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Applications of Neural Networks for Power Systems

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1. Introduction

With the introduction of new network topologies and improved training algorithms, the neural networks have demonstrated its feasibility and practicality in several power systems applications. An artificial neural network is modeled as a massively parallel interconnected networks of elementary processors or neurons. This highly connected array of elementary processors defines the system hardware. Various software algorithms are then crafted to synthesize a mapping between input and output variables by learning a set of arc weights and neuron thresholds based on training examples [1-4]. From the computational point of view, neural networks comes with the advantages of massive parallelism and are not restricted in speed by the Von Neumann bottleneck characteristics of conventional computation.

Layered perceptron is a specific neural network architecture where sets of neurons are arranged in layers. Currently, the layered perceptron is receiving the most attention as a viable candidate for several applications. Different from expert system that is taught by rules, the layered perceptron is taught by examples. The layered perceptron is operated in two modes: training and testing. In the training mode, a set of training data is used to adjust the weights of the network interconnects. Once these weights have been determined, the neural network is said to be trained. In the testing mode, the trained neural network is activated by test data. The response of the layered perceptron will be the representative of the data by which it was trained.

In power system applications, artificial neural networks have been recently proposed as an alternative for solving certain traditional problems where conventional techniques have not achieved the desired speed, accuracy or efficiency. Generally speaking, neural networks applications that have been proposed in the literature up to date can be broadly categorized into three main areas: Regression, Classification and Combinatorial Optimization. The application involving regression includes Load Forecasting [7-10], Transient Stability [16,24,25], Synchronous Machine Modelling [26], Contingency Screening [27-28], Harmonic Evaluation [29] and Control [21,30-32]. Applications involving classification include Static Security Assessment [11-13,37], Dynamic Security Assessment [38], Harmonic Load Identification [33] and Alarm Processing [34-36]. In the area of combinatorial optimization, Capacitor Control [20] and Topological Observability [39-40] are included. In the following sections, a representative applications from each category will be overviewed. A more in depth treatment of the material can be found in the respective references. The selected applications are load forecasting, static security assessment and capacitor control.

2. Layered Perceptron

In the NN, the neurons are arranged in layered structures. An input layer and output layer surrounds a hidden layers. The activations signals are transmitted from one layer to the next layer through a set of links that either attenuate or amplify the signals based on the respective weights [1-5]. On account of simplicity and effectiveness of structures, the layered perceptron is the most attractive in modern applications.

3. Load Forecasting

Load forecasting is a very useful tool for economic allocation of generation, energy transactions, system security analysis, optimal energy interchange between utilities, unit commitment and generator maintenance scheduling. Since there are several applications related to load forecasting, the accuracy of load forecasting model plays an important role in power system engineering. Considerable efforts are being invested by utilities for the development of accurate load forecasting techniques.

Basically, the conventional techniques used for load forecasting can be classified as time series approach and regression approach. In time series approach, one treats the load demands as a time series signal. However, numerical instability usually deteriorate the forecasting performance [6]. As to the conventional regression approach, the linear or piecewise-linear representations are usually adopted as a forecasting functions. The accuracy of this approach is dependent on the functional relationship between weather variables and electric load that must be known apriori. Moreover, it cannot handle the non-stationary temporal relationship between the weather variables and load demand.

The attractive features of the neural network approach is that NN can combine both time series and regression approaches to predict the load demand. Because NN can technically synthesize a mapping between input and output variables, the accurate functional relationship between weather variables and electric load is not required. In other words, the nonlinear mapping between the input and output is implicitly imbedded in the neural network.

The neural network approach proposed in [6] uses previous load data combined with actual and forecasted weather variables as inputs, where the load demand is the output. As an example, to predict the load demand at the k^{th} hour on a 24 hour period, the training data for NN are selected as follows:

Input data:

k:	Hour of the forecast (k)
T_p:	Forecast temperature at hour k
T(24,k), L(24, k):	Actual temperature and load 24 hours earlier
T(m, k), L(m, k):	Actual temperature and load m hours earlier

Output data:

L(k):	Load at hour k.

During training, the actual temperature T(k) is used instead of $T_p(k)$. Different NNs are trained to predict the load demands at varying lead times. The results are reported to be better than those obtained through some of the existing extensive regression techniques.

A sample of the test results from [6] is shown in Table 1 and 2. There were five sets of actual load and temperature data used in the study. Table 1 shows several sets of training data. Each set contains data corresponding to 8 consecutive days. The data did not include weekends or holidays.

Table 1. Test data sets.

Sets	Test data from
Set #1	01/23/89 - 01/30/89
Set #2	11/09/88 - 11/17/88
Set #3	11/18/88 - 11/29/88
Set #4	12/08/88 - 12/15/88
Set #5	12/27/88 - 01/04/89

Table 2 shows the NN forecasting error in percent. The results are averaged over a 24 hour period for each day. The average error for the 5 test sets was found to be approximately 1.40%.

Table 2. Error (%) of hourly load forecasting with one hour lead time

days	Set #1	Set #2	Set #3	Set #4	Set #5
day 1	(*)	1.20	1.41	1.17	(*)
day 2	1.67	1.48	(*)	1.58	2.18
day 3	1.08	(*)	1.04	(*)	1.68
day 4	1.4	1.34	1.42	1.20	1.73
day 5	1.3	1.41	(*)	1.20	(*)
day 6	(*)	1.51	1.29	1.68	0.98
average	1.35	1.39	1.29	1.36	1.64

(*: predicted temperature, T_p is not available)

4. Static Security Assessment

Static security assessment is defined as the ability of a power system to reach a steady state operating condition after disturbance that does not violate any given system operating constraints. The operating constraints may consist of bus voltage magnitude limits and the thermal limits of each line.

Static security assessment consists of three distinct stages: They are contingency definition (CD); contingency selection (CS) and contingency evaluation (CE). CD defines a probable contingency list. CS is the process to shorten the original long list of contingency by removing the vast majority of cases that have no violations. CE using a fast ac power flow is then performed on successive individual cases in decreasing order of severity. The resulting system attributes are checked for post contingency violations.

Security assessment is a classification problem where the combinations of certain topologies, states and contingencies give rise to insecurities. Concepts of neural network can be used to capture some common underlying characteristics between the pre-contingency system states and the post-contingency security status. The attractiveness of applying neural network to determine power system security is its speed. Once a reliable classifier is in place, classifying a new operating state of the power system into secure or insecure class is trivial compared to the cumbersome calculations involving analytical solutions.

For a large scale power system, a single NN may be an enormous computation exercise to handle [11]. One way of reducing the dimensional complexity is to use a modular approach where the security problem is divided into smaller sub-tasks. A modular NN can then be used to process each sub-task. A possible modular approach for a large-scaled power system problem is shown in Figure 1. This is necessary due to the variations in which a contingency exhibits itself based on the nature, location and clearing strategy. Furthermore, for a given contingency, the mechanisms leading to line and voltage violations are fundamentally different. Line violations are caused by real power overflows, while voltage violations are caused by an excess or a deficiency of reactive power. Therefore, it can be seen that separate NNs are trained for assessing line and voltage violations under the same contingency.

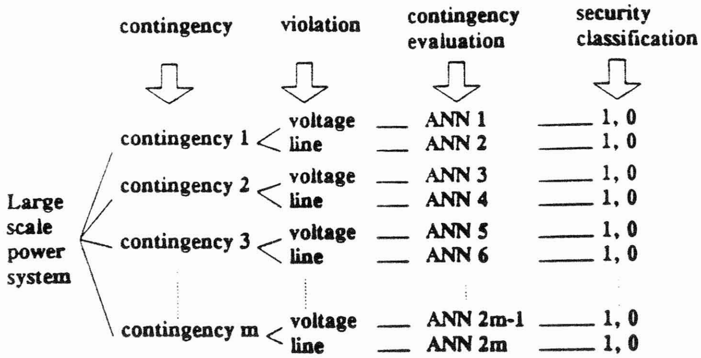

Figure 1. A modular neural network approach to static security assessment.

The tested system is depicted in Figure 2. It includes 4 generators, 8 loads and 16 transmission lines. The influence of the external networks is modelled by a bi-directional power flow at boundary buses #9 and #10 respectively. Table 3 shows the operating point and the allowed perturbation in the real and reactive loads at each bus. The tie line flow is considered to be either positive or negative depending on the direction of the current flow.

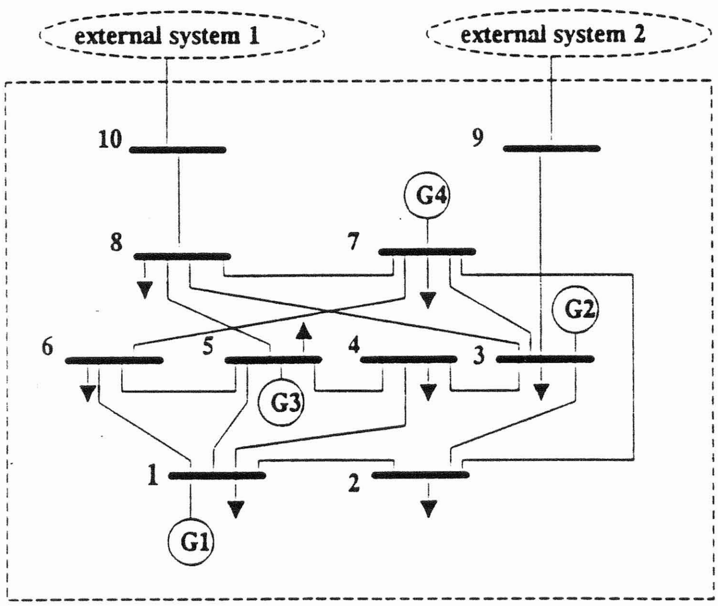

Figure 2. The tested power system.

Table 3. The range of load parameters.

bus #	bus type	real load limits (MW p.u.)	reactive load limits (MVAR p.u.)
1	slack	9.0 ~ 11.0	0.0 ~ 1.0
2	load	11.2 ~ 16.8	0.0 ~ 1.0
3	generation	13.5 ~ 16.5	0.0 ~ 1.0
4	load	14.0 ~ 16.0	0.0 ~ 1.0
5	generation	13.5 ~ 16.5	0.0 ~ 1.0
6	load	15.4 ~ 28.6	9.1 ~ 16.9
7	generation	9.0 ~ 11.0	0.0 ~ 1.0
8	load	0.0 ~ 2.0	5.0 ~ 15.0
9	boundary	-7.5 ~ 7.5	-7.5 ~ 7.5
10	boundary	-7.5 ~ 7.5	-7.5 ~ 7.5

In this test, the tripping of tie line #16 is investigated. A single pre-contingency pattern contains 54 different attributes including all the real and reactive generation (P, Q), real and reactive loads (P, Q), all the bus voltage magnitudes (V) and all the line currents (I) in the system. A feature extraction algorithm is used to reduce the inputs to six key features used in training. The training and testing statistics of the neural networks are given in Table 4.

Table 4. Training and testing statistics for the neural network.

Architecture and training information		Testing statistics	
inputs	6	testing data	500
outputs	1	true secure patterns	346
hidden layers	1	true insecure patterns	154
hidden neurons	6	false alarms	9
iteration step	0.05	false dismissals	4
momentum factor	0.01	% false alarms	2.601
training patterns	155 0	% false dismissals	2.597
iteration cycles	200 0	% false classifications	2.600

5. Capacitor Control

With the desire to improve power factor and voltage profile, compensating the reactive power flow in utilities is an area of continuous development. The reactive power compensation can be viewed as an optimization problem where several optimum sizes of capacitors can be placed at optimum locations to minimize line losses. Since this is a complex nonlinear optimization problem, there are many techniques such as gradient method, linear programming, nonlinear programming, integer programming and expert system method were investigated.

The application of neural network in capacitor control is demonstrated in [20]. The objective is to use 3 measurement quantities (P, Q, |V|) at specified locations and the current tap setting of the line capacitors to calculate the optimum tap settings of the capacitors. It can be seen that the capacitor control is a typical combinatorial optimization problem in neural network applications.

In [20], the problem is solved in two stages. Both stages use multi-layer perceptrons trained by back error propagation. In stage I, 6 NNs are trained to perform a power flow calculation at 6 specified locations. The output load currents (i_1 - i_6) from stage I are then taken as inputs for the stage II. In stage II, NNs are trained to select the optimum tap setting of 5 capacitors.

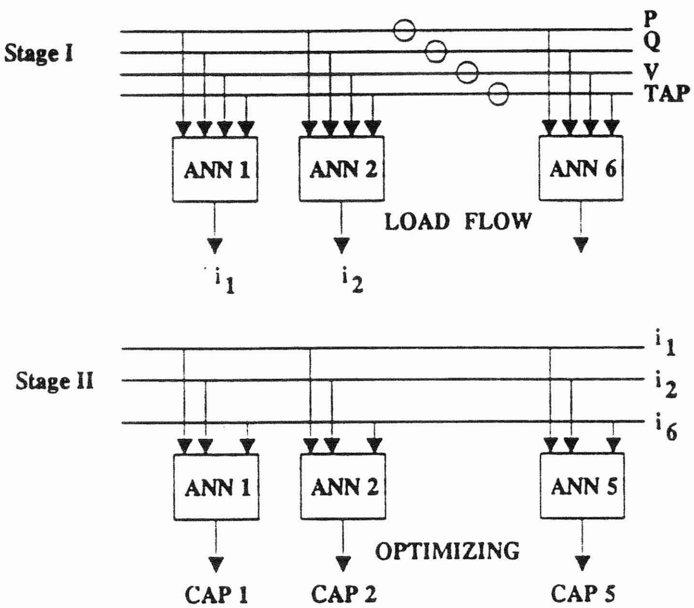

Figure 4. The capacitor control through NNs
(From [20] courtesy of IEEE, (C) IEEE, 1989)

With the hierarchical neural network approach, the combinatorial optimization of capacitor control problem is solved effectively.

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