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Original Article

# Support vector ensemble for incipient fault diagnosis in nuclear plant components

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A B S T R A C T

The randomness and incipient nature of certain faults in reactor systems warrant a robust and dynamic detection mechanism. Existing models and methods for fault diagnosis using different mathematical/statistical inferences lack incipient and novel faults detection capability. To this end, we propose a fault diagnosis method that utilizes the flexibility of data-driven Support Vector Machine (SVM) for component-level fault diagnosis. The technique integrates separately-built, separately-trained, specialized SVM modules capable of component-level fault diagnosis into a coherent intelligent system, with each SVM module monitoring sub-units of the reactor coolant system. To evaluate the model, marginal faults selected from the failure mode and effect analysis (FMEA) are simulated in the steam generator and pressure boundary of the Chinese CNP300 PWR (Qinshan I NPP) reactor coolant system, using a best-estimate thermal-hydraulic code, RELAP5/SCDAP Mod4.0. Multiclass SVM model is trained with component level parameters that represent the steady state and selected faults in the components. For optimization purposes, we considered and compared the performances of different multiclass models in MATLAB, using different coding matrices, as well as different kernel functions on the representative data derived from the simulation of Qinshan I NPP. An optimum predictive model - the Error Correcting Output Code (ECOC) with *TenaryComplete* coding matrix - was obtained from experiments, and utilized to diagnose the incipient faults. Some of the important diagnostic results and heuristic model evaluation methods are presented in this paper.


## 1. Introduction

In nuclear power systems, the nature of incipient and novel faults makes their diagnosis problematic. This largely results from the fact that the symptoms of these kinds of faults lie within the range of covered by the compensatory actions of the reactor control systems. Hardware degradation, cracks in components and leakages in valves and pipings that are not large enough to change the operating set point could remain undetected for a long time and are indicators of incipient faults. Undetected, incipient faults could result in large faults necessitating emergency shutdown, downtime and costly start-up procedures. In addition, the occurrence of faults in systems are mostly random, hence detection mechanism needs to be robust and dynamic. A number of models and methods for fault diagnosis using various mathematical/statistical inferences, but the seemingly elusive aspect - especially in nuclear plants - is the detection and diagnosis of incipient and novel faults. Detection of incipient fault is important because if such fault is allowed to propagate, it could have catastrophic consequences for the safety of the plant and environment, as well as human health.

In the applications of Failure Mode and Effect Analysis (FMEA) and failure probability calculations, not all failed components have catastrophic effects [1]. That is, if an increase in failure rate of a certain component does not have any considerable effect on the safety of the system, then further analysis of such components is of little importance [2]. A similar theory could be extended to fault diagnosis system. Hence, our research aims to diagnose marginal faults that could be a time-dependent catastrophe if not detected, diagnosed and managed promptly.

In this work, we propose a distributed training method for multi-class Support Vector Machine (SVM) modules, with each trained SVM model monitoring each sub-unit of the Reactor Coolant System (RCS) of a Pressurize Water Reactor (PWR) nuclear power plant. To optimize the SVM modules and select the best training algorithm, we consider and compare the performances of different multiclass implementation algorithms, using different

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coding matrices, as well as different kernel functions (linear and Gaussian kernel) on the representative data derived from the best-estimate simulation of Qinshan I NPP, and the data set is then utilized with MATLAB machine learning toolbox to obtain optimum result. Section II summarizes the past work on the use of SVM for multiclass modeling and Section III describes the SVM model as applied to fault diagnosis in RCS of a PWR. Section IV explains the fault modeling for the coolant system sub-unit and the assumptions made. The implementation and experimental result is presented in Section V and we summarized the paper in Section VI.

## 2. Background and related works

SVM is a branch of statistical learning theory that uses a linear plane or hyperplane in feature space (of higher dimension for linearly inseparable input space) to derive its hypothesis. The basic quadratic problem of SVM is to find the "smoothest" estimating function capable of predicting new instances based on previous know instances. When supervised, SVM act as a form of knowledge-based fault diagnosis system. When unsupervised, it is able to cluster parameters to diagnose novel faults. The common contention about data-driven algorithms is that the number of possible faults in complex systems like NPP is unbounded; hence the potential faults cannot be exhaustively identified. Meanwhile, the alternatives are not very inspiring. Physical models have limitations, including model inaccuracies and issues with linearization of nonlinear systems, among others.

In Ref. [3], the kernel-based Gaussian process is applied to predict faults in nuclear plant mechanical systems. The method utilized the learning ability of the Gaussian process to predict degradations in the system. Support vector machine is utilized to predict degradation in nuclear plant auxiliary components in Ref. [4], while in our previous work, we utilized the real-value output capability of support vector regression and the noise-reduction capability of feature selection algorithms to estimate the severity of rupture fault in the steam generator tubes Ref. [5]. These research papers [6,7] give a good discussion on SVM technique for fault diagnosis and their superior performances over other data-driven approaches for various classification tasks. However, appropriate selection of learning algorithm suitable for a particular task is important for effective utilization of SVM. Also, the plethoras of proposed techniques have not been implemented in operating nuclear plants. Some practical challenges identified as barriers to their implementation include model inconsistencies with the complexity of process dynamics, limited ranges of validity of the models, incomplete uncertain data, model complexity and inexact knowledge of parameters and driving forces [8]. We utilized our experience with reactor dynamics and the superior modeling capability of RELAP5 code to address most of these limitations. Moreover, traditional learning algorithms are bugged with few challenges: Over-fitting, generalization and local minima, exploding and impractical hypothesis, limitation of training examples and inconsistency issues. However, SVM's use of kernel function enables it to output a compact hypothesis space that handles most of the issues bugging other learning algorithms.

Support Vector Machine (SVM) application to various classification and regression problems (both supervised and unsupervised) have been researched [9,10]. In this paper, the selection of SVM for nuclear plant fault classification is based solely on performance. Fault detection is a classification problem, and research has shown that SVM performs better than other types of learning algorithms for classification problems [11]. Two key elements in the implementation of SVM are the techniques of mathematical programming and kernel functions, and the flexibility of kernel functions allows the SVM to search a wide variety of hypothesis by constructing an optimal separating hyper-plane in the hypothesis spaces.

Fundamental SVM algorithm has been used for binary classification purposes. In its simplest form, SVM binary classifier $f(x) = \omega^T\varphi(x_j) + b$ separates two different instances of a given linearly separable data $\{x_j, y_j\}_j^l$ into positives and negatives $(y_{j's})$ such that for $y_j = +ve$,

$$\omega^T\varphi(x_j) + b \geq 1$$

And for $y_j = -ve$,

$$\omega^T\varphi(x_j) + b \leq 1$$

Where $l$ the number of instances is, $\omega$ is the weighing parameter, and $b$ specifies the location of the hyper plane bias away from the origin; $x_i \in \Re^D$, $y_j \in \{-1, +1\}$, $\varphi(x_j)$ is a mapping function that defines the kernel function $k(x_i x_j) = \langle \varphi(x_i), \varphi(x_j) \rangle$. The nonlinear kernel technique is utilized to find the best separating boundary and classify training instances and that are not linearly separable. This kernel function maps the input space from a lower dimension to higher dimensional input space, where linear separation is possible. The decision function learned by such classifier has the form [12].

$$f(x) = sign\left(\sum_i \alpha_i y_i k(x_i x) + b\right)$$

Where $x$ is a generic test point, and $\alpha_i$ is the "embedding strength" of the pattern $x_i-$ the number of times misclassification of $x_i$ has caused a shift in $\omega$.

To guarantee the best generalization performance for a highly nonlinear system like NPP, a robust SVM for multiclass classification is required. Recent advances have seen SVM being used for multiple classifications and regression tasks in engineering systems [13,14]. This was achieved by using the existing powerful binary algorithms to break a multi-class problem into several binary problems and combine the results together [15]. Some of the methods used to achieve this are summarized in the following section, although a robust description of these algorithms can be found in Refs. [16,17].

### 2.1. Approaches for multi-class SVM

1. One-vs-all: Given $p-$class training instances (where $p \geq 2$), a binary SVM classifier is trained such that it can distinguish one class from the remaining $p-1$ classes. This approach exhausts all possible combination of classes as the number of binary classifiers equals the number of classes, although it has been shown that it gives unbalanced training sample sizes [18].
2. One-vs-one: For each binary learner, one class is positive, another is negative, and the software ignores the rest [19]. This design exhausts all combinations of class pair assignments. That is, for $p$ number of classes, one-vs-one requires $\frac{p(p-1)}{2}$ binary classifications to capture all the combinations in the data.
3. Multiclass Objective Function: This approach simultaneously computes multiclass classifiers in place of multiple binary classifiers. Weston and Watkins [20] give the modified objective function as:

$$\min_{W,b,\xi}\left[\frac{1}{2}\sum_{i=1}^{P}\|w\|^2 + C\sum_{i=1}^{k}\sum_{r\neq y_i}\xi_i^r\right]$$

Such that:

$$W_{y_i}.X_i + b_{y_i} \geq W_r.X_i + b_r + 2 - \xi\sum_i^r$$

Where $C$ is the margin-misclassification tradeoff (regularization) parameter, $\xi_i^r \geq 0$ are the slack variables; $i = 1, ..., k$ and $y_i \in \{1, .....P\}$ are the multi-class labels $r \in \{1, ...., P\}$ are multi-class labels excluding $y_i$.

4. Error-Correcting Output Code based approach: This approach extends the binary classifiers to solve multi-class problems by reducing multi-class problems to a set of binary classifiers and assigning a unique coding design to each class, codes that determine the training of classifiers and decoding of the predicted results. That is, for a P class problem, a coding matrix $U \in \{\pm 1\}^{P \times C}$ is derived. This approach has been shown to have better classification accuracy compared to other multiclass models [21,22].

## 3. The theory of distributed fault diagnosis using SVM

The effectiveness of data-driven approaches in diagnosing incipient faults in complex systems like NPP has been contested from the fact that component interactions could affect the integrity of the data used for training the model. That is, parameter deviations indicating faults in one component are passed to the other sub-unit through the effect of fluid pressure, temperature, flow, and even instrumentation and control systems. Instrumentation and control (I&C) system compensate for small transients and deviations in nuclear plant parameters. This compensatory action has made the diagnosing of incipient faults in NPP problematic. To this end, we propose a distributed fault diagnostic system which uses component-level data in diagnosing faults. This system has the capability to independently monitor components and use the data to detect and diagnose faults. We propose a categorization of the RCS into five (5) sub-units, each unit being monitored by a separately-built, separately-trained, specialized SVM module. Consequently, each SVM tracks the component's parameters real time, and any deviation is mapped, flagged and indicated on the operator support Human-Machine Interface. Also, for each monitoring system, calculated parameters and the corresponding measurements are compared respectively to judge whether sub-units are abnormal or not. Fig. 1 shows the schematic of this system.

As a result of the vast and possibly inexhaustible representation space for likely faults that can occur in a complex engineering system, the introduction of the data-driven approach has been discouraged in some industries. To address this issue, we propose the use of the DSVM to investigate those faults with a greater likelihood of resulting in a catastrophic accident if not properly managed. Integration of comprehensive FMEA result to fault diagnosis decision is a necessary step to achieve an efficient FDI system [23]. The FMEA is expected to specify and identify failure modes, severity and the probability of occurrence in order to categorize key faults that could lead to catastrophic failure. A modified illustration of such categorization is as shown in Table 1 [24].

Hence, we integrate aspects of FMEA into the fault diagnostic system. In analyzing how safety systems may fail, identifying the cause in term of a distinct fault mode has been useful when different fault modes could lead to different effects requiring different means and degrees of mitigation. FMEA details the manner in which faults could appear in safety-critical components and the effect of such fault on the safety functions. One of these analyses is the Leak Before Break (LBB) approach [25]. Leak before break aims to apply fracture mechanics technology to demonstrate that piping is very unlikely to experience double-ended-guillotine-break under all loading conditions. Following this philosophy, research progress has been recorded in the area of postulating ruptures and other faults in high energy piping systems. Nevertheless, there exist important questions about the manner in which faults could appear in safety-critical components and the effect of the fault on the safety functions.

When these key faults are identified, then a robust data-driven fault detection and isolation technique can be utilized for prompt diagnosis. A method for creating, implementing and evaluating such system is the aim of this research.

In this work, the faults are diagnosed by training distributed SVM based solely on the local datasets. That is, each trained SVM uses the local datasets to diagnose faults. This method has two advantages: Fault localization is easy, as each SVM module predicts local faults. Also, component level incipient faults can be diagnosed effectively. The implementation of the distributed SVM method that uses data from each sub-unit, based on this categorization, is explained in the following section.

## 4. Fault modeling and the simulated plant sub-unit

The success of any data-driven method depends largely on the quality of the training data. To obtain quality data that is representative of an operating NPP, RELAP5/Mod4.0 thermal hydraulics code was used to model and simulate faults in Qinshan I NPP. Qinshan phase I NPP is a two-loop 300 MW Chinese version of the PWR and RELAP 5/Mod4.0 is a best-estimate thermal-hydraulic computer code that is used for reactor system safety and uncertainty analysis. The purpose of this simulation is to test the method on characteristic data from Qinshan I NPP parameters that serve as a close representation of the dynamics common to the nuclear plant. To confirm model accuracy, Table 2 shows the comparison of a few selected initial condition (steady state) parameters used as the operating parameters for the Qinshan I NPP simulation and the actual operating parameters. In addition, Fig. 2 shows the nodalized sub-unit, consisting of a steam generator and pressurizer.

## 5. Demonstration of the proposed method

We investigated the robustness of the method by simulating five (5) different fault types in the RCS of the Qinshan I pressurized water reactor using RELAP5/Mod4.0. First, a general model of a reactor system for Qinshan I NPP is assembled and the parameter correlations with measured values are compared, as in Ref [5]. Then, this full model is sectioned, each section containing different sub-components. For the purpose of evaluating the proposed method, one of the sections is selected and studied. As shown in Fig. 2, the sub-unit analyzed is the loop #1 of the RCS, comprising of a hot leg, steam generator, and the pressurizer. The distributed SVM is applied to detect and diagnose faults in these components. In order to reflect the status of RCS, the process is summarized in the following steps:

1. The full RCS is first simulated using RELAP 5 code. To confirm model accuracy, this full RCS model is then debugged and the calculated result is compared with the measured steady-state operating plant parameters.
2. Secondly, the RCS is divided into five (5) sub-units and then one of these units is selected to investigate the effectiveness of the method. Similarly, the simulation model is debugged to ensure that simulated parameters are consistent with design parameters under all running conditions. Fig. 2 shows the selected sub-unit, and Table 2 shows the comparison between the calculated and measured steady-state parameters for the sub-unit.

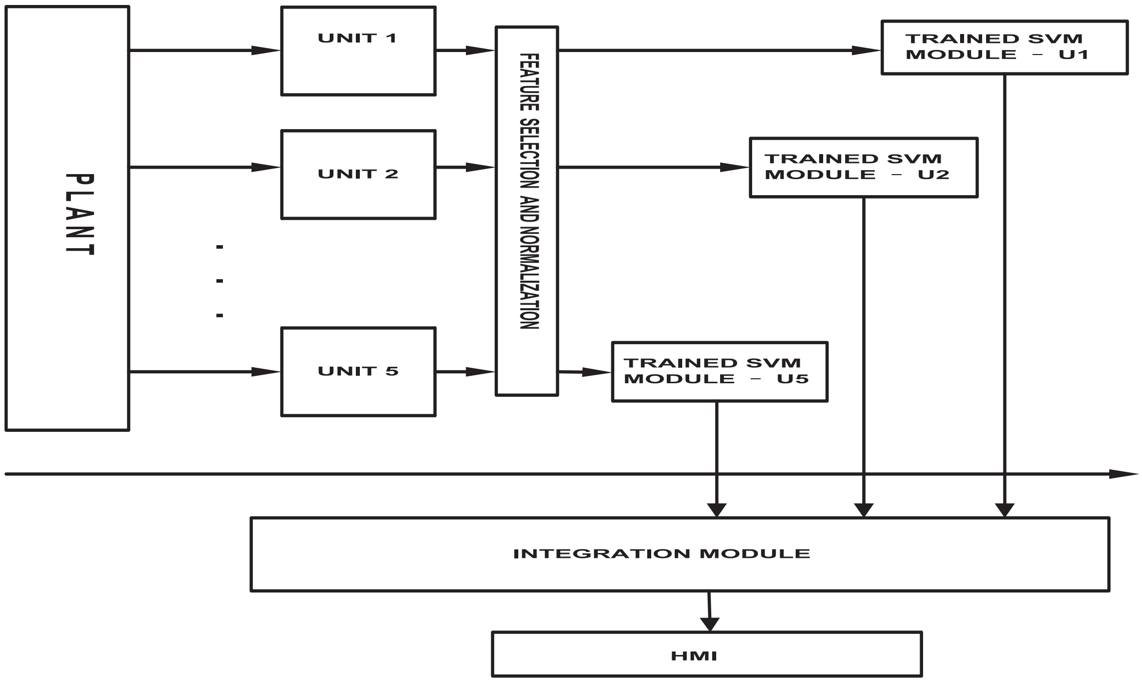


**Fig. 1.** Schematic of the distributed SVM for component level fault diagnosis.

**Table 1**
An illustration of FMEA results for fault categorization.

| Category | Classification | Definition |
|---|---|---|
| I | Catastrophic | A fault which may lead to a failure which could cause death or severe destruction. |
| II | Critical | A fault which may lead to a failure which may cause serious injury, major damage, and result in mission loss. |
| III | Marginal | A fault which may lead to a failure that could cause minor injury, minor system damage and result in delay or loss of availability or mission degradation |
| IV | Minor | A fault which could lead to a failure not serious enough to cause injury, property damage, or unscheduled maintenance repair. |

**Table 2**
Comparison between the calculated and measured plant steady-state parameters.

| Monitoring sub-unit | Parameters | Measured values | Simulated values | Error |
|---|---|---|---|---|
| Steam Generator | Feed water flow | 259.86 kg/s | 259.92 kg/s | 0.02% |
| | Steam outlet temperature | 270.21 °C | 271.9 °C | 0.6% |
| | Steam pressure | 5.5Mpa | 5.52Mpa | 0.36% |
| | SG water level | 10.47 m | 10.44 m | 0.21% |
| Pressurizer | Pressurizer pressure | 15.4 MPa | 15.3 MPa | 0.60% |
| | Pressurizer level | 5.400 m | 5.42 m | 0.37% |

3. Faults are simulated in the selected sub-unit. Fig. 3 shows the implementation in RELAP 5.
4. Data from the simulated faults are used to train the distributed SVM model, representing how it can be built in each sub-unit of the RCS.
5. The trained SVM is initialized after obtaining the related, real-time parameters indicating the steady state and the simulated faults in the sub-unit. Thus, the model can track the RCS sub-unit synchronously and separately.

### 5.1. Model assumptions and incipient faults description

This section describes the simulated faults and the assumption made in the plant model. The in-built fault diagnosis system in most nuclear power plants can detect cracks around 70 mm in length, with break flow rate above 0.5 kg/s [25]. Hence, we classify breaks below this threshold as incipient. We investigate faults such as the Leak Before Break (LBB) in pressurizer and the steam generator (SG), as flaws such as the LBB in the internal surface of the SG tube pipe can grow through the wall and could lead to a catastrophic break if undetected. This is a form of leak detection by detection of precursors. Hence, rupture in pipelines (incipient leaks and cracks) without Safety Injection System (SIS) activation is selected as a case study to verify the distributed monitoring system. Since the break flow is within the makeup capacity of the charging system, an automatic reactor trip will not occur and if the faults are rapidly detected and diagnosed, controlled shutdown of the reactor would be performed utilizing the appropriate non-emergency procedures. For this analysis, the following assumptions are made:

1. Makeup and letdown flow rates are constant.
2. Feed water and SG steam flow rates are constant.

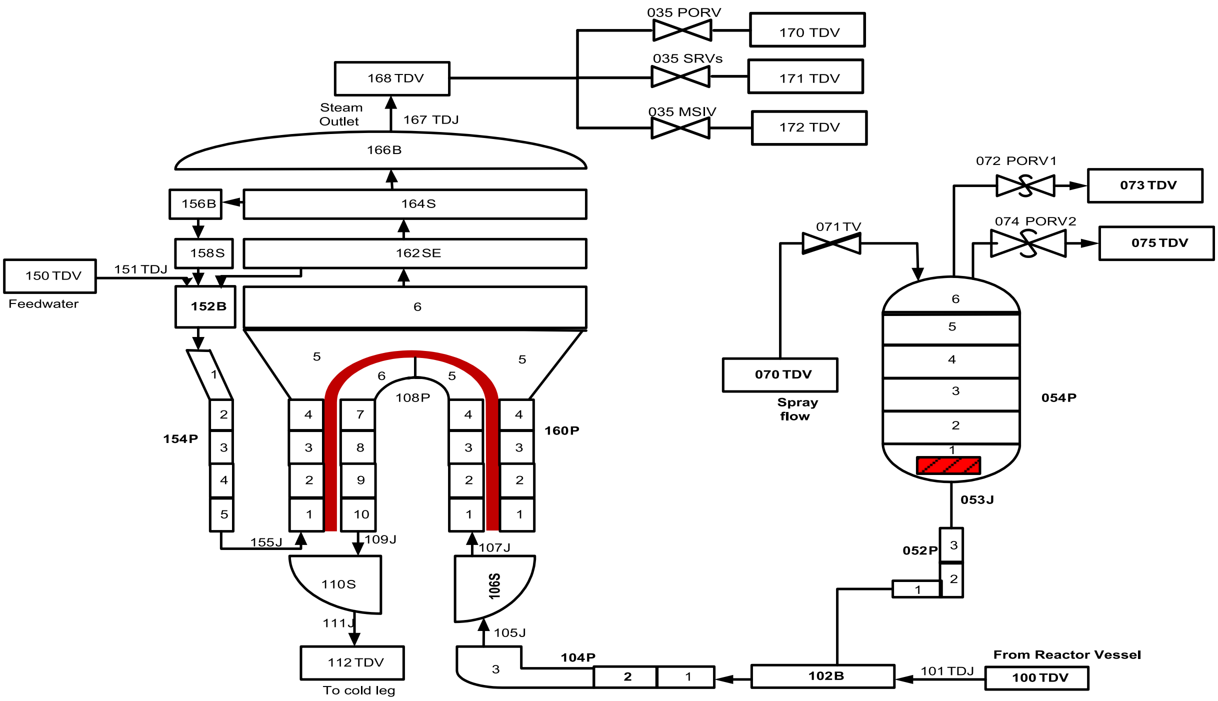


**Fig. 2.** The nodalized RCS sub-unit [5]

Fault 1&2: Incipient tube crack events (TC5mm$^2$ and TC10 mm$^2$) - A 0.20 kg/s fault (0.8 mm axial crack) and 0.4 kg/s (1.6 mm circumferential crack) fault in the steam generator u-tube were separately simulated. These kinds of cracks are difficult to detect and diagnose by the conventional fault diagnostic method and the leaking tube can be categorized as marginal, with the potential of being catastrophic if not detected on time. These cracks were simulated with a 5 mm$^2$ and a 10 mm$^2$ trip (break) valve, linking volume 6 of pipe 108 to volume 5 of pipe 160 in the nodalized sub-unit shown in Fig. 3. The valve trip signal is set to open after 100sec of steady-state operation.

Fault 3: Steam Generator Inlet Plenum Crack (SGIPC) - Similarly, a crack modeled with a break valve area of 5 mm$^2$ is simulated in the Steam Generator Inlet Plenum (SGIPC, Transient 2 in Fig. 3.) The trip signal for this fault is set at 50sec after steady state operation of the simulated RCS sub-units.

Fault 4: Crack in steam generator down-comer side (SGDC): We modeled a crack in the steam generator tube, down-comer side, with a break valve of area 5 mm$^2$, opening exactly 50sec after steady-state operations.

Fault 5: Pressurizer pressure boundary crack (PZRC): The last fault is a crack of area 5 mm$^2$ at the pressurizer, leading to slow depressurization of the RCS. This fault is also modeled using break valve and the trip is set at 200sec after steady calculations. Choking flow is represented by the break valve used in simulating all faults. Figs. 4–6 show parameter deviations for the steady-state and faults conditions.

### 5.2. Simulation result discussion and analysis

First, to reduce the dimensionality of the data set, and to aid the prediction speed of the trained model, we selected a subset of the measured features using the sequential feature selection function, *sequentialfs*, in MATLAB. This result in 9 features from the initial 21 parameters obtained from the simulation. The resulting features from the function are used in the selection of a classification model. Secondly, the features selected were utilized for the evaluation of appropriate classification model. The automatic training to select the best classification model type was performed using the classification learner application in MATLAB machine learning toolbox. This application performs automatic training using the data on classification models such as nearest neighbors, ensemble classifiers, logistic regression, discriminant analysis, support vector machine, and decision trees. The optimum result was obtained with Error Correcting Output Code support vector machine classification model. The next challenge is the selection of the optimum coding matrix.

The MATLAB implementation presents the ECOC learning algorithm with the option of selecting various coding matrix design with different kernel functions. That is, it gives an option of exploring different hypothesis space with the possibility of modifying the learning algorithm. In this paper, we evaluated the coding matrices available in the program, and test their performance on different amount of data set. We carry out this experiment to examine the possibility of increasing the computational speed of the SVM using a few data points. First, the Error Correcting Output Code (ECOC) learning algorithm was utilized to train the SVM model, using training data set composed of 1950 data points (390 observations for each class, 1–5). Each data points are labeled according to their fault name as shown in Figs. 3–5 above. Then, a template for the SVM classifier, *templateSVM* was specified as the learner algorithm. The template uses a default linear kernel function and the matrix is standardized. Furthermore, a *fitcecoc* function that fits a multiclass model using the ECOC learning algorithm is implemented, using *one-vs-one* default predictor first. All the ECOC models were cross-validated using k-fold option, with k = 10. The resulting model is a *ClassificationPartitionedECOC* cross-validated model, trained on 90% of the data. The remaining 10% is used as an in-sample test data, to evaluate the generalization capability of the model.

We repeated the experiment by training six (6) ECOC learners using binary SVM with standardized predictors and different coding matrices. We also estimated the error (loss function) on the test data using different cross-validation method. In this work, the loss

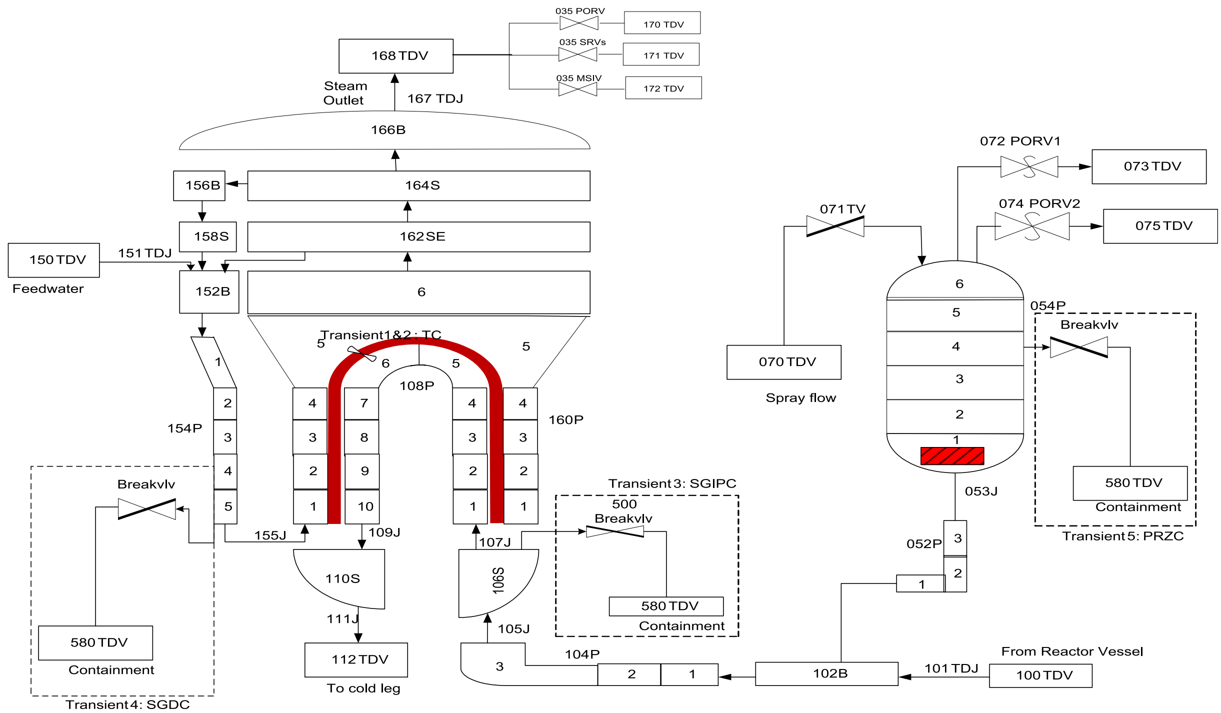


**Fig. 3.** Nodalized diagram of the RCS sub-unit with the faults modeled in RELAP 5.

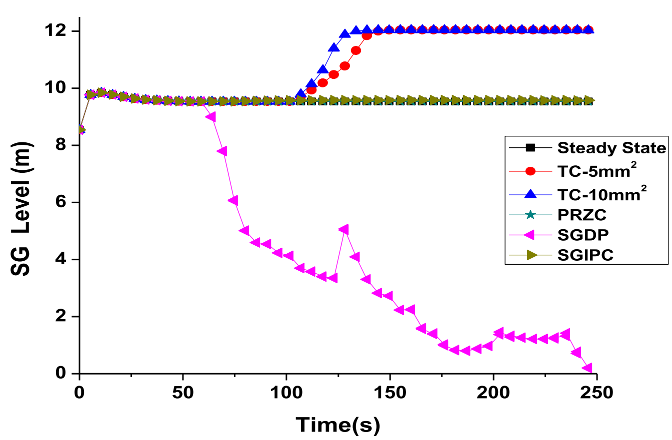


**Fig. 4.** Variation of steam generator level during steady state and for all simulated transients.

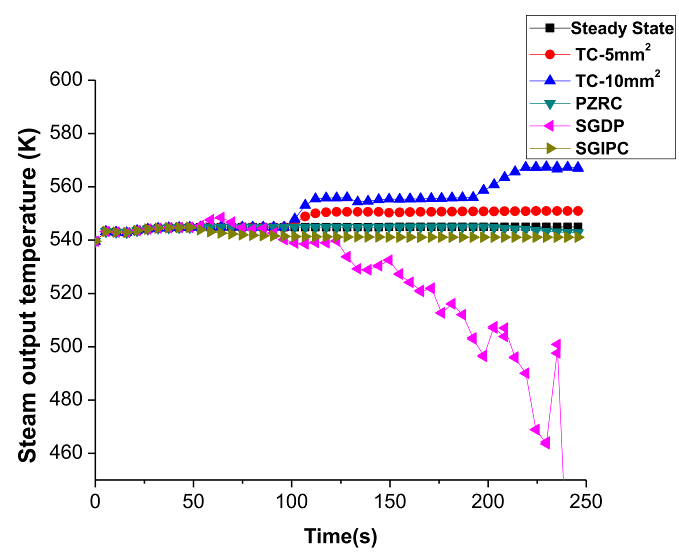


**Fig. 5.** Variations in steam generator outlet temperature during steady state and for all simulated transients.

functions or misclassification errors are the performance indicators of the proposed model. The predictive performance of the ECOC algorithm on the representative data using different cross-validation method and the description of the coding matrices available in MATLAB are as shown in Table 3. In addition, the results of the experiments using different kernel function and cross-validation method are displayed in the table. Hence, as shown in Table 3, the *one-vs-one* coding matrix has the best performance with the least loss.

To confirm that the model does not overfit, and to evaluate the effect of the training data size on the model, we trained another SVM classifier using 10845 training set. Following a similar procedure as described above, we also experimented with two kernel functions, the linear and Gaussian kernels. Moreover, we used a different out-of-sample test set comprising 1078 data points as an independent, test of the model. To examine how well the algorithm generalizes and evaluate the accuracy of the trained model on an independent out-of-sample test data, we called the function *Loss* on the test data, by estimating the test sample classification error, which returns the classification error for the test predictor data and the true class labels. The resulting loss values are compared as shown in Table 4.

In Table 4, it is observed that there is a marginal improvement in the prediction capability of some coding matrix using more training data, while for some others, no significant change. Furthermore, we observed a consistent, superior result for *one-vs-one* coding matrix. However, it is also observed that similar results (zero loss) are obtained from three different coding matrices, *one-vs-one,*

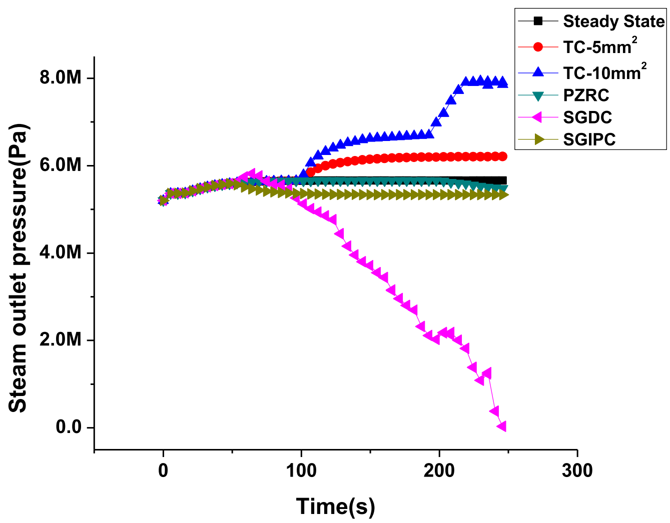


**Fig. 6.** Variations in steam generator output pressure during steady state and for all simulated transients.

*TenaryComplete,* and *SparseRandom.* That is, two other coding matrices also give good results, with zero loss. Hence, to determine the optimum model for our design, we compared the accuracy of the models from the three best-performing coding algorithms. The comparison was implemented by passing a new set of predictor (unlabelled) data and the models into the *compareHoldout* function in MATLAB. The function returns the comparison test decision by displaying three parameters: $h$ ε[0,1], which is the test of the null hypothesis that the trained classification models have equal ($h = 0$) or unequal ($h = 1$) accuracy for predicting the true class labels of the new data at 5% significance level; the mid-*p*-value McNemar test of the hypothesis, *p*, and the misclassification rate, *e*. Table 5 shows the results of the test.

In Table 5, all the three models have the same h-value, the *one-vs-one* model has a slightly lower p-value and *TenaryCcomplete* model has the least misclassification rate. The *p*-value is exactly 1 for both *TenaryComplete* and *SparseRandom* models, indicating strong evidence to not reject the null hypothesis that one model is less accurate than another. Hence, we select the best model based on the misclassification rate result.

Consequently, the ECOC model with the Gaussian kernel and *TenaryComplete* coding matrix is selected as the optimum model design, used to predict faults at each sub–unit of the reactor

**Table 3**
Results of the small data size model experiments with different coding matrices.

| Coding Matrix | Description | In-sample Loss(error) | Out-of-sample Loss |
|---|---|---|---|
| One-vs-one | For each binary learner, one class is positive, another is negative, and the software ignores the rest. | 6.7682e-04 | 6.7682e-04 |
| One-vs-all | For each binary learner, one class is positive and the rest are negative. This design exhausts all combinations of positive class assignments | 0.0267 | 0.0311 |
| Ordinal | For the first binary learner, the first class is negative, and the rest positive. For the second binary learner, the first two classes are negative, the rest positive, and so on. | 0.0403 | 0.0471 |
| DenseRandom | For each binary learner, the software randomly assigns classes into positive or negative classes, with at least one of each type. | 0.0217 | 0.0662 |
| BinaryComplete | This design partitions the classes into all binary combinations and does not ignore any classes. For each binary learner, all class assignments are −1 and 1 with at least one positive and negative class in the assignment. | 0.0196 | 0.0213 |
| TenaryComplete | This design partitions the classes into all ternary combinations. All class assignments are 0,-1, and 1 with at least one positive and one negative class in the assignment. | 0.0020 | 0.0091 |
| SparseRandom | The software randomly assigns classes as positive or negative with probability 0.25 for each coding matrix design, and ignores classes with probability 0.5. | 0.0322 | 0.0135 |

**Table 4**
Results of larger data size experiments with different coding matrices.

| Coding Matrix | Linear Kernel | | Gaussian Kernel | |
|---|---|---|---|---|
| | In-sample Test Loss | Out-of-sample Test Loss | In-sample Test Loss | Out-of-sample Test Loss |
| One-vs-one | 1.6228e-04 | 0.0014 | 0 | 0 |
| One-vs-all | 0.0122 | 0.0128 | 1.6228e-04 | 0 |
| Ordinal | 0.0446 | 0.0442 | 1.6228e-04 | 0 |
| DenseRandom | 0.0125 | 0.0143 | 1.6228e-04 | 0 |
| BinaryComplete | 0.0118 | 0.0128 | 1.6228e-04 | 0 |
| TenaryComplete | 0.0112 | 0.0114 | 0 | 0 |
| SparseRandom | 0.0028 | 0.0028 | 0 | 0 |

**Table 5**
Comparison test of the models from the best performing coding matrices.

| Testing parameters | Models | | |
|---|---|---|---|
| | One-vs-one Model | TenaryComplete Model | SparseRandom Model |
| *h* | 0 | 0 | 0 |
| *p-value* | 0.99973 | 1 | 1 |
| *e* | 0.24373 | 0.10394 | 0.20072 |

coolant system. Different faults were modeled and the implementation diagnosed the fault 100%. In our next research paper, we will demonstrate the integration of the solution in an NPP's operator support system human-machine interface in a safe and non-intrusive manner.

## 6. Conclusion, limitation and future work

This paper presents a distributed fault diagnostic technique using multi-class support vector machine. The system integrates separately-built, separately-trained, specialized SVM modules capable of component-level fault diagnosis into a coherent intelligent system, with each SVM module monitoring sub-units in a nuclear plant components. The implementation of this technique in an NPP has been demonstrated using the RELAP5/Mod4.0 to model an RCS sub-unit of the Chinese CNP300 PWR. A multi-class SVM model is trained with component level parameters that represent the normal and selected faults in the sub-unit. In order to optimize the generalization capability, we also trained the SVM using other coding matrices. The coding matrix experimentation also enabled the selection of a suitable algorithm for this classification task, and to compare the result with other risk minimizing coding technique. The result and main contribution of this paper can be summarized as follows:

1. The design and implementation of a distributed support vector machine technique for incipient fault diagnosis in a nuclear plant coolant system is presented.
2. Each SVM module predicts faults for different locations in the plant, and the distributive nature of the SVM modules take care of the fault location. Consequently, fault localization is addressed by the distributed SVM and fault severity is addressed by the magnitude of parameter deviation from the nominal value.
3. An effective method of selecting marginal faults using Failure Mode and Effect Analysis (FMEA) report and modeling important incipient faults with RELAP5/Mod4.0 is presented.
4. This work demonstrates the superior performance of Error Correcting Output Code learning algorithm with *TenaryComplete* coding matrix on the representative data from CNP300 NPP.
5. The training and testing error derived from using the distributed SVM modules is an improvement over other data-mining algorithms suggested in the cited journals, and the diagnostic system can be integrated into NPP human-machine interface to support operators in decision making.

We acknowledge that currently, sensor placements in the operating plants may not be suitable for obtaining appropriate parameters for each unit of the diagnostic models. Also, since redundancy in the safety-critical system is a valuable attribute in NPP, further research is required to determine the suitable diagnostics models and techniques to create a hybrid FDI system to fulfill redundancy requirement. In our future publication, we will address these issues, discuss the full implementation of the method in all units of an operating NPP and propose the modalities for its integration into the operator support system Human Machine Interface (HMI).

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