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A Computerized Operator Support System to Monitor the Technical Specification

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1. Introduction

Technical Specification (Tech Spec) defines the limits and conditions for operating nuclear power plants (NPPs) in a manner that is consistent with the evaluations in the final safety analysis report (FSAR) [1]. The purpose of the Tech Spec is to protect the workers and the public by operating the NPPs safely [2]. Monitoring the NPPs operation in compliance with Tech Spec is one of the important tasks for operators.

However, there are a lot of difficulties associated with using the Tech Spec. First, Tech Spec was comprised of the bulk of materials [3]. Second, the contents of Tech Spec are complicated [4]. Third, Tech Spec is open to interpretation [5]. Fourth, Tech Spec is time-dependent. Fifth, monitoring the Tech Spec causes high workloads on operators [4].

In this light, this study suggests a Technical Specification Monitoring System (TSMS), which is a computerized operator support system for monitoring the Tech Spec. The development of the TSMS consists of analysis, design, and implementation stages. The analysis identifies the functional requirements for the TSMS based on the existing Tech Spec. The design stage designs the functions of TSMS and suggests appropriate artificial intelligence (AI) algorithms for these functions. Last, this study develops a TSMS prototype. It was applied to a Westinghouse 930 MWe, three-loop pressurized water reactor (PWR).

2. Identification of Functional Requirements

This study identifies functional requirements by analyzing structure and surveillance requirements (SRs) of Tech Spec. As a result, nine high-level functional requirements are identified.

2.1 Analysis of Tech Spec

Figure 1 shows an example of the standard Tech Spec for Westinghouse plants [3]. It consists of four entities: 1) Limiting condition for operation (LCO), 2) Applicability, 3) Action, and 4) SRs. The LCO is the minimum level of performance or the working capacity of components and systems based on the safety analysis. The applicability means the operation mode to which a LCO applies. The action means actions required to enter the safe status within a limited time. The SRs mean periodic monitoring requirements to verify whether the LCO is violated or not.

3.4 REACTOR COOLANT SYSTEM (RCS)

3.4.2 RCS Minimum Temperature for Criticality

LCO 3.4.2 Each RCS loop average temperature (T_{avg}) shall be ≥ [541]°F.

APPLICABILITY: MODE 1,
MODE 2 with k_{eff} ≥ 1.0.

ACTIONS

CONDITION	REQUIRED ACTION	COMPLETION TIME
A. T_{avg} in one or more RCS loops not within limit.	A.1 Be in MODE 2 with K_{eff} < 1.0.	30 minutes

SURVEILLANCE REQUIREMENTS

SURVEILLANCE	FREQUENCY
SR 3.4.2.1 Verify RCS T_{avg} in each loop ≥ [541]°F.	[12 hours OR In accordance with the Surveillance Frequency Control Program]

Fig. 1. The standard technical specification for Westinghouse plant

This study identified types of monitoring that the TSMS needs to implement for the SRs. Four different types of data were identified: parameter, calculated parameter, graph, and system (component) status. The monitoring type “parameter” can be monitored directly from the plant system, for instance, reactor coolant system (RCS) temperature and pressure. For calculated parameters, operators need to calculate a parameter of plant, e.g., shutdown margin (SDM), and monitor this value. As for the graph, operators monitor whether the plant condition is located in the desired region of a graph like the Pressure-Temperature (P-T) curve. The next monitoring is related to system or component status. The Tech Spec requires to verify the status of system or component, check the channel of instruments, test operability, test setpoint, and verify personal performance (e.g., visual inspection of system or manual sampling).

2.2 Functional Requirements of TSMS

As a result of the analysis on the Tech Spec, the functional requirements for the TSMS can be summarized as follows:

- It should monitor LCO continuously.
- It should identify plant operation modes.
- It should monitor SRs.
- It should monitor parameters, e.g., pressure, temperature, and level for the determination of LCO violation.
- It should provide a function of calculation required in the Tech Spec, e.g., SDM.
- It should identify current operating region in graphs given in the Tech Spec, e.g., P-T curve.

- It should monitor status of systems and components.
- It should provide a signal when the LCO is violated.
- It should monitor whether the follow-up action is completed correctly within the required time.

3. Design of TSMS

Design stage consists of the system design and function design. In the system design, the architecture of TSMS is suggested, including required functions. In the function design, appropriate AI techniques are suggested for each function.

3.1 System Design

The TSMS consists of LCO violation monitoring function and action completion monitoring function, as shown in Figure 2. Particularly, the LCO violation monitoring function includes five sub-functions.

The operation mode monitoring function determines in which operation mode the current NPP status is located. This function generates an operation mode as the output. The output is transferred to the parameter monitoring, calculated parameter monitoring, graph monitoring, and system status monitoring.

The parameter monitoring function monitors parameters for the determination of LCO violation. This function receives plant parameters and operation mode as inputs. This function produces a violated LCO signal, violated LCO, and follow-up action, if any is violated. The output is provided to the action completion monitoring function and operators.

The calculated parameter monitoring function calculates a parameter of plant and monitors whether this value is within the desired range for the determination of LCO violation. The input and output value are same as for the parameter monitoring function.

The graph monitoring function monitors whether the plant condition is located in the desired region for the determination of LCO violation.

The system status monitoring function verifies the status of system or component, check the channel of instruments, test operability, test setpoint and verify personal performance. This function receives plant parameters, operation mode, and personal performance as inputs. The output of this function is transferred to the action completion monitoring function and operators.

The action completion monitoring function monitors whether the follow-up action is completed correctly within the required time. This function receives violated LCO signal, violated LCO, and follow-up actions from the parameter monitoring, calculated parameter monitoring, graph monitoring, and system status monitoring. As the output, it provides a signal for action success or failure. The output of this function is provided for the operators.

3.2 Function Design

Appropriate AI techniques are suggested for implementing the functions defined in the architecture of TSMS. Rule-based system is selected for monitoring operation mode, parameter, calculated parameter, system status, and action completion monitoring function because the decision criteria (i.e., IF) and subsequent action (i.e., THEN) in the Tech Spec can be clearly defined.

Support vector machine (SVM) is selected for monitoring graph. It is difficult to formulate rules from graphs in the Tech Spec. However, SVM has a

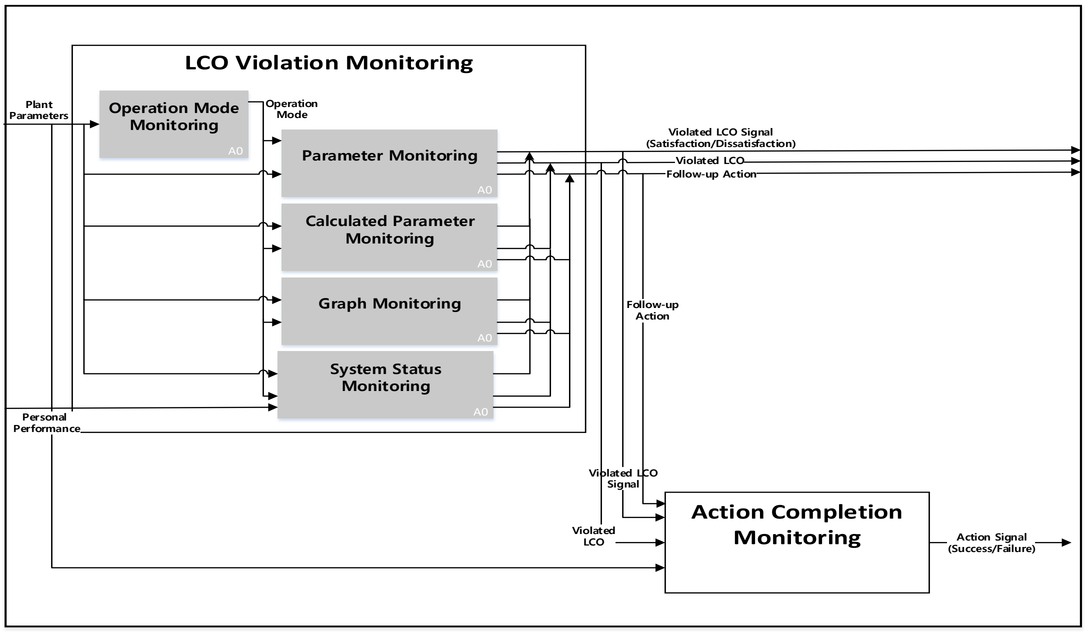

Fig. 2. The architecture of TSMS

capability of generating rules from the data itself by learning. In addition, SVM is applicable to non-linear problems and can be trained without large amounts of data, which is relevant for the graph monitoring function.

3.2.1 Rule-based System

Rule-based system generally has five components: the knowledge base, the database, the inference engine, the explanation facilities, and the user interface. The knowledge base is represented as a set of rules. Each rule has the IF (condition)-THEN (action) structure. The database includes a set of facts used to match against the IF (condition) parts of rules stored in the knowledge base. The inference engine carries out the reasoning whereby the expert system reaches a solution. The explanation facilities enable the user to ask the expert system how a particular conclusion is reached and why a specific fact is needed. The user interface is the means of communication between a user seeking a solution to the problem and an expert system [6].

The major advantage of the rule-based system is comprehensibility. When the condition and action are clear, it is easy to express if-then rules. On the other hand, disadvantages are an ineffective search strategy and inability to learn. In addition, a rule-based system with large set of rules can be slow in the run. Due to the inability to learn, it cannot modify its knowledge base, or adjust existing rules by itself [6].

Rule-based system of TSMS is organized as shown in Fig. 3. The knowledge base contains rules created from the Tech Spec. The plant data are obtained from the plant in real time. Then, the inference engine finds relevant rules based on the plant data and generates the result from the rule.

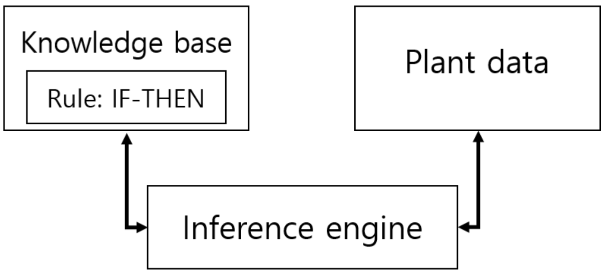

Fig. 3. The rule-based system structure

3.2.2 Support Vector Machine

SVM is one of the highest prominent and convenient techniques for solving problems related to the classification of data [7]. Each element of SVM is described as shown in Fig. 4. Support vectors are the data points that lie closest to the decision surface [8]. It executes the classification of data vectors by a hyperplane in immense dimensional space [9]. The maximal margin is used to find the hyperplane [10].

The major advantage of the support vector machine (SVM) is its overfitting resistance. It has similar performance to neural networks (NNs) but is stronger in overfitting problems than NNs.

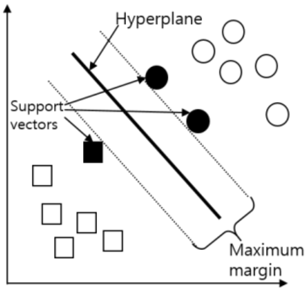

Fig. 4. The support vectors, hyperplane, and maximum margin

The implementation process of graph monitoring function with SVM is shown in Fig. 5. In Step 1, the datasets are prepared by extracting the feature of the graph to be monitored. These data are divided into training set and test set. In Step 2, an SVM model for training is developed and trained. The classification model uses a kernelized SVM that can categorize non-linear data. The best model is determined through navigation. In Step 3, by applying the test set to the trained SVM model, it is verified that the region of the graph classified through the SVM is correctly generalized.

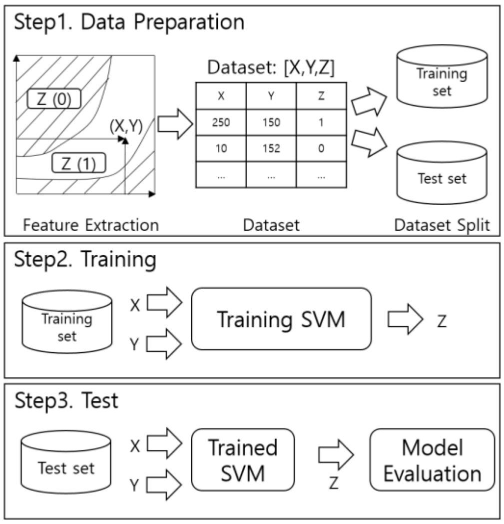

Fig. 5. The implementation process of SVM

4. Implementation

A prototype of TSMS has been developed in this study. A compact nuclear simulator (CNS) developed by the Korea Atomic Energy Research Institute (KAERI) was used as a testbed [11]. The reference plant of the CNS is Westinghouse 930Mwe 3-loop pressurized water reactors (PWRs). As the programming language, python was used.

Fig. 6 shows the architecture of the TSMS prototype. Plant parameters and personal performance (e.g., visual

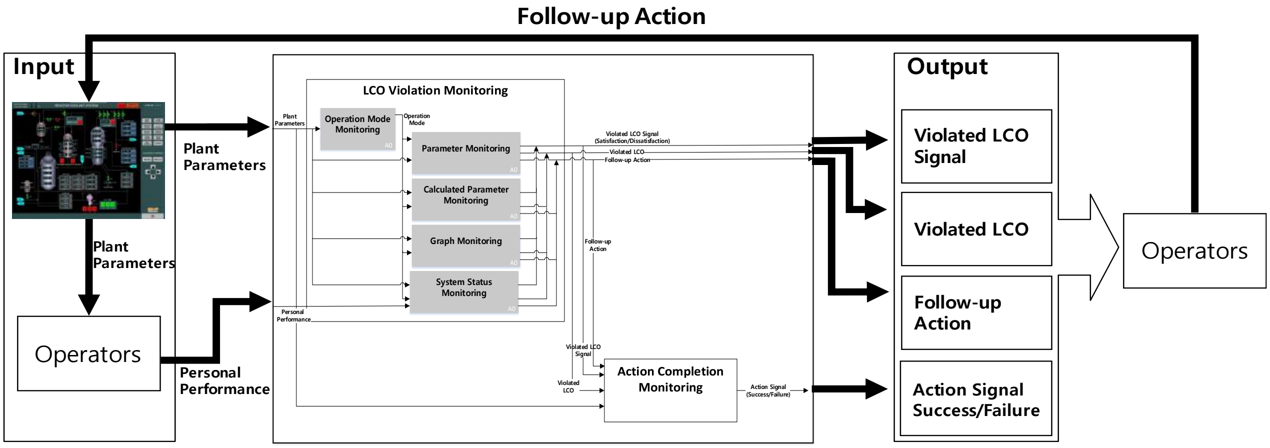

Fig. 6. The architecture of TSMS prototype

inspection by operators) are transferred to the TSMS as inputs. As outputs, TSMS generates violation signal, violated LCO, follow-up action, and action success/failure signal. When a violation signal occurs, operators should perform follow-up action to enter the NPP to the safe state.

As discussed in the previous section, rule-based systems are applied to parameter monitoring, calculated parameter monitoring, system status monitoring, and action completion monitoring. Especially, the calculated parameter monitoring has an additional sub-function which is the calculation function. Fig. 7 shows an example of the calculation process for the SDM.

As an example, the prototype implemented a P-T curve monitoring. Four hundreds of datasets were collected from the CNS, i.e., 300 for training and 100 for the test. As a result of test, it was confirmed that the region of P-T curve can be classified with 99% accuracy.

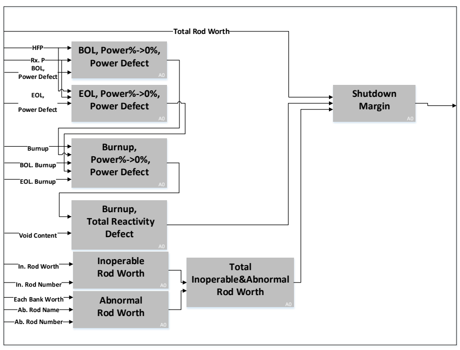

Fig. 7. The calculation process of SDM

5. Conclusions

This study presented a process for developing a TSMS and its prototype. Tech Spec in NPPs was analyzed and functional requirements for the TSMS was drawn. Then, a system architecture was suggested, including monitoring functions with appropriate AI techniques for implementation. Lastly, a prototype was developed by implementing the design into a CNS.

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