Artificial Neural Networks In Electric Power Industry

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C O N T E N T

INTRODUCTION

This work presents an initial survey of the uses of Neural Networks in the Electric Power Industry.

The objective of the Electric Power Industry is to supply electricity at the least possible cost with a constant service quality[1].

Among the factors that provoke difficulties in achieving this goal, the inherent variability of the load and the fast growth of the demand are foremost, followed by requirements of clean environment, weather, quality fuels, accelerated aging of the plants and fast changes in technology.

Recently, promising Artificial Neural Networks (ANN) approaches have been developed to solve problems in power plants and power systems --tuning of controllers, process identification, sensor validation, monitoring and fault diagnosis, in power plants, and security assessment, load identification, load modeling, forecasting and fault diagnosis, in power systems.

The information presented in this document is organized in 6 sections: in section 1 Power Plants, their context and control problems are introduced; in section 2, a brief survey of ANN in Power Plants is included; section 3 and 4 are dedicated to ANN in Power Systems. Concluding remarks and future research directions are included in section 5. References are given in section 6.

[1] The quality is measured considering number of interruptions in the supply, range of voltage and frequency variations, and amount of harmonic distortions.

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1 POWER PLANTS AND CONTROL PROBLEMS

A power plant converts energy from nonelectrical to electrical form. Based on the energy transformation, the plants are classified as fossil, nuclear, solar, geothermal, hydro, etc.

The main goal is to carry out this conversion in the best possble way. Safety, efficiency, reliability and availability criteria are taken into account as references.

A plant consists of several generating units which work together to meet the electric load demand. For a fossil power plant, each unit consists of three basic components: the boiler, the turbine and the generator.

The complexity of the operation comes from the variability of the load, and the high efficiency demanded over a wide range of operation. The main difficulties for the control task then arise by the high coupling among the process variables and the nonlinearities of the process.

Fossil plants at the beginning were designed to operate over a base-load. Single input - single output controllers were used. Control strategies using feedforward control action proved to satisfy the established requirements at that time. However, the high growth of the demand, the fuel crises and the new restrictions for environmental protection demanded different and more efficient types of operations for the electric power plants.

In more detail, there are three types of operation:

* Base-load
* Load-following
* Cyclic

* Base-load operation: This mode of operation is in general the most economic for the plants. Plants operate at fixed demand, at maximum capacity, with variations no bigger than 15-20% of nominal capacity over long periods of time (months). Plants in this mode basically require regulators or steady-state controllers.

* Load-following operation: Plants in this operation mode, along with those operating in cyclic operation are responsible for maintaining the fixed frequency at 60 Hz. These plants absorb the fast and random load

changes that occur during the day. The Automatic Generation Control (AGC) plays a very important role in these plants.

* Cyclic operation: In this mode of operation, plants follow the slow load variation during the day. Typically, they are old plants that have lost their economic advantages. Their main characteristic is the ability to start up and stop at the required times.

In order to achieve the objectives of the cyclic and load-following operation modes, modern control techniques are needed.

As a perspective and historical point of view, EPRI in [41]-1981 indicated the importance and necessity to began to use multi-input multi-output (MIMO) control techniques in power plants.

Modern multivariable techniques were classified as:

* "Modeling and Simulation
* "Multivariable Control Systems Design and Analysis
* " Multivariable Estimation Design and Analysis"

It is interesting to note that these techniques had proved to be useful in process control and aerospace problems a long time ago. However, for the electric industry in 1981 they were considered new.

Some of the reasons of the reluctance of the power industry were:

* Designed control systems had "proved" to be adequate
* Costs associated with simulation and modeling of multivariable control system was high
* Problems in design and implementation of such control systems were anticipated

At present, these arguments are no longer valid, and modern control techniques are providing some answers to the new operation problems.

In 1992, EPRI had experimented four algorithms ([56]-1992):

* State variable estimation algorithm
* Non-linear process model-based algorithm
* Optimal regulator algorithm for steam temperature control
* Concurrent front end controller algorithm.

The concept of having control systems that are able to predict and optimize operating conditions are now investigated. EPRI has stated that the performance of a power plant can be accurately predicted using ANN and/or state estimation techniques.

Up to this time, it has been noted that by improving the control systems and having adequate regulation over the main process variable, the important problem of accelerated aging of the plants is attenuated.

Also, it is observed that the instrumentation and control systems have the highest rate of technological change of the unit (approximately 5 years). So to replace obsolete equipment is another problem. The main consequences are bad regulation, lack of operator confidence, need for frequent calibration and decrease of safety and efficiency.

Today, programs of modernization, life extension, and heat-rate improvement in power plants consider the instrumentation and control systems among the most important elements.

With increased attention to the control systems, new functions are added:

* Heat-rate performance evaluation
* Sensor validation
* Fault diagnosis
* Identification and modeling
* Coordination

Note that these functions are important elements of the control hierarchy.

In the next section, ANN advances toward implementing these new functions are described.

2 NEURAL NETWORKS IN POWER PLANTS

There is a number of papers in the literature dealing with the use of ANN to power plants. Several of these are briefly described in the subsections below. They are grouped into papers dealing with identification & modeling, control, sensor validation, monitoring, fault diagnosis and prediction.

2.1 Identification and modeling

Uhrig, R.E., [13]-1993, presented one point of view about the use of ANN to deal with the modeling of nuclear power systems. The special emphasis was placed on the interrelationship among sensor outputs. An ANN is used to predict one or more of the sensor outputs. If there exist significant difference between the predicted and the actual outputs, then something in the components, system or instrumentation has changed. Topics described in the article: transient diagnostics, sensor validation, plant-wide monitoring, check valve monitoring, and analysis of vibrations. Interesting approach for sensor validation function and detection of incipient faults. Most of the works mentioned have been realized to demonstrate feasibility of some ANN approach (8 references).

Parlos, Atiya and Chong, [36]-1992, presented a procedure using ANN to identify the nonlinear empirical model of a steam generator. A hybrid feedforward/feedback ANN is used. The feedforward portion provides interpolation, while the feedback portion enables representation of temporal variations in the nonlinearities of the system. Simulation results showed that empirical models can be effectively used to predict transient responses; this approach appears to produce more accurate results than those reported in the literature based on conventional nonlinear identification techniques (24 references).

Guo and Uhrig, [37]-1992, addressed the problem of modeling the thermodynamic behavior of a nuclear power plant using a hybrid ANN. Measurements of heat rate acquired over 1-yr period were utilized. Original data were clustered and their centroids used as training patterns. Comparison between calculated and predicted heat rates gave an error of less than 0.1%. Then sensitivity analysis was performed. The reported methodology could be utilized by existing heat rate monitoring systems (5 references).

Upadhyaya and Eryurek, [38]-1992, addressed the problem of estimation of process variables using an ANN. An application was presented for sensor validation and plant wide monitoring. Operational data from an Experimental Breeder Reactor-I were used. A feedforward ANN with a backpropagation learning algorithm has been utilized. The high fidelity of predictions demonstrated that ANNs can be used in place of physical or empirical models (10 references).

2.2 Control

Chen, Ch-R. and Y-Y Hsu, [12]-1991, presented an investigation on tuning of power system stabilizers (PSS). The outputs of the neural net were the desired parameters of the PSS. The inputs were the generator real power and the power factor. Both are measured on-line and are representative of the operating conditions. Thus, the PSS parameters can be adapted in real time. Simulation results demonstrated the effectiveness of this approach. Multilayer feedforward neural networks were used. Since this approach doesn't require model identification, it is more efficient than the self-tuning controllers, and therefore more suitable for real-time applications (27 references).

Beaufays and Widrow, [29]-1993, presented the results of a project[2] which dealt with the problem of frequency control in power units under load variations. A feedforward neural network is trained to control the input steam flow to the turbine so the nominal value of frequency is restored. Two simulated examples are given: 1) a simple generator unit feeding a power line, and 2) a two-area system. Results showed better performance with the neural controller than current integral control. Future investigation will consist in building independent neural net controllers for different areas of a multi-area system. A decentralized architecture will have to be proposed to reduce exchange information between nodes of the power grid (9 references).

Adams, [30]-1993, presented a solution to an adaptive control problem via reinforcement learning neural networks with elements of conventional PD control. The plant model is taken to be a second-order dynamic system. The task control was taken from the article "Showcase of Adaptive Controller Design" presented in the 1988 American Control Conference. The proposed approach resulted in much more stable performance and covered a wider range of plant parameters than contemporary adaptive control methods reported previously (7 references).

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[2] Investigation sponsored by EPRI.

2.3 Sensor Validation

Khadem, Ipakchi and Alexandro, [14]-1993, demonstrated the feasibility of a method to verify the accuracy of the measurement of process variables using an ANN. The method employs a set of process variables which are measured, related to the target process variable, and used as inputs to the ANN. The ANN output is an estimate of the target process variable. This estimate is compared with its actual value. Agreement establishes that the target instrument is or is not operating properly. Application to the TMI-1 nuclear power plant took into account flowmeters in the two feedwater flow loops. Multilayer feedforward and backpropagation algorithms were used. Simulation results showed correct readings of the target variable. Robustness of the system is investigated (3 references).

2.4 Monitoring, Fault Diagnosis and Predictions

Ikonomopoulos, Tsoualas and Uhrig, [15]-1993, presented an approach based on ANNs and rule-based fuzzy expert system to monitor nuclear reactor systems. A model-reference approach was utilized. The expert system executes the basic interpretation and performs identification functions. The ANNs provide the model, classify general categories of system behavior and generate membership functions. These membership functions can be utilized as inputs to a fuzzy controller without the prerequisite of fuzzifying the measured input values. The system allows for monitoring of the equipment performance and infering of process variable values (virtual measuring). Excellent robustness to noisy and faulty signals was reported. System description is suitable for control applications (11 references).

Lukic, Stevens and Si, [16]-1993, presented the application of ANN methodology for recognizing transient events in a nuclear power plants. Classifying events attempts to cover anticipated accidents. Eleven transients/accident events and steady state operation for a Combustion Engineering System 80 pressurized water reactor (PWR) were studied. Simulations were used to obtain the plant process parameters. Feedforward ANN and the backpropagation algorithms were used. The network was able to classify all transient events after 5 minutes following event initiation. Reliable results were obtained for up to 5% sensor input noise (5 references).

Bashers, Sailor and Wood, [17]-1993[3], described a method to automatate the analysis of wear scars in nuclear reactors. Currently human operators perform the analysis. Present methods of analysis based on inspection data are intensive, do not offer reliable and accurate recognition of wear features and are sensitive to the measurement noise. The companies involved in the project were: EPRI Knowledge Based Technology Application Center (KBTAC), Koman Sciences Corporation, Syracuse University and Duke Power Company. The software, as product, has the following functions: 1) identify and extract wear sections in the nuclear reactor, 2) determine wear information and 3) organize this information in a data-base. The results have been found very encouraging by Duke Power and EPRI. In the next phase, integrated software will extract the features from data files, run the neural net, compute the wear properties and place the results in a data base (4 references).

Doremus, R., [18]-1993, presented a computational tool (SAMSON)[4] based on ANN technology to recognize accidents in nuclear power plants and to predict damages. The accidents currently recognized include ruptures of the steam generator tubes and loss of coolant. This tool also provides information about recovery strategies and the status of plant sensors. SAMSON uses a three layer neural net trained with the backpropagation algorithm. The software has been developed for Commonwealth Edison Company. An excellent work on the features of the man-machine interface is also described. Future proposed research deals with overriding decisions, improving accuracy of predictions and increasing the number of recognized accidents (4 references).

Chow and Yu, [11]-1991, reported their work concerning on-line incipient faults in single-phase squirrel-cage induction motors. The detector is composed of two ANNs: one to filter out the transient measurement, and the other to detect incipient faults. Simulation results proved satisfactory performance, 95% to 99% correct fault diagnosis. The methodology presented in this paper, with the appropriate modification, could also be applied to many others types of rotating machines. Also this fault detector showed to be robust to noise and disturbance (36 references).

Agogino, Tseng and Jain, [31]-1993, dealt with the problem of monitoring and fault diagnostics in a power plant [5]. The focus is the integration of Probabilistic Neural Network (PNN) with influence diagrams. These diagrams were utilized to define the structure of the Neural Net, the number of neurons and type

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3 EPRI is one of the companies involved in this project.

4 The prototype was delivered to Commonwealth Edison Company in February '92. The final delivery was scheduled for December '92.

5 Project supported by EPRI and Sargent & Lundy.

of connections required. The PNN is trained to estimate and update conditional probability distributions from on-line sensor information. Once the neural net has been trained, influence diagrams were utilized for monitoring new on-line data and answering not only predefined but also arbitrary diagnostics queries in its framework. To improve the results, a self-organizing PNN was designed. Less complexity in both representation and inference was obtained. The presented approach allows the performance engineer or operator to see both the most likely failure causes and a probability ranking of them. The effectiveness of incorporating subjective and empirical information is then demonstrated (4 references).

Bartlett and Uhrig, [35]-1992, demonstrated the feasibility of using ANN as a diagnostic tool to recognize the operating status of a nuclear power plant. An ANN was trained to classify accidental conditions based on normal operating and potentially unsafe conditions. A self-optimizing stochastic learning algorithm ANN with dynamic node architecture was investigated. It was shown that this approach is a successful connectionist methodology for the investigated plant accident. The next step is to be able to diagnose more accidents. Another idea is to use an expert system together with the ANN to perform diagnosis verification and validation (11 references).

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3 A PERSPECTIVE OF POWER SYSTEMS

While Power Plant topics mainly concern electric power generation, those corresponding to Power Systems concern transmission, subtransmission and distribution of electric power.

An Electrical Power System (EPS) can be seen as a network of interconnected components with the purpose of:

* converting nonelectrical energy into electrical form;
* transforming electrical energy into a specific form subject to strict requirements;
* transporting electrical energy over long distances;
* converting electrical energy into another energy form.

The (EPS) can be classified in five subareas:

1.- Generation
2.- Transmission
3.- Subtransmission
4.- Distribution
5.- Use

1)<u>Generation</u>: represents the sources of Electrical Energy. It implies convertion of the energy from nonelectrical form into electrical form. Power plants such as nuclear, geothermal, solar, are used for this purpose. 2) <u>Transmission</u>: Considers the movement of the power from generation sites to the areas of use (voltage range: 115-765 KV. and capacities: 100-4000 MVA). 3) <u>Subtransmission</u>: Saying " yesterday's transmission is today's subtransmission" (voltage range: 12-69 KV. and capacities: less 100 MVA). 4) <u>Distribution</u>: Considers the individual circuits from the substation to the customer's location (voltage range for primary distribution: 2.4-12 KV., for secondary distribution: 120, 240, 480 V). 5) <u>Use</u>: All electrical devices which convert electrical energy into more usable forms such as light, heat, sound, motion of mechanical force, etc. ([40],1986).

Among the applications of ANNs in power systems, alternative solutions to problems related with security assessment, transient stability, load modelling, forecast and fault diagnosis have been proposed. To have a complete idea of the kind of problems, the applications areas are outlined in the subsections below.

3.1 System Security

"System security corresponds to the ability of the power system to withstand some unforseen but probable disturbances with the minimal disruption of service or its quality." [39]-1988.

Security assessment is a function that predicts the vulnerability of the system to possible events on a real-time basis. Note the system being operated is different from that which was planned. Maintenance requirements, forced outages, and different pattern loads make the differences. Thus the system security levels are constantly changing.

Security assessment can be seen as an algorithm that forecasts the future evolution of the system, assesses the probability of a security violation into determined period of time and determines if a preventive control action should be taken to prevent hazardous operating conditions.

The security assessment is based on ([58]-1982):

* Knowledge of system dynamics
* Measurement of system variables
* Models for measurement uncertainty and system disturbances
* Well-defined criterion for security.
  Maximal admissible currents of the transmission gives the boundaries of the secure domain of the state space (operating point are defined by a vector whose components are active and reactive power).

In the field of power system operation, system security can be seen as the counterpart of system reliability in the field of system planning. In reliability assessment, the configuration of the system and the probability distributions of individual component failures are given. The process of planning then consists of adding components (e.g. generating units) or reconfiguring the system in order to meet accepted system reliability. Since this analysis is carried out via a planning mode, the chosen options can be implemented in due time.

R. E. Bourguet, P. J. Antsaklis, "Artificial Neural Networks in Electric Power Industry," Technical Report of the ISIS (Interdisciplinary Studies of Intelligent Systems) Group, No. ISIS-94-007, Univ of Notre Dame, April 1994.

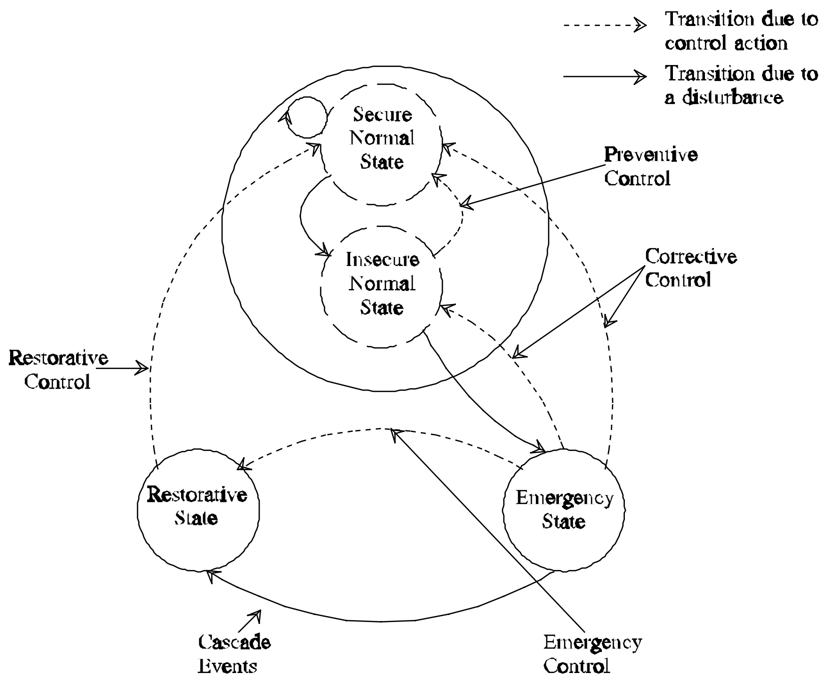

Figure 1 EPS Operation States Reference [39, 1988]

Operating States (see figure 1):

Normal: Voltage and frequency specifications are met without violating limits on any power device for all system loads.

Emergency: Some operating limits are violated (overvoltage, very low frequency, overloaded lines)

Restorative: Portion of the system loads are not met (partial or total blackout) but the operating portion is in a normal state.

Static security corresponds to those states where the transients following a disturbance have died out. In these states the system has some limit violations that can only be tolerated for a short period of time (i.e. overloads line, overvoltage conditions). If a corrective action is not possible, then the pre-disturbance state must be classified as seriously insecure and should be avoided by preventive measures.

Dynamic security corresponds to the investigation of disturbances which may lead to transient instabilities (e.g. loss of synchronism among generator). Dynamic security assessment is a very complex and difficult task. The difficulties arise from a compounding of the following elements:

* The EPS is time-varying, highly non-linear, and very large scale.
* The inputs of interest are multidimensional statistical distributions of random events,
* It requires complex and time-consuming forecasts (since robustness evaluation of the system is carried out over a future interval) of the system behavior for all possible random events.
* The assessment must be executed on-line.

In the past several approaches have been proposed using dynamic estimation, statistical modeling events and perturbations, stochastic forecasting and stochastic contingency evaluation.

3.2 Transient stability

An electrical power system is a nonlinear, high order system which is subjected to both predictable and unpredictable disturbances. These disturbances can also be classified as internal (random load) and external (lightning strikes, wind).

Transient stability problems are those related to large-scale disturbances which cause the lose of synchronization in a portion of the system, and in extreme cases, instabilities of the system.

Stability of power systems deals with the character of the electromechanical oscillations of synchronous generators created by disturbances in the power system conditions.

Electromechanical oscillations represent exchange of energy among generator rotors (via the interconnection network) which is caused by the instantaneous unbalance between generation and consumption of electric power.

This imbalance is inherent to an AC power system and varies from low levels during normal changes of system operating conditions, to relatively large levels in the case of major disturbances such as faults. In both cases, the system stability depends on its capability to efficiently preserve synchronous operation of all its parts and damp out electromechanical oscillations between them.

When the disturbance is small, the system is confined to a small region around an equilibrium point. Linear models are used and the stability properties of this equilibrium point are studied. If the disturbance is large, the subsequent oscillatory transient will be of significant magnitude. And now the stability of the system is determined following the trajectories related to the attraction region of the equilibrium point. In this case both nonlinear model and theory are used.

Existing approaches to assess transient stability:

1. Numerical integration
2. The second method of Lyapunov
3. Probabilistic Methods
4. Pattern recognition
5. Neural Networks

1. Numerical methods

   The system dynamics are described by a set of first order differential equations. These are solved during the fault and post-fault period by numerical integration algorithms such as Runge-Kutta and its variations. Real-time operation constraints make it difficult to apply this method to power systems.

2. Second Method of Lyapunov

   The main idea is to evaluate the Lyapunov function at the instant of the last switching in the system. If the value is smaller than a reference value then the post-fault transient process is stable.

3. Probability method

   Probability of stability is defined as the probability that the system remains stable should the considered disturbance occur.

   Security is measured in terms of the probability of a transition from normal state to the emergency or "in extremis" state measured relative to a threshold.

4. Pattern Recognition (PR)

   The transient stability studies using PR have focused on the selection of the initial system description, feature extraction and on the design of classifiers.

Dynamic programming and modified search methods are used to improve the future extraction processes. Several kinds of classifiers have been studied: adaptive hyperplane nearest neighbor, adaptive sphere and prototype hyperplane. The last one has the best performance of the three.

On the selection of the initial system description four kind of parameters are used:

- the voltage magnitude and phase angle at each system bus.
- the active and reactive power of each generator plant.
- the active and reactive power of each bus load.
- the active and reactive power flow of all the lines.

These parameters refer to static system conditions. It's mentioned ([1]-1991) that improvements in the classification can be obtained using transient measurements such as individual kinetic energy of all generators.

5. Neural Networks

This recent technique is being used as pattern classifier and recognizer in this kind of problems. Up to now, the literature has reported only simulation results taking into account real data.

3.3 Load Forecasting

Load forecasting is an important task which allows the system operator:

* to schedule spinning reserve allocation;
* to decide for possible energy interchange with other utilities, and
* to assess system security

Two approaches have been traditionally suggested. One treats the load patterns as a time series signal and predicts the future load based on time series analysis. Another one, regression approach, recognizes the heavy dependency between the system load pattern and weather variables and finds a functional relationship. The future load is then forecast by inserting the predicted weather information into the relationship.

In the time series approach, inaccuracies of the prediction and numerical instabilities are general problems. For the regression approach, conventional techniques assume a linear or piece-wise linear relationship without justification; also the approach considers no variation in the spatio-temporal elements and it reports averaged results, being in fact a non stationary process ([8],1991).

ANN's seem a useful technique to solve these kinds of problems.

3.4 Fault Diagnosis

One of the major causes for power system outages is the failure of electrical equipment. Reliability, security, and availability of the system can be improved by having good detection and diagnosis systems.

ANNs are being studied as classifiers of failures in electrical apparatus, and successful results have been reported. For example, for failure diagnosis during transformer testings, ANNs are trained off-line with all possible signals of simulated faults. A well known model of a transformer is used. After the training period the ANN is ready to act as experienced evaluator. An extra advantage is that ANN not only can record the failures but can also reproduce them [43]-1993. Another example is the study of underground oil switches [44]-1993. ANNs proved to be a successful pattern classification systems to determine the condition (corrosive or non-corrosive) of a given switch. The main advantage is that the diagnosis is carried out without interrupting the service or dismantling the switch. Actual data are used to train the ANN.

To date, promising approaches based on ANN are applied in security assessment, load modeling, load forecasting and fault diagnosis. Advances on these applications are described in the next section.

4 NEURAL NETWORKS IN POWER SYSTEMS

Several papers dealing with ANN applications in power systems are briefly described in the subsections below. They have been grouped with respect to the following application areas: Static and dynamic security assessment, transient stability assessment, identification, modelling and prediction, control, load forecasting and fault diagnosis.

4.1 Static and Dynamic Security Assessment

Sobajic[6] and Pao, [1]-1989, presented a key-work of the use of Artificial Neural Networks (ANN) in electric power systems. This work, referenced by the most of the authors in ANNs and power systems, dealt with the assessment of dynamic security. An adaptive pattern recognition approach based on a Rumelhart feedforward neural net with a backpropagation learning scheme was implemented to synthesize the Critical Clearing Time (CCT). This parameter is one of paramount importance in the post-fault dynamic analysis of interconnected systems. The net successfully performed the estimation task for the variable system topology conditions. This work encouraged the investigation (commented in the following paragraph) of a preprocessing step that was able to "discover" what features were relevant to the learning task and what were not (36 references).

In [4]-1992, the same authors described the results of the investigation to "discover" relevant ANN training information. Simulations results showed how autonomous feature discovery was carried out in terms of direct system measurements instead of pragmatic features based on the engineering understanding of the problem. In this case unsupervised and supervised learning paradigms in tandem were used. Agreement between estimated and actual CCT values was very good (19 references).

In [21]-1993, the same authors presented a new method for transient security assessment of multimachine power systems. The stability boundary was constructed using tangent hypersurfaces. ANNs were used to determine the unknown coefficients of the hypersurfaces independently of operating conditions. Numerical results and comparisons between CCT analytically obtained and ANN-based indicated that this approach provides quick assessment of power system security (5 references).

6 Dean J. Sobajic: Editor of the "Neural Network Computing For The Electric Power Industry: Proceedings Of The INNS Summer Workshop, 1993"

In [25]-1993, the authors (joined with Lee) presented a methodology applying ANN to carry out real-time stability analysis of power systems. Near-term transient stability of the system, mid-term and long-term dynamic security analysis were performed. The first one dealt with whether the system can return to steady-state, and the second one dealt with the manner of the final state is reached. Predicting transient violations allows the operator to take anticipatory actions (6 references).

Niebur and Germond, [5]-1993, demonstrated the feasibility of load pattern classification for power system static security assessment using ANN. They utilized the Kohonen Neural Net as classifier of power system states. The relation among the number of clusters, the number of neurons and the size of the power systems were investigated. Simulation results demostrated the successful generalization property of the ANN. Future works will address scaling issues for large size power systems (24 references).

Aggoune, [9]-1991, presented the results of a study to assess the capability of ANN to give on-line accurate stability assessment. The important feature is that correct assessment was obtained not only when the net was queried with an element of the training set of data, but also at other operating conditions. The input stimulus for the net were contingency parameters such as transmission line status, machine excitations and generation level. Feedforward ANNs were used (19 references).

Chen and Hsu, [10]-1991, presented a refined Nilsson's learning machine. Its effectiveness is demonstrated through a steady-state analysis on a synchronous generator. This generator was connected to a large power system. As input to the net, real power, power factor and power system stabilizer parameters were used. The output was a discrete signal: dynamically stable or unstable. The proposed ANN was compared with the multilayer feedforward with a backpropagation-momentum learning algorithm. It was determined that the convergence of the proposed ANN was much faster and its misclassification rate was lower than using the backpropagation-momentum method. It is said that the proposed ANN is more suitable for discrete output values. An important feature of this ANN is that it can serve as an on-line aid to the operators to analyze steady-state stability as well as tune power system stabilizers (25 references).

Avramovic, [20]-1993, dealt with the problem of voltage security assessment in power systems. The primary focus covers two aspects: 1) a long learning time, and 2) generation and sampling of systems trajectories in order to obtain representative input/output sets. Capability of ANN to provide means for accurate tracking of postcontingency, in this case voltage was illustrated (10 references).

4.2 Transient Stability Assessment

Ostojic and Heydt, [7]-1991, presented a pattern recognition methodology in the frequency domain (main result) to asses the transient stability of a interconnected power system. A decision-making system (DMS) based on a preprocessor (parallel computational structure) and on two layers of equivalent neurons were used. The important difference between DMS and multilayer ANN is that the DMS doesn't require a backpropagation learning rule but a perceptron convergence procedure. The reliable and efficient DMS uses telemetered measurements of electromechanical oscillations to assess transient stability (17 references).

Mori, [22]-1993, presented an ANN based method to monitor voltage instability. A hybrid ANN was utilized: a multilayer perceptron was used to estimate indices of voltages instability, and a Kohonen self-organization mapping to trace the trajectories of power system conditions. Changes of network configurations were taken into account. A decentralized scheme for voltage stability monitoring to deal with real-size systems was also presented (17 references).

4.3 Identification, Modeling and Prediction

Hartana and Richards, [6]-1990, explored the use of an ANN, in conjunction with state estimation to monitor harmonic sources in power system with nonlinear loads. The ANN generates estimates which are used as pseudomeasurements for harmonic state estimation. Simulation tests showed that this approach produces good results. A feedforward ANN and backward error propagation were used (7 references).

Ren-mu and Germond, [19]-1993, worked with the problem of dynamic load modeling. The authors presented the analysis and comparison between two models: a multi-layer feedforward ANN using backpropagation learning, and a conventional difference equation (DE) approach using recursive extended least square identification. Measured data from Chinese Power Systems were used. The results showed that ANN can represent well the voltage-power nonlinear relationship using the measurement-based dynamic load modeling method. However DE cannot. More research on the ANN models interpolation and extrapolation were suggested (3 references).

Parlos and Patton, [26]-1993, dealt with the empirical modeling of operational power plant dynamics and long-term electric load forecasting. A recurrent multilayer perceptron was used. High fidelity on transient response predictions and improved forecasting accuracy were obtained. Comparative forecasting results between the conventional and proposed approach were shown. The potential benefits of empirical modeling using an ANN as a nonlinear state-space model structure were demonstrated (12 references).

Samad, T., [27]-1993, described two approaches for modeling and identification using ANN: black-box neural net models (trained ANN is the model itself), and parametric identification with Neural Net (ANN outputs the model, pre-trained NN identifies structural features and parameter values for a parametric model). Models can be used for purposes such as prediction, control, and plant optimization (10 references).

Wan, [28]-1993, provides several examples to show the potential uses of an ANN architecture, which models synapses as FIR filters, for time series prediction and modeling. Chaotic time series were used to illustrate performance of the network. Reconstruction of underlaying chaotic attractors was carried out using phase-space plots. The results of the investigation could be applied to multivariate load forecasting. If control inputs are present, the basic framework can be used for the problems of system identification and control (12 references).

4.4 Control

Santoso and Tan, in [2]-1990, presented an ANN approach for the optimal control of capacitors on distribution systems. The specific case was to control the multitap capacitors installed in a distribution system for nonconforming load profile, such that the system losses were minimized. The development involved a computationally efficient strategy based on an expert system and two-stage ANN. The control net had two parts: one to predict the load profile and another to select the optimal capacitor. An ANN was used as a pattern recognizer and an expert system as an inference engine. Satisfactory results were obtained. Much less computation time was required when compared with that for an optimization process. This approach is suitable for implementation of on-line control even in a very large distribution system (12 references).

Novosel and King, [23]-1993, focused on the development of an ANN for intelligent load shedding. The IEEE 30 bus overhead test system was selected. The purpose of the scheme was to detect overloaded lines and make intelligent decisions about where the load should be dropped and how much load to shed. Instantaneous system emergency state is adapted regardless of changes in topology, load and generation. Findings showed that the scheme is advantageous compared to the existing method and technologies (2 references).

4.5 Load Forecasting

Park, D.C. et al.,[8]-1991, showed the potential of the ANN in electric load forecasting. Intervals of one hour and one day were considered. Simulations results showed that the proposed approach had less average error than conventional techniques. The ANN is a layered perceptron. Information of weather (temperature) and load were used. The algorithm does not require assumption of any functional relationship between load and weather. Due to differences in load profile, the authors have also experimented with one ANN for days with similar load profile and another ANN for each day with distinct load profile, obtaining good results (30 references).

Germond, Macabrey and Baumann, [32]-1993, presented an application of Kohonen's self-organizing map to short-term forecasting of peak electrical loads. The results were evaluated by using one year of hourly load data of a real system and forecasting the daily peek hour loads for the next year. Results were satisfactory, however they could be improved, says the author, by the selection and pretreatment of the variables. The optimal size of the network needs to be investigated (28 references).

Khadem and Dobrowolski [7], [33]-1993, presented an approach using ANN to forecast electrical load for the next 168 hours (1 week). Historical weather parameters such as temperature, relative humidity and sky cover are used. The ANN is trained for each day type and each weather-defined season. A multi-layer neural net and backpropagation algorithm are used. Results showed an absolute relative error of 2.5%. The use of a Kohonen neural network is now being investigated (9 references).

Cheung, Chance and Fogan, [34]-1993, examined the use of hierarchical neural nets for load forecasting. The present works differs from previous approaches in that the modeling and prediction is influenced by known characteristics of the load. It is shown that the ANN which incorporates known load characteristic is smaller and perform better than the straight forward networks (4 references).

7 The former author collaborates with ABB Systems Control, and the latter with Philadelphia Electric Company.

4.6 Fault Diagnosis

Ebron, S., et.al., [3]-1990, applied ANN to detect incipient faults on power distribution feeders. Specifically, the potentials of the ANN approach was demostrated in the detection of High-Impedance Faults (HIF). Feedforward nets and backpropagation learning algorithms were employed. Simulation results showed agreement in most of the cases. The net apparently had difficulty distinguishing between two high frequency activities: capacitor switching and HIF. More effective evaluation will require actual field data. The approach showed great potential as well as more effective strategy for detecting HIF. This work was considered highly theoretical and would require further investigation (22 references).

Chan, Markushevick and Adapa[8], [24]-1993, presented the results of applying an Interpretive Alarm Processor (IAP) based on ANN for steady-state power systems. Objective, scope, methodology and statistical analysis are described. The approach showed a high degree of steady-state problem determination and high accuracy level under realistic operating conditions. Future investigation should include: "1) Investigation of alarm pattern behavior under dynamic operating conditions; 2) Categorization of the problems into a smaller number of cases; 3) Investigation of the capability of recognition of a wide range of problems, and 4) Full scale system testing with dynamic power simulator (no references).

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[8] R. Adapa collaborates with EPRI.

5 CONCLUSIONS AND FUTURE RESEARCH

The demonstrated success of ANN applications in a broad range of problems and the increasing interest of researchers, vendors and electric power companies indicate the strength and applicability of the ANN technology. In fact, power systems computing with neural nets is considered one of the fastest growing field in power system engineering.

In order to provide an overview of the applications of ANN in Electric Power Industry, a representative number of research projects have been outlined. These projects were categorized in two groups: applications for Power Plants and applications for Power Systems.

To summarize all this work, the nature of problems, the type of neural nets used and their main functions are shown in tables 1, 2 below.

Table 1. Applications of ANN for Power Plants

Nature of the Problem	ANN and Learning Algorithm	Use of the ANN	References
Identification and modelling	Hybrid Feedforward/ Feedback	Prediction of transient responses	36
	Hybrid Self-organization/ Backpropagation	Prediction of heat-rate in nuclear plants	37
	Recurrent multilayer perceptron and Backpropagation	Modelling of power plant dynamics	26
Control	Feedforward and Backpropagation	Tuning of power system stabilizers	12
	Feedforward and Backpropagation	Control of load-frequency	29
	Feedforward and Backpropagation	Adaptive Control	30

Sensor Validation	Feedforward and Backpropagation	Estimation of process variables in nuclear plants	38, 14
	not specified	Prediction of sensor outputs	13
	Self-organizing and Specht's Probabilistic Neural Network	Estimation of Probability Density Function of Process Variables	31
Monitoring and Fault Diagnosis	Feedforward and Backpropagation	Generation of membership functions for a fuzzy expert system in nuclear plants	15
	Feedforward and Backpropagation	Recognition and classification of transient events in nuclear plants	16
	Feedforward and Backpropagation	Recognition and classification of wear scars in nuclear reactors	17
	Feedforward and Backpropagation	Recognition of accidents in nuclear plants	18
	Feedforward and Backpropagation	Recognition of incipient faults in rotating machines	11
	Perceptrons and Self-optimizing stochastic learning algorithm with dynamic node architecture.	Classification of accidental conditions in nuclear plants	31

Table 2. Application of ANN in Power Systems

Nature of the problem	ANN and Learning Algorithm	Use of the ANN	References
Static and Dynamic Security Assessment	Feedforward and Backpropagation	Estimation of post-fault parameter	1, 4, 21
	Functional link Net and not specified, just supervised and unsupervised	Prediction and estimation of the state of the power system	25
	Kohonen's self-organizing and unsupervised Feedforward and Backpropagation	Classification of states of power systems	5, 9, 10
	Feedforward and Backpropagation	Prediction of postcontingency voltages	20
Transient Stability Assessment	Decision Making System (comparable with a feedforward and Backpropagation)	Mapping transient stability assessment problem into the frequency domain	7
	Hybrid Perceptron and Kohonen's NN	Classification of power system conditions and prediction of voltage instability indices.	22
Identification, modelling and prediction	Feedforward and Backpropagation	Estimation of harmonics	6
	Feedforward and Backpropagation	Modelling of dynamic load	19
	not specified	General treatment of modelling and identification in the electric power industry	27
Control	Feedforward and Backpropagation	Prediction of load profile (used for an expert system in optimum capacitor control)	2
	not explicitly specified	Control of load Shedding	23

Load Forecasting [9]	Feedforward and Backpropagation	Forecasting of one hour and day	8
	Kohonen's self-organizing	Forecast of short-term of peak-loads	32
	Feedforward and Backpropagation with knowledge incorporated in its construction	Forecasting of short-term and long-term	34
	FIR ANN (Finite Impulse Response and ANN) Feedforward with synapses as adaptive FIR linear filter	Prediction and Modelling of time series	28
	Recurrent multilayer perceptron and backpropagation	Prediction of long-term	26
	Feedforward and Backpropagation	Forecasting of the next week	33
Fault diagnosis	Feedforward and Backpropagation	Detection of incipient faults in power distribution feeders	3
	not specified	Fault detection of lines, transformers and buses	24

Backpropagation has been mentioned as a general classification. However, each application presents particular modifications.

The significance of feedforward ANN and backpropagation training algorithm has been clearly demonstrated in tables 1 and 2 above.

With regard to ANN investigation support in the Electric Power Industry, the EPRI through its office of Exploratory and Applied Research has been playing an important role. A. Martin Wildberger, Executive Scientist of the EPRI mentions (preface in [5]-1993): "EPRI has supported neural network investigations, and will continue to so, with two goals in mind: (1) Finding innovative and valuable applications of neural network computing specific to the electric power industry, and (2) establishing fundamental theory and/or more reliable procedures for neural net design and development".

[9] Short-term forecast refers to hourly, daily and weekly forecast. Long-term involves annual, 5-year, and 10-year forecast.

Future Research

In fundamental theory, two issues remain to be addressed thoroughly:

* Determination of a theoretical basis to design ANN based on a priori knowledge of the process or system in question.

* Learning algorithms.

Some alternative approaches for both issues have been introduced by Moody and Antsaklis, [47]-1993 and [51]-1993; Sartori and Antsaklis, [48]-1992, [52]-1992, [53]-1991, Hou and Antsaklis, [49]-1992; Narendra and Parthasarathy, [50]-1990.

In the field of applications, several directions can be suggested, following the guidelines of EPRI [59]-1993, plan for the period 1993-97; one of these directions is shown in the target 4.1.2.1 on Productivity Improvement:

"Produce tools by 1995 to improve fossil steam plant heat rate and equivalent availability by an average of 3% over 1990 levels and reduce non-fuel O&M[10] cost by 15% and sustain these improvements trough the year 2000."

In this target, the following categories call the attention:

C.1) "Predictive O&M Systems: Demonstrate on line real time predictive O&M Systems

A) By 1995 develop performance monitoring system to improve heat rate by 1% and provide input for predictive maintenance analysis of plant components: demonstrate at 10 plants.

C.3) "New equipment, Instruments, and Maintenance practices: Develop new equipment, instruments and maintenance practices.

K) Develop and demonstrate next generation diagnostics and controls to significantly reduce plant O&M costs, including advanced sensors, fuzzy logic, advanced controls, and robotics.

10 Operation and Maintenance

C.4) "Control Retrofit Technology: Improve fossil plant control retrofit technology.

M) By 1995, develop and demonstrate improved controls hardware and algorithms to improve heat rate by 0.5%, minimize emission, and reduce outages due to instrument failure.

C.6) "Operator improvements tools: Develop operator improvement tools.

R) By 1995, publish guidelines for simulator training, develop computer-aided software engineering (CASE) tools for simulators, and assemble a library of training simulators. Demonstrate a 5% improvement in operator performance and a 25% reduction in the cost of simulator training at 5 utilities."

Certainly, for all the above issues, the technology of ANN can offer viable solutions. Such is the case, for instance, systems designed to integrate control and failure detection, as described by Konstantopoulos and Antsaklis in [54,55]-1994, neurocontrollers in [54,55,56,57,58], sensor validation by Khadem, et.al. in [14]-1993; Upadhyaya et.al. in [38]-1992, and simulators by Guo and Uhrig in [37]-1992.

To date the ANN technology has proved to be worthy of further investigation, and there exists a demand for applying this technology in the Electric Power Industry.

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APPENDIX A: MAIN INFORMATION SOURCES (CONSULTED)

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2 IEEE Transactions on Power Delivery, 1990-1992.
3 IEEE Transactions on Energy Conversion, 1990-1992.
4 Neural Network Computing For The Electric Power Industry: proceedings Of The 1992 INNS Summer Workshop, 1993.
5 Nuclear Technology
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