Development of CEDM Digital Twin to Support Operator Actions

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1. Introduction

The availability of a huge amount of data combined with the difficulties of understanding the physics behind some phenomena increased the interest in using data-driven modeling to improve the safety, availability, and reliability of nuclear-related systems.

With the wave of digitalization and big data analysis, Digital Twinning of critical systems and components in the Nuclear Power Plant (NPP) can improve its performance and provide a significant role in the system's life cycle; planning, design, and, operation stages. Digital Twinning can be utilized to provide informed decision making, anomaly detection, prognostics, and health management to optimize the maintenance and operation process in the NPP [1].

This work focuses on the application of Digital Twin in modeling the control element drive mechanism system using a data-driven approach for anomaly detection and supporting the operator in decision making in order not to violate limiting conditions for operations (LCO).

2. Control Element Drive Mechanism (CEDM)

Control Element Drive Mechanism (CEDM) is one of the most important components of the pressurized water reactor. Control rods with its driving mechanisms are required for safe and reliable operation of a NPP. The control rods are used for core reactivity control. Reactivity control in APR 1400 relies on the CEDM during startup and shutdown modes, and normal operation for power transitions. The magnetic jack CEDM of APR1400 is of type controlled linear motion to a CEA through an Extension Shaft Assembly (ESA) in response to operating signals received from the Digital Rod Control System (DRCS) for reactivity insertion [1].

A magnetic jack type mechanism is an electro-mechanical device working by applying electrical flux to the magnetic parts located inside the pressure boundary causing latching (stationary position) or moving the control element assembly (CEA) by insertion or withdrawal. So, maintaining the CEDM working properly and avoiding any failures that may occur is critical as it directly affects reactor operation which makes the control rod drive system is subjected to the maintenance rule and must undergo a periodic evaluation and testing of its performance [2].

In abnormal situations or failures of CEDM, the operator has to make a decision depending on his awareness of that situation and the time limitation under that critical situation. Also, he must follow and manage information from procedures and operation limits. Due to time limitation or misunderstanding of procedures, information management may be confusing for the operator under these situations.

So, an advisory system that can quickly process the input signal and provide the operator or the maintenance engineer with the recommended action according to LCO or procedures will support the operator in decision making. To improve and achieve good performance of operators, a Digital Twin with a recommender system can be used to provide fast recommendations in abnormal situations.

3. Concept of Digital Twin technology

There is no unique definition of the Digital Twin till now. The Digital Twin concept was first introduced in the aerospace field by NASA as "*A Digital Twin is an integrated multi-physics, multi-scale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin*" [3].

Generally, Digital twin could be defined as a digital representation of the physical system or product to reflect the current state of it and enable real-time optimization, predictive maintenance, or informed decision making according to sensed data.

The Digital Twin concept, as shown in Figure 1, starts with data collection from field sensors, actuators, or other devices that can be transmitted. The communication step ensures the bi-directional connection between physical and digital objects and real-time transmission between them.

Data preprocessing and storage is carried out in the aggregation stage to be processed and analyzed in the next step of the analysis. This analysis step makes a data-driven model to analyze the sensed data and generate insights used for decision making. The insights from the previous step can be visualized to provide the required decision to be fed back to the physical system. The output can be connected to a display unit that can serve as an interface between humans and the machine.

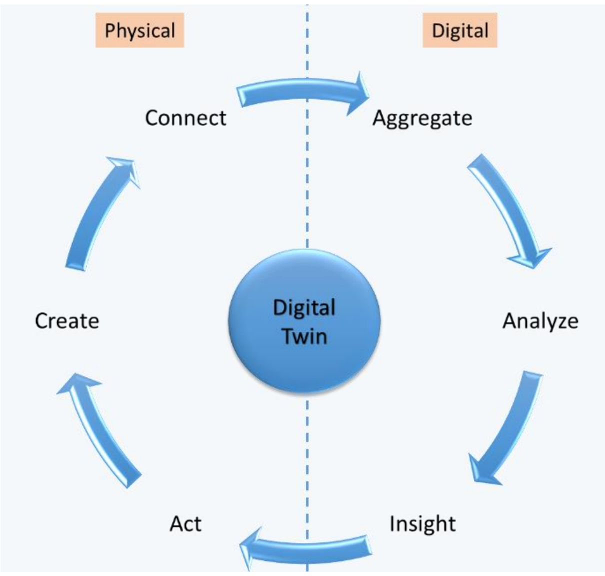

Figure 1. General Digital Twin flow

4. CEDM Digital Twinning

Utilization of Artificial Intelligence and Machine Learning play key roles in the field of Digital Twin [4]. Detecting CEDM misalignment is implemented using different Machine learning techniques to provide a decision to the operator.

The LCO covers the possibilities of CEDM misalignment and the recommended action for each case. By including the technical specifications in the database of the Digital Twin, it can extract the action required according to the sensed data. The LCO describes the three possible situations of CEDM [5]:

1. All CEAs shall be operable and be aligned to within 16.8 cm (6.6 in) of their groups (normal operation).
2. One or more CEAs are misaligned from their group within a band between 16.8cm and less than 48.3cm. or, one CEA is misaligned from its group by more than 48.3cm.
3. Two or more CEAs are misaligned by more than 48.3 cm.

State 2 requires action to reduce the thermal power in one hour and restore CEAs alignment in 2 hours. State 3 requires action to put the plant in mode 3 within 6 hours.

According to the CEDM status in the technical specifications, the problem became a multi-label classification. Machine Learning Classification algorithms using Python programing language were implemented to detect the status of CEA misalignment. Three classification algorithms are used:

1. Support Vector Machine (SVM) classifier.
2. Decision Tree (DT) classifier.
3. K-Nearest Neighbors (K-NN) classifier.

A Support Vector Machine classifier is a kind of supervised machine learning algorithms. From labeled training data, This algorithm forms dividing hyperplanes that classify the new data points. It defines a line (hyperplane) in multidimensional space that classifies outs classes.

A Decision Tree classifier is a straightforward representation for classification techniques, it is a supervised machine learning algorithm that constantly splits the data according to a specific parameter. It acts like a tree having nodes, branches, and leaf nodes.

Nodes represent the criteria of data selection or division, the branches correspond to the output from the node and connect to the leaf node, the leaf node is the terminal that represents the final class. The decision tree is built by a binary recursive partitioning process. This is an iterative process to split the data into different divisions And then divide it over on each of the branches.

K-Nearest Neighbors is a simple algorithm that can be used for classification or regression. It stores all data and classifies the new input value according to a class that is common among its K-NN measured by the distance between this point to its nearest neighboring points. For example K=1, so the point is simply assigned to the class of its nearest point.

5. Results

By applying the previously mentioned algorithms for classifying the status CEDMs, its normal, misaligned in state 2 or state 3, the three algorithms classified the data but with different prediction accuracies. The confusion matrix of each algorithm represents the number of correct predicted data and incorrect class predictions.

Figure 2 represents the K-NN classifier. There is just two data point in the testing dataset that is miss classified and all the remaining is correctly classified.

Figure 3 represents the decision tree algorithm. This algorithm misclassified five data points.

Figure 4 represents the support vector machine algorithm. This algorithm misclassified 13 data points.

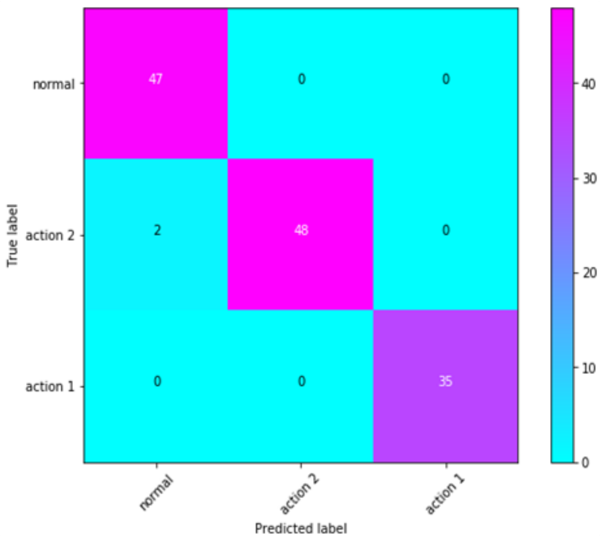

Figure 2. K-NN confusion matrix

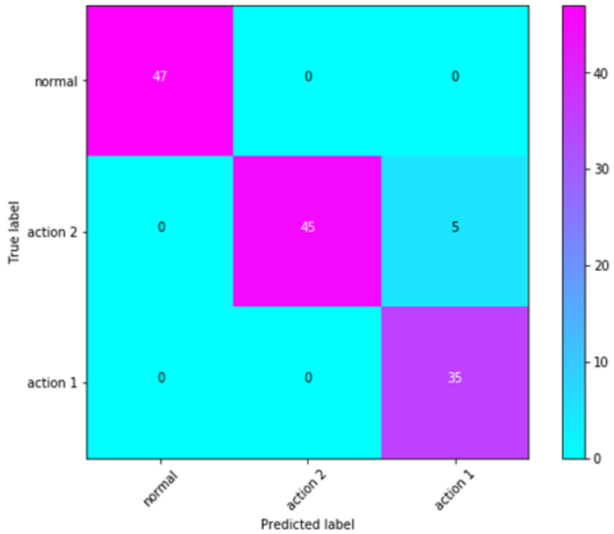

Figure 3. Decision Tree confusion matrix

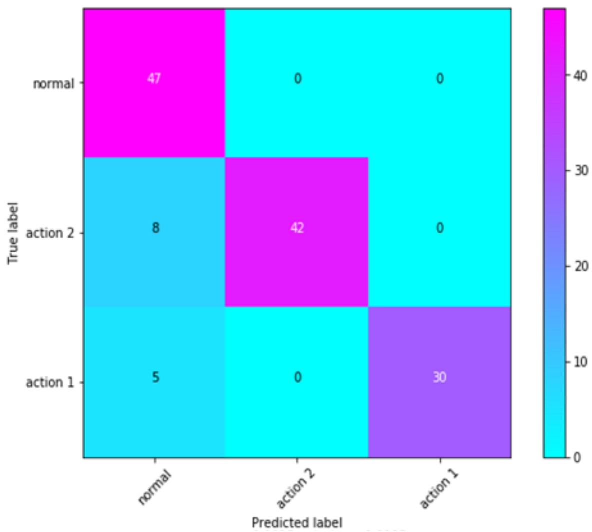

Figure 4. SVM confusion matrix

Finally, the K-Nearest Neighbors algorithm gives the best performance in classifying the CEDM positions to detect the misalignment problem in terms of predicted accuracy as shown in Table 1.

Table 1 Classification algorithms accuracy

No.	Algorithm Name	Accuracy
1	K-Nearest Neighbors	98.48 %
2	Decision Tree	96.21 %
3	Support Vector Machine	90.15 %

5. Conclusions

Research in the field of Digital Twin is still in progress. There are many definitions for Digital Twin, each definition according to the field of application.

A CEDM Digital Twin application is introduced in this work. Modeling and analysis of sensed CEDM positions are performed as apart of CEDM Digital Twin. The supervised machine learning algorithms presented in this study predicted the status of CEDM alignment with high accuracy, which is then will be used to support the operator in a nuclear power plant in the decision-making process.

The K-Nearest Neighbors algorithm gave the best performance with the highest accuracy compared with the other two algorithms.

Acknowledgments

This research was supported by the 2020 Research Fund of the KEPCO International Nuclear Graduate School (KINGS), the Republic of Korea.

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