AN INTELLIGENT MONITORING SYSTEM FOR ELECTRIC POWER VARIATION IN A NUCLEAR POWER PLANT

R. Çağlar caglar@elk.itu.edu.tr
E. Ayaz ayaz@elk.itu.edu.tr
S. Şeker seker@elk.itu.edu.tr
E. Türkcan turkcan@elk.itu.edu.tr

Istanbul Technical University, Faculty of Electrical and Electronics, Department of Electrical Engineering, 34396 Maslak, Istanbul, Turkey

Key words: Power plant monitoring, nuclear power plant, neural network, active power, reactive power, power factor.

ABSTRACT

This paper presents an electric power monoring based on Artificial Neural Network (ANN) for the nuclear power plants. The Recurrent Neural Networks (RNN) and the feed-forward neural network are selected for the plant modeling and anomaly detection because of the high capability of modeling for dynamic behaviors. Two types of Recurrent Neural Networks (RNN) are used. The first one *Elman* type of RNN which has a feed-back from hidden layer to the input layer neurons while in the *Jordan* type, from the outputs of the neural net to the inputs of the neural net. Although this approach enables to realize the whole system condition monitoring in operating nuclear power plant (NPP), we are especially focused on active power and reactive power monitoring as well as power factor monitoring. Today, competition in electric power supply industry needs to properly evaluate plant capabilities and produced power quality, so the monitoring of active and reactive power becomes an important issue. Therefore active and reactive power and their variations are monitored taking their signals using the assigned channels and the electric power coefficient is simultaneously monitored from these measured reactive and active electric power signals.

I. INTRODUCTION

The modern electric power system has been continuously and rapidly developing to perform the functions for generating, transmitting and delivering of electric power. With this progress, the complexity of the system has grown. To manage this complex system, monitoring, control and operation functions are computer assisted. The systems for computer control of electric power systems have evolved as computer and monitoring technologies evolved. Monitoring is a key element in assuring quality and reliable power. It can assess the overall performance of a power plant and identify trends that can help reduce or even eliminate the impact of disturbances.

In this paper we give an attention the power monitoring issue in the nuclear power plants contributing previously published paper, which presents a method for an on-line monitoring system for the nuclear power plants developed utilizing the neural networks and the expert system[1,2]. Automated monitoring of large power plant is a well-established practice in the industry. Several computer systems are employed today in a control room to monitor various parts of the power plant[3,4]. Introduction of advanced data acquisition systems and intelligent technique have accelerated development of new monitoring systems. Recently, promising ANN approaches have been developed to solve problems like tuning of controllers, process identification, sensor validation, fault diagnosis and monitoring in power[1-5]. Table 1 shows some ANN and learning algorithm with use of ANN for Power Plants [6].

A real-time condition monitoring at nuclear power plants (NPPs) is one of the most important tasks for operational safety. Conventional monitoring methods in the present NPPs can detect anomalies when the monitored signals exceed their error boundary. However, it is difficult to detect the symptom of anomalies with this method because of the wide error boundary covering about 30% to full power operation. Therefore, we proposed a neuro-expert methodology that is more preferable than the threshold-level-based one for early fault detection. The main purpose of this monitoring system is to complement the conventional alarm system and to support operators. Neural network techniques already have been applied to plant monitoring and shown good performance for early fault detection[7,8]. However, the neural network itself can merely detect a deviation from the normal state, and requires an interpretation of the deviation by an expert to diagnose the cause. On the other hand, establishing independent expert systems for plant monitoring involves too many complicated tasks such as collecting knowledge and rules about plant design. This motivates the integration of neural networks and an expert system for plant monitoring.

Table 1. Application of ANN for Power Plants

Nature of the problem	ANN and Learning Algorithm	Use of ANN
Identification and modeling	Hybrid Feedforward / Feedback	Prediction of transient responses
	Hybrid self organization / Back propagation	Prediction of heat-rate in nuclear power plants
	Recurrent multilayer perceptron and Backpropagation	Modeling of Power Plant Dynamics
Control	Feedforward / Backpropagation	Tuning of power systen stabilizers
	Feedforward / Backpropagation	Control of load frequency
	Feedforward / Backpropagation	Adaptive control
Sensor validation	Feedforward / Backpropagation	Estimation of process variables in NPP
	Not specified	Protection of sensor outputs
	Self-organizing and Specht's Probabilistic Neural Network	Estimation of probability density function of process variables
Monitoring and fault diagnosis	Feedforward / Backpropagation	Generation of membership functions for a fuzzy expert system in NPP
	Feedforward / Backpropagation	Recognition and classification of transient events in NPP
	Feedforward / Backpropagation	Recognition and classification of wear scars in NPP
	Feedforward / Backpropagation	Recognition of accidents in NPP
	Feedforward / Backpropagation	Recognition of incipient faults in rotating machines
	Perceptron and Self-optimizing stochastic learning algorithm with dynamic load architecture.	Classification of accidental condition of NPP

In this study, as an application of electric power monitoring and detecting abnormal operational condition, we proposed to use ANNs. Hence the rising operation effect was followed and determined from active power, reactive power factor variations by means of various ANNs structures.

II. BASIC ELECTRIC POWER QUANTITIES TO BE MONITORED

Most of time, an electric power system operates under sinusoidal steady state condition, i.e. the voltages and currents anywhere in the system are considered to be near perfect sinusoids. This operating condition is reffered as Sinusoidal Steady State Condition (SSSC). This assumption and resulting analysis methods are appropriate to describe the operation of the system for a rather large number of applications, such as power flow, short circuits, etc. It is also possible that certain components of the system may results in deviations from the pure sinusoidal steady state operation. The voltage and electric current waveforms may be periodic but they are not sinusoidal. This operating condition is reffered as Periodic Steady State Conditiom (PSSC). Many power system analysis problem are based on the following assumptions; -the power system operates under SSC, -the power system exitation is a pure sinusoid, -the power system comprises only linear elements. Accepting above conditions we can express voltages and electric currents anywhere in the system a pure sinusoidal forms.

$$v(t) = V_m \cos(\omega t + \theta) \tag{1}$$

$$i(t) = I_m \cos(\omega t + \varphi) \tag{2}$$

where V_m is the maximum value of the voltage
I_m is the maximum value of the electric current
ω is the angular frequency
θ is the phase of the voltage
φ is the phase of the electric current

The instantaneous power flowing into the device is:

$$p(t) = v(t) \cdot i(t) \tag{3}$$

Realizing this multiplication reveals that the power consists of two terms: one which is independent of time and another terms which is sinuoidal function of time and its angular frequency is double of that of voltage or electric current. This time dependent power is pulsating, i.e. flows into and out of the device with zero net. Then the averge power is

$$P = \frac{1}{T}\int_0^T p(t).dt \tag{4}$$

$$P = V_{rms} I_{rms} \cos(\theta - \varphi)\,. \tag{5}$$

The difference between the voltage phasor's angle and the current phasor's angle is defined as power factor angle.

$$\phi \equiv (\theta - \varphi) \tag{6}$$

The last term of the Eq.5 is reffered as the power factor since many decades ago.

$$\text{power factor} \equiv cos\phi \tag{7}$$

Where $V_{rms} = \dfrac{V_m}{\sqrt{2}}$, $I_{rms} = \dfrac{I_m}{\sqrt{2}}$.

There are four quantities expressing power but they are all phsycaly different quatities. To distinguish them, the following nomeclature shown in Table 2, has been adopted many years ago and it is used in power engineering [9]:

Table 2. Electric Power Quantities.

Quantity	Name	Units
S	Coplex Power	VA (Volt Ampere)
Sa	Apparent Power	VA (Volt Ampere)
P	Real Power	W (Watt)
Q	Reactive Power	VAr (Volt Ampere, reactive)

$$S = \tilde{V}_{rms} \tilde{I}^{*}_{rms} \tag{8}$$

$$S_a = V_{rms} I_{rms} \tag{9}$$

$$S = S_a \cos(\theta - \varphi) + jS_a \sin(\theta - \varphi) \tag{10}$$

$$S = P + jQ \tag{11}$$

$$P = V_{rms} I_{rms} \cos(\theta - \varphi) \tag{12}$$

$$Q = V_{rms} I_{rms} \sin(\theta - \varphi) \tag{13}$$

Then the power factor can be computed using following relation.

$$\text{power factor} = \frac{p}{S_a}$$

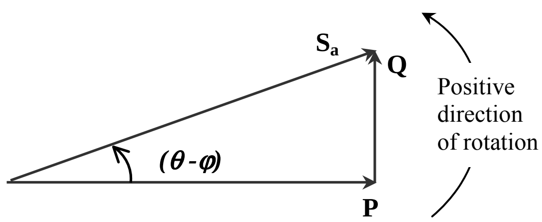

Figure 1. Phasor Representation of Apparent Power, Active Power and Reactive Power.

We can decide the power factor is lagging or leading by observing the voltage and current phasors. Generally supply voltage regarded as the reference quantity. The power factor is lagging when the current lags the supply voltage and leading when the current leads the supply voltage. A majority of loads served by a power utility draw current at a lagging power factor. When the power factor is unity then active power equals apparent power (P=S). But, when the power factor is less then unity, say 0.7, the power utilized is only 70%. This means that 30% of apparent power is being utilized to supply reactive power, VAr demand of the system. It is therefore clear that the higher the power factor of the load, the greater the utilization of apparent power [10].

In the deregulated environment, competition in the electricity supply industry distincly differentiates between generation and transmission functions of a conventional verticaly integrated utility. Open access permits all players to inject real power into a system with few restirictions. As generator also provide reactive power to the system. While the competition for active power is quite evident from this distinction, it is also has a significant cansequences on the ensuring of reactive power. Adequate reactive power support and voltage regulation services are required by the system to enable secured transaction of active power. Therefore their reactive power outputs should be financially compensated. The paper in Ref.[11] state that a generator's Q-outputs has double applications. One is to support the shipment of its own active power, and the other is to support system security. Therefore compensation should be made the second component only. Reactive power support and valuations take a great attentions in last years, trying to answer to the questions of usage allocation, -what fraction of reactive capability of a generator is used to supply a particular load[12] An other great interest comes from voltage stability analysis using VAr reserves[12,13]. Most important reactive power support is dynamic or variable Var support provided by synchronous condenser and generators.

III. MONITORING SYSTEM OVERVIEW

The Borssele NPP represented in the Fig. 2. is a two-loop pressurized water reactor with nominal electric power output of 477 MWe.

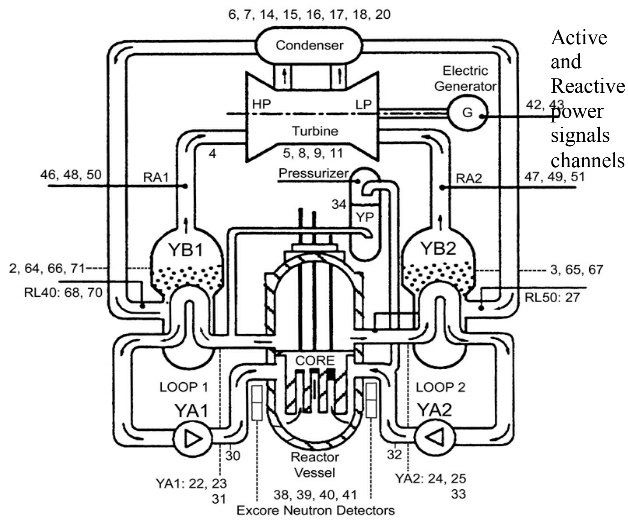

Figure 2. Reactor System

A new data collection and diagnostics system is devised by the year of 2001 and extensively used in the new operation in the start-up of the new core 29 September 2001 and thereafter. New measuring system of the Borssele NPP has been presented in Ref.[14]. The 480 MWe Borssele PWR (KCB) is owned and operated by NV Electriciteits-Productiemaatschappij Zuid- Nederland (EPZ), and located near the Westerschelde estuary. The single unit plant was built over the years 1968 to 1973 by Siemens/KWU and achieved a life time load factor above the 80% over the first 24 years. In the first half of 1997 the world's most ambitious nuclear backfitting project successfully finished[15] and the power plant operation in the core cycles in '98 and '99 achieved to average load factor above 91%. The new plant data collection and processing system consists of two sub-systems:

a) Monitoring of plant DC signals of the plant (max 96 signals) with fixed sampling rate of 10 samples/sec. used for continuous operational history recording with the aid of plant transient analysis (MR-System).
b) The reactor noise diagnostic system with measuring 32 AC/DC signals (MS measuring system) with aid of reactor noise and primary coolant pumps induced vibrations and core barrel motions [16].

Both systems are built in National Instrument's (NI) hardware and Labview software system and the continuous data of the both system is connected through the LAN for the continuous observation of the plant behaviour. In this paper we used the signals of the continuous operation of the plant through the DC measuring system (MR) with 96 process signals.

IV. RECURRENT NEURAL NETWORKS AND FEED-BACK CONCEPT.

Recurrent Neural Networks (RNNs) are a special type of the dynamic neural nets. In this sense, there are two kinds of the recurrent networks, one of them is Elman’s recurrent neural net [17] and another one is Jordan’s net [18]. According to general principle of the recurrent networks, there is a feed-back from outputs of some neurons in hidden or output layer to neurons in input layer. These feed-back connections in the Elman’s neural nets are from the outputs of neurons in hidden layer to the input layer neurons and in Jordan’s nets are from output layer to nodes in input layer, which are called as context nodes. This part of the input layer that includes the context nodes is named as context layer and it plays role to store internal states in the Elman’s and Jordan’s nets. These types of RNNs can be easily trained using the Back-Propagation (BP) training algorithm, which is well known algorithm in related literature.

V. APPLICATION

In this study, three types of time-independent (patterns) neural networks, which are BP, Elman and Jordan type RNN, were applied to Borssele NPP data for anomaly detection. All three networks architectures have 44 inputs and outputs nodes and 50 hidden nodes to follow various process signals and a pair of them is electric power signals. Here, output vectors are the same as the input vectors. To train the all neural network, 1 minute sampled data of the power rise from 200 MWe to full power 480 MWe were used including the re-calibration period of power and sensor signals. After sufficient learning iterations the neural network performances were tested using the steady-state data acquired for different time periods.

An example of the neural network performance during the learning period is given in Fig. 3 for the BP, Elman and Jordan methods with their deviations from the observed power rise to steady-state full power operation period. After the learning period is succeeded, the operational data sampled with 1 sample/second is used for the following of the operation of the power plant using all three networks for testing the performance of three different networks:

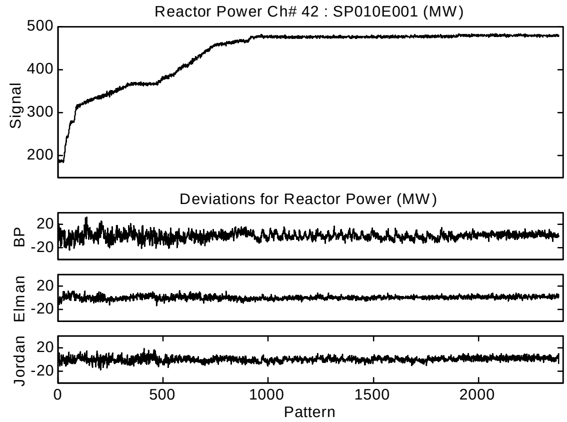

Fig. 3 - Neural networks’ training results for Elcetric Power variations (Channel 42 in Fig.2).

In this sense Fig. 4 shows the performance of three diffferent NNs to reflect operational changing in the stady state region of the data.

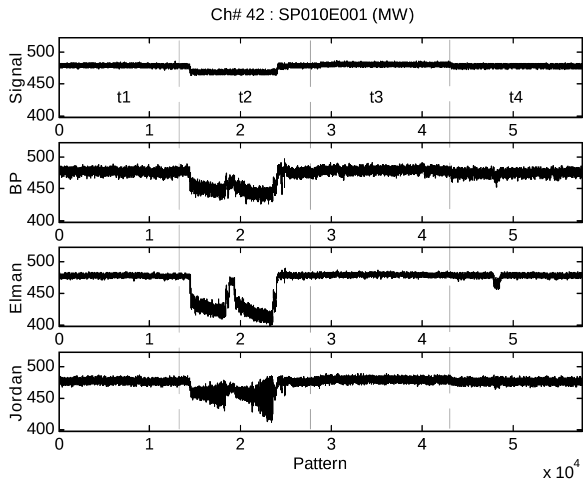

Fig. 4 - Neural networks’ test results for steady-state data.

Where time t_1 is the last steady-state operation (data of an operation between November 8, between time midnight 00 hrs to 07:30 hrs of 2001) with 1s/s data included to the learning period. The t_2 (Nov. 15, midnight time 00 hrs to 07:30 hrs) period is the full power operation period of the recall of the three different neural networks. In this period reactor power is changed due to the rinsing operation (condenser spooling) in time duration of about 4 hrs.

While in the learning period such an operation is not included, the all three neural networks indicates the operational deviations depending on the network characteristics. The t_3 (Nov. 22, midnight 00 hrs to 07:30 hrs) and t_4 (Nov. 29, midnight 00 hrs to 07:30 hrs) are periods of the normal power operation. Testing of the neural networks is periodically continued for each 4 weeks. According to the results of the Fig.4, the most dominant results can be revealed by the Elman's neural network.

VI. CONCLUSION

Application of the neural networks was satisfactorily implemented with the present system for filtering the reactor power operation with one-second time interval that is even five times faster than the plants processing system that works only 5s time intervals. In this study three different neural networks BP, recurrent neural networks Elman and the Jordan worked well but different manner. According to results, it is concluded that is Elman-RNN amplifies the deviations with clear picture, Jordan-RNN shows deviations but with oscillating behaviour that it can be improved by selecting smaller initial weights, BP method is less sensitive to the smaller deviations in the signals.

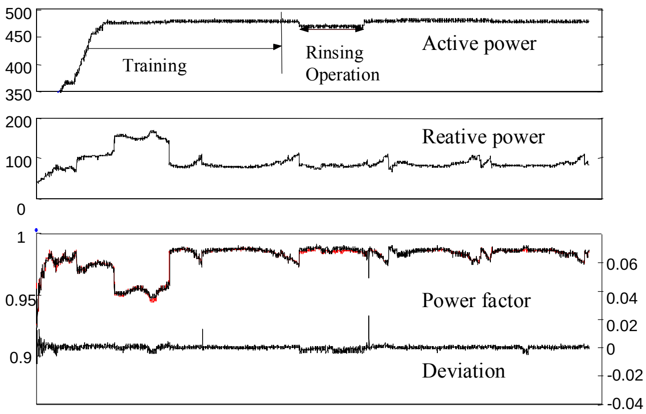

Figure 5. The monitoring results of powers and power factor by Elman's NN.

In this sense, the best performance is exhibited by the Elman's RNN defined in this study which is the modified BP structure based on the feedback concept. Therefore we prefere to use the Elman's RNN stuructures in terms of following the active and reactive power together with power factor variations as shown in Fig. 5. Hence the rinsing operation effect can be easily detected from the active power variations. Also this effect can be slightly seen from the reactive power variation, but this property mentioned above can be observed by small signal variations from the power factor variation comparing with the reactive power variation.

REFERENCES

1. Ayaz E., Seker S., Barutcu B., Turkcan E., Comparisons between the various types of neural networks with the data of wide range operational conditions of the Borssele NPP, PROGRESS IN NUCLEAR ENERGY 43 (1-4): 381-387 2003.
2. Nabeshima K, Suzudo T, Seker S, Ayaz E, Barutcu B, Turkcan E, Ohno T, Kudo K, On-line neuro-expert monitoring system for Borssele nuclear power plant PROGRESS IN NUCLEAR ENERGY 43 (1-4): 397-404 2003.
3. M. Kezunoviç et all, Real time generator monitoring system, Engineering Intelligent System, Vol. 6 no.2 pp. 83-89, June 1998.
4. Shankar R., On-Line Monitoring of Power Plant Systems, the paper is appearing the following side http://www.epri.com/journal/pdfs/321_Shankar_OnlineMonitoring.pdf
5. Neural Network Computing For the Electric Power Industry: Proceedings of the 1992 INNS Summer Workshop, Editor Dejan J. Sobayic, Lawrence Erlbaum, Associates, Publishers, pp. 47-50, 51-54, 55-58, 612-619, Hillsdale, N.J., 1993.
6. Technical Report of the Interdisciplinary Studies of Intelligent Systems (ISIS) Group at the University of Notre Dame, "Artificial Neural Network in Electric Power Industry", ISIS-94-007 April, 1994. The paper is appearing the following side www.nd.edu/~isis/techreports/isis-94-007.ps.gz
7. Nabeshima K., Suzudo T., Suzuki K. and Türkcan E. (1998), Real-time Nuclear Power Plant Monitoring with Neural Network, *Journal of Nuclear Science and Technology, Vol.35, 93-100*.
8. Upadhyaya B. R. and Eryurek E. (1992), Application of Neural Networks for Sensor Validation and Plant Monitoring, *Nucl. Tech., Vol.97, 170-176*.
9. Bergen A.R., Vittal Vijay, Power System analysis, Second Edition, 200, Prentice-Hall, Inc. ISBN 0-13-691990-1, New Jersey, 07458.
10. Abraham A., Nath B., "Artificial Neural Networks for Intelligent Real Time Power Quality Monitoring Systems", In Proceedings of First International Power & Energy Conference, (INT-PEC'99-Australia) (CD ROM Proceeding), Isreb M. (Editor), ISBN 0732 620 945, Australia, 1999.
11. da Silva, L.C.P.; Wang, Y.; Wilsun Xu; da Costal, V.F.; Power Engineering Society Summer Meeting, 2001. IEEE, Vol. 3, 15-19 July 2001 pp: 1616 -1620
12. Kirshen D., Strabac G., Tracing Active and Reactive Power between Generators and Load Using Real and Imaginary Currents, IEEE Transactions on Power Systems, Vol. 14, No.4, November 1999.
13. Syed Ahmet, Goran Strbac, A Method for Simulating and Analysis of Reactive Power Market, IEEE Transactions on Power Systems, Vol. 15, No. 3, August 2000.
14. Türkcan E., Winkelman A., Brevoord J., Stok P. (2001), Trend Monitoring Noise Signal Processing System for Borssele NPP. *Annual Meeting on Nuclear Technology 2001*, 606, Dresden, Germany.
15. Gruhl H.H. and Kalverboer C. (1997), Backfitting Borssele. *Nuclear Engineering International*.
16. Real time reactor noise diagnostics for the Borssele (PWR) nuclear power plant Barutcu B, Seker S, Ayaz E, Turkcan E PROGRESS IN NUCLEAR ENERGY 43 (1-4): 137-143 2003
17. Elman J. (1990), Finding Structure in Time. Cognitive Science, 14, 179-211.
18. Jordan M. I. (1986), *Attractor Dynamics and Parallelism in a Connectionist Sequential Machine*, Proceedings of the 1986 Cognitive Science Conference, 531-546.