A Hybrid Approach for Minimizing Spurious Trips in Hard Real-Time Systems

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Abstract: In this paper a hybrid neural network and rule based approach for spurious trips minimization in hard real time systems such as nuclear reactor power plants is proposed. This approach is a hybrid or a mix of rule base and neural network. The purpose is to learn from experience in the same way as humans learn from their past experience in operation of nuclear power plant. The approach would use artificial neural network as well as a rule based approach for intelligent decision-making. The patters of data will be taken from the modern control systems like DCS, PLC etc. via OPC and is fed to the trained ANN. The output of the algorithm will be a optimized decision. The operator can improve his decision making based on suggested values by the Algorithm. [Journal of American Science 2010;6(7):281-286]. (ISSN: 1545-1003).

Keywords: Spurious trips, Hard Real time system, OPC, rule base, Backpropagation.

1 Introduction

Whenever accidents occur in nuclear power plants [12], operators will attempt to detect the seriousness by observing drifts of parameters presented on HMIs to obtain first hand information of plant's current status which may steer towards accident [10]. The shift operators are unaware of whole data statistics about all parameters and only have a partial future trend behavior so, it is extremely hard for operators to forecast the development of the proceedings by just looking at time-based **tendency** of some important variables on huge sized mimics in the main control room [7], [8]. Also, in this brief time abnormality, hundreds of parameter values coming from instruments will be looked after by that will show some characteristic patterns of that momentary transient [33] , [26]. In most of the situations for severe accidents of nuclear power plants operators should be able to accurately forecast transient scenarios [33], so that they can make accurate decisions regarding safety of personnel as well as reliable operation of the plant [12]. Normally the operators always go for easy decisions like shutting down the power plant. Shutting down a nuclear power plant always costs a huge revenue loss to owner as well as power shortage to countries, already facing energy crisis, like Pakistan [15]. Unlike thermal power plants nuclear power plants always take more time to operational state again. So it is the need of the hour to efficiently operate the plant and to minimize nuclear power plant shutdowns. This can be achieved by taking advantage of latest research trends [4]. Lots of power plants in the world are using artificial intelligence techniques to improve the reliability and to minimize the plant outages. Alexander *G.* Parlos & Benito Fernandez, used ANN for control & identification of various components of Nuclear Power Plant [14], [17]. Lots of AI methods/techniques comprising of ANN and techniques/methods of fuzzy inference to numerous nuclear engineering regions have been utilized fruitfully, such as optimal fuel loading [29], [30], [25] & [26], plant diagnostics [27], [28] , power plant control [31], signal validation [24], event identification [23], [32], [33], and so on. A few more applications of neural networks to nuclear power plant's engineering structures can also be found in the references [18], [19], [20], [21], and [22].

2 Background of the problem

The KANUPP (Karachi NUclear Power Plant), which is a CANDU type reactor [5], [3], was in total control of Pakistani engineers and scientists after Canadians left our country. Lots of challenges were encountered by the plant in its operation. After the sanction from key nuclear countries we lost vendor support in 1976 [15], for the purpose of repair, modifications, or maintenance the plant shutdown kept for long time. In this hard period our committed self-belief in PAEC employees took plant to its old operational status [15]. Throughout its operational history although there is no major accident occurred but plant faced many spurious shutdowns, which could have been avoided through better decision-making. These spurious shutdown decisions have caused PAEC a great amount of revenue loss over its operational history [9], [15]. So the task is to minimize spurious shutdowns by using artificial intelligence techniques that will assist the operators towards better decision-making. A central control was there to monitor the plant. A twenty square meter room was used as control center for a single-unit CANDU. 2 walls were dedicated for the instruments panels. There was a main work area in control room dedicated to operators & their assistants. [34]. All aspects of the plant are controlled by operator from this central seat. Several resources and systems are there to provide information to the operator. Status of the plant is inferred from panel locations and consol workstations. The plant operator has to keep an eye on numerous parameters before taking a major decision (such as shutdown) in abnormal condition. These days KANUPP is not operated at full power (i.e 137Mwe). It is operated only at 90 MWe these days. Table 1 displays the list of only important parameters [9], [15].

Still there are lots of parameters not shown. So taking a decision based on that much number of parameters is a difficult task. Some times an abnormal shift in the value of a parameter can be ignored if some other parameter values are normal and some time only a single parameter value (e.g PHT outlet temperature 580 F) becomes so important that the operator takes an important decision. Because the abnormal situations arises less in the operational history so data patterns noted and the corresponding decisions taken are in less number. Therefore the task is to achieve higher accuracy with small training data samples for and ANN [6], [1].

3 The Proposed hybrid Methodology

The proposed methodology is actually a hybrid of two AI methodologies. This is neural network plus rule-based [6]. The desired patterns of data collected from the power plant operational history data are used as the training the artificial neural network using Backpropagation algorithm [13], [6], [16], [11], [2]. Then that trained artificial neural network in combination with rule based approach is used in the final decision making in plants shutdown. This methodology has been proposed to solve the spurious reactor trips problem in the KANUPP [9]. The purpose of introducing this hybrid methodology is to improve the decision making ability of the power plant operators. This will ultimately help in minimizing the spurious reactor trips and therefore the loss of revenue.

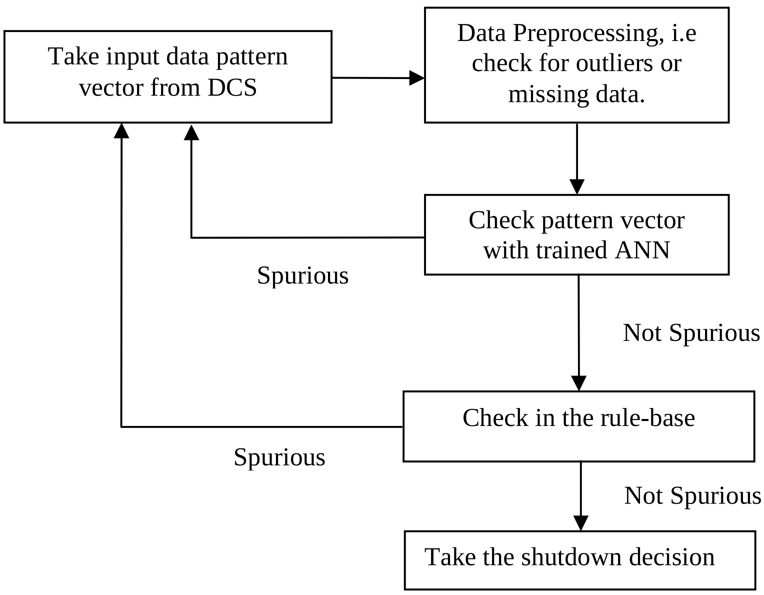

Figure 1: The proposed hybrid approach

4 Case Study

As a case study we considered the operational data of KANUPP. There are hundreds of the parameters in the nuclear power plant [9], we mention some of the variables used as input to the artificial neural network are listed in table 1 shown below.

Table 1: List of some parameters used in the training data

SN	Parameters	Normal operating values
1	Electrical Power (MWe)	90
2	Moderator Level	182
3	Moderator temp (F)	140
4	PHT inlet temperature (F)	478
5	PHT outlet temperature (F)	535
6	Steam Pressure (psi)	550
7	Steam Temp (F)	474
8	Calendria spray flow (igpm)	1500
9	Boiler feed water pressure (psi)	900
10	Condensate water pressure (psi)	200
11	Turbine RPM	3000
12	Generator RPM	3000
13	Boiler feed water pressure (psi)	900
14	Condensate water pressure (psi)	200
15	Exhaust hood temp (F)	110
16	Charging tank level	127
17	Charging tank temp (F)	140
18	Generator hydrogen pressure (psi)	30
19	Turbine shell expansion (mil)	210
20	Hydrogen seal differential pressure (psi)	8.5

The values listed in table 1 are the normal operating values. The training data samples for transient or abnormal conditions have been generated through the simulator. The total number of training data samples generated through the simulator is 255 [35]. Data has been divided into training, validation, and test sets. Out of these samples 60% are used for training, 20% for testing and the remaining 20% for validation [16]. In order to ensure that there is no over fitting the validation data set is utilized. To independently measure how well the ANN can perform on a data that have never been used in its training, a test set is used.

5 Results & Discussion

5.1 Optimizing the Number of Hidden nodes

The optimized value for the number of hidden nodes for this specific problem is found through a series of experiments for the Levenberg-Marquardt backpropagation. The results are shown in the table 2.

Table 2: Results for different no. hidden nodes.

No. of Hidden Neurons	Execution time	Regression Coefficient	Epochs	Comments
14	41.432071	0.8668	27	Validation stop
15	42.502456	0.8733	24	Validation stop
16	61.86331	0.9736	32	Validation stop
17	41.658935	0.9512	19	Validation stop
18	36.618649	0.9794	15	Validation stop
19	33.517457	0.9943	12	Validation stop
20	16.929745	0.9976	5	Performance goal met
21	21.89272	0.9973	6	Performance goal met
22	20.199239	0.9977	5	Performance goal met

23	26.361702	0.9974	6	Performance goal met
24	27.891669	0.9977	6	Performance goal met
25	43.87587	0.9974	6	Performance goal met
26	32.988149	0.9973	6	Performance goal met
27	34.791656	0.998	6	Performance goal met
28	37.71092	0.9963	6	Performance goal met
29	40.136347	0.9984	6	Performance goal met
30	42.629025	0.9972	6	Performance goal met
31	46.077593	0.9967	6	Performance goal met

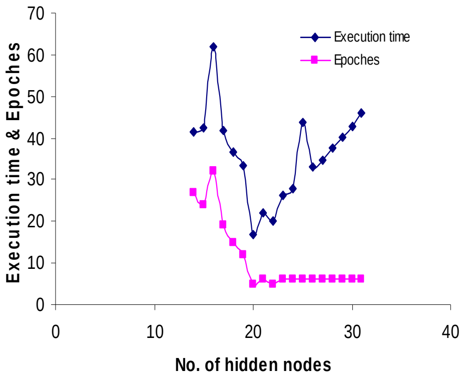

Figure 2: Plot of No. of hidden neurons against execution time & Epochs

From the table 2 it is clear that numbers of hidden nodes are insufficient up to 19. The performance goal was only met when the number of hidden neurons are 20 or above. From the figure 1 it is clear that the optimized numbers of hidden nodes are 20 for this specific problem. Below twenty there are not enough number of hidden neurons that are not sufficient to solve this problem. It means that the there are not enough number of nodes that can store all the features present in the input patterns. Hidden nodes are actually the feature detectors of the input pattern vectors. So as the size of the input pattern vector increases the required number of optimized hidden neurons also increases. It is also clear from the above figure that as we increase the no. of hidden neuron beyond the optimized number, the execution time increases. Also the storage requirement for hidden neurons is increased which in turn affects the system response time, and that will be fatal if you are dealing with a system that require a real time response.

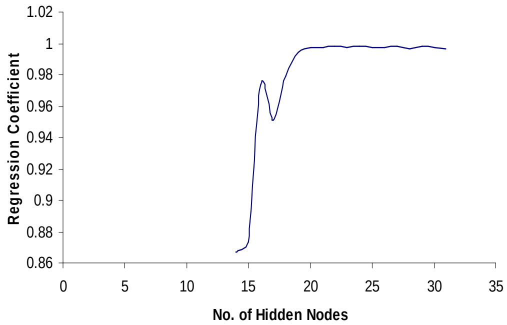

Figure 3: Plot of No. of hidden neurons against regression coefficient

Also from the figure 2 it is clear that regression coefficient has reached its maximum value when the no. of hidden nodes is 20. If we further increase the number of hidden nodes the regression is the same, i-e reached its maximum value. Value one mean a perfect match. Therefore it is useless to further increase the hidden nodes. Therefore it is the optimized number for this particular example.

5.2 Performance Comparison of different neural network training algorithms

Different backpropagation algorithms have been employed for the training of this nuclear power plant data [36]. The following table shows the results collected by implementing various algorithms. For this comparison case study the performance goal was set = 0.001, it is clear from the table 2 that the first three training algorithms were not able to meet the performance goal. The remaining training algorithms all met the performance goal. The algorithm that achieved the performance goal fastest is Conjugate Gradient with Powell/Beale Restarts (traincgb). The second algorithm that achieved the performance goal with second minimum time is Variable Learning Rate Backpropagation (traingdx). But as the performance goal made further difficult i-e of the order of *1e-15*, then only algorithm that achieved the goal in minimum time was Levenberg-Marquardt (trainlm). Therefore whenever you need highest accuracy like in a nuclear power plant, this algorithm, Levenberg-Marquardt, is the most useful.

Table 2: Results for different training algorithms

Training Method	Execution time	Regression Coefficient	Comments
BFGS Quasi-Newton (trainbfg)	304.465443	0.9977	Validation stop
Fletcher-Powell Conjugate Gradient (traincgf)	4.520266	0.9961	Validation stop
Variable Learning Rate Backprop. (traingdx)	2.33319	0.9861	Validation stop
One Step Secant (trainoss)	10.050495	0.9978	Performance goal met
Resilient Backpropagation (trainrp)	6.204507	0.9966	Performance goal met
Conjugate Gradient with Powell/Beale Restarts (traincgb)	1.832672	0.9987	Performance goal met
Scaled Conjugate Gradient (trainscg)	3.128176	0.9965	Performance goal met
Levenberg-Marquardt (trainlm)	16.929745	0.9976	Performance goal met

6 Conclusion

The approach used in this paper was aimed towards the problem of spurious reactor trips. Human operators are always prone to errors. It is difficult for human operators to take accurate decisions by keeping an eye on enormous number of parameters and by analyzing a pattern of parameters. This approach assists the operators in their decision about reactor trip based on the past historical data. Nuclear plant operators can benefit from decision support system for improvement in their decision-making. This is one of the solutions to minimize revenue loss to the plant owner. The operator will not be bound to take decision suggested by the DSS; he will still be free to take decision of his own choice. The DSS will be there only for his support.

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