OPTIMAL CAPACITOR SWITCHING WITH NOVEL NEURAL NETWORK MODEL FOR RADIAL DISTRIBUTION SYSTEM

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Abstract**:** *The optimal capacitor switching (OCS) is an important measure for loss minimization of distribution systems via an optimal capacitor dispatch schedule. The OCS is used to improve the voltage profile and minimize system losses. A novel neural network based approach uses minimum number of iterations to solve the OCS problem in radial distribution systems. For a typical distribution network, where a power flow is used in an unbalanced phase, it is necessary to optimize the number of switched banks in the bus of each single phase independently. The NN based OCS is used to find the size and location of the capacitor for loss reduction and to improve the voltage profile in Radial Distribution System (RDS).*

Keywords**:** *Radial Distribution System (RDS), Optimal Capacitor Switching (OCS), Neural Network (NN), Forward-only Algorithm, Capacitor suitability index (CSI)*

NOMENCLATURE

PLI : Power loss Index
PV : Per unit Node Voltage
CSI : Capacitor suitability Index
V_{min} : Minimum node voltage
V_{max} : Maximum node voltage
V_i : Rated voltage at node i
E_{loss} : Energy loss
C_{system} : Total system cost
C_p : Cost coefficient of peak power loss
Q_c : Capacitor kVAr at node i
C_e : Cost coefficient of peak power loss
$P(i)$: Active power load at node i
$Q(i)$: Reactive power load at node i
$p_l(i)$: Active power loss in branch terminating at node i
$q_l(i)$: Reactive power loss in branch terminating at node i
p_{loss} : Total active power loss of the system
q_{loss} : Total reactive loss of the system
P_{base} : Base power for the system
$Q_c(i)$: Value of capacitor placed at node i
Ic : Capacitive Current
np : Neurons patterns
nx : Weights of neurons
nn : Neuron network
no : Neuron output
ny : Weights connected to neurons

I. INTRODUCTION

Capacitor placement is a hard problem in power system research, because it involves integer variables for determining the placement, locations and discrete variables for deciding the number of capacitor banks to be installed [1]. It is a large-dimension constrained optimization problem considering the system and investment constraint. In this paper, neural network based approach is proposed to solve this problem. The size and solution quality of the resulting candidate solution set is reduced and improved iteration by iteration, and a good enough capacitor placement pattern in the final iteration is obtained. The test results show that the approach is superior for the capacitor placement problem.

A. Problems in Capacitor placement

Conventionally capacitor placement problem is formulated as a problem of minimization of the total system cost. The total system cost is defined as the summation of the capacitor installation cost, cost of peak power loss and cost of energy loss. The objective function is minimized subject to the nodal voltage regulations maintained within the permissible limits. The problem is thus stated as,

Min:

$$C_{\text{system}} = \sum_{i=1}^{n} f_{\text{cost}_i}(Q_{c_i}) + P_{\text{loss,peak}} \cdot C_{\text{p}} + E_{\text{loss}} \cdot C_{\text{e}} \quad \ldots (1)$$

Subject to: $$V_{\min} \leqslant V_i \leqslant V_{\max} \quad \ldots (2)$$

where, $f_{cost\,i}$ is the capacitor installation cost at node i, Qc_i the capacitor *kvar* at node i, $P_{peakloss,}$ the peak power loss, E_{loss} the energy loss, C_p the cost coefficient of peak power loss, C_e the cost coefficient of energy loss. As the capacitors are commercially available in discrete sizes $f_{cost\,i}$ varies in discrete steps. Capacitor cost has two parts (i) fixed part and (ii) variable part depending upon the *k*VA*r* capacity. The capacitor installation cost is shown in Table 1 where

Rs/KVAr represents the scaling factor and is chosen as listed in Appendix I.

Table 1 Capacitor installation size and costs

Normalise Qc(kVar)	Rs/kVAr	Normalise Qc(kVar)	Rs/kVAr
0.037	30	0.556	9.82
0.074	21	0.593	10.2
0.111	15.18	0.629	11.34
0.148	13.2	0.667	11.22
0.185	16.56	0.704	10.98
0.222	10.98	0.741	10.8
0.259	13.68	0.778	11.7
0.296	10.2	0.815	10.44
0.333	12.42	0.852	11.28
0.372	12.06	0.889	10.2
0.407	11.54	0.926	10.98
0.444	11.22	0.963	10.92
0.481	12.66	1	10.74
0.516	10.56		

B. Objective of the work

The objective of the capacitor placement problem is to determine the locations and sizes of the capacitors so that the power loss is minimized and annual savings are maximized [6]. Even though considerable amount of research work was done in the area of optimal capacitor placement, there is a need to develop more suitable and effective methods for the optimal capacitor placement. Although some of these methods to solve capacitor allocation problem are efficient, their efficacy relies entirely on the goodness of the data used [8] and does not compensate for any lack of uncertainty in the data. To overcome this, this work integrates heuristics judgments into the capacitor allocation optimization process. Furthermore, the solution obtained from the proposed algorithm is adaptive and can be quickly assessed to determine their feasibility in being implemented in a distribution system [9].

C. Background of the proposed development

The purpose of placing capacitors is to improve the node voltages and to reduce system losses. It is well known that for voltage drop in a power system, reactive power flow is more responsible than the flow of active power. Moreover, a large portion of power system loads being of constant power type, low voltage becomes responsible for high power losses [3]. Thus, the neural based capacitor placement methods are developed using node voltages and active and reactive branch power losses [7]. These neural methods are very sensitive to the weighting factors representing the membership functions. These weighting factors are tuned properly in order to have the best results. There is no guarantee that the same set of factors will perform uniformly for all the networks. The novelty of this work is to explore the development of Neural Network, which are less dependent on the above set of factors.

II. PREVIOUS WORK

Shyh-Jier Huang [2000] proposed an Immune Algorithm (IA) based optimization approach for solving the capacitor placement problem. Shikha Gupta et al., [2011] presented an efficient approach for capacitor sizing and location on a RDS using Artificial Intelligence Technique. S. Ghosh et al., [1999] proposed a simple and efficient method for the load flow of RDS network using the evaluation based on algebraic expression of receiving end. Sundhararajan [1994] presented the capacitor placement problem in a distribution system using a genetic algorithm. Prakash [2007] presented a novel particle swarm optimization based approach for capacitor placement on RDS. M. Damodar Reddy et al., [2008] proposed the placement of capacitors on the primary feeders of the RDS to reduce the power losses to improve the voltage profile. Haque M.H. [1999] proposed the capacitor placement problem is to determine the locations and sizes of the capacitors so that the power loss is minimized and annual savings are maximized. Ng H.N. et al., [2000] proposed the capacitor placement problem by using fuzzy approximate reasoning. K. Ellithy, [2008] proposed the location and sizes of the capacitor to be placed in distribution networks in an optimal manner to reduce the energy losses and peak power losses of the networks. Usha Reddy et al., [2011] presented a fuzzy and differential Evolution (DE) method for the placement of capacitors on the primary feeders of the RDS to reduce the power losses and to improve the voltage profile. S.K. Bhattacharya [2009] proposed a new fuzzy based solution of the capacitor placement in RDS. Youman, et al., [2001] proposed an approach with fuzzy variables is for solving the capacitor-switching (CS) problem in RDS. Aravindhababu P., et al., [2009] presented a new algorithm for optimal locations and sizing of static and/or switched shunt capacitors, with a view to enhance voltage stability. Y.M. Deng, et al., [2003] presented an approach which uses fuzzy variables to solve the (CS) problem in RDS. Khalil, et al., [2006] presented a binary particle swarm optimization (PSO) for optimal placement and sizing of fixed capacitor banks in radial distribution lines with nonsinusoidal substation voltages. Baskaran, et al., [2006] proposed a non-traditional optimization technique, a Genetic Algorithm (GA) is conjunction with Fuzzy logic (FL) is used to optimize the various process parameters involved in introduction of FACTS devices in a power system. S. Jshak, et al., [2004] proposed a technique to determine the location of the SVC in order to minimize loss in the system. Changcheng Zhao, et al., [2002] proposed an algorithm for reactive power optimization with time-varying fuzzy load model for medium-high voltage distribution network. [19] Mohmoud A. Sayed and Takaharu Takeshita, "Load Voltage Regulation and Line Loss Minimization of Loop Distribution Systems using UPFC" IEEE Transactions, 2008. Sayed et al., [2008] presented new methods for achieving line loss minimization and voltage regulation in the loop distribution system. [20] S. Chandramohan, et al., [2010] presented to use a non-dominated sorting genetic algorithm (NSGA) for reconfiguring a radial Distribution Corporation (DisCo) to minimize its operating costs considering real and reactive power costs while maximizing its operating reliability and satisfying the regular operating constraints.[21]H.Yu et al., [2010] proposed second order algorithms such as Levenberg Marquart algorithm are recommended for neural network training. [22] B. M. Wilamowski et al., [2010] developed second order algorithm Neuron by Neuron (NBN) to train close to optimal architecture.

III. NEURAL NETWORK BASED CAPACITOR LOCATION

Figure 1 proposes the capacitor placement for typical 33 bus system

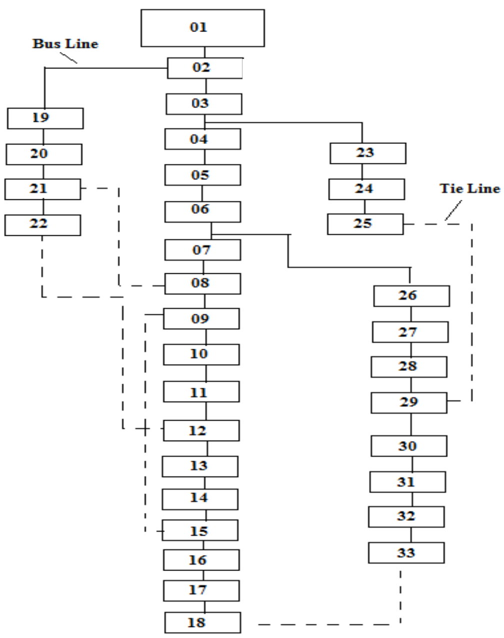


Fig.1. 33 Bus system

In Figure 1, along with the optimizations of reactive power is the minimization of total active power losses and control of voltage in real-time. This is achieved by placing the optimal value of capacitor at proper locations in the electrical distribution systems. The proposed methodology uses an intelligent NN approach of critical buses detection for optimal placement and sizing of capacitor banks. The critical node is also determined using Neural Network along with the sizing of capacitor banks [2].

A. Algorithm for Capacitor Placement

step1
  Read INPUTS PLI; PV
step2
  Normalize INPUTS $\in$[0, 1]
step3
  OP = Neural (INPUTS)
  Normalize OP
step4
  If [OP >=threshold]
  Place Capacitor
 else
  No change

The node voltages and power loss indices are the inputs to the neural network used to determine the suitability of a node in the capacitor placement problem. The suitability of a node is chosen from the capacitor suitability index (*CSI*) at each node. The higher values of *CSI* are chosen as best locations for capacitor placement. The power loss indices are calculated as,

$$PLI(i)=(LR-LMAX)/(LMIN-MMAXN),\ i=2,\ldots N \quad ...(3)$$

where, L_R : Loss reduction,
L_{MIN}: Minimum reduction,
L_{MAX}: Maximum reduction,
N: Number of bus

To determine the critical buses the voltage and power loss index at each node is calculated.

A close study of the capacitor placement problem reveals that the capacitor locations are only dependent upon the node voltages and branch power losses. The relation between PLI (input), PV (input) and CSI (output) is given in Table 2.

Table 2 Determine optimum capacitor location

0 to 1 PLI(Inputs)	0.9 to 1.1 PV(Inputs)	0 to 1 CSI(Output)
0.125	0.9	0.25
0.125	0.95	0.25
0.125	1	0.125
0.125	1.05	0.125
0.125	1.1	0.125
0.25	0.9	0.5
0.25	0.95	0.25
0.25	1	0.25
0.25	1.05	0.125
0.25	1.1	0.125
0.5	0.9	0.75
0.5	0.95	0.5
0.5	1	0.25
0.5	1.05	0.125
0.5	1.1	0.125
0.75	0.9	0.75
0.75	0.95	0.75
0.75	1	0.5
0.75	1.05	0.25
0.75	1.1	0.125
1	0.9	1
1	0.95	0.75
1	1	0.5
1	1.05	0.25
1	1.1	0.25

The magnitudes of the active and reactive loads of the nodes also are equally important deciding factors. Figure 2 shows the capacitor (fixed or switched type) placement algorithm (to be installed at a specific node), which is based on the system minimum and maximum reactive power demands, $Q_{L\text{-min}}$ and $Q_{L\text{-max}}$ in a defined period. They are chosen such that the reactive power is drawn from fixed capacitors and once optimal locations are acquired the switched capacitor is chosen. The available value of capacitor from i_c is chosen as

$$\left\{ \sum_{m=2}^{mn} Q_{L-m} \leq Q_{L-\min} \right\} \quad \ldots (4)$$

$$\left\{ Q_{L-\min} \leq \sum_{m=2}^{mn} Q_{L-m} \leq Q_{L-\max} \right\} \quad \ldots (5)$$

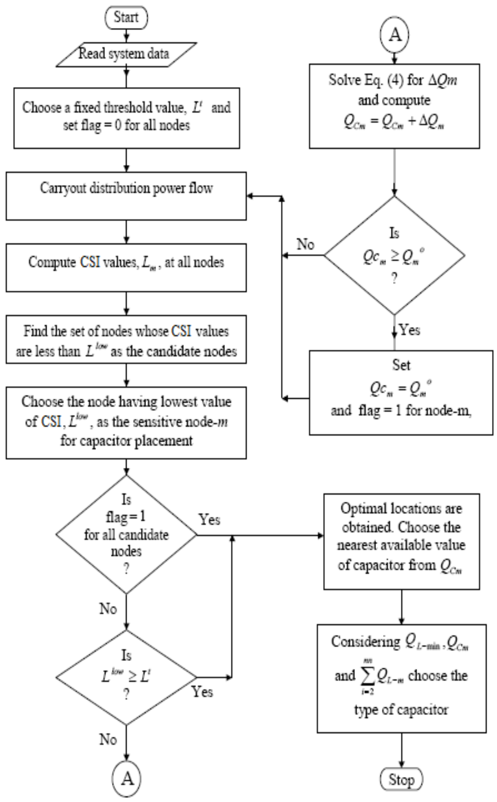


Fig. 2 Flow chart of the Capacitor placement

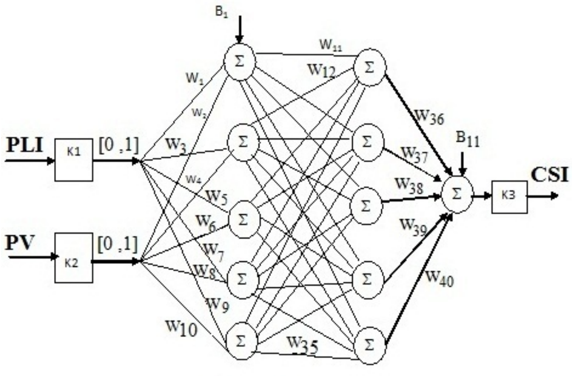
IV. NEURAL NETWORK WITH BACK PROPAGATION SCHEME

The back propagation algorithm is used in layered feed-forward NN, which means the artificial neurons are organized in layers and send their signals "forward" and then the errors are propagated backwards. The idea of the back propagation algorithm is to reduce this error, until the ANN learns the training data. The training begins with random weights and the goal is to adjust them till the error is minimal.

The Neural Networks uses traditional designs, (i) (most popular training algorithm) Enhanced back propagation (EBP) algorithm and (ii) Multi Layer Perceptron (MLP) network. The constraints to be considered in the NN design are,

(i) Large size
(ii) Poor generalization ability

The BPN based NN with the inputs PLI, PV and the output CSI is shown in Figure 3 where K1, K2&K3 are scaling factors chosen suitably to prevent NN saturation.



[2 - 2 - 5 - 5 - 1]

Fig. 3 BPN based neural network specifications

A. Problems in Second Order Training Algorithms (Memory Limitation)

Conventional second order training algorithms are such that, the update formula has the form given in eqn. [6],

$$(\mathbf{J}^T\mathbf{J} + \mu\mathbf{I})^{-1} \qquad \ldots (6)$$

where,

$$\boldsymbol{J} = \begin{bmatrix} \frac{\partial e_{11}}{\partial w_1} & \frac{\partial e_{11}}{\partial w_2} & \cdots & \frac{\partial e_{11}}{\partial w_N} \\ \frac{\partial e_{12}}{\partial w_1} & \frac{\partial e_{12}}{\partial w_2} & \cdots & \frac{\partial e_{12}}{\partial w_N} \\ \cdots & \cdots & \cdots & \cdots \\ \frac{\partial e_{1M}}{\partial w_1} & \frac{\partial e_{1M}}{\partial w_2} & \cdots & \frac{\partial e_{1M}}{\partial w_N} \\ \cdots & \cdots & \cdots & \cdots \\ \frac{\partial e_{P1}}{\partial w_1} & \frac{\partial e_{P1}}{\partial w_2} & \cdots & \frac{\partial e_{P1}}{\partial w_N} \\ \frac{\partial e_{P2}}{\partial w_1} & \frac{\partial e_{P2}}{\partial w_2} & \cdots & \frac{\partial e_{P2}}{\partial w_N} \\ \cdots & \cdots & \cdots & \cdots \\ \frac{\partial e_{PM}}{\partial w_1} & \frac{\partial e_{PM}}{\partial w_2} & \cdots & \frac{\partial e_{PM}}{\partial w_N} \end{bmatrix} \qquad \ldots.. (7)$$

The size of matrix is proportional to the size of networks and as the size of networks increases, second order algorithms may not be as efficient as the first order algorithms [21, 22].

(i) The size of Jacobian matrix J is $P \times M \times N$
(ii) P is the number of training patterns
(iii) M is the number of outputs
(iv) N is the number of weights

Practically, the number of training patterns is huge and is encouraged to be as large as possible. It involves matrix inversion,

In conventional algorithm, the computational duplication exists, i.e.

(i) Forward computation (calculate errors) and
(ii) Backward computation: error back-propagation

There exists an architecture limitation and also neuron by neuron computation. In second order algorithms, the error back-propagation process has to be repeated for each output. Hence, this is very complex and inefficient for networks with multiple inputs and outputs.

B.Second Order Improved Derivation Computation

In neural network training, considering each pattern is related to one row of Jacobian matrix and patterns are independent of each other. The weight update equation is given by,

$$\Delta \boldsymbol{w} = \left(\boldsymbol{Q} + \mu\, \boldsymbol{I}\right)^{-1} \boldsymbol{g} \qquad \ldots (8)$$

Computation of Q in equation (8) where

$$\boldsymbol{Q} = \sum_{p=1}^{P} \sum_{m=1}^{M} \boldsymbol{q}_{pm} \qquad \ldots (9)$$

Computation of q_{pm} (Sub Matrix) in equation (9) where

$$\boldsymbol{q}_{pm} = \boldsymbol{j}_{pm}^T \boldsymbol{j}_{pm} \qquad \ldots (10)$$

$$\boldsymbol{q}_{pm} = \begin{bmatrix} \left(\frac{\partial e_{pm}}{\partial w_1}\right)^2 & \frac{\partial e_{pm}}{\partial w_1}\frac{\partial e_{pm}}{\partial w_2} & \cdots & \frac{\partial e_{pm}}{\partial w_1}\frac{\partial e_{pm}}{\partial w_N} \\ \frac{\partial e_{pm}}{\partial w_2}\frac{\partial e_{pm}}{\partial w_1} & \left(\frac{\partial e_{pm}}{\partial w_2}\right)^2 & \cdots & \frac{\partial e_{pm}}{\partial w_2}\frac{\partial e_{pm}}{\partial w_N} \\ \cdots & \cdots & \cdots & \cdots \\ \frac{\partial e_{pm}}{\partial w_N}\frac{\partial e_{pm}}{\partial w_1} & \frac{\partial e_{pm}}{\partial w_N}\frac{\partial e_{pm}}{\partial w_2} & \cdots & \left(\frac{\partial e_{pm}}{\partial w_N}\right)^2 \end{bmatrix} \qquad \ldots (11)$$

Computation of g in equation (8) where

$$\boldsymbol{g} = \sum_{p=1}^{P} \sum_{m=1}^{M} \boldsymbol{\eta}_{pm} \qquad \ldots (12)$$

Computation of η_{pm} (Sub Vector) in equation (12) where

$$\eta_{pm} = j_{pm}^{T} e_{pm}$$

… (13)

$$\eta_{pm} = \begin{bmatrix} \frac{\partial e_{pm}}{\partial w_1} e_{pm} \\ \frac{\partial e_{pm}}{\partial w_2} e_{pm} \\ \cdots \\ \frac{\partial e_{pm}}{\partial w_N} e_{pm} \end{bmatrix} = \begin{bmatrix} \frac{\partial e_{pm}}{\partial w_1} \\ \frac{\partial e_{pm}}{\partial w_2} \\ \cdots \\ \frac{\partial e_{pm}}{\partial w_N} \end{bmatrix} \times e_{pm}$$

… (14)

Computation of j_{pm} in equation (10) where

$$j_{pm} = \begin{bmatrix} \frac{\partial e_{pm}}{\partial w_1} & \frac{\partial e_{pm}}{\partial w_2} & \cdots & \frac{\partial e_{pm}}{\partial w_N} \end{bmatrix}$$

… (15)

This differs from conventional weights update algorithms which employs,

$$\Delta w = (J^T J + \mu I)^{-1} J^T e$$

C. Advantages of Second Order Computation

The training scheme has the following merits:

(i) No need for Jacobian matrix storage
(ii) Vector operation instead of matrix operation
(iii) Significant memory reduction
(iv) Memory reduction benefits and increased computation speed

D.Pseudo code of Integrated Training algorithms

In forward-only computation, the backward computation is replaced by extra computation in forward process and is given in Figure 4.

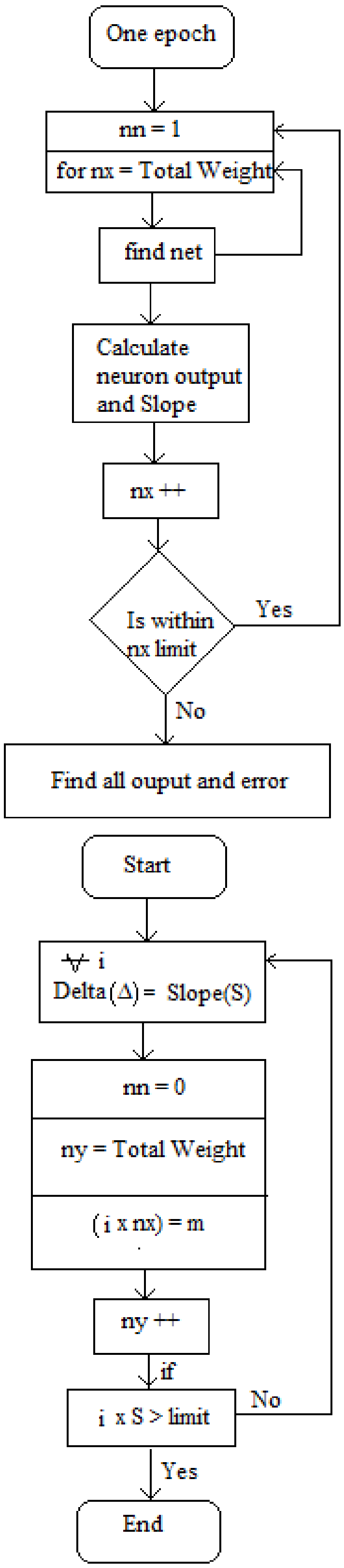


Fig. 4 Conventional forward-backward algorithm

V. RESULTS AND DISCUSSION

The capacitor selection and trained NN output is given in Table 3 and Table 5 respectively.

Table 3 Capacitor Selection

Branch					
Project					
Final PF	0.92				
Load Details	Initial PF Ratings in Assured	KW	QTY	Total	kVAr Reqd.
Motors	0.8	200	2	400	130
Motors	0.8	100	1	100	40
Transformer Ratings in KVA		1000	1	1000	100
Total kVAr Reqd. We are assumed Motors are operating at 75% Load	Given in 25KVAr Units				275
With MPP-S ($)	61875 (Approx.)				
With MPP-H ($)	82500 (Approx.)				
With MD-XL ($)	128150 (Approx.)				
With MD ($)	128150 (Approx.)				
With FF/APP Double ($)	128150 (Approx.)				
With FF/APP-Single ($)	93500 (Approx.)				

The capacitor placement and kVAr requirement is given in Table 4.

Table 4 Results of 33-bus system

Bus No.	kVAr Requirements
7	60
12	70
22	170
15	110
24	20
27	100
31	120

Table 5 Neural network input and output results

I/P PLI	PV	CSI O/P
0.72	0.1	0.2
0.76	0.1	0.1
0.8	0.1	0.2
0.84	0.1	0.1
0.88	0.1	0.1
0.72	0.2	0.4
0.76	0.2	0.2
0.8	0.2	0.2
0.84	0.2	0.1
0.88	0.2	0.1
0.72	0.4	0.6
0.76	0.4	0.4
0.8	0.4	0.2
0.84	0.4	0.1
0.88	0.4	0.1
0.72	0.6	0.6
0.76	0.6	0.6
0.8	0.6	0.4
0.84	0.6	0.2
0.88	0.6	0.1
0.72	0.8	0.8
0.76	0.8	0.6
0.8	0.8	0.4
0.84	0.8	0.2
0.88	0.8	0.2

VI. CONCLUSION

It is much easier to use a training algorithm of the neural network even when the number of neurons is larger than the conventional one. However, with a small number of neurons the neural network has much better online application. This means it will respond correctly to closely related pattern other than the one used for training. In this paper, the proposed Network is less dependent on the weighting factors and are more generic than other Neural Network based capacitor placement methods. Also, the use of forward-only algorithm simplifies the computation process in second order training that can handle arbitrarily connected neural networks and has speed benefit for networks with multiple outputs.

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Appendix –I

Typical multiplier to determine capacitor kVAr requirements for Power Factor correction

Original Power Factor	**Desired Power Factor**																				
	0.80	0.81	0.82	0.83	0.84	0.85	0.86	0.87	0.88	0.89	0.90	0.91	0.92	0.93	0.94	0.95	0.96	0.97	0.98	0.99	1.0
0.50	0.982	1.008	1.034	1.060	1.086	1.112	1.139	1.165	1.192	1.220	1.248	1.276	1.306	1.337	1.369	1.403	1.440	1.481	1.529	1.589	1.732
0.51	0.937	0.962	0.989	1.015	1.041	1.067	1.094	1.120	1.147	1.175	1.203	1.231	1.261	1.292	1.324	1.358	1.395	1.436	1.484	1.544	1.687
0.52	0.893	0.919	0.945	0.971	0.997	1.023	1.050	1.076	1.103	1.131	1.159	1.187	1.217	1.248	1.280	1.314	1.351	1.392	1.440	1.500	1.643
0.53	0.850	0.876	0.902	0.928	0.954	0.980	1.007	1.033	1.060	1.088	1.116	1.144	1.174	1.205	1.237	1.271	1.308	1.349	1.397	1.457	1.600
0.54	0.809	0.835	0.861	0.887	0.913	0.939	0.966	0.992	1.019	1.047	1.075	1.103	1.133	1.164	1.196	1.230	1.267	1.308	1.356	1.416	1.559
0.55	0.769	0.795	0.821	0.847	0.873	0.899	0.926	0.952	0.979	1.007	1.035	1.063	1.093	1.124	1.156	1.190	1.227	1.268	1.316	1.376	1.519
0.56	0.730	0.756	0.782	0.808	0.834	0.860	0.887	0.913	0.940	0.968	0.996	1.024	1.054	1.085	1.117	1.151	1.188	1.188	1.277	1.337	1.480
0.57	0.692	0.718	0.744	0.770	0.796	0.822	0.849	0.875	0.902	0.930	0.958	0.986	1.016	1.047	1.079	1.113	1.150	1.150	1.239	1.299	1.442
0.58	0.655	0.681	0.707	0.733	0.759	0.785	0.812	0.838	0.865	0.893	0.921	0.949	0.979	1.010	1.042	1.076	1.113	1.113	1.202	1.262	1.405
0.59	0.619	0.645	0.671	0.697	0.723	0.749	0.776	0.802	0.829	0.857	0.885	0.913	0.943	0.974	1.006	1.040	1.077	1.077	1.166	1.226	1.369
0.60	0.583	0.609	0.635	0.661	0.687	0.713	0.740	0.766	0.793	0.821	0.849	0.877	0.907	0.938	0.970	1.004	1.041	1.041	1.130	1.190	1.333
0.61	0.549	0.575	0.601	0.627	0.653	0.679	0.706	0.732	0.759	0.787	0.815	0.843	0.873	0.904	0.936	0.970	1.007	1.048	1.096	1.156	1.299
0.62	0.516	0.542	0.568	0.594	0.620	0.646	0.673	0.699	0.726	0.754	0.782	0.810	0.840	0.871	0.903	0.937	0.974	1.015	1.063	1.123	1.266
0.63	0.483	0.509	0.535	0.561	0.587	0.613	0.640	0.666	0.693	0.721	0.749	0.777	0.807	0.838	0.870	0.904	0.941	0.982	1.030	1.090	1.233
0.64	0.451	0.474	0.503	0.529	0.555	0.581	0.608	0.634	0.661	0.689	0.717	0.745	0.775	0.806	0.838	0.872	0.909	0.950	0.998	1.068	1.201
0.65	0.419	0.445	0.471	0.497	0.523	0.549	0.576	0.602	0.629	0.657	0.685	0.713	0.743	0.774	0.806	0.840	0.877	0.918	0.966	1.026	1.169
0.66	0.368	0.414	0.440	0.456	0492	0.518	0.545	0.571	0.598	0.626	0.654	0.682	0.712	0.743	0.775	0.809	0.846	0.887	0.935	0.995	1.138
0.67	0.358	0.384	0.410	0.436	0.462	0.488	0.515	0.541	0.568	0.596	0.624	0.652	0.682	0.713	0.745	0.779	0.816	0.857	0.905	0.965	1.108
0.68	0.328	0.354	0.380	0.406	0.432	0.458	0.485	0.511	0.538	0.565	0.594	0.622	0.652	0.683	0.715	0.749	0.786	0.827	0.875	0.935	1.078
0.69	0.299	0.325	0.351	0.377	0.403	0.429	0.456	0.482	0.509	0.537	0.565	0.593	0.623	0.654	0.686	0.720	0.757	0.798	0.846	0.906	1.049
0.70	0.270	0.296	0.322	0.348	0.374	0.400	0.427	0.453	0.480	0.508	0.536	0.564	0.594	0.625	0.657	0.691	0.728	0.769	0.817	0.877	1.020
0.71	0.242	0.268	0.294	0.320	0.346	0.372	0.399	0.425	0.452	0.480	0.508	0.536	0.566	0.597	0.629	0.663	0.700	0.741	0.789	0.849	0.992
0.72	0.214	0.240	0.266	0.292	0.318	0.344	0.371	0.397	0.424	0.452	0.480	0.508	0.538	0.569	0.601	0.635	0.672	0.713	0.761	0.821	0.964
0.73	0.186	0.212	0.238	0.264	0.290	0.316	0.343	0.369	0.396	0.424	0.452	0.480	0.510	0.541	0.573	0.607	0.644	0.685	0.733	0.793	0.936
0.74	0.159	0.185	0.211	0.237	0.263	0.289	0.316	0.342	0.369	0.397	0.425	0.453	0.483	0.514	0.546	0.580	0.617	0.658	0.706	0.766	0.909
0.75	0.132	0.158	0.184	0.210	0.236	0.262	0.289	0.315	0.342	0.370	0.398	0.426	0.456	0.487	0.519	0.553	0.590	0.631	0.679	0.739	0.882
0.76	0.105	0.131	0.157	0.183	0.209	0.235	0.262	0.288	0.315	0.343	0.371	0.399	0.429	0.460	0.492	0.526	0.563	0.604	0.652	0.712	0.855
0.77	0.079	0.105	0.131	0.157	0.183	0.209	0.236	0.262	0.289	0.317	0.345	0.373	0.403	0.434	0.466	0.500	0.537	0.578	0.626	0.685	0.829
0.78	0.052	0.078	0.104	0.130	0.156	0.182	0.209	0.235	0.262	0.290	0.318	0.345	0.376	0.407	0.439	0.473	0.510	0.551	0.599	0.659	0.802
0.79	0.026	0.052	0.078	0.104	0.130	0.156	0.183	0.209	0.236	0.264	0.292	0.320	0.360	0.381	0.413	0.447	0.484	0.525	0.573	0.633	0.776
0.80	0.000	0.026	0.052	0.078	0.104	0.130	0.157	0.183	0.210	0.238	0.266	0.294	0.324	0.355	0.387	0.421	0.458	0.499	0.547	0.609	0.750
0.81		0.000	0.026	0.052	0.078	0.104	0.131	0.157	0.184	0.212	0.240	0.268	0.298	0.329	0.361	0.395	0.432	0.473	0.521	0.581	0.724
0.82			0.000	0.026	0.052	0.078	0.105	0.131	0.158	0.186	0.214	0.242	0.272	0.303	0.335	0.369	0.406	0.447	0.495	0.555	0.698
0.83				0.000	0.026	0.052	0.079	0.105	0.132	0.160	0.188	0.216	0.246	0.277	0.309	0.343	0.380	0.421	0.469	0.529	0.672
0.84					0.000	0.026	0.053	0.079	0.106	0.134	0.162	0.190	0.220	0.251	0.283	0.317	0.354	0.395	0.443	0.503	0.646
0.85						0.000	0.027	0.053	0.080	0.108	0.136	0.164	0.194	0.225	0.257	0.291	0.328	0.369	0.417	0.477	0.620
0.86							0.000	0.026	0.053	0.081	0.109	0.137	0.167	0.198	0.230	0.264	0.301	0.342	0.390	0.450	0.593

0.87								0.000	0.027	0.055	0.083	0.111	0.141	0.172	0.204	0.238	0.275	0.316	0.364	0.424	0.567
0.88									0.000	0.028	0.056	0.064	0.114	0.145	0.177	0.211	0.248	0.289	0.337	0.397	0.540
0.89										0.000	0.028	0.056	0.086	0.117	0.149	0.183	0.220	0.261	0.309	0.369	0.512
0.90											0.000	0.028	0.058	0.089	0.121	0.155	0.192	0.233	0.281	0.341	0.484
0.91												0.000	0.030	0.061	0.093	0.127	0.164	0.205	0.253	0.313	0.456
0.92													0.000	0.031	0.063	0.097	0.134	0.175	0.223	0.283	0.426
0.93														0.000	0.032	0.066	0.103	0.144	0.192	0.252	0.395
0.94															0.000	0.034	0.071	0.112	0.160	0.220	0.363
0.95																0.000	0.037	0.079	0.126	0.186	0.329
0.96																	0.000	0.041	0.089	0.149	0.292
0.97																		0.000	0.048	0.108	0.251
0.98																			0.000	0.060	0.203
0.99																				0.000	0.143
1.00																					0.00