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Online fault monitoring based on deep neural network & sliding window technique

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ABSTRACT

Nuclear power plants have proved their worth in energy sector by providing clean and uninterrupted power over decades. However, a Nuclear Power Plant (NPP) is a complex, dynamic system with potential radioactive release risk which makes it crucial to achieve highest standards of safety. Specially, in preview of massive monitoring data received in modern NPPs which makes it difficult for operators to extract vital information about actual plant state in a timely and accurate manner. On the other hand, advancements in latest machine learning methods have made it possible to process such massive data for operators to act accordingly. However, current machine learning approaches cited for this field, fall short of required capabilities needed for such safety critical industry. In manuscript, an online fault monitoring system is proposed which utilizes deep neural networks and sliding window technique. The proposed model not only fulfills the requirement of validity but also encompass all necessary diagnosis functions like detection, identification, assessment and robustness. The model allows for a fault to be identified and assessed in different plant states and then validate the predicted results through online correlation of simulation vs original data. The study was conducted for IP-200 NPP utilizing RELAP5 thermal-hydraulic code. The proposed model was verified by inducing 04 different faults for different states and severities. The results were found to be conducive for improving reliability and accuracy of next generation fault monitoring systems of Nuclear Power Plants.

1. Introduction

Nuclear industry is ever working to make more efficient and safe reactors for its next generation plants. One of the key requirements to achieve that goal is to assist operators in making right decisions in case of any abnormality/fault, thus increasing the level of safety for these reactors. Whereby fault monitoring techniques could play an important role in enhancing the safety standards of these plants. To this very end, intelligent fault diagnosis methods have become an active research field because of inherent drawbacks in traditional methods (Ma and Jiang, 2009). The current trend denotes machine learning as the popular choice for future fault diagnosis technology (Patan, 2008).

In the field of Nuclear Energy, Artificial Neural Networks (ANN) and Support Vector Algorithms (SVM/SVR) are the most common techniques employed for development of intelligent fault diagnosis systems. Examples include (Ayodeji et al., 2018) investigation of performance ability among Elman & Radial Basis Neural Networks for Steam Generator tube rupture and locked rotor. In another work, Elman Neural network was applied for fault severity estimation while using Principle Component Analysis & Signed Directed Graph for fault detection & identification (Yong-kuo et al., 2018). Leak Before Break condition was estimated by applying Back Propagation & Genetic Neural Networks (Zhang et al., 2017). Feed Forward Neural Network was applied for transient identification (Ayo-Imoru and Cilliers, 2018). LOCA break sizes were estimated through Multi-Layer Perceptron (Tian et al., 2018). Application of support vector regression is also applied for predicting core behavior and recognizing transient parameters (Zeng et al., 2018). Support Vectors have also been fairly applied for classification task to identify faults in nuclear power plants like designing of a Support Vector Classification module for transient state identification (Yoo et al., 2018). Researchers (Ayodeji and Liu, 2018) have also applied SVMs for identification of incipient faults in a NPP.

However, current ANN, SVR and SVM approaches detailed in literature fall short in two ways: (i) These approaches does not amply fulfill the required capability gap like catering for dynamic behavior of a Nuclear Power Plant (NPP parameters are often changing like power level changes/control action effects) or avoiding misdiagnosis. We believe these capabilities must be built inherently in any automatic fault monitoring technique to ensure that such a technique is of any practical

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Nomenclature

LOCA	Loss of Coolant Accident
SVM	Support Vector Machine
SVR	Support Vector Regression
NPP	Nuclear Power Plant
ANN	Artificial Neural Network
DCNN	Deep Convolution Neural Network
RBFNN	Radial Basis Function Neural Network
LSTM	Long Short-Term Memory
MSE	Mean Square Error
PORV	Pressure Operated Relief Valve
RCP	Reactor Coolant Pump

value. (ii) More importantly, ANN & SVM applied in literature have 1-dimensional architecture at their core. This invariably means that such networks are only able to process instantaneous measurements instead of trend analysis for different plant parameters which is the key to fault detection in such a complex system. Moreover, such simple architectures limit the capability of machine learning to learn complex non-linear relationships between various intervening variables. In order to fully extract the advantages of machine learning, it is necessary to make use of deep architecture networks which has the ability to provide these required capabilities.

Shallow neural networks generally consist of only 1 or 2 hidden layers while deep learning refers to a class of machine learning techniques where many layers of information processing stages in deep architectures are exploited for pattern classification and other tasks (Deng, 2014). In comparison to shallow networks, deep neural networks have the ability to handle substantial amount of data. Moreover, it employs multiple non-linear transformations through large number of processing stages and thus has the ability to model higher levels of abstraction. Deep neural networks/deep learning has proved their capability over shallow networks in many fields like Game of GO (Silver et al., 2016), Image recognition (Russakovsky et al., 2015), Speech recognition (Dahl et al., 2012) and particle physics (Baldi et al., 2014). From aforementioned examples, it can be concluded that Deep neural networks show greater potential than shallow networks but in the field of intelligent fault diagnosis for NPPs, very few researchers have proposed this methodology. In one example, Correlation Analysis and Deep Belief Network (Peng et al., 2018) was utilized for fault diagnosis. However, in manuscript, the network was applied through dimensionality reduction which basically undermine the capabilities of deep networks.

In manuscript, we propose a novel technique to overcome the

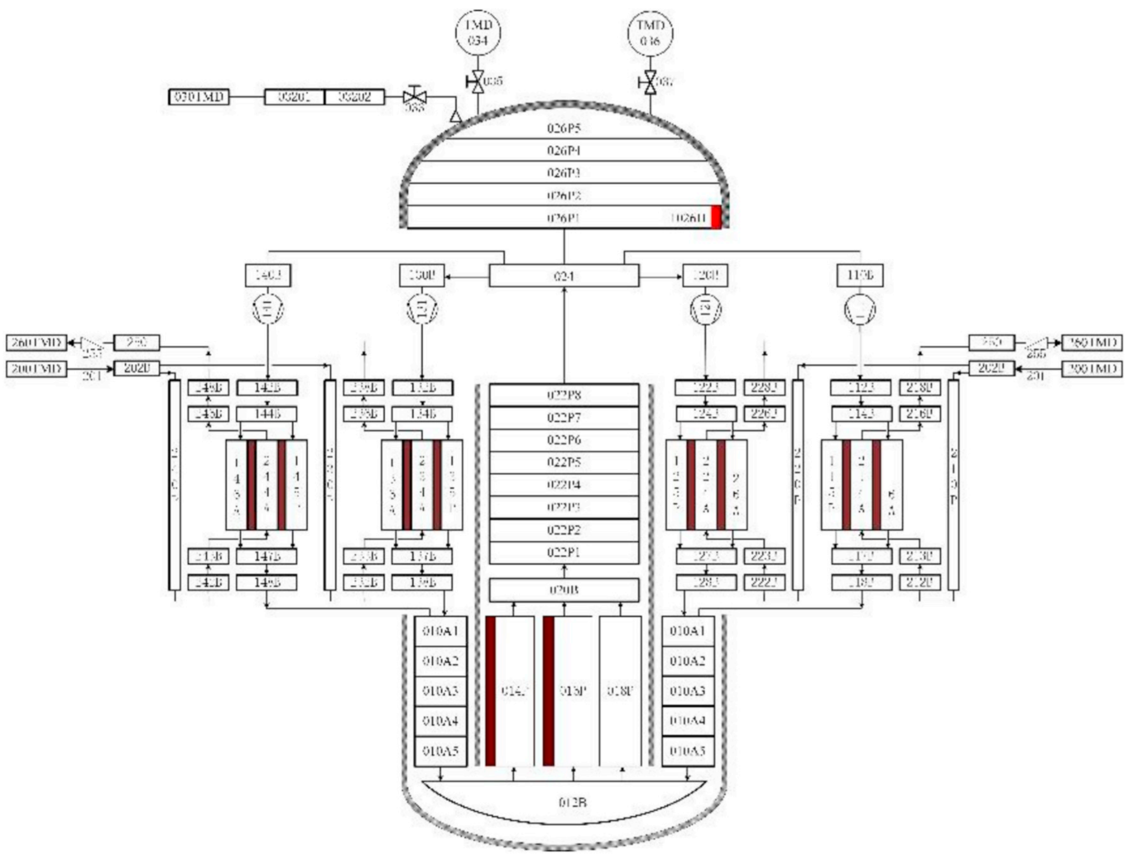

Fig. 1. IP-200 nodalization.

Table 1
IP-200 Designed vs simulated values.

Parameters	Design Values	Simulated Values	Tolerance
Core Thermal Power	220 M W_{th}	220 M W_{th}	0.00%
Core inlet temp	557.15 K	556.79 K	0.06%
Core outlet temp	595.15 K	595.77 K	0.10%
Primary pressure	15.31 MPa	15.3 MPa	0.07%
Primary coolant mass flow rate	1000 kg/s	1006 kg/s	0.60%
Feed water temperature	373.15 K	373.25 K	0.03%
Steam temperature	510 K	509.64 K	0.07%
Feed water flow rate	90 kg/s	89 kg/s	1.11%

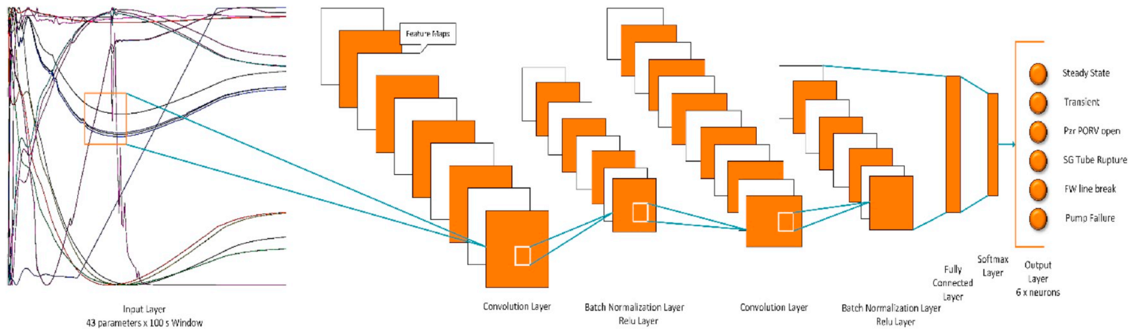

Fig. 2. Layers of DCNN

Table 2
DCNN final parameters.

Parameter	Value
Input size	43 × 100
Convolution size	10 × 20
Max Epochs	50
Initial learning rate	0.0001
Output size	6

deficiencies in common ANN-based fault diagnosis approaches. This approach employs deep convolution neural network (DCNN) utilizing sliding window technique to achieve adaptive feature learning which would enable this technique to be employed in real-time scenario more effectively. The DCNN is first trained offline and then applied dynamically for online monitoring. Moreover, severity assessment and diagnosis verification are also made an integral part of this method to ensure that such a method may have practical viability. The paper is organized as: Section 2 introduces the reactor and architecture of proposed DCNN. Section 3 provides a comparative analysis of 2-D deep architecture over shallow networks. Section 4 details the proposed fault diagnosis model and its efficacy is subsequently proved through random fault scenarios. Paper is concluded in Section 5.

2. Methodology

2.1. IP-200

IP-200 is a small modular reactor (Instrumentation and Contr, 2017) designed by Harbin Engineering University. It is a kind of Integrated Pressurized Water Reactor (IPWR) as all its primary components are

Table 3
IP-200 simulated states.

S No	Condition	Value
1	Steady State	100% Power
2	Transient	60%–80% Power
3	Pressurizer PORV struck open	100%
4	Steam generator tube rupture	10%
5	Feedwater line break	50%
6	RCP failure	1 out of 4

Fig. 3. Network accuracy progress.

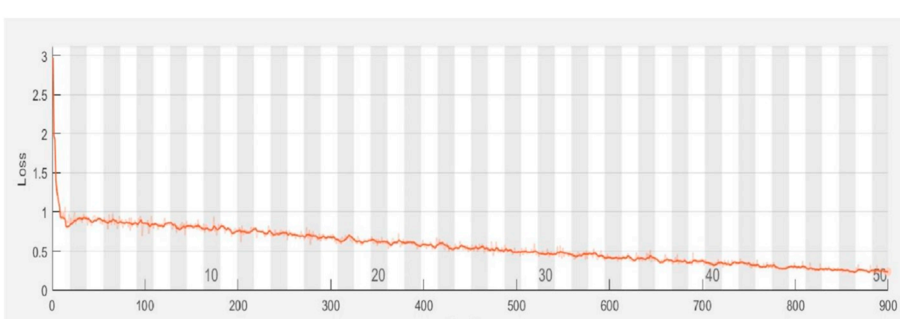

Fig. 4. Network loss progress.

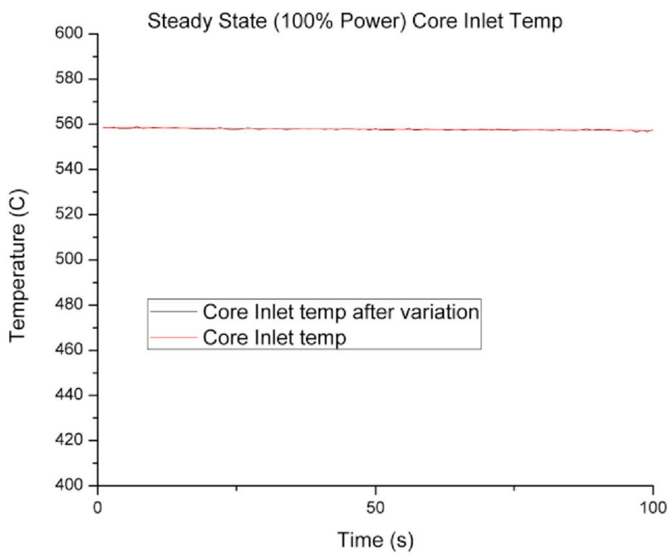

Fig. 5. Core inlet temperature for steady state.

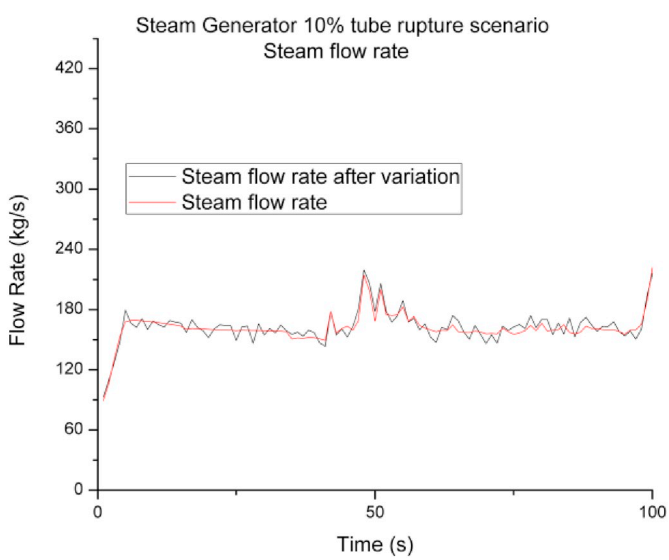

Fig. 6. Steam flow rate for steam generator tube rupture.

Table 4
DCNN vs SVM performance.

No of Wrong Categorizations (Per 600 Cases)	CNN	SVM
In Sample	0	0
Out Sample	0	257

Table 5
LSTM vs RBFNN performance.

MSE	LSTM	RBFNN (Gaussian)
In Sample	1.81e-4	2.11e-4
Out Sample	7.58e-4	0.11

housed inside the reactor vessel. Fig. 1 shows its nodal diagram. Its working is comprehensively detailed in literature (Zhao et al., 2013; Du et al., 2015; Xia et al., 2016; Sun et al., 2017a; Jiang et al., 2018). Current study has been conducted on IP-200 IPWR; however, same study can be extended to any other reactor.

RELAP5 was used for reactor thermal hydraulic modeling of IP-200 NPP. For the purpose of this study, characteristic data from IP-200 simulations acted as close representation to an actual plant system. The model was first debugged to achieve accuracy with steady state designed values of plant parameters. This is highlighted in Table 1 which shows comparison of few designed parameters with simulated values along with % tolerances.

2.2. Convolution neural network

Current research apply Deep Convolution Neural Network (Ince et al., 2016; Wen et al., 2017; Sun et al., 2016, 2017b; Jing et al., 2017) for assessing plant behavior. Convolution neural network can be regarded as one of the most popular and successful algorithms when it comes to deep learning and therefore, was selected for this study. Its auto feature extraction capability has allowed it to surpass human benchmarks in image recognition (Russakovsky et al., 2015). Convolution is a blending technique that highlights the correlation of two functions f and g. Convolution of two functions can be expressed as:

$$(f*g)(t)=\int_{-\infty}^{\infty} f(\tau)g(t-\tau)d\tau=\int_{-\infty}^{\infty} f(t-\tau)g(\tau)d\tau \tag{1}$$

where f and g are two continuous functions and τ denotes the shift in moment t. In discrete form, it can be written as

$$(f*g)(n)=\sum_{m=-\infty}^{\infty} f(m)g(n-m)=\sum_{m=-\infty}^{\infty} f(n-m)g(m) \tag{2}$$

Here g is the kernel function for a specific feature f and n is the moment while m denotes the shift in that moment. If discrete g support is (-M, …. M), then

$$(f*g)(n)=\sum_{m=-M}^{M} f(n-m)g(m) \tag{3}$$

Similarly, convolution can be extended to other dimensions as

$$(f*g)(x,y)=\sum_{m=-M}^{M}\sum_{n=-N}^{N} f(x-n,\ y-m)g(n,m) \tag{4}$$

Here discrete support for the two dimensions are (-M, ….M) and (-N, …. N) respectively while each dimension has separate moment i.e. x and y. In such a network, convolution technique is applied for feature extraction using learnable filters or kernels. In other words, convolutional networks use convolution function in place of general matrix multiplication (Goodfellow et al., 2016). Apart from multiple convolution layers, deep network consists of other layers like Batch normalization layer, Relu layer, Fully connected layer, Softmax layer, input & output layers. Fig. 2 shows different layers of designed CNN.

2.3. Network parameters

Before designing a network for fault diagnosis of a nuclear power plant, we first assessed the nature of data. It was noted that any data received from a nuclear power plant is 2-Dimensional (time-series) in nature because fault diagnosis of any plant is based on trend analysis of its parameters and their intervening relationships. Instantaneous values of plant parameters are not true representative of plant state. Thus, we can say that plant state is a function of parameters' trend over time. In the second stage, a 2-D Convolution Neural Network was designed for which optimal architecture as well as selection of hyper-parameters was determined through trial & error. Table 2 lists finalized parameters. The network was then trained on plant data using Stochastic Gradient Descent with Momentum (SGDM) algorithm coupled with early stopping to avoid any overfitting. Figs. 3 and 4 show the results of network

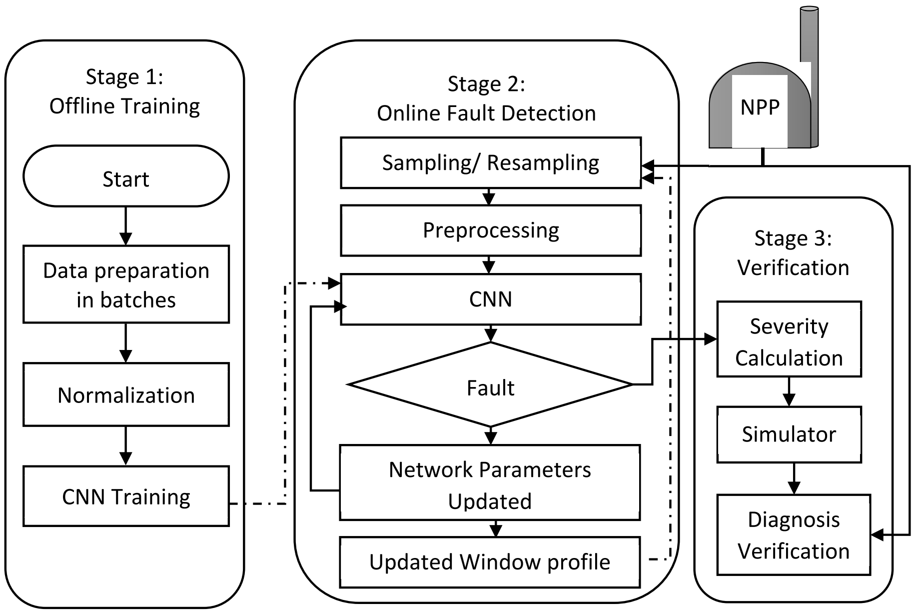

Fig. 7. Proposed fault monitoring system.

Table 6
Testing scenarios.

Class	Fault	Plant State (Power)		
1.	Normal Operation	100%–20%		
2.	Pressurizer PORV struck open	100%	80%	40%
3.	Steam generator tube rupture	100%	70%	30%
4.	Feedwater line break	100%	50%	20%
5.	RCP failure	100%	60%	50%

training.

3. Comparison

In any fault diagnosis system, identification of a fault is the first step. In machine learning, identification is usually carried out through classification algorithms. In order to ascertain the efficacy/superiority of deep CNN, we compared it with commonly used, SVM algorithm (Wang et al., 2019). The two networks were designed using optimal parameters through set of trial and error. Subsequently, both were trained on conditions listed in Table 3.

It is worth noting that the results achieved during training and validation for SVM were in agreement with those presented in literature (Ayodeji and Liu, 2018). In the next step, each network was tested on two different datasets i.e. In sample dataset and Out sample dataset. Each dataset contains 600 cases (100 case of each condition listed in Table 3). In sample dataset consist of testing data taken from within the training data (usually how it's done in literature) while out sample dataset consists of same cases and similar data with very minute changes so as to model parameter variations in actual plant like sensor drift, noise, component degradation or interference effects. The reason for selecting these two different types of datasets was to check network response for realistic data that can be expected from an actual plant as all the cases that authors studied in literature usually divide the same data into training, validation and testing which is not a realistic assumption. For Out Sample data, we set the noise to 50dBW so that it can simulate noise of actual plant measurements which tend to fluctuate a bit during operation. To understand the difference between both datasets, Figs. 5 and 6 show core inlet temperature for steady state and steam flow rate for steam generator tube rupture respectively. Examples in Figs. 5 and 6 clearly shows that both datasets are almost identical and their difference is negligible. However, the effect of this small change on shallow networks is prominent as shown in Table 4.

As can be seen from Table 4, both CNN and SVM algorithms performed very well on in sample dataset; however, accuracy/performance of SVM algorithm dropped drastically when faced with similar but little different dataset. We believe it is due to 1-D architecture of SVM network. Fortunately, deep networks are capable of processing multi-dimensional data. Thus, are more robust and therefore, more viable for application in a practical plant system.

We took this analysis a step further and carrying all of the above stated steps, designed two optimal regression networks i.e. Radial Basis Function Neural Network (1-D shallow network) also known as Gaussian Network and Long Short-Term Memory Network (2-D deep network) (Zhao et al., 2018; Yuhai et al., 2018; Qin et al., 2018; Xiao et al., 2018). Table 5 shows the comparison of the two networks. Here, performance indicator is Mean Square Error (MSE). The comparison showed a similar trend whereby RBNN/Gaussian Network showed a respectable accuracy for in sample testing similar to that reported in literature by other researchers (Ayodeji et al., 2018). However, its performance dropped sharply when faced with varied data. On the other hand, LSTM's consistent performance is evident.

4. Application model for fault diagnosis

Implementation of static networks means that their feature extraction capability is fixed and cannot be altered during run-time. Such networks will therefore work correctly in normal states of system. But when encountered with power level changes or transients, their detection capability is prone to degrade. To counter this, we propose implementation of Deep CNN using adaptive feature learning through application of sliding window strategy.

Sliding window strategy is a commonly employed technique in data mining (Noh et al., 2015; Izzeldin et al., 2012). The basis of this technique is the fact that in time varying systems, current data received for analysis is more relevant than the past data streams. It works by updating the old system parameters with those corresponding to new data. Due to adaptive nature of this technique, it provides the ability

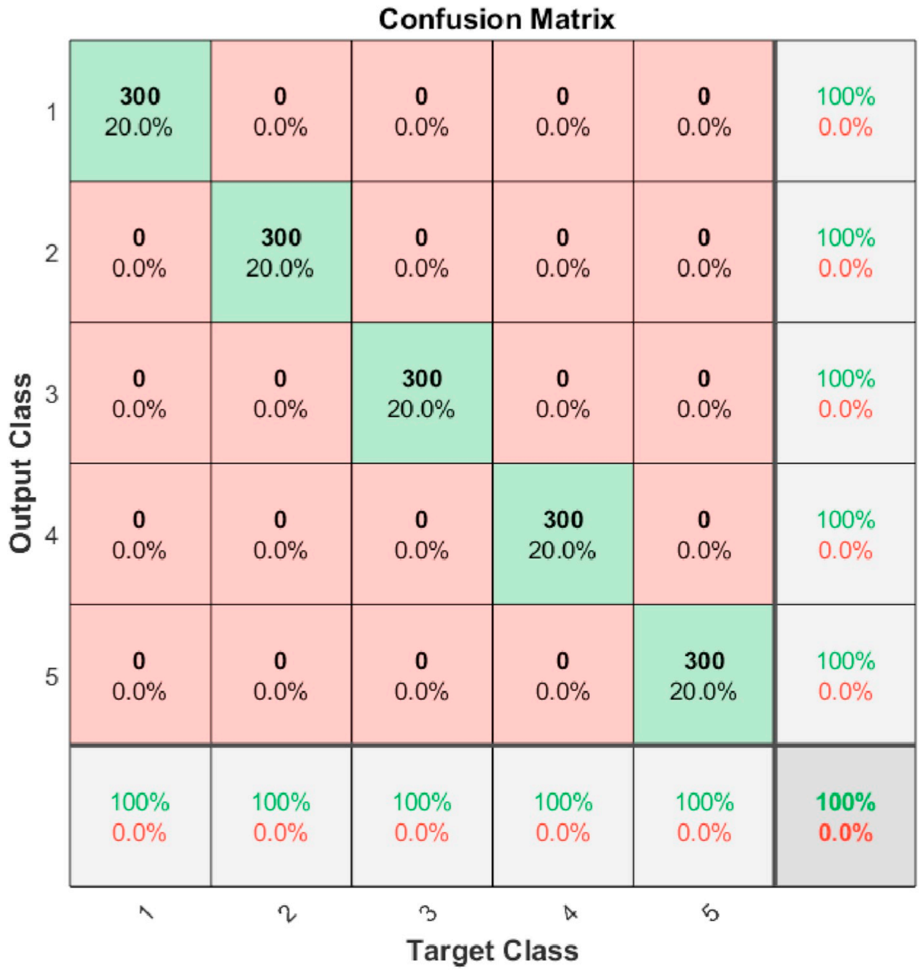

Fig. 8. Confusion Matrix for DCNN response.

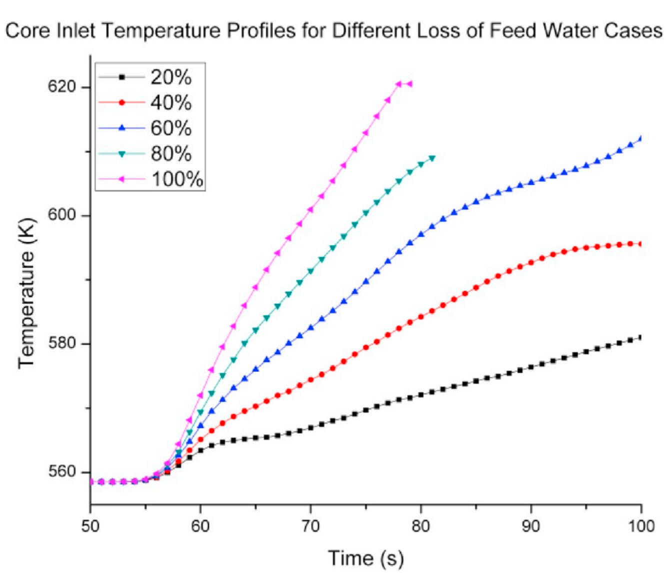

Fig. 9. Example of correlation between system parameter & fault severity.

needed to diagnose correctly in such a dynamic system. Fig. 7 shows the structure of proposed algorithm.

The model consists of two stages, first is the offline training. In this stage, data is sorted in batches according to plant conditions and faults expected, as present in knowledge database. Then the data is preprocessed and normalized. After that, the network is trained. Subsequently, in online monitoring stage, continuous data stream from a NPP are first sampled, preprocessed and applied to the trained CNN. If fault is not detected, then Network parameters are updated according to latest plant state along with new window profile.

In case a fault is detected then another network is applied for severity calculation of that fault. We have applied Long Short-Term Memory Network (LSTM) for that very purpose. For each kind of fault, a correspondingly trained LSTM network will be applied. The design and training of such LSTM network is explained in our previous publication (Saeed et al., 2020). Here, fault diagnosis is carried out through DCNN while severity calculation is a regression problem and is better suited for LSTM network. The purpose is to provide a complete analysis of fault and plant state. With a fault detected and its impact calculated, we can use a faster than real-time simulator to predict actual plant condition. Finally, the predicted plant state and actual data from a plant are compared for diagnosis verification.

In our previous paper (Saeed et al., 2020), deep networks of CNN and LSTM were concurrently applied to calculate confidence level of machine diagnosis so that operator can know the level of trust, they can have on a particular diagnosis. While, PCA was applied for anomaly detection only. In current research, CNN is applied through sliding window strategy to provide dynamic fault diagnosis capability. Subsequent to fault diagnosis, LSTM is utilized for severity calculation in both papers. Therefore, LSTM was applied at two stages in previous scheme while only applied once in current model. As current research is about run-time monitoring system; therefore, a verification stages is desirous.

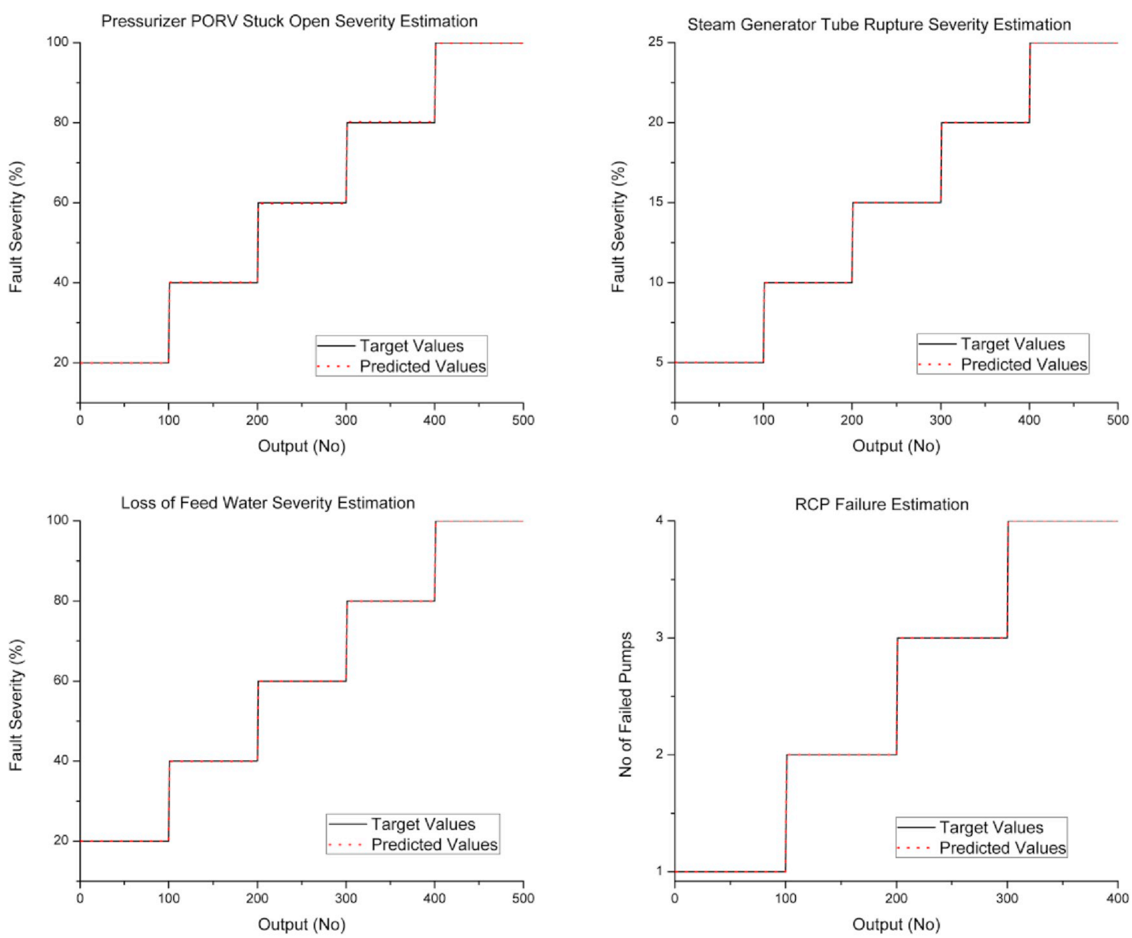

Fig. 10. Results of fault severity estimation.

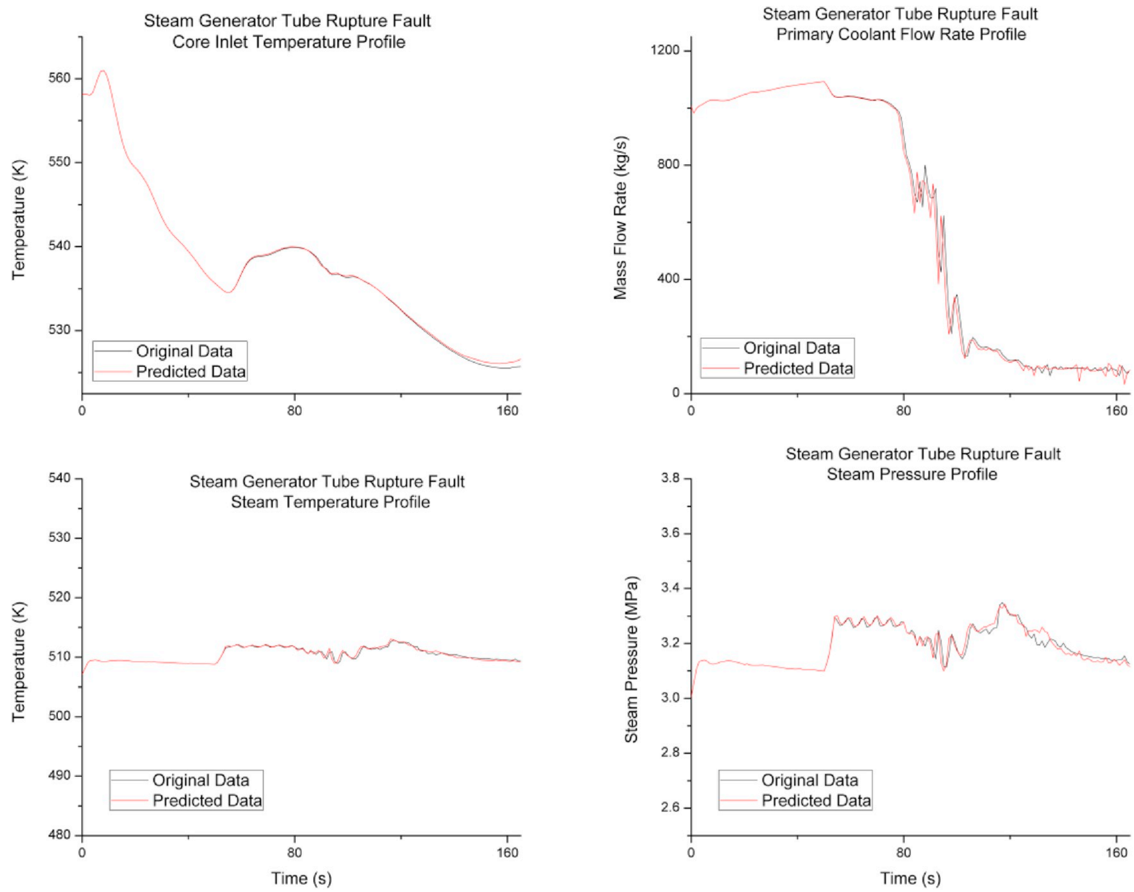

Fig. 11. Case 1, Examples of system vs predicted parameters.

This necessitates calculation of fault magnitude which is the function of LSTM network here.

In order to test the efficacy of the proposed model, a 2-D Convolution Neural Network was designed with parameters discussed in previous section. Then the network was trained to identify steady state and 4 faults (Table 3, S.No. 3 to 6) in offline mode. It is pertinent to mention that all of these faults were simulated and trained at only 100% power. After completion of offline training, the network was tested on these scenarios at different plant states (Table 6). Fig. 8 shows the results of network response. Thus, by dynamically responding to system changes, the proposed model is able to accurately diagnose each fault even when fault occurs at any plant state.

During the next stage, severity of each fault was calculated to achieve a comprehensive diagnostic assessment of situation. We know that as the severity of a fault is changed, there is a systematic variation in system parameters. This correlation between system parameters and fault severity forms the basis for development of a regression mapping. An example of this relation can be seen in Fig. 9 where a system parameter (Core Inlet temperature) vary as a function of fault (Loss of Feed Water) severity.

Thus, we can say that

$$\text{Fault Severity} = f(x_1, x_2, x_3, \ldots, x_n) \tag{5}$$

where x is a system parameter. The number and exact parameters to be analyzed depends on the type of fault. Therefore, we trained 04 different LSTM networks corresponding to each type of fault injected. Fig. 10 shows the validation results of fault severity estimation for trained cases.

Even though our proposed diagnosis scheme is able to accurately detect and assess faults in a timely manner, we still believe that any practical fault diagnosis model must be able to verify its judgement/results. This is the only way to guarantee safe and reliable operation of artificial intelligence based system in a sensitive environment such as Nuclear power plant where wrong judgement of a machine or operator may lead to serious consequences. Therefore, once severity of any fault is calculated we can utilize a faster than real-time simulator to calculate the accuracy of the proposed model in a real time environment through calculating MSE between plant data stream and predicted data stream from simulator. This will not only ensure viability of such machine learning techniques for Nuclear industry but also achieve operator confidence on artificial intelligence based diagnostics.

To validate our proposed diagnosis scheme, the model was verified through injecting 02 x fault cases with random conditions. First was Steam Generator tube rupture at 68% Power with 14% fault severity and second was Pressurizer PORV stuck open at 33% power with valve stuck at 78% value. The model was able to achieve MSE of 0.0027 and 0.000010384 for Steam Generator tube rupture and Pressurizer PORV stuck open respectively.

Although the MSE for both cases were calculated on complete input spectrum, Figs. 11 and 12 show the comparison results of only few parameters due space constrains. It can be seen that both deep networks were able to produce accurate results and the simulation which was carried out based on these results is able to mimic the original data streams. Furthermore, calculated MSE represents the degree of separation between predicted results and original data stream. So, the only question remains, is that, which value of MSE should be taken as threshold value between accurate diagnosis and wrong judgment. In this paper, the authors have not put any constraints on this value as it is an open-ended question and will invariably depend on the type of plant, the actual implementation strategy of the proposed model and other regulatory requirements.

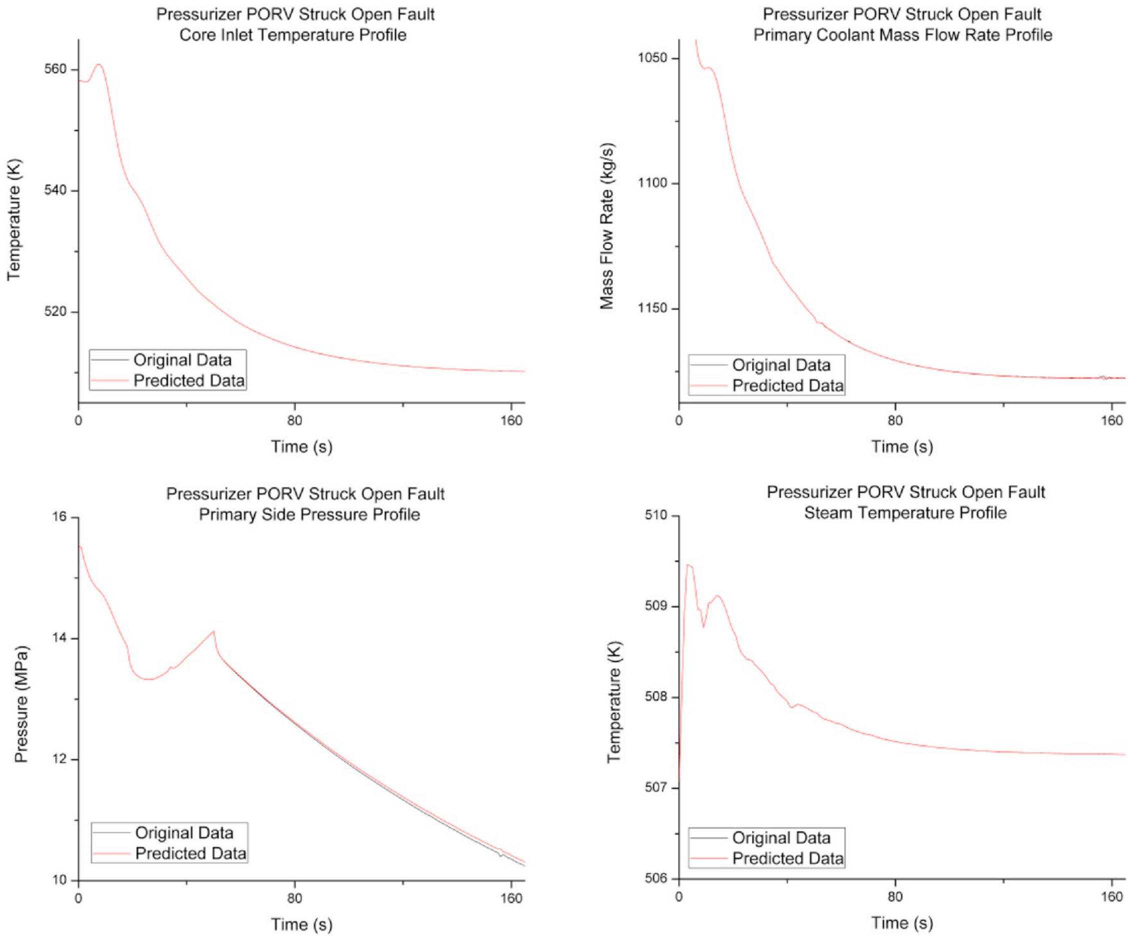

Fig. 12. Case 2, Examples of system vs predicted parameters.

5. Conclusion

This paper presents an online fault monitoring paradigm for NPP which encompasses all diagnosis functions (detection, identification, assessment, robustness and verification). Two types of deep learning based Neural Networks i.e. CNN & LSTM were chosen for implementation after comparison with commonly used ANNs. Two separate datasets were applied for training and verification of this comparison. This allowed for more realistic implementation of simulation model. Deep Convolution Neural Network and Sliding Window technique were used in tandem for online monitoring. Through integration of these two techniques, the model is able to correctly detect and classify faults at any plant state thereby achieving robustness. Modular functions of fault assessment and verification are also an integral part of proposed model as we know that, during fault development, if operator misconducts plant operation due to wrong judgement, it will cause severe deterioration of fault and may lead to a disaster. Therefore, in order to inculcate operator and industry confidence on latest machine learning technology, fault is first assessed through LSTM network and then verified through simulation at run-time. This will achieve reliability and robustness of the proposed model. Therefore, we can say that the proposed model has not only proved its accuracy over commonly used machine-learning techniques but also will improve safety and reliability of NPP systems. Our future work will focus on implementation strategies to integrate this model into actual plant systems.

Declaration of competing interest

All authors have no conflicts of interest to declare.

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References

Ayo-Imoru, R., Cilliers, A., 2018. Continuous machine learning for abnormality identification to aid condition-based maintenance in nuclear power plant. Ann. Nucl. Energy 118, 61–70.
Ayodeji, A., Liu, Y.-k., 2018. Support vector ensemble for incipient fault diagnosis in nuclear plant components. Nucl. Eng. Technol.
Ayodeji, A., Liu, Y.-k., Xia, H., 2018. Knowledge base operator support system for nuclear power plant fault diagnosis. Prog. Nucl. Energy 105, 42–50.
Baldi, P., Sadowski, P., Whiteson, D., 2014. Searching for exotic particles in high-energy physics with deep learning. Nat. Commun. 5, 4308.
Dahl, G.E., et al., 2012. Context-dependent pre-trained deep neural networks for large-vocabulary speech recognition. IEEE Trans. Audio Speech Lang. Process. 20 (1), 30–42.
Deng, L., 2014. A tutorial survey of architectures, algorithms, and applications for deep learning. APSIPA Trans. Signal Inf. Process. 3.
Du, X., Xia, G., He, L., 2015. Operation characteristic of integrated pressurized water reactor under coordination control scheme. Ann. Nucl. Energy 75, 658–664.
Goodfellow, I., Bengio, Y., Courville, A., 2016. Deep Learning| the. MIT Press, Cambridge, Massachusetts.
Ince, T., et al., 2016. Real-time motor fault detection by 1-D convolutional neural networks. IEEE Trans. Ind. Electron. 63 (11), 7067–7075.
Instrumentation and Control Systems for Advanced Small Modular Reactors, 2017. International Atomic Energy Agency, Vienna.
Izzeldin, H., Asirvadam, V.S., Saad, N., 2012. Overview of data store management for sliding-window learning using MLP networks. In: 2012 4th International Conference on Intelligent and Advanced Systems (ICIAS2012). IEEE.
Jiang, N., Peng, M., Cong, T., 2018. Simulation analysis of an open natural circulation for the passive residual heat removal in IPWR. Ann. Nucl. Energy 117, 223–233.

Jing, L., et al., 2017. A convolutional neural network based feature learning and fault diagnosis method for the condition monitoring of gearbox. Measurement 111, 1–10.
Ma, J., Jiang, J., 2009. Applications of fault diagnosis in nuclear power plants: an introductory survey. IFAC Proc. Vol. 42 (8), 1150–1161.
Noh, S., Shim, D., Jeon, M., 2015. Adaptive sliding-window strategy for vehicle detection in highway environments. IEEE Trans. Intell. Transp. Syst. 17 (2), 323–335.
Patan, K., 2008. Artificial Neural Networks for the Modelling and Fault Diagnosis of Technical Processes. Springer.
Peng, B.-S., et al., 2018. Research on intelligent fault diagnosis method for nuclear power plant based on correlation analysis and deep belief network. Prog. Nucl. Energy 108, 419–427.
Qin, X., et al., 2018. Sensor fault diagnosis of autonomous underwater vehicle based on LSTM. In: 2018 37th Chinese Control Conference (CCC). IEEE.
Russakovsky, O., et al., 2015. Imagenet large scale visual recognition challenge. Int. J. Comput. Vis. 115 (3), 211–252.
Saeed, H.A., et al., 2020. Novel fault diagnosis scheme utilizing deep learning networks. Prog. Nucl. Energy 118, 103066.
Silver, D., et al., 2016. Mastering the game of Go with deep neural networks and tree search. Nature 529 (7587), 484–489.
Sun, W., et al., 2016. A sparse auto-encoder-based deep neural network approach for induction motor faults classification. Measurement 89, 171–178.
Sun, L., et al., 2017. Numerical study on coolant flow distribution at the core inlet for an integral pressurized water reactor. Nucl. Eng. Technol. 49 (1), 71–81.
Sun, W., et al., 2017. Convolutional discriminative feature learning for induction motor fault diagnosis. IEEE Trans. Ind. Inf. 13 (3), 1350–1359.
Tian, X., et al., 2018. A study on the robustness of neural network models for predicting the break size in LOCA. Prog. Nucl. Energy 109, 12–28.
Wang, H., et al., 2019. A Hybrid Fault Diagnosis Methodology with Support Vector Machine and Improved Particle Swarm Optimization for Nuclear Power Plants. ISA transactions.
Wen, L., et al., 2017. A new convolutional neural network-based data-driven fault diagnosis method. IEEE Trans. Ind. Electron. 65 (7), 5990–5998.
Xia, G., Su, G., Peng, M., 2016. Analysis of natural circulation operational characteristics for integrated pressurized water reactor. Ann. Nucl. Energy 92, 304–311.
Xiao, D., et al., 2018. fault diagnosis of asynchronous motors based on LSTM neural network. In: 2018 Prognostics and System Health Management Conference (PHM-Chongqing). IEEE.
Yong-kuo, L., et al., 2018. A cascade intelligent fault diagnostic technique for nuclear power plants. J. Nucl. Sci. Technol. 55 (3), 254–266.
Yoo, K.H., et al., 2018. Smart support system for diagnosing severe accidents in nuclear power plants. Nucl. Eng. Technol. 50 (4), 562–569.
Yuhai, G., Shuo, L., Linfeng, H., 2018. Research on failure prediction using DBN and LSTM neural network. In: 2018 57th Annual Conference of the Society of Instrument and Control Engineers of Japan (SICE). IEEE.
Zeng, Y., et al., 2018. Machine learning based system performance prediction model for reactor control. Ann. Nucl. Energy 113, 270–278.
Zhang, J., et al., 2017. Prediction of LBB leakage for various conditions by genetic neural network and genetic algorithms. Nucl. Eng. Des. 325, 33–43.
Zhao, L., et al., 2013. Thermal–hydraulic performance analysis of IPWR during full pressure start-up mode. Ann. Nucl. Energy 60, 28–33.
Zhao, H., Sun, S., Jin, B., 2018. Sequential fault diagnosis based on lstm neural network. IEEE Access 6, 12929–12939.