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NEURAL NETWORKS FOR SENSOR VALIDATION AND PLANT-WIDE MONITORING

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Neural Networks for Sensor Validation and

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The feasibility of using neural networks to characterize one or more variables as a function of other related variables has been studied. Neural network or parallel distributed processing is found to be highly suitable for the development of relationships among various parameters. A sensor failure detection is studied, and it is shown that neural network models can be used to estimate the sensor readings during the absence of a sensor.

Signal Validation and Neural Networks

In large power generating systems and process control systems, sensor outputs from many different channels are used in control systems, protection systems and plant-wide monitoring systems. It is necessary to validate these signals to increase the reliability of operator decisions. Signal validation is one of the ways that can help to increase the reliability of control and protection systems. Signal validation is used to check the consistency of the redundant measurements of selected process variables, estimate their expected values from measurements, and detect, isolate, and characterize the type of the anomaly in the measurement channel outputs [1].

The routine validation of critical signals in a reactor is useful for monitoring incipient changes in sensor behaviour and for improving the control strategy with less challenge to the control systems. Plant-wide monitoring is another useful aid which can improve the reliability of control actions. Plant-wide monitoring is a type of signal validation which is performed by tracking multi-sensor outputs simultaneously. Instead of estimating only one sensor output at each time, multi-sensor outputs can be estimated by using the plant-wide monitoring system methodology.
Signal validation and process monitoring problems require the prediction of one or more process variables in a system. The prediction of system state variables is performed traditionally using either physical or empirical models. Empirical models require knowledge of all variables having significant effect on the signal to be modeled. The model characterizes a critical signal as a function of a set of other measurements which is modeled [1]. Model-based prediction assumes a fixed structure for characterizing steady-state or dynamic relationships among process variables. The generation of an accurate model requires an effort which is proportional to the size and complexity of the system. An alternative new method, neural network (distributed parallel processing), offers several advantages in signal validation when compared to the traditional model-based techniques.

1. It is not necessary to define a functional form relating a set of process variables,
2. The functional form as defined by an Artificial Neural System (ANS) is implicitly nonlinear,
3. Neural networks do not require the detailed system specifications for the models,
4. Neural networks are more fault tolerant than the traditional techniques.

What Are Neural Networks?

Neural networks are intrinsically parallel and non-algorithmic methods; these features of neural networks make real-time processing of data and information feasible. Neural networks, NNs, have been trying to fill the gap for which traditional techniques have, so far, failed to offer a reasonable solution. Continuous speech recognition, image pattern recognition, processing of real-world imperfect knowledge, adaptive robot movement control, and analysis of large systems are some of the current problems for which NNs can offer acceptable solutions but traditional computing techniques cannot.

Neural networks are made up of highly interconnected processing elements, PEs, which are organized into series of layers. Usually, a typical neural network consists of an input, an output, and one or more hidden layers. Hidden layers are used to represent the nonlinear properties of the data. The basic concept of the neural network approach is based on the functions of a brain. A brain has the ability to think, observe, understand, process information, react and many other functions some of which are still not clear to the neuro-scientists. All these functions are performed by billions of densely connected neurons, the basic component of the biological nervous system. There are various types of neurons in a brain, which perform in different ways; essential functions of these neurons are: combining the input signals, and producing an output after passing through a threshold. Neurons receive the input signals through dendrites, and if the combined signals exceed the threshold then that neuron fires, producing an output which is transmitted to other neurons using the axon. The output of one neuron can be one of the inputs for the other neurons.

Neural networks are mathematical models of theorized brain and mind activities. The fundamental part of neural networks are formed by the processing elements, PEs, which are analogous to neurons. These processing elements also have many input paths, they combine the inputs and produce an output after using an appropriate threshold function. These processing elements are also highly interconnected, the connection types vary from one network algorithm to another. There are many algorithms that require fully connected architectures. Also, there are algorithms which are using partially connected architectures. The network architecture depends on the network algorithm; one-layer lateral feedback, two-layer feedforward, two-layer feedback, and multi-layer feedforward topologies are some of the commonly used network architectures. Different threshold functions are used for different algorithms; step, ramp, linear, and sigmoid threshold functions are the basic threshold (activation) functions for neural networks.

There are two major stages in the applications of neural networks: learning and recalling. Learning is the first and the most important phase where the connection weights are adjusted by using training laws, according to the presented external data set, in order to capture the characteristic features, and relationships within the data set. Recalling is the second stage where the pre-adjusted connection weights after the learning phase are used to capture the characteristics of a new data set (usually different from training data set).
Learning algorithms are generalized into two major groups: supervised learning and unsupervised learning. Supervised learning is a learning procedure such that the desired output is presented to the network during the learning phase. Unsupervised learning is the one in which the hidden relationships within the data set are found by the network itself without using any external force or information.

The Backpropagation Network (BPN) Algorithm

The backpropagation network algorithm uses the generalized delta rule [2] for training. Figure 1 shows the topology of the network. The first layer receives the information, and feeds it to the inner layer. The second layer which is commonly known as a hidden layer receives information from the input layer, modified by the weights on the connection and propagates this forward. Hidden layer size and number of hidden layers are one of the important issues in the development of the network architecture. The hidden layer is used to characterize the nonlinear properties of the system to be analysed. The last layer is the output layer where the desired output values received from the outside world and the calculated values are presented to the environment. The BPN is a fully connected network in which a neuron is connected to all neurons in the next layer (there are no lateral connections). The BPN algorithm computes the connection weights between pairs of processing elements such that the difference between the actual output and the network output is minimized in a least-squares sense. It is important to note that this architecture accepts analog signals, thus binary representation is not necessary. The learning procedure involves the presentation of input and output values to the network. First, the system uses a set of inputs to produce its own output vector, and then compares this output with the desired output. If there is no difference, there will not be any further learning; if there is a difference, then the connection weights will be changed to reduce this difference.

The most commonly used multi-layer neural network algorithm, namely Backpropagation Network (BPN), is developed and implemented on a VAX workstation with a new adaptive learning rule which speeds up the convergence and improves the accuracy of the network models [11]. Also, an approach has been developed to estimate the optimum size of the hidden layer,

\[ H = \frac{I \times \log_2 N + 1}{V} \]

which is the most important part of the multi-layer network algorithms. This experimental approach is developed by using Shannon's information theory. In the formula \( N \) is the number of training patterns, \( I \) is the size of the input vector. The formula seems to be working for the signal validation and diagnosis applications

Applications of BPN

The on-line signal analysis system designed for the multi-level mode operation is capable of monitoring the plant states by tracking 32 different signals simultaneously [3]. The data used for this study was acquired from the Borssele nuclear power plant (NPP) by using the on-line monitoring system during various operations. The Borssele NPP is a two-loop pressurized water reactor with 477 MWe power. The power plant is operated by EPZ, an electricity production company in the south of the Netherlands.

The BPN algorithm is used during the signal validation, plant-wide monitoring, fault detection, and sensor validation applications at the Netherlands Energy Research Foundation (ECN). Some of the studies which are completed can be listed as:

- estimation of power level during a shut-down transient (Figure 2) and normal operation conditions,
- monitoring of power level, hot leg temperature, cold leg temperature, and core-exit temperature,
- sensor validation of a neutron detector (Figure 3),
- finally, the on-line implementation of neural network approach for plant-wide monitoring is being studied currently.
First a network is created using data set of Stretch-out of Borssele NPP; inlet and outlet temperatures of both primary system coolant loops signals are the input signals of the network model where the generated electric power is the output signal. The network is trained with 137 patterns (samples) out of possible 569 patterns, using every 1 minute sampling. Three out of four patterns were skipped and those skipped patterns were not presented during the training phase. The last 21 patterns were not included in the training set so that the extrapolation performance of the model could also be tested after the training. The network modelling error was 1.4% for the recall data which included the entire set, 569 patterns. Figure 2 gives the results of the measured and predicted values of the network model.

The application of a sensor validation is discussed below. For effective control strategies in process industry systems, it is necessary to validate signals from plant sensors and to monitor a multitude of variables. Although many vital signals have redundant measurement sensors, sometimes it is necessary to validate the readings coming from sensors. The case studied in here involves with the estimation of one of the ex-core neutron detectors. During the routine operations of nuclear power plants, detector calibrations take place before the new fuel cycle. This calibration is usually done during shut-down of a power plant. There are four different ex-core neutron detectors which send information to the on-line monitoring system located at ECN. Each detector is removed and calibrated separately. During the absence of the detector there is no reading coming to the on-line monitoring system. The main goal of this study is to have a neural network model which can estimate the values of that sensor readings during its absence. It is important to realize that this could be a sensor failure as well. If an important sensor fails, and the control system requires immediate information from that sensor, then the operation could be in a critical situation.

The network model is created by using generated electric power, hot and cold leg temperature signals as input. The output of the network will be the estimates of the ex-core neutron detector readings. The network is tested by simply presenting the signals coming from generated electric power, hot and cold leg temperature signals to estimate the readings of the ex-core neutron detector, during the absence of the sensor the network was able to estimate the values correctly, figure 3 displays the estimated and the measured values of ex-core neutron detector and the estimation error. This unique application shows that neural network models can be used as a sensor validator and that they can give acceptable estimates during a sensor failure.

Also other applications feasibility of using neural networks to characterize one or more variables as a function of other related variables were studied [4]. Neural network or parallel distributed processing is found to be highly suitable for the development of relationships among various parameters. A sensor failure detection is studied, and it is shown that neural network models can be used to estimate the sensor readings during the absence of a sensor.

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References

Figure 1. Multi-layer network topology for signal validation applications.

Figure 2. Estimation of generated electric power, using inlet and outlet temperature signals as input to the network model for the Stretch-out data set.
Figure 3. Estimation of neutron detector sensor readings during a shut-down transient of Borssele Reactor. Generated electric power level, hot leg temperature, and cold leg temperature readings were used as input signals to the neural network model. Then network was able to predict the sensor readings during the absence of the neutron detector sensor.