Applications in Power System Planning

Planning is an exercise involving many experts and areas: resources (generation and fuel), transmission, and demand-side management. It is essential to have a comprehensive picture of the whole in the form of a decision framework where linkages among various components are identified. Since reliable data or empirical relationships are not always available to deal with these adequately, the perceptions and opinions of experts become valuable. Expert systems can model the interactions of various planning functions to help in critical analysis of otherwise unquantifiable planning options. The following are some promising areas where these expert system tools can make a difference in system planning.

Training. Though training has been widely mentioned as one of the areas where expert systems can make important contributions, planning practices differ significantly among different utilities. Thus, generic expert systems will not be very useful for this purpose, and it may not be cost-effective to develop tools that represent or model all types of planning practices. It may, however, be possible to provide the utility planner with expert system shells and other knowledge acquisition tools. These can help them develop rulebases describing how certain system planning functions (e.g., load flow, stability, reliability analysis) are done. These rule bases can then be used to develop training modules for people moving into new jobs.

Data. Another item may be filtering input data-data sanity and reasonableness check. Since many planning models are data intensive, checking for completeness and consistency of the input data would be very valuable and time saving for the planner. Based on the material available in the literature, it appears that algorithms can be developed to check the completeness and consistency of input data.

Stability Studies. Expert systems may be used to analyze and interpret the results of base-case stability studies, and identify cases for which detailed analysis are to be performed. This will reduce the time needed to prepare and run stability cases. But more importantly, this will help focus attention to critical areas that are sometimes overlooked because of the large volume of cases to be examined.

Load Forecasting. With the advent of direct load control, self-generation, cogeneration has become very complex. Expert systems may be employed to sort out some of these complexities.

Outage Scheduling. Long refueling periods required for nuclear power plants and the repowering of many fossil-fuel power plants results in uncertainty and requires flexibility in the outage scheduling activity in the utility. Since some of these decisions are subjective, expert systems or other AI-based tools will be valuable for outage scheduling purposes.

Ranking of Alternatives. In the age of limited resources, pervasive regulations and multiplicity of alternatives, the traditional decision-analysis type tools are inadequate for comparing the often-unquantifiable attributes, and providing the necessary rankings. AI-based tools can help to quantify many of these uncertainties and thus rank alternatives more objectively.

Power Transaction Evaluation. Opportunities to buy and sell in order to efficiently run large units, save fuel, and meet environmental restrictions, have resulted in large scale power transactions in many parts of the country. Constantly changing priorities and prices, and the possibility of getting power from many resources, have given the transmission planner a mix of options that are sometimes difficult to evaluate. An AI-based tool may help the planners sort out these options.

Evaluation of Third-Party Generation Alternatives. With the advent of IPPs, third-party generation has become a bona fide alternative to be considered for capacity expansion plans. The utility generation planner, however, does not always have the full information about the reliability of supply, maintenance requirements, and the wheeling arrangement of the IPPs. In the absence of such quantitative information, the planner is often forced to seek data that describes the relative merits of one IPP generator versus another. Expert system tools can be developed to analyze such relative information and rank the strengths and weaknesses of third-party generation vis-a-vis the utility's own generation.

Problems and Opportunities

Expert systems and other AI tools can provide very useful support to power system operations and planning functions. However, the choice of application areas must be prudent so that the expert system can be effective. For example, if an algorithmic solution to the problem is possible, it must be pursued vigorously. On the other hand, if the expert system has to be applied, three conditions must be fulfilled:

- Human expertise must be available for providing domain specific knowledge
- Expert-system based search and inference have to be fast and reliable
- The expert system must be capable of explanation and justification.

Characteristics of expert systems, and the problems/opportunities in power system operations and planning areas offer some complementary qualities. There are several areas where early applications of expert systems are possible. These promising application areas have to be examined on a case-by-case basis, and a select few can initially be implemented that are practical and cost-effective. In addition, the introduction of expert systems must be slow and deliberate, such that both the developer and the user can get comfortable with the tools and the process. Such close partnership between these parties will make the expert system project successful and useful. It is expected that with further developments in the theory of AI and the availability of more powerful and versatile AI tools, it will be possible to achieve more comprehensive application of these tools in many others areas of power system operations and planning.

What Role Can Neural Networks Play in Power System Engineering?

Mohamed A. El-Sharkawi and Robert J. Marks,
University of Washington

Neural networks (NNs) have been studied for many years with the hope of achieving human-like performance in solving certain problems in speech and image processing. There has been a recent resurgence in the field of NNs due to the introduction of new network topologies, training algorithms, and VLSI implementation techniques. The potential benefits of NNs, such as parallel distributed processing, high computation rates, fault tolerance, and adaptive capability have lured researchers from other fields such as controls, robotics, and energy systems to seek solutions to their complicated problems.

What in an ANN?

An artificial neural network (ANN) can be defined as a loosely connected array of elementary processors or neurons. Algorithms are then crafted about this architecture. Neurons are linked with interconnects analogous to the biological synapse. This highly connected array of elementary processors defines the system hardware. Commonly used neural networks, such as the layered perceptron, are said to be trained rather than programmed in the conventional sense.

Proposed neural network applications can be broadly categorized as regression, classification, or combinatorial optimization

Neural networks have been found to be effective systems for learning functional mappings from a body of examples. This is done by adjusting arc weights and node thresholds of a set of interconnected neurons according to a specific learning rule. The high degree of connectivity brings about desirable properties, such as generation, fault tolerance, and noise rejection, which are useful in any model.

Computationally, neural networks have the advantage of massive parallelism and are not restricted in speed by the von Neumann bottleneck characteristic of conventional computation. Neural networks, in most cases, are significantly fault tolerant.

At this writing, the layered perceptron is receiving the most attention as a viable candidate for application to power systems.

How Does an ANN Learn?

The layered perceptron is taught by example, as opposed, for example, to an expert system, which is taught by rules. The preponderance of data typically available from the power industry, coupled with the ability of the layered perceptron to learn significantly nonlinear relationships, reveals it as a viable candidate in the available plethora of solutions for solving significant power systems engineering problems.

A layered perceptron can be used as either a classifier or a regression machine. As a classifier, the layered perceptron categorizes the input into two or more categories. In power system security assessment, for example, the trained perceptron will categorize the system as either secure or insecure in accordance to the current system states. For regression applications, the output of the layered perceptron takes a continuous value. Electric load forecasting is an example of regression application.

A neural network can be treated, from the training sense, as a model with unknown parameters. The existing technologies of parameter identification can be utilized in the learning process. The only modification that might be employed is to tune the identification algorithm to allow for speedy training.

Most of the parameter identification algorithms require a cost index as a measure of the accuracy of model being identified. For neural networks, the cost index is usually a least squares' function that represents the accumulated difference between the desired response and the NN output.

The layered perceptron is trained using supervised learning. The perceptron is told of the desired output for each input pattern. Unsupervised learning, on the other hand, does not require knowledge of the output. The classifier, rather, looks for similarity of structure in input patterns and groups them accordingly. The most visible of neural network's paradigms using unsupervised learning is *adaptive resonance training* that exists in various forms. In general, a classifier will train better when supervised than when not.

Unsupervised learning, on the other hand, can be the only available option in some scenarios.

There is a difference between *training* and *memorization.* A trained classifier or regression machine can respond with confidence to a pattern that it has not seen before. The ability to properly classify data that has not bean seen before is referred to as generalization. Memorization, on the other hand, guarantees that, when presented with a specific element in the training data set, the classifier will respond in exactly the same manner in which it was trained. In the case of memorization, the response to data other than training data is not considered in the paradigm.

The ability to interpolate among the training data does not necessarily imply good generalization. A properly trained classifier or regression machine should respond with the same error to training data as to test data. This is a necessary not sufficient condition. If the error from the test data is much higher than that from the training data, then chances are, the neural system is over determined. In other words, the degree of freedom in the classifier or regression machine is too high.

The degree of freedom of the neural network, equal to the number of interconnects and therefore proportional to the number of hidden neurons, must be matched, in some sense, to the complexity of the classification boundary.

Certain problems' characteristics to the layered perceptron are problems of the problem. The challenges would be encountered with all classifiers or regression machines trained by example. Other problems are specific such as the following:

- **Problems with back error propagation:** Although back error propagation if the most widely used method to train multilayer perceptrons, it in not the only nor necessarily the best approach. Indeed, most any algorithm that searches for a minimum can be used to train a layered perceptron. Back propagation is attractive because it can be performed within the neural network structure. However, the technique has a number of limitations. For example, since the back error propagation technique is not designed to be adaptive, all data must be used every time the weights are updated. If a set of old data becomes irrelevant, the NN is retrained by using the entire new data set. Also, when new data is in conflict with old data (data inconsistency), the effect of old data cannot be removed unless the is retrained without the old data. The importance of some data can not be easily weighted. In addition, if the size of the NN is not adequately selected, or the convergence criterion is not realistic, thousands of iterations can be required to train a layered perceptron in even a simple problem.
- **Scaling:** The scaling problem can be illustrated through the curse of dimensionality. Specifically, for a problem of similar partition complexity, the required cardinality of the training data set grows exponentially with respect to the number of input nodes.
- **Diminished learning:** The more you learn, the harder it is to learn. Indeed, in the absence of data noise, additional learning takes place in a multilayered perceptron only if new data is introduced that the neural network improperly classifies. The closer the representation comes to the concept, the smaller the chance that this happens. This is a characteristic of least squares and steepest descent techniques.

In supervised learning, each feature vector is assigned a classification (or regression) value or values. There is usually a cost associated with this assignment, such as the cost of performing an experiment, computational overhead, or simply time. This process is similar to presenting to an *oracle* the feature vector. For a cost, the oracle will reveal to us the proper classification or regression value associated with that vector.

Another approach to query based learning is, in effect, to ask a partially trained classifier or regression machines: "What is it you don't understand?" The response of the classifier or regression machine is to the oracle for proper, categorization and the result is added to the training data set. The classifier is then further trained and the process repeated.

Hydro Quebec has acted as a power industry pioneer in the intelligent systems domain and is showing many successful applications

How might we apply this query approach to a trained layered perceptron classifier with a single output? If the output neuron is thresholded at one half to make the classification decision, the representation boundary in feature vector space is the locus of all inputs that produce an output of one half. This locus of points corresponds to feature vectors of maximum confusion. In other words, when presented with such a vector, the neural network is uncertain to the corresponding classification. If there were a technique to find a number of these points, they could taken to the oracle to clear the confusion. The data from the oracle could then be used for training data. The perceptron can then be retrained to yield a higher accuracy. The question is, how can the locus of confusion he generated? The answer is through inversion of the neural network.

Neural Network Applications to Power Systems

Neural network applications that have been proposed in the literature up to date can be broadly categorized under three main areas:

- Regression
- Classification
- Combinatorial optimization.

The applications involving regression include transient stability, load forecasting, synchronous machine modeling, contingency screening, harmonic evaluation, and control.

Applications involving classification include harmonic load identification, alarm processing, static security assessment, and dynamic security assessment.

In the area of combinatorial optimization, there is topological observability and capacitor control.

Most of these, and other applications, are also reported in the first and second *International Fora on Applications of Neural Networks to Power Systems*. The Fora proceedings include other promising applications, such as fault diagnosis, protection, dynamic load modeling, power quality, training simulator, unit commitment, economic dispatch, and reactive power control.

✤

Intelligent Systems in Operation at Hydro-Quebec

Radu Manolliu, NOVASYS

As power systems are evolving towards an increasing level of complexity, intelligent systems are increasingly popular among utilities. We find that the term *intelligent systems* (IS) is more adequate than those of expert systems (ES) or knowledge-based systems (KBS). The main reason behind this relies on the fact that in power systems, ESs or KBSs represent only a part of more complex sets. Simulation modules, databases, PMI, sometimes telecommunication subsets, constitute a broad variety of building blocks that are instrumental in the design of a piece of software for the power industry.

Hydro-Quebec has acted as a pioneer in this domain since 1988 and is already showing a lot of successful applications.

Four systems are already in operation throughout the industry, and some of them are even in an initial stage of commercialization. Sharing the same concern as other utilities, Hydro-Quebec is aiming towards an improved service to customers. Consequently, the reliability and the availability of the power system represent high-priority items on Hydro-Quebec's agenda. Responding to this demand, the utility's developers placed emphasis on online and offline tools designed to improve the grid operation.

One example in this field is represented by LANGAGE, an IS for alarm processing in Hydro-Quebec's EMS. LANGAGE is already commissioned to three regional control centers and has demonstrated already a remarkable performance.

SEDA is another IS in operation. SEDA is aiming towards giving the diagnosis of eventual failures in power transformers. In this respect, SEDA is an invaluable tool for preventive maintenance of very costly equipment.

Another IS, TRANSEPT, is aiming towards the preliminary design of power networks. TRANSEPT is encapsulating the expertise of highly skilled individuals. Capitalizing on this expertise, TRANSEPT is a high-level tool that shrinks dramatically the space of research for detail simulation. Moreover, TRANSEPT represents a very pertinent tool in the process of giving the outlines for future electrical grids, as well as for allowing rough estimation. By playing with diverse parameters of a network, TRANSEPT is also instrumental in sensitivity studies.

In the process of the development of ISs, Hydro-Quebec has acquired a large amount of competence in KBS technology, as well in the methodologies which are pertinent to this discipline. High-level languages, such as LISP and PROLOG, are part of Hydro-Quebec's current practice, as well as a broad range of other tools and environments (OPS-5, OPS-83, NEXPERT-OBJECT, ART-IM, etc.). Hydro-Quebec applications run on very diverse platforms, such as PCs, VAX-Stations, SUN Sparc Stations, etc.

Some interesting lessons were learned by Hydro-Quebec during this 6-year experience. The paper qualifies them in three categories:

- Major pitfalls to avoid
- Principal hurdles
- Success factors.

Among the pitfalls to avoid one can remember: lack of user acceptance, incorrect application selection, educational gap, lack of corporate awareness, mismatch of tools, etc.

The principal hurdles mentioned are focused mainly on difficulties in knowledge acquisition, scarceness of knowledge engineers, lack of expert consensus, resistance to change, unavailability of the experts, etc.

Finally, in accordance to Hydro-Quebec's experience, the following factors have to be considered in order to ensure a successful application: the availability of a technology *champion*, as well as of a project *champion*, the first application has to be successful, the presence of the end-user in the project team, top and middle management awareness, etc.