# APPLICATION OF NEURAL NETWORKS TO POWER SYSTEMS

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**Abstract -** In recent years, ANNs (Artificial Neural Networks) have attracted considerable attention as candidates for computational system due to the variety of advantages they offer over the conventional computational systems. Among these advantages, the ability to memorise, rapidity and robustness are the most profound and interesting properties which have attracted attention in many fields. The paper critically reviews the ANN related publications involving typical power system problems during last decade. A brief overview of the ANN theory, different models and their applications is given.

## INTRODUCTION:

The paper describes a overview on ANNs in power systems. Artificial neural networks (ANNs) are the distributed processing systems that have been inspired by the biological nerve system. They consist of a group of units called "neurous" that are analogous to nerve neurous. Each neuron is connected to each other with the weights. For example, the inductive learning process finds out the weights so that the relationship between input and output variables is determined. The methods throw up new possibilities of parallel or distributed computing.

Recent years have witnessed a rapidly growing interest in two important

Artificial intelligence technologies viz., expert systems (ES) and ANNs. In recent
years, another term 'intelligent control' has come to embrace diverse methodologies combining conventional control and emergent techniques based on physiological metaphors, such as ANNs, fuzzy logic, genetic algorithms and a wide variety of search and optimization techniques [20]. In this paper we will mainly concentrate on ANNs and their application to power systems.

ANNs have been studied for many years with the hope of understanding and achieving human-like computational performance. Appealing benefits include massive parallelism, architectural modularity, fast speed, high fault tolerance and adaptive capability. These have lured researchers from controls, robotics and power systems to seek NN solutions to some of their more complicated or unsolved problems.

NN applications to power systems can be categorised under three main areas: regression, classification and combinatorial optimization. Applications involving regression include transient stability analysis, load forecasting, synchronous machine modelling, contingency screening and harmonic evaluation. Applications involving classifications include harmonic load identification, stataic and dynamic security analysis. The area of combinational optimization includes unit commitment and capacitor control.

## OVERVIEW OF ARTIFICAL NEURAL NETWORKS:

Artificial neural networks are made up of simple highly interconnected processing units called neurons each of which perform two functions: aggregation of its inputs from other neurons or the external environment and generation of an output from the aggregated inputs. A connection between a pair of neurons has an associated numerical strength called synaptic weight. The development of ANN involves two phases: training or learning phase and testing phase. Training of ANN is done by presenting the network with examples called training patterns. During training, the synaptic weights get modified to model the given problem. As soon as the network has learnt the problem it may be tested with new unknown patterns and its efficiency can be checked. (testing phase). Depending upon the training imparted, ANN can be classified as supervised ANN or unsupervised ANN.

### Supervised ANN

The supervised ANN requires the sets of inputs and the outputs for its training. During the training, the output from the ANN is compared with the desired output (target) and the difference (error) is reduced by employing some learning algorithm. This training is repeated till the actual output acquires an acceptable level. Supervised ANN may be a feed forward or nonrecurrent network such as Multi Layer Perceptron (MLP), Functional Link Net (FLN) and Radial Basis Function (RBS), or a feedback or recurrent ANN

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such as Hopfield network, often used in power system applications.

**Multi-layer Perceptron Model:**

It comprises an input layer, one or more hidden layer(s) and an output-layer. It is used practically in all power system applications and is trained by a back propagation (BP) algorithm [7]. BP is an iterative, gradient search, supervised algorithm and consists of three phases: forward execution, back propagation of the error and weight update. It works well with a sigmoidal activation rule.

**Functional Link Network:**

The FLN [8] not only increases learning rate but simplifies the learning algorithm. The inputs are expanded and are used for training with the actual input data.

**RBF Network Model:**

Radial basis function model [9] consists of three layers: the input, hidden and output layers. The training of RBF network requires less computation time since only the second layer weights have to be calculated using an error signal.

**Parallel Self-organizing Hierarchical Neural Network:**

Parallel, self-organizing, hierarchical neural network (PSHNN) are multistage networks [10], in which each stage neural network (SNN) is usually a 3-layered feed forward ANN having linear input and output units and nonlinear hidden units. The revised back propagation algorithm is used to train each SNN. The training of the PSHNN is carried out for a number of sweeps till convergence is achieved.

**Hopfield Model:**

Hopfield model [11] is a recurrent neural network (RNN) having feedback paths from their outputs to their inputs and consists of a single layer of neurons, acting both as output and input using self-organizing associative memory. Neurons with graded response (or sigmoidal input-output relation) are used in Hopfield Neural Network.

The output of each neuron is linked with the previous value of its own activation and therefore individual neurons have time dependent behaviour. It can recognize patterns by matching new inputs with previously stored patterns. The Hopfield model is particularly used for application to combinatorial optimization problems such as unit commitment.

**Unsupervised ANN:**

The artificial neural network which does not require a supervisor or teacher for training is known as unsupervised ANN. In competitive or unsupervised learning units of the output layer compete for the chance to respond to a given input pattern. Kohonen's Self-organizing Feature Map (SOFM) and Adaptive Resonance Theory (ART) are examples of unsupervised learning.

## ANN APPLICATIONS TO POWER SYSTEMS

Several key features that distinguish NNs from other AI techniques are: learning by example in real time, distributed memory and associated recall, fault tolerance and graceful degradation, real time pattern recognition, intelligent association and synthesis.

Despite its numerous advantages, distributed memory causes a major flaw in NNs, because knowledge in a NN is stored as a pattern of weights and connections. Other stumbling blocks and how more work is going on to tackle them is discussed in the next section.

This section deals with typical ANN application areas in power systems. The areas in order of decreasing amount of work already published are:
Planning, security assessment, fault detection/diagonosis, control, analysis, protection and design. Most popular problems are: (i) load forecasting, (ii) security assessment and (iii) fault detection/diagonosis.

**Load Forecasting:**

Load forecasting is a suitable problem for ANN application due to the availability of historical load data on the utility databases. ANN schemes using perceptron network and SOFM have been successful in short-term [46,49] as well as long-term load forecasting with impressive accuracy. A combined use of unsupervised and supervised learning was done for short-term load forecasting [12]. Dash et al. [13] used Kalman-filter based ANN algorithm for faster convergence and improved prediction accuracy. The RBF network was found superior to MLP or BP model in terms of training time and accuracy.

ANN does not need additional memory for storing the history of load patterns. 1% improvement in accuracy of STLF can save upto Rs. 700 million for a typical power utility.

**Security Assessment:**

Static and dynamic security assessment often require on-line computation. In order to evaluate solution efficiently, the nonlinear mapping of MLP is utilized to reduce computational burden and deal with the characteristics of power systems. This allows us to carry out on-line monitoring/assessment in transient, small signal stability, and voltage instability.

Though contingency ranking and sensitivity factor methods have reduced the number of critical contingencies to be computed, ANNs have played a challenging role in security area.

In ref. [14], a 4-layered feed forward ANN trained with BP algorithm was discussed for predicting bus voltages following an outage. The P's and Q's that affect bus voltages most were selected as the inputs to ANN using an entropy function. Ghosh et al. [15] designed a feedback ANN for line-flow contingency ranking. A New type of performance index, the severity index was considered as output of the neural network.

Jayasurya [16] proposed an ANN to provide an energy measure which is an indication of the power system's proximity to voltage collapse.

**Fault Detection/Diagnosis:**

Fault detection/diagnosis is one of challenging problems in power systems. MLP identifies the type and location of facults with a given set of power system conditions, measurements, alarms, etc. KN (Kohonen net) is applied to handle the classification of fault patterns. The diagnosis of the power apparatus is done to judge what kinds of faults the apparatus suffered from. KN is inferior to MLP in terms of the solution accuracy due to unsupervised learning. RBF and BP models [17] were developed for fault diagnosis problem. The BP network had given superior performance while training of RBF network was much faster as compared to BP network.

**Economic Load Dispatch:**

Park et al. [18] presented a method to solve ELD problem with piecewise quadratic cost function using Hopfield NN. The ANN based approach turned out to be much simpler and accurate. Ref. [29] deals with combined ED and emission dispatch using improved BPNN. Adaptive Hopfield NN is recently used for ELD [41,47]

**Hydroelectric Generation Scheduling:**

Liang and Hsu [19] proposed NN based approach for the scheduling of hydro-generations. System hourly loads and the natural inflow of each reservoir were considered as inputs to the ANN.

**Power System Stabilizer Design:**

Power system stabilizer (PSS) has been widely used in modern power systems to provide damping for lower frequency oscillations in the power system. MLP based P.S.S. was proposed by several workers [21]. In Ref. [22], a fuzzy technique and NN based method for PSS control by superconducting magnetic energy storage have been developed. .

**Load Flow:**

LF is a must for solving a large number of power system problems. Kalra et al. [23] developed a fast load flow method based on MLP model with real and reactive load demands at load buses as inputs. The output nodes provided $|V|$ and $\delta$ at all PQ buses. Ref. [24] presents an MLP based adaptive loss evaluation algorithm for power transmission system.

**Voltage and Reactive Power Control:**

In Ref. [25], Kojima et al. proposed an RNN based algorithm for learning the inverse dynamics and applied the algorithm to VQ control called "neuro VQC", It was found to be more stable and accurate.

There are many other power system problems for which ANN is increasingly being used such as load modelling [42,50], HVDC [36,48], power system reliability studies [40], topology [39], non-conventional energy source [35], load frequency control [33], maintenance scheduling [31], unit commitment [30].

## STUMBLING BLOCKS

ANN faces several problems to be solved inspite of attractive features discussed earlier. The main difficulities with ANN implementation are discussed below.

**Optimal Structure of ANN:**

It is essential to findout the network size (the number of input and output neurons in MLP, and the number of output neurons in KN). Further, pruning is necessary to obtain more reasonable models.

**On-line Efficient Learning Algorithm:**

The BP algorithm requires many iteration counts. It is not suitable for on-line learning scheme. It is necessary to have a learning algorithm with better convergence. Efficient global optimization technique is needed to evaluate the weights.

**Alleviation of "Curse of Dimensionality":**

The direct application of ANN to large scale real-size power system requires large-scale ANN. It is not easy to findout the optimal weights in terms of accuracy and the computational effort.

**Consideration of Network Topologies:**

We have to cope with network topologies if the problem is related to transmission lines. Actually, ANN applications to one or several snapshot are not convincing.

**Necessary Amount of Learning Data:**

The efficient guideline for finding out the necessary amount of the learning data is not available in constructing ANN. The inefficient data creates inappropriate models while too much data needs excesive computation time.

It is normal that in spite of good performance on training data, worse performance is obtained on test data. This may be due to the fact that the training data is not uniformly distributed. The accuracy of ANN model depends on the number of training patterns in a given range.

**Other Factors:**

In literature no systematic procedure is available on choice of initial weights assigned to the interconnections between two nodes in neural network. Ref. [26] proposes use of some functions for this.

The present AI implementation can reach the perfection only if it acquires the level of human competence. Unlike ES, ANN implementation suffers from a lack of end-user interaction. Kalra et al. [27] presented various models concerning the synergism of ES and ANN.

It is important to handle normalization of input data so that feature extraction is obtained and solution accuracy is improved.

## FUTURE WORK:

Research would continue to enhance ANN performance. It is a natural research direction to make use of other emerging technologies [30,32,34,43,44,45] to overcome drawbacks of ANNs.

It is known that ES, FS (fuzzy system), genetic algorithm (GA) and ANN have strong credentials to deal with uncertain, incomplete and noise polluted data. ANN is a good approximator of non-linear functions and performing well for non-linear regression. FS, GA, chaotic dynamics are presently used to reduce the training time and pruning of the ANN. Fine training or defuzzification can be done by ANN.

## CONCLUSION

Neural networks are robust. Even if input-data are not complete or have some noise, the ANN can still give good results. ANNs have adaptivity and can adjust to the new environment easily. Modern control techniques like adaptive, variable structure, H (infinite) controls can be learned by ANN from a series of training sets and once the learning phase is over ANN can be used as a robust controller. Special purpose hardware designed to implement and evaluate ANN technologies and variety of NNs (eg. recurrent) are being seriously tried for solving PS problems.

An overview on ANNs in power systems has been presented in this paper. This paper has focussed on MLP, HN and KN as typical ANNs. It may be seen that, MLP is the most popular owing to the surpervised learning that is superior in terms of accuracy. As the application areas, load forecasting, security assessment and fault detection/diagnosis were of main importance though there exits a variety of application areas. The present day practical difficulties and their proposed solutions are reviewed. Finally, the integration of ANNs with other emerging technologies such as FS, GA etc. was discussed as a future research direction.

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