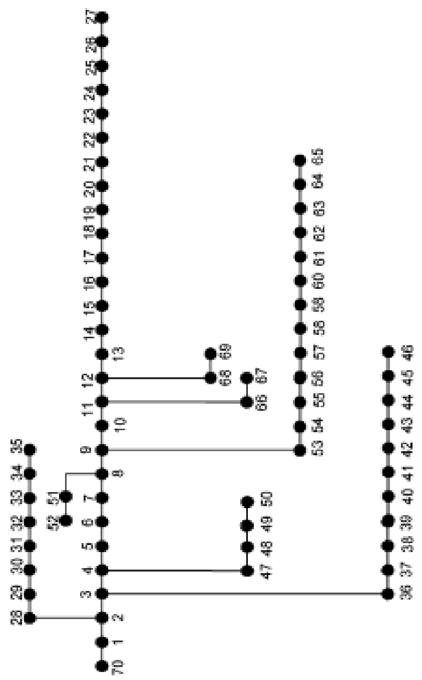

Fig.-2 : 12.66 kV, single line 70-Bus test system

Weight Factor of the System load Low = (Sum of the instants (Low) counted per day per period) / (Sum of all the instants counted per day per period).

Similar formula can be used to find the weight factor for medium and high load levels. The following is the ELM procedure to determine the ON-OFF state of switchable capacitor:

i. The centralized control unit contains ELM architecture and it dynamically accepts system loads and other input values through sensors. The designed ELM has 294 input nodes (power loss index, voltage and system load) and 31 output nodes. The given ELM is a Feed Forward Neural Networks with two hidden layers using sigmoidal activation function.
ii. For each system load flow (Low, Medium or High), large amount of generated input-output patterns are fed into the FEM algorithm and trained.
iii. The output of the trained FEM (called capacitor placement suitability) tells the exact position to install the capacitor.
iv. Then, apply capacitor size algorithm to find the size of each capacitor.
v. The information regarding the site and the size of the capacitors is sent to the respective candidate from the centralized control unit through the sensors.

Based on the output, we find that some of the site positions are mandatory for all type of system loads. For example, in the 70-bus test system, the capacitor installation at site number 22 is a must for all the methods with 200 kVar capacity, namely Heuristics Search, Particle Swarm Optimization, Fuzzy Expert systems (Ng et al., 2000), ANN, and ANFIS (Ravichandran et al., 2011).

Finally, we have achieved the following: (i). Based on the system load, the centralized control units activate the relevant switching capacitors to ON state and rest of the switching capacitors to OFF state, (ii). ELM training accuracy is maintained at 1e-05 error, and (iii). Stability of the voltages is maintained in the range of 0.968324 p.u to 1.002011 p.u after the capacitor installation. When compared to other methods, ELM maintains acceptable range of voltage stability throughout the system and its stability diagram is given in Fig.-3.

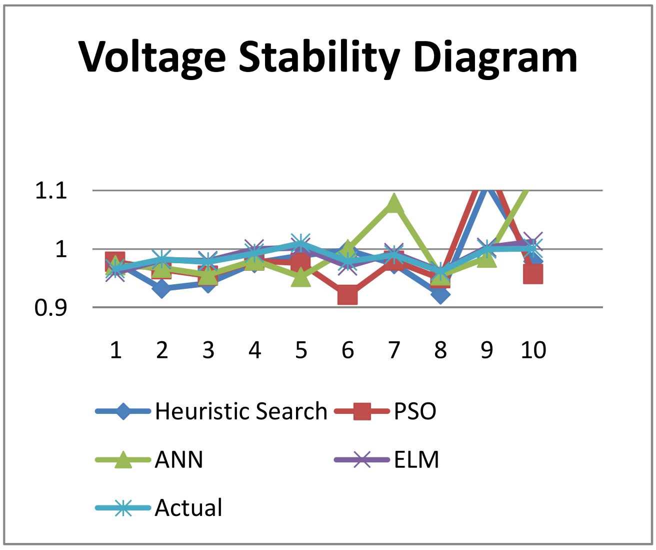

Fig.-3 : Voltage Stability Diagram (X: different instances, Y: Voltage Stability after Capacitor Installation)

For testing an ELM algorithm, simulate 1000 data set for each system flow. After testing ELM algorithm, it finds that the percentage of mismatch is roughly about 1.52. That is, out of 1000 input data patterns, totally there are 31000 output values. Therefore 1.52% of 31000 output values, namely 471 values are mismatched with the original data and the remaining 30529 values are exactly matched with the original data. The correlation coefficient between the testing data and the actual data is 0.999651. Again, comparing the computational time with ANN, it is 58 times faster than ANN and 158 times faster than the conventional methods.

Table 1: Analysis of the status of capacitors for the system level at a particular point of time

Site Number	Status – 1 (ON/OFF)	Status -2 (Switchable / Fixed)	Capacitor Size (kVar)
7	OFF	---	---
8	OFF	---	---
9	OFF	---	---
10	OFF	---	---
11	OFF	---	---
12	ON	Switchable	200
13	OFF	---	---
15	OFF	---	---
17	OFF	---	---
18	OFF	---	---
19	OFF	---	---
22	ON	Fixed	200
25	OFF	---	---
27	OFF	---	---
29	OFF	---	---
43	OFF	---	---
45	OFF	---	---
50	OFF	---	---
51	OFF	---	---
52	OFF	---	---
55	OFF	---	---
56	ON	Switchable	200
60	ON	Switchable	400
62	ON	Switchable	400
63	ON	Switchable	400
65	OFF	---	---
66	OFF	---	---
67	OFF	---	---
68	OFF	---	---
69	OFF	---	---
70	OFF	---	---

For example, the bus number 63 is at ON state when the system load is considered at any point of time and it is switchable mode. There are three switchable capacitors installed at the bus 63, whose sizes are 200 kVar.

Depending upon the requirement, two of the capacitors at bus 63 are in ON state and remaining are in OFF state. For example, if the system load is considered at a particular point of time, 400 kVar sized capacitors at site number 63 is required to be ON and the remaining 200 kVar are OFF. Hence, depending upon the requirement, at bus number 63, it may be switched to either 200kVar or 400 kVar or 600 kVar. The site positions vary from method to method, but in the proposed method, it minimizes the power loss as well as its savings is better when compared to other methods. The total power losses and cost savings with respect to the system load is given in Table-3. The power losses can be calculated as an average of all low, medium and high instants at any period of time as for as this methodology is concerned.

The optimal power flow before capacitor placement for all levels is given in table -2. The energy cost is assumed to be 0.06 US$ /kWh for all the levels and computation time can be calculated by using Pentium IV processor with 3.1 MHz.

Table-2: Total Losses before Capacitor Placements

Load Level	Losses (kW)	Cost of Losses (US$)
Low	173.44	10406.4
Medium	985.54	59132.4
High	1993.22	119593.2
	3132.20	189132.0

The performance chart of ANN, ANFIS and FELM with respect to percentage of accuracy is given in Fig.4 and it is analyzed through matlab:

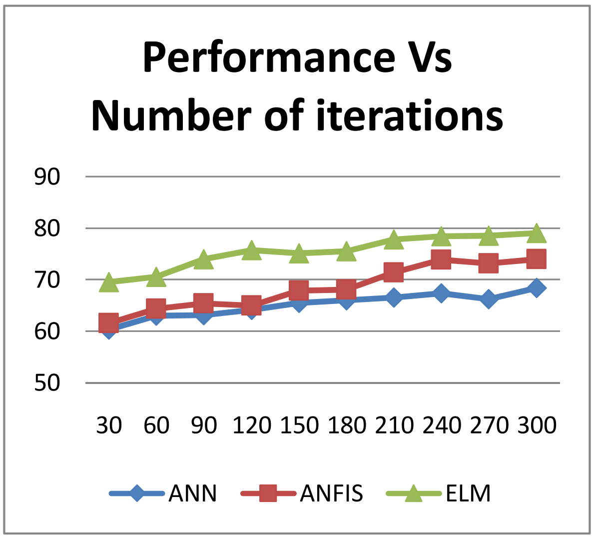

Fig.4 : Performance chart between the number of epochs and the percentage of accuracy attained

Table-3: Comparison and Analysis chart for the proposed method and other methods (Load Level: L –Low, M-Medium and H-High)

Method	Conventional Methods			Fuzzy Expert Systems			Heuristic Search Methods			Artificial Neural Networks (ANN)			Adaptive Neuro-Fuzzy Inference systems (ANFIS)			Particle Swarm Optimization (PSO)			Proposed Method		
Load Level	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H
Losses(kW)	152.31	824.42	1543.22	137.44	801.21	1388.91	131.65	788.66	1354.08	136.31	806.64	1399.11	128.09	779.23	1380.66	132.72	795.23	1389.03	126.87	774.65	1345.51
Cost of Losses (US$)	151197.00			139653.60			136463.40			140523.60			137278.80			139018.80			134821.80		
Cost of Savings (US$)	37935.00			49478.40			52668.60			48608.40			51853.20			50113.20			54310.20		
CPU Time	2.54 Seconds			1.76 Seconds			1.25 Seconds			1.39 Seconds			1.36 Seconds			1.39 Seconds			0.83 Seconds		

V CONCLUSION

In this paper, we discuss the optimal switching capacitor placement model based on ELM under stochastic environment. To achieve better prediction and fast decision making to activate switchable capacitor, ELM mechanism is incorporated with intelligent automation power system. The proposed ELM performs with less computational time and more accuracy. ELM intelligent automation system is an intelligent way of predicting better site and size of the capacitor. Depending upon the system load, the centralized control unit intelligently controls all the switchable capacitors at either ON or OFF state and it is well suited for dynamic environment.

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