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Original Article

Predictive maintenance architecture development for nuclear infrastructure using machine learning

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ABSTRACT

Nuclear infrastructure systems play an important role in national security. The functions and missions of nuclear infrastructure systems are vital to government, businesses, society and citizen's lives. It is crucial to design nuclear infrastructure for scalability, reliability and robustness. To do this, we can use machine learning, which is a state of the art technology used in various fields ranging from voice recognition, Internet of Things (IoT) device management and autonomous vehicles. In this paper, we propose to design and develop a machine learning algorithm to perform predictive maintenance of nuclear infrastructure. Support vector machine and logistic regression algorithms will be used to perform the prediction. These machine learning techniques have been used to explore and compare rare events that could occur in nuclear infrastructure. As per our literature review, support vector machines provide better performance metrics. In this paper, we have performed parameter optimization for both algorithms mentioned. Existing research has been done in conditions with a great volume of data, but this paper presents a novel approach to correlate nuclear infrastructure data samples where the density of probability is very low. This paper also identifies the respective motivations and distinguishes between benefits and drawbacks of the selected machine learning algorithms.

1. Introduction

In nuclear power plants, monitoring and timely detection of emergent faults are critical for operational safety and performance enhancement. Furthermore, the nuclear power industry operates under high levels of safety, capability and reliability. Nuclear power plants incorporate critical infrastructure systems and require the collection of real-time data to ensure efficient and secure operations. For example, in the smart grid, renewable energy sources, distributed energy storage, and energy generation need to be efficiently integrated and managed through complex and computationally intense models, real-time analysis, and visualization. A massive amount of data will be generated from the power grid and transmitted to the energy management system (EMS) in order to enable efficient system operations [1]. To be cost effective, nuclear power plants must be run at maximum capacity with minimal downtime. To achieve higher availability and reliability, it is necessary to maintain plant equipment in optimal condition, which increases operating costs tremendously. The solution to this problem is to perform corrective and predictive maintenance of the nuclear power plant components. Deviation from normal operating conditions could result from a fault in a single system component or simultaneous faults in multiple components [2]. Often, it is difficult for the operator to detect such issues and locate the associated equipment in a timely manner, especially if it evolves slowly.

Similarly, in a safe and reliable nuclear power plant system, various sensors will be installed on system components and deployed to collect information and transmit data to the operation center. With a large amount and variety of equipment dynamically running in a nuclear power plant system, huge volumes of streaming data (big data) are generated by monitoring variations in plant functioning (e.g., condition of rotating machinery, speeds,

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valves, etc.) [3] For example, a real-world SHRP2 dataset is over a petabyte in size. Thus, the mounting volume of stored and processed data, along with the continuously increasing requirements of storage and processing capacity, pose significant challenges which hinder the effectiveness of monitoring a nuclear power plant system.

To support highly secured nuclear power plant systems, a generic predictive analytics system using big data will be developed to mitigate failures. Monitoring sensor data will help detect anomalies and help plant personnel respond in a timely manner. Analyzing data generated by various sensors of the power plant is a trivial solution for predicting component failures to increase the power plant efficiency. Predictive analytics involves building a big data framework to continuously monitor asset performance through sensor data analytics to provide advance warnings of component failures. The amount of data from different temperature sensors, pressure sensors, and other parts of nuclear sub-systems is huge; hence, a big data framework coupled with machine learning can be implemented to solve this problem. Identifying problems before they occur helps to reduce unscheduled downtime, improve plant maintenance and optimize asset performance.

This research paper focuses on the design and development of an advanced predictive maintenance analytics system using machine learning algorithms. This robust system will be used to predict nuclear power plant failures to protect the environment. The primary objectives of the current research are given below:

- Research into various potential failures of nuclear power plants and machinery
- Analyze nuclear power plant functionalities from the nuclear sensor data
- Collect various nuclear sensor data using intelligent drivers and store it on a non-SQL server
- Apply and optimize machine learning algorithms to verify results and accuracy
- Compare results of the machine learning algorithms for final decision making
- Continue to improve the proposed framework and support heterogeneous data collected from different sources.

2. Background and existing work

In this segment, we studied the existing work and literature on big data issues in nuclear power plant systems, to assist in identifying possible operation failures and anomaly detection.

2.1. Nuclear power plant and big data machine learning

Governments, research communities, and enterprises can all make use of the overwhelming amounts of digital data which is available, creating new opportunities and nurturing powerful business intelligence for decision support [4]. Big data usage is very common in industries like healthcare, agriculture, transportation, and more. The massive amount of data is an issue not only for industry engineers but also for researchers in various fields. The need to process a large scale of data for nuclear power plants has been studied in the past [5–8]. For example, Lee, Jang and Moon et al. [9] discussed the overall process for critical human error anticipation through big survey data analysis applied in nuclear power plants and concluded that big data analytics is possible and useful to anticipate human errors. Liu, Seraoui, Vitelli and Zio et al. [10] proposed an approach for prediction of the condition of nuclear power plant components for condition monitoring. Ma and Jiang et al. [11] performed pattern classification for fault diagnosis in nuclear power plants using semi supervised classification. Kim, Na and Heo et al. [12] presented condition-based maintenance with monitoring, diagnosis and prognosis of thermal efficiency analysis in nuclear power plants using big data techniques. Additionally, Baraldi, Maio, Rigmonti, Zio and Seraoui et al. [13] highlighted unsupervised fuzzy C-means clustering for fault diagnosis in nuclear turbine shut-down transients.

2.2. Nuclear power plant and machine learning anomaly detection

There have been several research studies implemented on nuclear power plants for anomaly detection [14–16]. C.K. Maurya and D. Toshniwal et al. [17] performed experiments on real data coming from a nuclear power plant to demonstrate the effectiveness of the algorithm as well as finding anomalies in the data set. K. Agarwal, D. Toshniwal, P. K. Gupta, V. Khurana and P. Upadhyay et al. [18] introduced a nearest-neighbor-based technique for performing anomaly detection over time series data to predict needed maintenance in nuclear power plants. S. J. Schmugge et al. [19] proposed improved anomaly detection by reducing fragmentation of segmentation by iteratively linking possibly broken short lines and minimizing false positive rates by filtering out areas to improve classification.

The proposed predictive maintenance framework for nuclear infrastructure using machine learning is different from existing research efforts and can enable secured and efficient operations of nuclear power plants, which is novel. The proposed nuclear power plant predictive and defense maintenance system is generic and can integrate various mechanisms to effectively conduct security monitoring. Furthermore, the large storage and high computational resources in the predictive analytics platform (PAP) can handle big data processing and computation, which could further improve the maintenance efficiency of nuclear power plants.

3. Research framework design

The proposed system is for predictive maintenance of nuclear infrastructure with machine learning algorithms to capture and analyze the heterogeneous data from the various sensors on the nuclear power plant equipment. As shown in Fig. 1, the system will import streaming data from temperature sensors, vibration sensors, pressure sensors and accelerometers and other subsystems of the nuclear power plant. The intelligent secret drivers, controller and monitor will extract and transfer nuclear sensor data to an intelligent listener. An intelligent listener collects and stores the various nuclear data on a transmitter server to perform data analytics.

3.1. Intelligent nuclear data acquisition

Intelligent nuclear data acquisition is the platform to extract, load and store various types of nuclear data. In the proposed research framework, we have proven the intelligent nuclear data acquisition platform and intelligent listener component mathematically. This intelligent nuclear data acquisition platform is the collection of three different components: 1) intelligent drivers, 2) controller, and 3) intelligent monitor.

3.1.1. Intelligent drivers

Intelligent drivers are used to perform data integration. The purpose of intelligent drivers is to understand, extract, and validate nuclear data. In this research effort, intelligent drivers have been developed using various loaders which can load text, numeric data, graphics, audio, video and images. Nuclear infrastructure systems include a collection of various sensors and generates a variety of

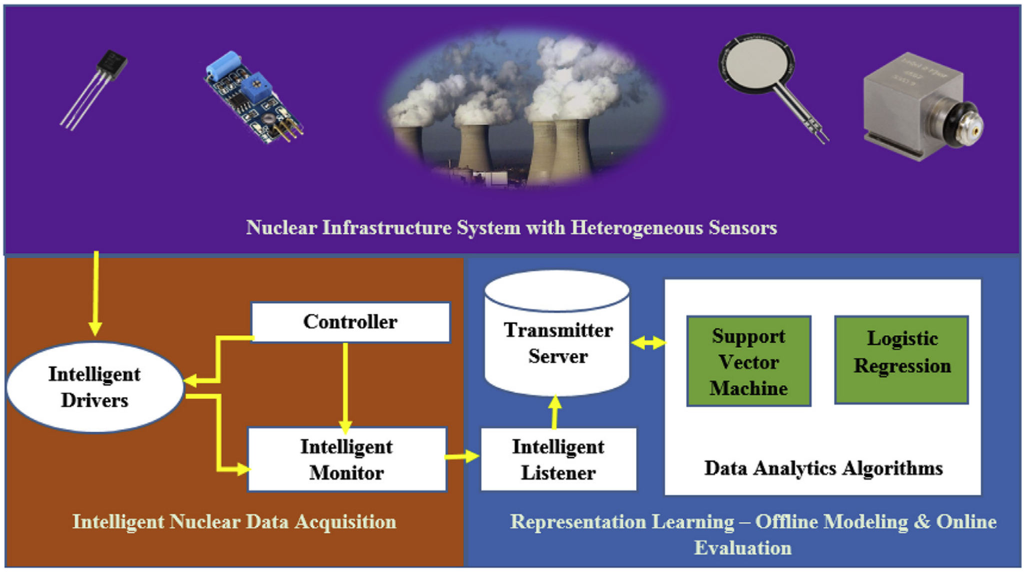

Fig. 1. Predictive Maintenance Framework using Machine Learning.

data. So, as a component of the intelligent nuclear data acquisition platform, intelligent drivers play a very important role to support the integration of this versatile data.

To optimize nuclear data acquisition, we employed a combination of extraction, loading, transformation, and validation of nuclear sensors data. First, the intelligent drivers shown in Fig. 1 are calculated using the predicted phase-lag among the various sensors as follows:

$$\delta(x) = \sum_{S=1}^{n}\left(E_n + L_n + T_n + V_n\delta + b_n \sin\frac{n\pi x}{S}\right) \tag{1}$$

Here, δ(x) is the value of a single-phase cycle using various nuclear sensors at a time. Sigma shows the integration of extraction E, loading L, transformation T, and validation V of all sensor data for a different data cycle. This paralleled process is much faster and supports various types of data extraction from different sensors.

3.1.2. Controllers

The controller is the manager of the intelligent nuclear data acquisition platform. It manages the intelligent drivers and intelligent monitor. The controller is controlling the multiple loaders available in the intelligent drivers and also controls the overall functionality and tasks of intelligent nuclear data acquisition.

3.1.3. Intelligent monitor

The intelligent monitor is used to monitor the nuclear data extracted by the intelligent drivers. It also monitors and communicates with the intelligent listener, which collects and inserts data into the database.

3.2. Representation learning

Representation learning is a component of the proposed framework to store the nuclear data collected with the help of the intelligent listener and machine learning algorithms to generate useful results.

3.2.1. Intelligent listener

The intelligent listener's purpose is to sanitize and transfer the nuclear data collected and sent by intelligent data acquisition. This component of the representation learning platform has been written to handle several concurrent connections by multiple nuclear sensors. The actual implementation of the intelligent listener consists of a single daemon object which spawns an intelligent listener for every nuclear sensor connection it detects.

The intelligent listener is a very important component of representation learning. We have a single transmitter which is a non-SQL server. So, we are required to maintain a transmitter queue using the intelligent listener. In this paper, we propose the following notation to represent the intelligent listener functions.

$$IL_q = \frac{p^2}{1-p} \tag{2}$$

Here, the intelligent listener (IL) queue is one in which there is one non-SQL server to store the data collected from various sensors. For scheduling, there are two different possibilities: 1) nuclear data arrival time and 2) insertion time.

In equation (2), inter-arrival time and insertion time are exponentially distributed whereas, in equation (3), inter-arrival time is exponentially distributed and insertion time is generally distributed.

$$IL_q = \frac{\lambda^{2\sigma_S^2} + p^2}{2(1-p)} \tag{3}$$

Equations (2) and(3) are based on the Pollazcek-Khintichine formula [20] discovered in 1930. There is a third inter-arrival and insertion scenario of the intelligent listener. Both the inter-arrival time and insertion time vary in distribution. Here, we cannot have an exact result. So, the approximate result is calculated in equation (4) which is based on Marchal in 1976 [21].

$$IL_q \approx \frac{p^2\left(1+K_S^2\right)\left(K_a^2+p^2K_S^2\right)}{2(1-p)\left(1+p^2K_S^2\right)} \tag{4}$$

Please note that, if the mean value for arrival time is λ and $\sigma_a^2\sigma_a^2$ donates the variance of inter-arrival time, then:

$$K_S^2 = \frac{\sigma_a^2}{(1/\lambda)^2} \tag{5}$$

In the same way, if μ is the rate of insertion and $\sigma_a^2\sigma_a^2$ is the time of insertion, then:

$$K_S^2 = \frac{\sigma_a^2}{(1/\mu)^2} \tag{6}$$

Thus, the intelligent listener is faster to collect and insert data into the transmitter. It can collect multiple nuclear sensor data at a time and store it into the non-SQL server named transmitter.

3.2.2. Transmitter

The transmitter server is another major component of the representation learning platform. It is a non-SQL server to store heterogeneous nuclear data collected from the intelligent data acquisition platform with the help of the intelligent listener.

3.2.3. Data analytics

The data analytics component performs machine learning. A comparative study with better accuracy of different algorithms will be used to predict nuclear power plant maintenance and failures.

Details for the machine learning algorithms for performing data analytics are discussed in next section.

4. Machine learning implementation

The machine learning component reads the data from the transmitter and applies machine learning algorithms to guide preventive maintenance. This component provides feature selection and algorithm optimization, thereby improving the performance and scalability of the proposed research. The experiments are implemented in Python using scikit-learn [22]. The source code will be available upon request. We have used support vector machine and logistic regression algorithms for the machine learning implementation.

4.1. Support vector machine (SVM)

The support vector machine algorithm is a classification algorithm that makes use of boundaries to make predictions. The algorithm will attempt to find boundaries for certain features where the classes can be separated and then use those boundaries for predictions.

4.2. Logistic regression (LR)

LR is a linear model where the probabilities describing the possible outcomes of a single trial are modeled via a logistic (logit) function. The parameters of the model are estimated with maximum likelihood estimation, using an iterative algorithm.

SVM algorithm used for classification problems similar to LR. LR and SVM with linear Kernel generally perform comparably in practice. The objective to choose SVM and LR is to perform comparative study for both. Our observation is, SVM tries to maximize the margin between the closest support vectors while LR the posterior class probability. Thus, SVM find a solution which is as fare as possible for the two categories while LR has not this property. In addition, LR is more sensitive to outliers than SVM because the cost function of LR diverges faster than those of SVM.

The performance of the models developed with these algorithms can be measured by computing the difference between the predicted class for a given input versus the actual class of the input. For example, the correct classification will predict data as benign if the input data was benign. To quantify the detection performance of the classifier, the 2 × 2 confusion matrix is used (shown in Table 1) as it provides all the possible outcomes of a prediction and has the forms True Positive, True Negative, False Positive, and False Negative of the classifier.

5. Algorithm implementation, results and evaluation

Presently, we don't have appropriate nuclear power plant real time data. We are still collecting nuclear data using Lidar sensors to perform predictive maintenance. It was also necessary to check our proposed predictive maintenance framework and its accuracy. So, to implement and verify the optimized advanced data analytics, we have used a turbofan engine degradation simulation data set [23]. The National Aeronautics and Space Administration (NASA) carried out an engine degradation simulation using C-MAPSS. After successful implementation of the data analytics component of the proposed framework in turbofan engine data, we are going to experiment with the same framework for commercial nuclear power plants.

5.1. Feature selections

The feature analysis and selection involves identifying the features that have maximum influence on the label to perform prediction. The features with the most influence on the label are selected for machine learning implementation. Low quality and unrelated features can make it harder for algorithms to converge and need to be removed using technique variance and correlation. This method was designed by Francis Anscombe, who illustrated distinct datasets with the same mean, variance and correlation to emphasize important feature selection.

5.2. Results

The following figures show the results of a predictive maintenance framework for nuclear infrastructure using machine learning. In the proposed framework, logistic regression and support vector machine has been used.

Using logistic regression and SVM, we were able to answer two questions about the state of an engine. First, we wanted to know what the chances were of an engine failing in the next n cycles, where one (1) hour is equal to one (1) cycle. This became a classification problem; we applied labels to a set of training data. For each cycle of an engine, if the engine did not fail within the next n cycles, we assigned a negative label. If it did fail within the next n cycles, we assigned a positive label. The training and testing sets were split by selecting a random sample of the engine numbers.

The second question was related to scoring. At each cycle, we wanted to know how likely it was that an engine was about to fail. Similarly, the training and testing sets were split by sampling the engine numbers.

Table 1
Confusion matrix with values.

Class	Failed Prediction	Non Failed Prediction
Engine Failed	871(TF)	125 (FP)
Engine Not Failed	774 (FN)	11326 (TN)

True Positive Rate = True Positive/(True Positive + True Negative).
False Positive Rate = False Positive/(False Positive + True Negative).
Precision = True Positive/(True Positive + False Positive).
Recall = True Positive/(True Positive + False Negative).
Accuracy = True Positive + True Negative/(True Positive + True Negative + False Positive + False Negative.

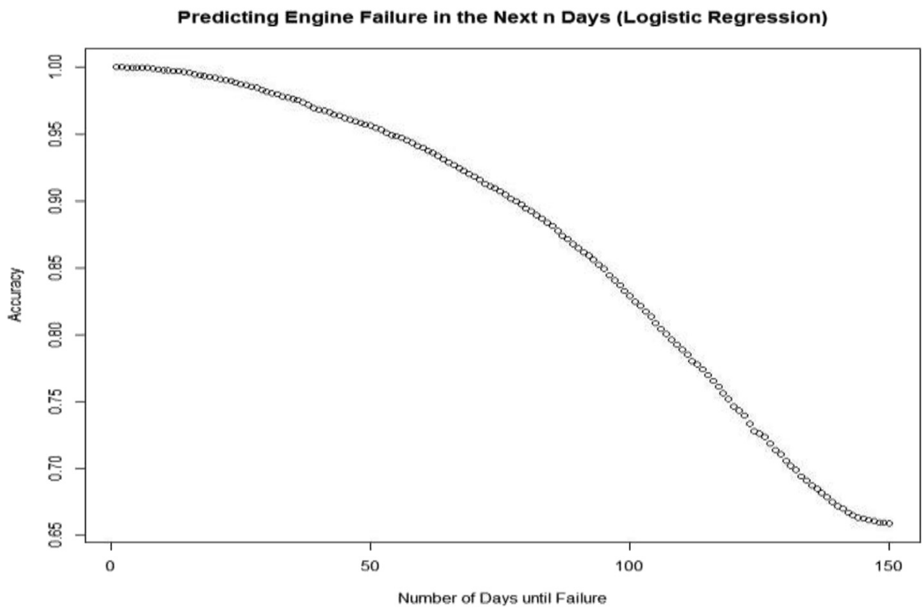

Fig. 2. Predicting nuclear power plant failures in next N days using logistic regression.

5.3. Prediction

For the first question, a logistic regression algorithm was implemented. Given the condition of the sensors, we made a prediction on whether the engine will survive the next n cycles. The number of cycles was varied; with a lower number of cycles, the model did not have to learn a large range of sensor values that exist in one class, making predictions relatively easy. As the number of cycles increased, the data was not so easily separable.

For the scoring question, each cycle was scored using the SVM model. A lower score would indicate that an engine was in a healthier state, a higher score would indicate an engine was about to fail.

In Fig. 2, accuracy on the Y axis presents the power plants failure predictions with respect to the number of cycle on the X axis.

Fig. 3 shows the prediction of engine failures in n cycles using logistic regression. The X axis shows the life of engines in cycles and the Y axis shows the probability of failure for 30 cycles, 70 cycles

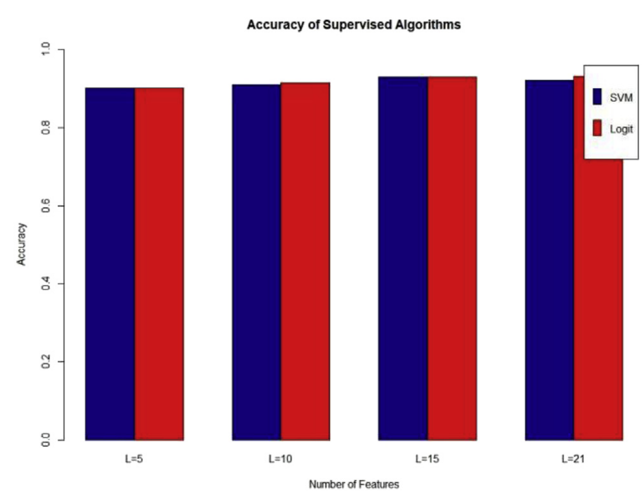

Fig. 4. Confusion matrix using Svm & Lr.

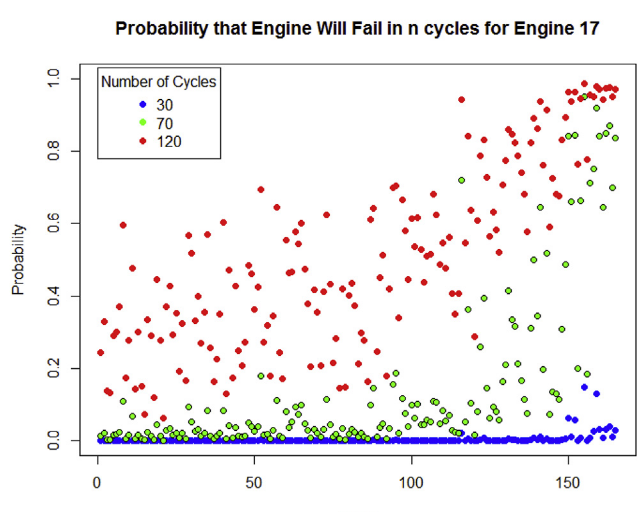

Fig. 3. Predicting engine failures in N cycles for engine 17 using logistic regression.

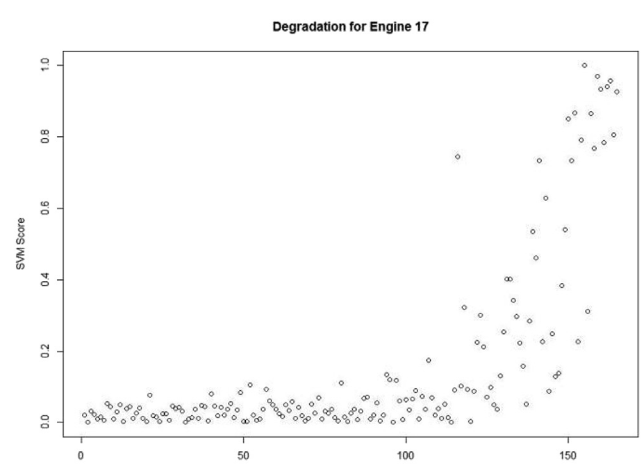

Fig. 5. Likelihood of Degradation score of specific engine using support vector machine.

Table 2
Comparison of results with other existing nuclear power plants preventive maintenance using machine learning.

Existing Work	Feature Types	Machine Learning Algorithms	Accuracy
[24]	PCA	Linear	80%
[25]	RFE	LR,RF,MLP	67–75%
[26]	Multiple	SVN,ANN	Vary
[27]	Timely	ANN,LSTM	Vary
Proposed Work	No Variance & Co-related	SVM, LR	95%

Table 3
Proposed work functionality comparison with existing work.

Functionality	[24]	[26]	[27]	Proposed Work
Hidden anomaly of nuclear infrastructure engines	✓	✗	✓	✓
Schedule Synchronization	✓	✓	✗	✓
Different level of plants monitoring	✗	✗	✗	✓
Automated prediction	✗	✓	✗	✓
Machine learning approaches	✗	✗	✓	✓
Heterogeneous Data	✗	✗	✗	✓

and 120 cycles. Fig. 4 shows the SVM plot of engine failure with the number of cycles for Engine 17. The X axis shows the number of cycles of engine operation and the Y axis shows the SVM score for prediction of engine failure. This plot shows that if the life of an engine increases in cycles, the SVM model has scored a high degree of failure for the increased life of the engine cycles.

In the proposed research, we have also observed a number of cycles of specific plant components which require maintenance or have a likelihood to fail. Fig. 5 shows failure prediction of specific engine 17 from Turbofan Engine Simulation Dataset. It shows the pattern of degradation by generating score using SVM.

5.4. Evaluation of proposed research

A comparison was undertaken to highlight the significance of our proposed research work. We have compared our work with existing work and found our proposed framework has a higher accuracy. We have performed the comparison in two different ways.

Table 2 presents a comparison of results with existing research performed by other researchers on nuclear power plants to perform prediction of maintenance. It explains varying feature types and selection techniques with different machine learning algorithms. As represented in the confusion matrix and Figs. 1, 2 and 4, the accuracy of the proposed work is higher than the literature we referenced.

Table 3 presents the various functionalities included in the proposed work and a comparison with existing work. As described, our proposed work includes hidden anomaly identification for nuclear infrastructure specific engine, scheduling synchronization among all nuclear plant sensors, different level of plants monitoring and automated prediction. The robust framework we designed is faster to perform predictive maintenance of nuclear infrastructure.

5.5. Applications, conclusion and future work

The proposed predictive maintenance framework can be applied in many applications other than nuclear infrastructure. As per state of art technologies, it can be applied in IoT equipment maintenance, The ARC group study states [28], however, that worldwide, only 18% of equipment has failed due to its age, while 82% of failures occur randomly. In this case, proposed framework is very much useful. The other potential applications of proposed predictive maintenance framework are listed below [29]:

- Identifying motor amperage spikes or overheating from bad bearings or insulation breakdowns
- Finding three-phase power imbalances from harmonic distortion, overloads, or degradation or failure of one or more phases
- Locating potential overloads in electrical panels
- Measuring supply side and demand side power at a common coupling point to monitor power consumption
- Capturing increased temperatures within electrical panels to prevent component failures

Detecting a drop-in temperature in a steam pipeline that could indicate a pressure leak.

In this research, we have presented the design and development of a predictive maintenance framework for nuclear infrastructure using machine learning techniques. The framework is able to predict the failure of nuclear plant infrastructure and engines and is also capable of classifying the number of cycles. Furthermore, it provides higher accuracy with no performance overhead. In the future, we would like to extract real-time nuclear power plant data using the proposed intelligent data acquisition system and perform similar experiments with the added scope. We are also looking into additional machine learning algorithms to increase options and improve accuracy.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.net.2019.12.029.

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