Lecture Notes in Mechanical Engineering

Prabhakar V. Varde
Gopika Vinod
N. S. Joshi *Editors*

Advances in Risk and Reliability Modelling and Assessment

Proceedings of 5th International Conference on Reliability Safety and Hazard (ICRESH 2024)

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Preface

The evolving national programs and the global world-order can be considered to be driven by three major factors, viz., economics, security and sustainability. It is interesting to note that de-risking (that deals with security and safety) and reliability are the two factors that provide support to the top-level objectives, viz. economics, safety, security and finally to sustainability. The current engineering systems, having its roots in technological evolution, are essentially governed by rules or specifications, best practices, hands-on learning, experience, peer review and enforcement systems. Here the scope for interpretation at times is limited toward arriving at decisions.

There is a phenomenal progress in science and technology that is reflected in advanced technologies that not only support but effectively enhance safety and reliability objectives. The advancement in safety and reliability technology in safety critical systems, viz. structural, process, nuclear, space, defense, water transport, rail and road transport, software, is a testimony or tribute to the success of state-of-the-art in science and technology. However, when we look at the history of accidents and societal challenges, we still see that further efforts are required. One of the observations has been that human factor is one of the major contributing factors to accidents and unrests. As a result, one still wonders—*'a lot has to be done even now'*. On the positive side, the risk assessment tools and methods themselves have evolved like failure analysis or to be precise the root cause analysis, human factor development, modeling for digital systems, surveillance and condition monitoring techniques, etc. that provides the required and needed edge for development of advanced applications. However, the new challenges are popping perpetually due to new and complex scenario that pushes development of advanced tools and methods to achieve the higher level of maturity, e.g., demands for higher capability in terms of capturing dynamic scenario, modeling and management of fuzzy aspects, monitoring and prognosis of common cause failure, human factor considerations, data and models such that the targets associated with improvement in prediction capability on one hand and acceptable level of risk and uncertainty, on the other, are met.

Probabilistic Risk Assessment (PRA) framework is now considered matured and dependable enough to support effectively the risk-informed and further risk-based engineering applications. This is due to the reason that PRA provides an integrated, structured and quantified model with provision to characterize uncertainty documented and ready for any review and evaluation. Here, PRA provides a needed platform to either complement or supplement the existing deterministic methods as part of risk-informed approach or as an alternate or standalone approach for not only risk assessment but also development of risk-based applications requiring identification and prioritization, e.g., risk-based in-service inspection, maintenance management, safety significance identification to support prioritization of regulatory review management, etc.

There appears silver lining in the context of de-risking our systems, structures and components. The phenomenal growth of advanced technologies particularly the digital technology, availability of complex computing systems, artificial intelligence and machine learning tools, advances in physics-of-failure and data-driven-based prognostics and health management approaches coupled with improved availability of plant design and operational experience, that is creating the needed ecosystems for advanced research and implementation tools and methods for addressing real-time challenges in the industry. One of the major developments in say nuclear industry, design and development of the plants with inherent safety features has potential to support the safety objectives of advanced and next general systems. One of the interesting examples which created waves is design and development of small modular reactors (SMRs). This is truly a promising in terms of achieving higher safety and reliability and eventually meeting the sustainability objectives.

The 5th International Conference on Reliability, Safety and Hazard-2024 (ICRESH 2014) was organized during February 21–24, 2024, at DAE Convention Centre in Mumbai, India. The three major technical programs were plenary sessions, pre-conference tutorials and parallel sessions. A separate book has been published based on the 17 keynote talks by distinguished experts. The pre-conference tutorials were organized on February 21, 2024 and focused on the theme topics in the area of risk reliability. The parallel technical sessions were most exciting and vibrant and formed core component of this event. The motivation here was to address some of the areas that are directly related to existing complex engineering systems and offer some ideas for future systems. The conference received overwhelming response, and this book is based on the invited and contributory talks covered in three parallel sessions spread over three days.

This book entitled *Advances in Risk and Reliability Modelling and Assessment—Proceedings of 5th International Conference on Reliability Safety and Hazard (ICRESH 2024)* is based on the contributory and invited talks presented during the parallel sessions of the conference. Total 72 papers were presented that included both contributory and invited papers. The major theme of the parallel sessions was reliability methods mainly focusing on probabilistic risk assessment (PRA), Reliability, Availability Maintainability and Safety (RAMS), Hazard Studies, development and application of risk-informed approach, artificial intelligence and machine learning (AI&ML) in support of risk modeling and analysis, human factor considerations, and the major application areas such as nuclear systems, structural systems, electronics and software systems, etc. The distribution of papers in the above areas shows that there is an active interest in the R&D areas dealing with development, challenges and future directions for risk and reliability modeling toward application of risk-informed approach to complex engineering systems. The presentation from students and scholars in the areas related to the risk and reliability like AI&ML for real-time applications was one of the major features of ICRESH 2024. Another interesting aspect was that there were number of presentations on external events. Based on the reports of sessions chairs and suggestions of experts, recommendations will be made in respect of future, R&D, availability of resources, collaborative requirements and creation of advanced infrastructure at national and international levels, such that risk and reliability research and development provide effective support to industries and societal applications.

We sincerely thank all the experts, academic, researchers, practicing professionals and not the least our scholars and students who contributed to the ICRESH 2024. We thank them for their support and presenting their work capturing their R&D and professional experiences. Special thanks to Springer team, Ms. Priya Vyas and colleagues for development and management of the tasks associated with this volume and publishing this book, well in time.

Mumbai, India
December 2024

Prabhakar V. Varde
Gopika Vinod
N. S. Joshi

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About the Editors

Prof. Prabhakar V. Varde started his carrier at Bhabha Atomic Research Centre in 1983 as a nuclear engineering trainee of BARC Training School in 27th Batch and joined erstwhile Reactor Operations and Maintenance Group now Reactor Group and served initially as commissioning and later operations engineering for Dhruva—a 100 MW research reactor at BARC and rose through the administrative ladder and retired in 2019 as an associated director, Reactor Group. During his service, he completed his Ph.D. from IIT Bombay in 1996 in AI-based operator advisory system and later focused his research on nuclear safety in general and risk-based engineering in particular, while working for reactor-related services responsibilities.

Alongside his regular duties, he continued R&D in the area of risk and reliability and academics. He also served as a senior professor, guide and member of the Board of Studies in Engineering Sciences of Homi Bhabha National Institute, Mumbai.

Dr. Gopika Vinod joined with Reactor Safety Division of Bhabha Atomic Research Centre as a scientific officer from 37th batch of training school after completing her graduation in computer engineering. She received her doctoral degree in Reliability Engineering from Indian Institute of Technology, Bombay, and has also been post-doctoral fellow at Steinbeis Advanced Risk Technologies, Germany. She is a recipient of DAE Young Engineer Award 2007 and DAE Group Achievement Award (2015, 2019). Currently, she is heading the Probabilistic Safety Section of Reactor Safety Division of BARC. She also holds faculty position as a professor and dean academic (Engineering Sciences-2 to BARC) with Homi Bhabha National Institute. She is also a fellow at Indian National Academy of Engineering.

N. S. Joshi completed his Bachelor's degree in Mechanical Engineering from Shivaji University, Kolhapur, and joined Bhabha Atomic Research Centre (BARC), Mumbai, in the year 1990 and started his career in Operations and Maintenance of Nuclear Research Reactors. For over three decades, he has been serving in BARC. Apart from operations and maintenance, his expertise also includes root cause analysis and human resource development. He was actively involved in development of a full-scope simulator for research reactor, Dhruva, at BARC for operator training and human factor development. He was also involved in preparation of probabilistic risk assessment of research reactors at BARC and other nuclear facilities.

He is a founder member of the Society for Reliability and Safety and currently working as a managing editor of Springer International Journal on Life Cycle Reliability and Safety Engineering.

Artificial Intelligence

A Support Vector Machine Model for Detection of Transients in Nuclear Reactor

V. Arunprasath, T. V. Santhosh, Gopika Vinod, P. K. Guchhait, N. Gohel, and S. Sengupta

1 Introduction

Timely identification of transients is a growing area of research in the safety of nuclear reactors. Reactors generally are equipped with various supporting systems for the operator, including plant instrumentation, operator display & data acquisition systems, alarm annunciation systems, system safety logics, etc. Additionally, the operator must adhere to standard & emergency operating practices in the event of any abnormal scenarios. These traditional processes and procedures do, however, have drawbacks. They can only respond to certain occurrences that fall under the scope of their fundamental principle models. Additionally, it is difficult to find accurate models of nuclear reactors based on physical principles, which makes it impractical to use model-based diagnosis procedures. Data-driven procedures don't necessitate in-depth understanding of the process system, in contrast to physical principle model-based approaches. Data-driven strategies create empirical models using process data that are measured in the plant.

In nuclear reactors, the operator's ability to evaluate a number of alarms and annunciations, and to take correct action well within the stipulated time is crucial. It is well-known that one of the major variables that might result in severe accidents in reactors is human error. Vast amounts of data are nowadays available due to improvements in fast data recording systems that makes it possible to create Machine

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Learning models to accurately forecast transients and support operators in early actions.

Various techniques in identification of transients are studied and these results benefits in ensuring safe and cost-effective operation. Typically, these techniques extract features using pattern recognition techniques to describe system interactions or to identify anomalous reactor status from related process data [1]. Data based strategies in monitoring reactors have gained popularity recently [2]. A neural network-based observing of sensor status in reactors was discussed by Hines et al. [3]. An abnormality detection system by neural network integrated with plant knowledge base was discussed by Ohga et al. [4]. Use of ANN for the diagnosis of accidents and the determination of the state of nuclear power plants was discussed in Refs. [5–7]. Sirola and Hulsund [8] discussed identification of sensor degradation and remaining life prediction using data analysis and clustering techniques. Whereas Saeed and Peng [9] presented a diagnosis scheme using neural networks and principal component analysis which also calculated severity of faults in sensors.

Support Vector Machine (SVM) is a very popular machine learning technique used in solving regression and classification problems. References [10, 11] discussed application of SVM for monitoring health of components & anomaly detection in nuclear power plants. In this paper, an SVM machine learning model is proposed for detection of transients in a research reactor. SVM is chosen because they provide good generalized classification accuracy while being simple to implement with computational efficiency [12]. In this study, a technique to obtain an optimal SVM model from various models with different hyper-parameters ranked using a grid search algorithm is presented. Among the many built models, the proposed method produced a classification model with the highest accuracy and quickest computation time.

2 Transient Detection

Identifying hypothesized transients in a conventional pool type research reactor is the problem under consideration here. In these reactor configurations, the core is submerged in a water pool, cooled continuously via forced circulation and passive valves in case of pump trip. Additionally, cooling towers act as heat sinks. Critical plant parameters, including process signals, valves and equipment statuses, are continuously monitored and recorded. Such reactors often have extensive instrumentation generating & recording large number of process data [13].

In the context of such research reactors, certain transients are often postulated and these transients represent significant abnormal events in the reactor. These transients could potentially lead to severe consequences if not appropriately mitigated. Consequently, the timely detection of these transients during reactor operation is of paramount importance. Hence, in this study, the problem of identifying and classifying the major transients hypothesized for such pool type research reactors is addressed using a SVM model.

Table 1 Transients modeled for detection

S. No.	Transient
1	Loss of flow due to pump trip (LOFA1)
2	Loss of Flow accident due to pump seizure (LOFA2)
3	Loss of coolant accident due to pipe break at pump discharge header (LOCA)
4	Loss of heat sink (LOHS)

3 Dataset

For creating data based models for recognizing transients, it is imperative to have a dependable and readily accessible dataset. In this study, we employ simulated transient data generated using the RELAP5/MOD 3.2 code, developed by INL specifically for analyzing transients and accidents in light water reactors (LWRs). By utilizing thermal–hydraulic codes, RELAP5 replicates the dynamic behavior of reactor parameters in accidental scenarios in Light water reactors including research reactors [14, 15]. Transients occur if the reactor transitions from normal to any abnormal operating conditions, often resulting from various factors such as system/component failures, human errors, and internal or external events. For the reactor being studied, transients were determined as per IAEA SSR-3 [16]. Here, four distinct types of transients are considered utilizing simulated data from these scenarios. Table 1 shows the transients taken for this work, representing the main process deviations anticipated in such reactors.

In each transient, trends in plant parameters over time are depicted by the event sequence simulation. All the simulated plant parameters comprising 16 signals are utilized for modeling as these are found to be contributing to the four considered transients. The input data for modeling comprises a labeled dataset categorized into five classes including normal reactor state. The parameters encompass vital analog and digital plant data, including level of pool, power, flow of reactor coolants, and temperatures at inlet & exit of heat exchangers, among others.

4 SVM Algorithm

SVM is a powerful supervised machine learning algorithm widely used for classification and regression tasks. An SVM's primary goal is to identify the best hyperplane in a high-dimensional feature space for separating data points from various classes. This hyperplane serves as a decision boundary, facilitating the classification of new, unseen data points. The key idea behind SVMs is to identify the hyperplane that maximizes the margin, which is the distance between the hyperplane and the nearest data points (support vectors) of each class. SVMs look for the hyperplane that not only divides the data into classes but also maintains a wide gap between them to improve generalization to new data [17].

Basic SVM algorithm are applied for classification of binary data. SVM binary classifier separates two data points of a linearly separable data (x_i, y_j) in to positives and negatives such that

$$w^T x + b \geq 1 \quad \text{for cases where } y_j \text{ is positive} \tag{1}$$

and

$$w^T x + b \leq 1 \quad \text{for cases where } y_j \text{ is negative} \tag{2}$$

with the classifying hyperplane given by

$$w^T x + b = 0 \tag{3}$$

Following is the SVM optimization problem is to calculate the weight w and the bias b:

$$\min_{w,b} \frac{1}{2} w^T w + C \sum_{i=1}^{N} \xi_i \tag{4}$$

such that

$$y_i \left(w^T x_i + b \right) \geq 1 - \xi_i \quad i = 1, 2, \ldots, N, \tag{5}$$

$$\xi_i \geq 0, \quad i = 1, 2, \ldots, N \tag{6}$$

If the hyperplane separating the two classes is not linear, a function $\Phi()$ can be used to transform the data points to a higher dimensional feature space where the data is linearly classifiable using the 'kernel trick'. The decision function in SVM is given by:

$$f(x) = \text{sign}\left(b + \sum_{i=1}^{N} \alpha_i y_i K(x_i, x) \right), \tag{7}$$

where $\alpha_i s$ are the Lagrange multipliers and K is the kernel function given by

$$K(u, v) = \Phi(u).\Phi(v) \tag{8}$$

Some of the most common kernels used are Radial Basis Function (RBF) kernel

$$K(u, v) = \exp\left(-\frac{||u - v||^2}{2\sigma^2} \right) \tag{9}$$

and polynomial function kernel. C is the regularization parameter that accounts for the balance between the training accuracy and the margin since C decided the penalty for misclassifications during the training process. C is a hyper parameter to be tuned in selecting an SVM model. Other hyperparameters are the parameter $\gamma = \frac{1}{2\sigma^2}$ of the RBF kernel that sets the spread of the kernel and the degree of polynomial in a polynomial kernel [17].

SVMs are effective in datasets where high dimensionality is involved. They work relatively well when there is a clear margin of separation between classes. They also work well with non linear decision boundaries with the help of the kernel trick. SVMs are memory efficient, as only the support vectors need to be stored. And they are robust against overfitting, as regularization is built into the optimization. However, it is significant to note that performance of SVMs can be dependent on the choice of kernel and the setting of regularization parameters [18].

5 Methodology

In preparation for training the SVM model on the input data, a series of crucial preprocessing steps are undertaken. Firstly, the data undergoes z-score normalization, a pivotal procedure that ensures each feature within the dataset exhibits a mean of zero and a standard deviation of one. Subsequently, the data is randomly divided into two distinct subsets: a development dataset and a validation dataset, thereby laying the foundation for rigorous model evaluation.

To construct multiple SVM models, a set of hyperparameters is defined, encompassing the regularization parameter, denoted as C, the hyperparameter Gamma, and a selection of diverse kernel functions. These kernels encompass linear, Radial Basis Function (RBF), and polynomial variations. C ranges from 0.01 to 100, while Gamma spans from 0.001 to 1. This parameter space facilitates the creation of diverse SVM models, each offering unique combinations of C, Gamma, and kernel functions.

A grid search algorithm is employed to fit these SVM models to the training data, utilizing the development dataset for this purpose. In this grid search process, we employ k-fold cross-validation to assess the performance of the classifier models. The input dataset is often divided into k subgroups for k-fold cross-validation, ensuring that each subgroup has roughly the same amount of samples. Each subgroup acts as the testing subgroup and the training subgroup $k-1$ times throughout the training phase. In essence, k classification models are created using $k-1$ subgroups for training and the remaining one for testing when using k-fold classification validation. The results from these k classification models are averaged to determine how well the final classification performed.

In this study, the k folds are generated using a stratified sampling strategy. In order to retain the same proportion of samples of different classes as the original dataset, every subgroup is created to have a balanced distribution of data points across various labels. This method guarantees that the subgroups that are produced accurately reflect the statistical distribution within the original dataset.

The methodology revolves around the construction of multiple SVM models through the grid search algorithm, culminating in the identification of the optimal model for classifier fitting. To achieve this, we first evaluate all estimators generated by the grid search algorithm using testing data generated through k-fold cross-validation. Subsequently, these estimators are ranked based on their performance accuracy scores. A predefined threshold accuracy is established, serving as a filter to retain estimators with performance scores above this threshold. The ultimate selection of the fastest-fitting model is deemed the optimal SVM model.

This chosen optimal SVM model undergoes a refinement phase, where it is retrained using the complete development dataset and subsequently employed for classification tasks. Following this training, the fine-tuned model is rigorously tested using the separate hold-out validation dataset, which was initially partitioned from the overarching dataset.

A visual representation of this optimization process is illustrated in Fig. 1, providing a clear overview of the steps involved in the approach.

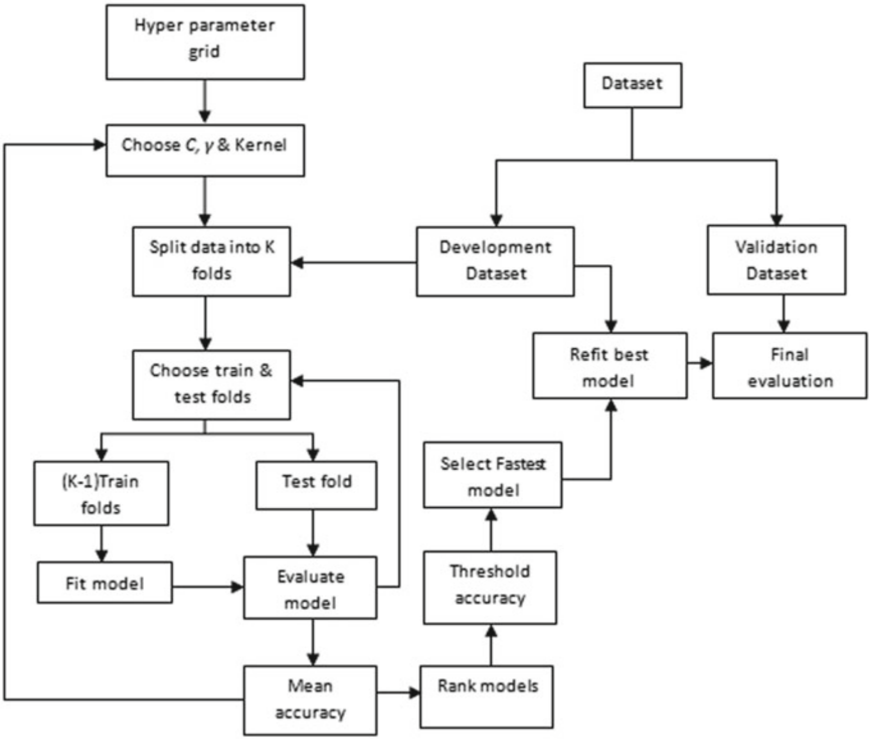

Fig. 1 Methodology for SVM model selection

6 Results

The grid search strategy yields multiple SVM models, each with distinct hyperparameters. These models undergo thorough training and testing through a k-fold cross-validation approach. Accuracy scores, derived from hold-out test data folds, are computed for each model, subsequently leading to their ranking based on performance. Table 2 provides a listing of the top 10 ranked models, complete with their associated hyperparameters, kernel and mean accuracy scores.

Notably, all of these models exhibit performance accuracy exceeding the predefined threshold of 97%. Following ranking, the optimal model is determined as the fastest among them, characterized by the lowest prediction time. The model which gives good mean accuracy score and quickest prediction time is found as RBF kernel SVM with hyperparameters $C = 10$ and $\gamma = 0.1$.

The identified best model, established through the aforementioned strategy, is subject to further refinement by fitting it to the entirety of the development dataset before being deployed for predictive purposes on the validation dataset. Figure 2 presents performance plots showcasing the optimal model's behavior across different hyperparameters, specifically C and Gamma within the RBF kernel.

To evaluate the model's performance for each transient, we derive the confusion matrix of the SVM classifier. The matrix serves as a vital tool for assessing the classification algorithm's effectiveness. It represents data instances based on actual class labels in rows and predicted labels in columns, as presented in Fig. 3.

Assessment of the SVM classifier model's performance under the validation dataset is tabulated in Table 3, including class-specific performance. The model performs well in identifying the individual transient with good precision & recall. A good measure combining precision and recall is the F1 Score which is the harmonic mean of both the metrics. It can be seen that for all the classes, the F1 metric of the model is close to1 which is a very good score. Overall validation accuracy of the optimal SVM model is found to be 96.87%.

Table 2 Top 10 SVM models obtained by Grid-search strategy

Rank	C	γ	Kernel	Mean accuracy score
1	100	0.01	RBF	0.972948
2	10	0.1	RBF	0.972248
3	10	0.01	RBF	0.971549
4	1	0.1	RBF	0.971549
5	100	0.001	RBF	0.971316
6	1	1	RBF	0.971082
7	100	0.1	Polynomial	0.971082
8	0.1	1	Polynomial	0.971082
9	10	0.1	Polynomial	0.970616
10	100	0.1	Polynomial	0.970149

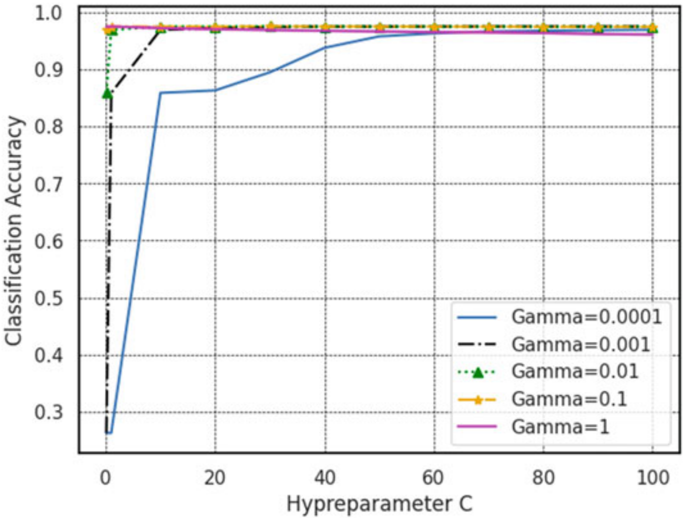

Fig. 2 SVM model classification accuracy versus hyperparameter C for different γ

Fig. 3 Confusion matrix for the SVM model

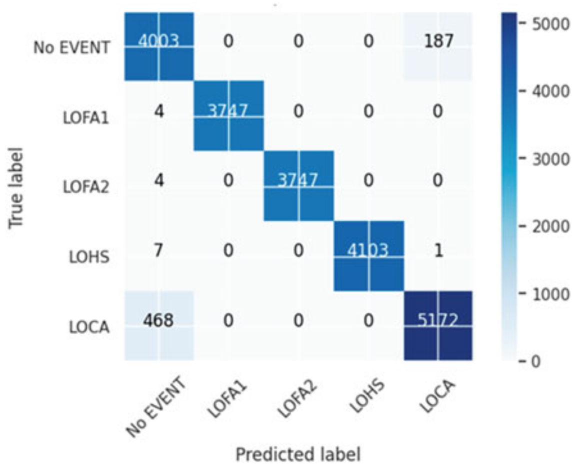

Table 3 Performance metrics for the SVM model

Class	F1 score/accuracy
NO Event	0.92
LOFA1	1.00
LOFA2	1.00
LOHS	1.00
LOCA	0.94
Overall accuracy	96.87%

Furthermore, the impact of noise on the classifier model is investigated by introducing random Gaussian noise, corresponding to a Signal-to-Noise Ratio (SNR) of 20 dB, into the dataset. Notably, the SVM model retains its ability to classify a majority of samples, albeit with a marginal reduction in the overall classification accuracy, which settles at 94.5%.

7 Conclusion

This paper addresses the crucial task of early transient identification within the context of safe nuclear reactor operation. This study leverages a Support Vector Machine (SVM) model to detect and classify transients in a research reactor of pool type. A technique for selecting the optimal SVM model from a diverse set of candidates, generated through grid search optimization is proposed. This approach has yielded a classification model characterized by good performance. Throughout the study, simulated transient dataset, comprising 16 critical plant parameters, served as the input for data-driven modeling. The results showcase the efficacy of the proposed methodology. The selection of the optimal model was based on both accuracy and computational efficiency, ensuring faster prediction of events. Assessment of model performance across various transients, was done using confusion matrix and F1 scores. This comprehensive evaluation provides valuable insights into the classifier's effectiveness across classes. Lastly, the study explored the model's robustness by introducing random Gaussian noise. Despite the noise, the SVM model maintained its ability to accurately classify a majority of samples with marginally reduced accuracy. With inclusion of additional parameters and with more data the accuracy can further be improved even when the number of events to be predicted becomes large. In summary, this work contributes to the growing field of early transient detection in research reactors, offering a data-driven approach that helps decision-making processes thus enhancing reactor safety.

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Reinforcement Learning for Mission Reliability Based Selective Maintenance Optimization

Ram S. Mohril, Tarun S. Kudali, Bhupesh K. Lad, and Makarand S. Kulkarni

1 Introduction

In numerous engineering applications, it is necessary for systems to execute missions in a continuous manner, punctuated by a maintenance break that occurs between two consecutive missions. The feasibility of conducting maintenance on all system components is hindered by the short period of the maintenance break, as well as several other constraints. In such situations, the decision-maker needs to decide on a subset of components to perform maintenance. This maintenance strategy is called Selective Maintenance (SM), and it is defined as a policy of determining a subset of maintenance actions to perform when given a set of limited maintenance resources such as time, cost, spares, and crew [1]. Irrespective of the complexity involved, it is necessary to solve the SM problem in the minimum possible duration. As the limited available maintenance duration is itself a constraint in the problem, any approach that requires higher computation time is undesirable since the decision-making process itself will consume most of the maintenance duration.

The initial research on SM Optimization (SMO) was mostly centered around using the enumeration approach. However, it was shown that this approach was not viable when applied to problems characterized by larger solution space. This led to the development of the next generation of methods coupled with heuristics, like tabu search [2], genetic algorithm [3, 4], particle swarm optimization [5], differential

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