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The Development of Anomaly Diagnosis Method Using Neuro-Expert for PWR Monitoring System

by

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Abstract

The monitoring system for a huge and complex Pressurized Water Reactor (PWR) is one of the most important tasks but difficult due to dynamic system with a lot of plant signals. The research performed previously a development of PWR monitoring system integrated with data acquisition system. The combination of neural network and expert system (neuro-expert) is utilized to improve the time-process of anomaly detection. The advanced research considered the online anomaly diagnosis using expert system to complete the monitoring system tasks.

Keywords: Pressurized water reactor, Real-time, Monitoring system, Back propagation, Neural network, Anomaly detection

1. Introduction

A regulation of smart application for nuclear reactor, NS-G-1.1 was introduced by IAEA due to the necessity trend of online smart application in the nuclear reactor. The smart monitoring system has applied in some nuclear reactor for supporting the operators with useful information based on all reactor signals. In detail, the monitoring system task is to check and analyze the parameter signal to implement anomaly detection system, which is proposed to be integrated in the reactor-safety system. The application of neural network using back-propagation algorithm was done in several problems[1)]. In case of nuclear reactor application, the combination of neural network and expert system techniques already have been applied to online plant monitoring and shown good performance for early anomaly detection by Nabeshima et all[2)]. In addition, in real case, neuro-expert also has been applied at Borselle PWR in Netherlands with off-line test by Nabeshima et al[3)].

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However, monitoring system must have adequate computer engine and method to compute and monitor some complex parameters in real-time mode. The calculation using nuclear physic methods in today's most powerful computer still have time-lag calculation process and difficult for real-time monitoring. The using of neural network simplifies the model to approach directly the input-output mapping and memorize the knowledge in network weights during learning.

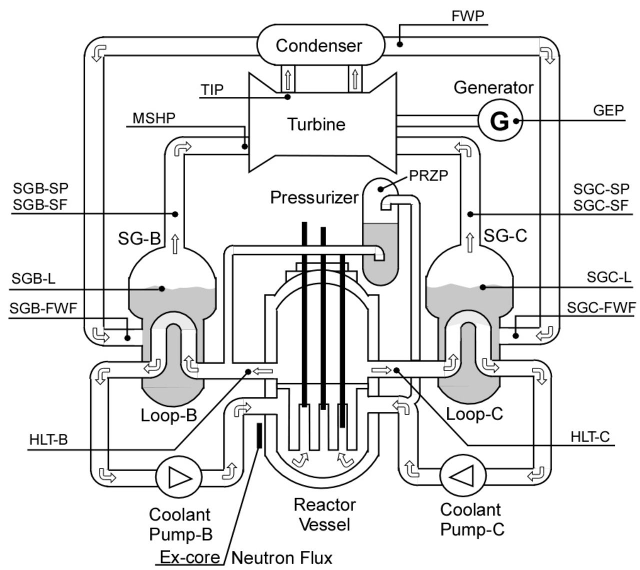

Fig.1 Surry-1 simulator schema [3].

In this research, the monitoring system utilizes 22 inputs of reactor parameter taken from data-acquisition simulation and transfers the input signals to neuro-expert engine to determine the reactor operation condition. Anomaly test using the data of PWR simulator, Surry-1, USA (722MWe) was done as well as the previous research by Nabeshima with different type of neural network. The simulator schema is shown in **Fig. 1**. SG-B indicates steam generator loop B and SG-C indicates steam generator loop C. The primary loop consists of hot leg temperature (HLT-B and HLT-C) and pressurizer (PRZP). The secondary loop consists of steam pressure (SP), steam flow (SF), feed water flow (FWF), feed water pressure (FWP), and also steam generator level (SGB-L and SGC-L). However, the neural network itself can merely detect an error from the normal state, and needs an interpretation of the error by an expert to diagnose the causes[3)]. The research developed the prototype of monitoring system including data acquisition system, server-client with TCP-IP communication in a full-integration distributed architecture as well as the application for the High Temperature engineering Test Reactor (HTTR) [4,5)]. The exploring of the method development has started for anomaly detection using neural network with simple expert rules[6)]. The other development that more advanced than the development of HTTR monitoring system is in progress and the new methods of Time Synchronizing Signal Multilayer Perceptron (TSS-MLP) and Time Delayed Jordan Recurrent Neural Network (TD-Jordan RNN) for special case have also introduced for pursuing and exploring the technology of monitoring system [5,7)].

Focusing to the anomaly diagnosis, some difficulty may cost trouble to the monitoring system. The problem of dynamic model degradation should be considered in which the learned pattern and the dynamic model are unmatched due to the operating condition has changed over time. The initial learning should be updated and the re-learning should be carried out to anticipate the degradation.

Indeed the neural networks require long time learning times and offline calculation. Another problem is anomaly diagnosis after given alert and it is difficult to determine the anomaly cause by alert only. The proposed method of neuro-expert is a combination of neural network and expert system as well as done in previous research for neuro-expert using recurrent neural network (RNN)[3] and multilayer perceptron (MLP) with simple expert rules[4]. The neural network will detect the anomaly early and give alert when channel fault detected. Parallelly, the expert system diagnoses the alert information and gives determine the anomaly cause. The research aims to improve the previous MLP development with advanced expert rule as a complete method for anomaly diagnosis.

2. Anomaly Detection Using Neural Network

2.1 Backward pass and forward pass of neural network

The neural network consists of two passes through the different layers of the network: a forward pass and a backward pass (shown in **Fig. 2**). In the forward pass, an input vector is applied to the network sensory nodes, and its effect propagates through the network layer by layer. The linear combiner output is

$$a_j = \sum_{i=1}^{p} w_{ij} x_i \ , \qquad (1)$$

The network learning on an iteration by iteration basis can fix or adapt a synaptic weight w_{i1}, w_{i2}, . . . , w_{ij} of the network. The output of every neuron in the hidden layer is using logistic function, the function (output) signal of neuron *j* is

$$o_j = \frac{1}{1+\exp(-a_j)} \qquad (2)$$

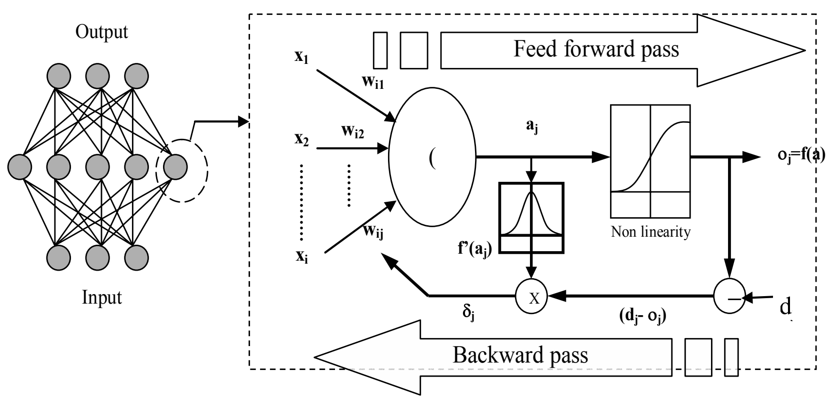

Fig.2 Backward pass and forward pass of neural network.

Finally, a set of outputs is produced as the actual response of the network. During the forward pass the synaptic weight of the network are all fixed. During the backward pass, the synaptic weights are all adjusted in accordance with an error correction rule. Specifically, the actual response of the network is subtracted from a desired response to produce an error signal. The difference of the desired output d_j and the calculated output o_j gave an error signal e_j. This error signal is then propagated backward through the network against the direction of synaptic connection as known error back-propagation algorithm. The synaptic weights are adjusted to make the network actual response move closer to the desired response in a statistical sense.

The adjustment of network weight based on backpropagation algorithm is using the equation below:

$$\Delta w_{ij}(t) = -\eta \frac{\partial \mathrm{E}(t)}{\partial W(t)} \tag{3}$$

where i is input index, j is output index, and η is learning rate for an active neuron. The principle of backpropagation is the local gradient δ_j for output neuron j that equals to the corresponding error e_j and the derivative a_j of the associated activation function. Then the network weights are fixed by equation:

$$w\ (t+1) = w(t) + \Delta w(t) \tag{4}$$

Network iterations search an optimum weight based on error correction. This process is called learning of neural network.

2.2 Initial learning

The neural network needs initial learning data of operating PWR at normal condition and finds the optimum intelligence knowledge correlated with optimum weight. However, the monitoring performance is also given by the learning and in the future, there is some possibility to re-learn other operation data and update the memory displacement for long period, because the dynamics of the plant can be changed.

Table 1 PWR channel.

Channel	Signal Name	Unit
1	Ex-core neutron flux-A	%
2	Ex-core neutron flux-B	%
3	Ex-core neutron flux-C	%
4	Ex-core neutron flux-D	%
5	Average coolant temperature	°C
6	Pressurizer pressure	%
7	Volume control tank level	%
8	Turbine impulse pressure	%
9	Steam generator level (B)	%
10	Steam generator level (C)	%
11	Steam flow (loop-B)	t/h
12	Steam flow (loop-C)	t/h
13	Feed water flow (loop-B)	t/h
14	Feed water flow (loop-C)	t/h
15	Main steam header pressure	%
16	Feed water pressure	%
17	Hot-leg temperature (loop-B)	°C
18	Hot-leg temperature (loop-C)	°C
19	Steam pressure (loop-B)	kgf/cm^2
20	Steam pressure (loop-C)	kgf/cm^2
21	Average neutron flux	%
22	Reactor power	MW

In the initial learning, every dataset pattern consists of 22 input signals to perform 22 monitoring channel objects. The input signals are also normalized in [-1, 1] before entered to neural network to make all the input elements lie normally between 1 and -1. **Table 1** show the PWR channel which used in the research as neural network inputs and outputs.

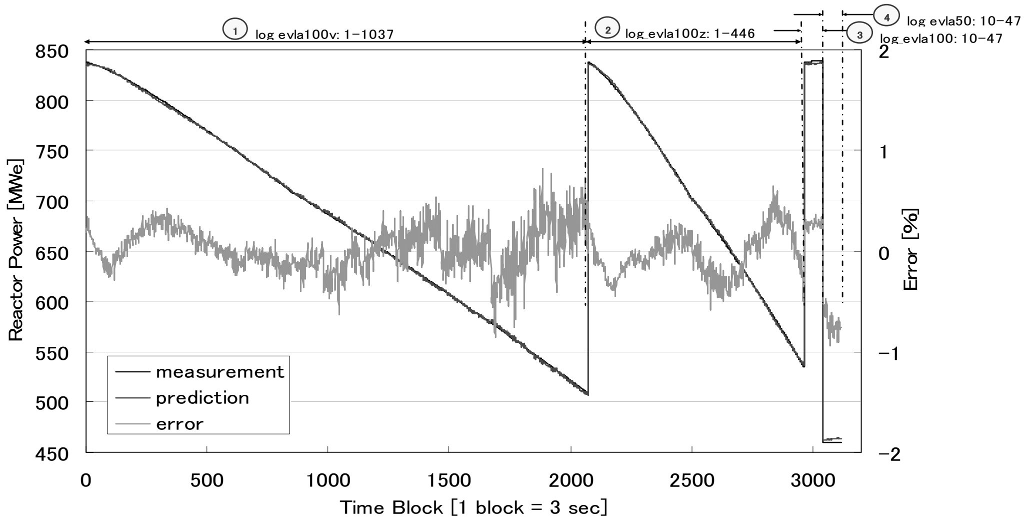

Fig.3 Initial learning dataset.

Table 2 Result of Initial learning.

Channel	Min Value	Max Value	Square Error	Max Error [%]	Fault Level [%]
1	37.758	98.688	0.142	1.866	3.0
2	37.782	98.681	0.137	1.761	3.0
3	37.724	98.740	0.140	1.725	3.0
4	37.240	98.679	0.130	1.669	3.0
5	293.50	302.73	0.000	0.092	1.0
6	33.374	46.347	0.048	0.975	1.5
7	49.486	70.827	0.038	0.491	1.0
8	15.387	36.440	0.077	1.169	3.0
9	43.518	45.825	0.003	0.154	1.0
10	43.544	45.819	0.003	0.252	1.0
11	650.51	1591.9	0.079	1.078	3.0
12	650.55	1590.1	0.080	1.076	3.0
13	672.97	1600.3	0.076	1.185	3.0
14	673.44	1601.1	0.073	1.272	3.0
15	51.077	61.466	0.012	0.619	1.5
16	78.409	94.592	0.005	0.231	1.0
17	301.53	319.64	0.001	0.099	1.0
18	301.50	319.60	0.001	0.106	1.0
19	52.527	62.007	0.010	0.577	1.5
20	52.547	62.040	0.010	0.569	1.5
21	37.574	98.346	0.139	1.782	3.0
22	436.50	837.00	0.062	0.934	1.5

The used dataset for learning consist of 1037 patterns of 1.5%/min power decreasing, 446 patterns of 3.5%/min power decreasing, 37 patterns of 100% steady state power and 37 patterns of 50% steady state power operation. Total pattern number in a dataset is 1557. The initial learning dataset has converged as shown in **Fig. 3**. The learning with random order input for every iteration cycle was carried-out.

The convergence is less than 2% of maximum error after 600 iteration cycles or epoch. The initial learning results are showed in **Table 2**. The maximum error is 1.866% with mean square error of 0.142%. Here, the maximum error is defined as maximum deviation between the offline measured signals and the corresponding values predicted by neural network. The error is expressed in percentage to show the comparison of deviation value to the measure value. In the online monitoring, the small deviation indicates the reactor operation is normal. In contrary, higher deviation than the setting fault level indicates the anomaly in the reactor operation. Furthermore, the maximum deviation or error should be given to give a critical decision between normal condition and anomaly condition, named fault level. The given fault levels were decided by below expression:

- If maximum error in channel less than 0.5%, fault level is 1.0%,
- If maximum error in channel less than more than 0.5% and less than 1%, fault level is 1.5%,
- If maximum error in channel less than more than 1% less than 2%, fault level is 3.0%.

3. PWR Anomaly Detection Test

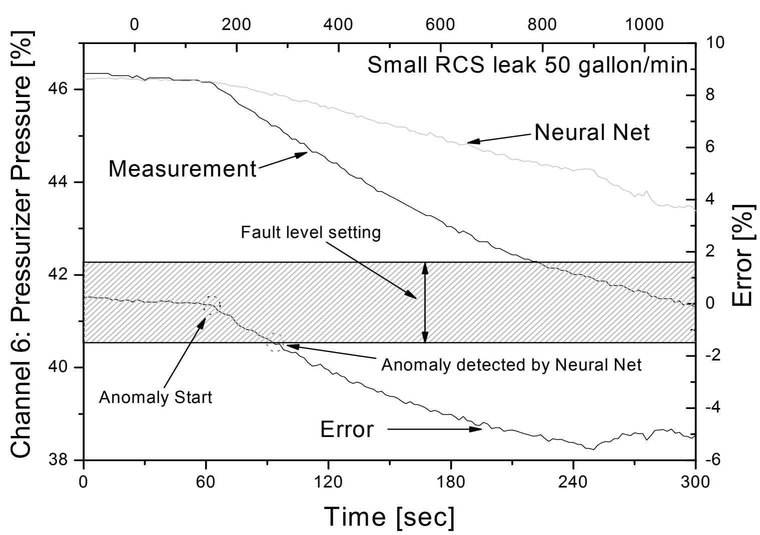

Fig.4 Anomaly detection test using neural network.

The simulation test for determining the anomaly condition was done. An anomaly sample as described in **Fig. 4** is taken from signal number 6 for pressurizer pressure parameter monitoring; fault level error was set to 1.5%. This anomaly sample simulated *small reactor coolant system (RCS) leak* anomaly at 100% operation. Anomaly was successfully detected quickly. The measurement value comparing with predicted value of neural network indicated the error or deviation and the expert system diagnosed the deviation value and the alert position to decide the anomaly condition, when the deviation was getting higher than fault level boundary. At the same time, monitoring application gives an alert and an anomaly determination result message to operator after the diagnosis process finished. When an anomaly was happened, one warning indicates an anomaly, but with time process running, the anomaly condition become serious anomaly spread to the other anomaly. A serious anomaly condition for small RCS is happened after 77 second from first pressure anomaly detected.

Figure 4 shows anomaly detection test using neural network. The anomaly detection for offline data of small RCS leak 50 gallon/min was demonstrated by the developed prototype. The anomaly was detected in 34 seconds with the deviation of pressure level (channel 6) exceeding the setting fault level, faster than conventional alert which has respond time of 5 minutes 30 seconds for the same case. If the fault of feedwater pressure signal (channel 16) was detected after channel 6 anomaly, the expert system may determine the anomaly cause with the related accident rule. The same pattern may be used for diagnose other anomaly, but the system need more advanced method to diagnose drift error.

Table 3 Anomaly detection test at 100% steady state operation.

Case number	Anomaly Simulation	Detection Time [minute: second]	
		Conventional Alert	Neuro-Expert Alert
1	*Small Reactor Coolant System Leak 100 Gallon/min*	01: 49	00: 18
2	*Small Reactor Coolant System Leak 50 Gallon/min*	05: 30	00: 34
3	*Leakage of Atmospheric Steam Dump Valve 100%*	00: 34	00: 02
4	*Leakage of Atmospheric Steam Dump Valve 50%*	01: 58	00: 02
5	*Partial Loss of Feed Water 3x453.6 Ton/hour*	03: 44	00: 02
6	*Volume Control Tank Level Control Fails Low*	00: 01	00: 02
7	*Steam Generator Level Control Fails in Low Direction*	00: 01	00: 02
8	*RTD Failure High in Cold Leg of Loop A*	02: 00	00: 02
9	*"C" Steam Generator Tube Rupture*	01: 00	00: 10
10	*Pressurizer Spray Control Valve Fails Open*	10: 34	00: 34
11	*Both Pressurizer Spray Control Valve Fails Close*	03: 59	02: 06
12	*Dropped Reactor Control Rod P6 Control Bank A*	00: 01	00: 02
13	*Turbine Governor Valves Fails Closed*	00: 02	00: 01

Focusing to the detection test results, **Table 3** shows the complete anomaly detection tests during 100% steady state condition. The test results showed that neuro network has better time-respond than conventional system in anomaly condition for all cases, because the application has efficiency and robustness due to system simplification. The detection sensitivity and precision is adjustable in fault level setting. Complement advanced programming improved the application prototype to have a high compatibility to communicate with other secondary or redundancy application using TCP-IP technology. Hence the prototype may support wide-scale monitoring system applied multi-agent based on distributed architecture[4)].

4. Application Development

The monitoring viewer developed on windows is shown in **Fig. 5**, where the monitoring data is shown based on sampling time. Anomaly warning is showed by red flicker alert in graphical user interface. The information is completed by the analysis result given by expert system after a few second to get adequate information of other alert. The expert system processes the channel position of the alert and matches the rule order to decide the anomaly cause. The detection time of an alert affected by an anomaly signal has mentioned in **Table 2** to knowing the application responds.

If the anomaly signal is detected at certain channel number, the expert system diagnoses the increased deviation of the operating parameter determined by neural network and the measurement result. If malfunction started; the application could send an alert and localize the malfunction position in the power plant instrument. Faster information to the operator after malfunction started gives more time for operator act to anticipate the anomaly so that bigger damage caused by its anomaly is avoidable.

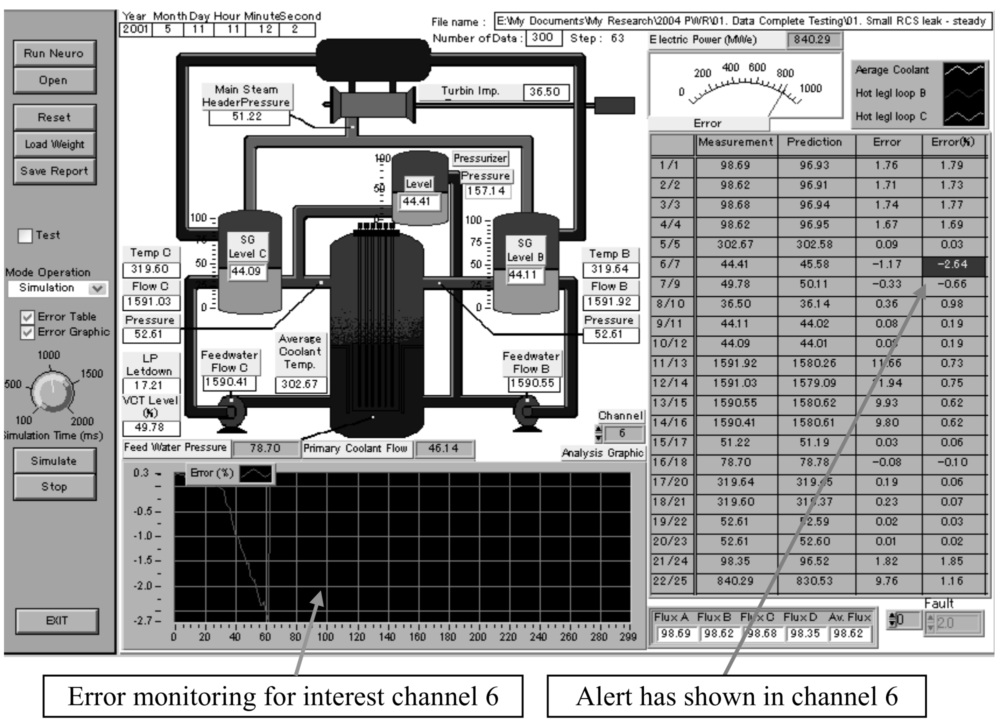

Fig.5 Developed monitoring system panel.

Figure 5 shows the prototype panel of monitoring system. In the panel, the operator will receive clear information of power plant condition virtually. The table in right side of **Fig. 5** shows the signal quantity of error in percentage and gives red area caution if the error exceeded the fault level. The analysis aid by expert system is still limited to the simple rule to study the neural network respond time and alert characteristic affected by anomaly detection.

In the real condition, expert system should be enhanced to distinguish the drift deviation defined as slow rate of deviation increase change, and drastic change of deviation increase. The research investigated the drastic change of deviation increase and the respond time of neural network. Other case of online validation is possible to work parallel for the signal from neutron flux sensors, but for other signal is difficult due to redundancy signal input.

5. Expert System Role for Anomaly Analysis

The arrangement of expert rule requires an anomaly pattern given by some anomaly detection testing. **Table 4** shows the specific characteristic of anomaly detection using neural network for expert rule development. The neuro-expert gives alert at firstly a channel fault detected, and identifies the cause of that anomaly by the knowledge matching involved in expert rule, for example:

- *if operating at steady state 100%,*
- *and if fault of channel 6 was detected,*
- *and if fault of channel 7, 22 was detected with the flow time from first detection to second detection is about 46 minutes.*
- *Then* "*The small RCS leak 50 gallon/min*" will be detected.

Table 4 Specific characteristic of anomaly detection using neural network for expert rule development.

Case Number	Detection Time and Channel Fault					
	First (time after malfunction started)		Second (time after first fault)		Third (time after second fault)	
1	00:18	CH: 6 Small error	00:22	CH: 7, 22 Small error	No need expert rule	
2	00:34	CH: 6 Small error	00:46	CH: 7, 22 Small error	No need expert rule	
3	00:02	CH: All, Error for CH 1,2,3,4,8 >10%	00:02	CH: All, error increase - decrease	No need expert rule	
4	00:02:	CH: 6, 7, 11, 12, 16, 22 Small error	00:02	CH: All, small error	No need expert rule	
5	00:02:	CH: 1, 3, 4, 13, 14, 16, 21, 22. Error CH 13, 14 > 10%	00:02	CH: 11, 12 Error CH 16 > 10%	00:02	CH: 7 Error CH 13, 14 > 20%
6	00:02	CH: 1, 2, 3, 4, 6, 7, 16, 21 Error CH 7 > 35%	No need expert rule		No need expert rule	
7	00:02	CH: All except CH 5,9,10,17,18 Error CH 14 > 20%	00:02	CH: All except CH 5,10 Error CH 14 > 25%	00:02	CH: All except CH 5 Error CH 14 > 25%
8	00:02	CH: 5, 7, 9, 10 Small error	00:10	CH: 16 Small error	00:16	CH: 1, 2, 3, 4, 8, 15, 21, 22 Small error
9	00:10	CH: 6 Small error	00:16	CH: 7 Small error	00:06	CH: 1, 2, 3, 4, 21, 22 Small error
10	00:34	CH: 6 Small Error	00:36	CH: 7 Small Error	01:00	No CH detected Small error for CH 6, 7
11	02:06	CH: 6 Small Error	03:20	CH: 7 Small Error	00:24	CH: 1, 2, 3, 4, 21 Small Error
12	00:02	CH: 1, 2, 7, 8, 21 Small Error	00:02	CH: 3, 4, 9, 10 Error for CH 2 > 38%	00:02	Error for CH 2 > 42% Error for CH 21 > 15%
13	00:02	CH: All except CH 5, 9, 10, 17, 18, 22. Small Error	00:02	Error for CH 8 >15% Error for CH 13, 14 > 10%	No need expert rule	

CH: Channel
Time is described in minute:second

The expert rule in programming processes the knowledge in **Table 4** become forward chaining above. The complete expert system's rule base in application is made up of many such inference rules. An inference rule is a statement that has two parts, an *if-clause* and a *then-clause*. The rule is what gives expert systems the ability to find solutions to diagnostic and prescriptive problems. It is possible to understand how the diagnosis was reached from the drawn rule. However, avoiding the change of setting fault level is necessary to keep stable the accuracy of expert rule because the setting change will trigger the other channel alert, change the alert rule characteristic, and impair the diagnosis result.

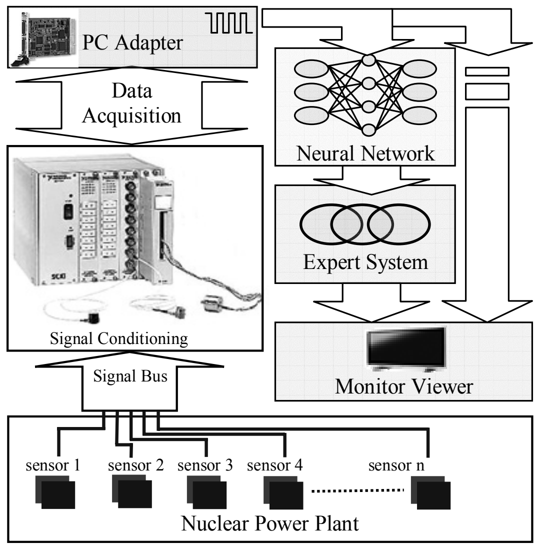

Fig.6 The coupling method of neural network and expert system.

Figure 6 shows the coupling method of neural network and expert system. For real implementation, the monitoring system requires data acquisition to get the raw signal from selected sensor. The signal conditioning circuitry for general measurement is fairly straightforward. It consists of the signals itself (come from each sensor), an instrumentation isolated amplifier to boost the sensor's signal level and isolate its signals, a low pass filter to reduce noise and prevent aliasing in the data acquisition system, and finally, simultaneous sample and hold circuitry to keep the signals properly timed with respect to each other. After data acquisition, the digital data could be utilized by the developed application of neuro-expert.

6. Conclusion

The anomaly diagnosis method using neuro-expert for real-time PWR monitoring system has been developed. The anomaly detection tests were demonstrated using the output of Surry-1 PWR simulator. Maximum error of initial learning is 1.866% and the fault level was concluded with a simple expression to determine the critical value for anomaly detection. The neuro-expert system detected the anomaly faster than the conventional alarm system. The expert rule approached the knowledge of neural network characteristic during anomaly detection and the processed knowledge becomes inference rule in expert system application. In the future works, the prototype of monitoring system could be applied to the actual real-time data acquisition system which is online to PWR instruments.

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