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# A Systems Engineering Approach for CEDM Digital Twin to Support Operator Actions

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**Abstract** : Improving operator performance in complex and time-critical situations is critical to maintain plant safety and operability. These situations require quick detection, diagnosis, and mitigation actions to recover from the root cause of failure. One of the key challenges for operators in nuclear power plants is information management and following the control procedures and instructions. Nowadays Digital Twin technology can be used for analyzing and fast detection of failures and transient situations with the recommender system to provide the operator or maintenance engineer with recommended action to be carried out. Systems engineering approach (SE) is used in developing a digital twin for the CEDM system to support operator actions when there is a misalignment in the control element assembly group. Systems engineering is introduced for identifying the requirements, operational concept, and associated verification and validation steps required in the development process. The system developed by using a machine learning algorithm with a text mining technique to extract the required actions from limiting conditions for operations (LCO) or procedures that represent certain tasks.

***Key Words*** : Systems Engineering, Digital Twin, Recommender System, Machine Learning

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## 1. Introduction

The control element drive mechanism (CEDM) is a very important safety and reactivity control element in the nuclear power plant. The purposes of the control element assemblies are to provide fast and sufficient negative reactivity to shut down the reactor, Provide reactivity additions to allow reactor start-ups and limited power escalations, and allow control of the reactor's axial flux distribution in response to operational signals received from the digital rod control system (DRCS). So, maintaining the (CEDM) working properly and avoid 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 periodic Evaluation and testing of its performance.[1]

Even after periodic maintenance and assessment of CEDM, according to the United States Nuclear Regulatory Commission (USNRC) event notification reports for 2007 - 2014, there was a history of multiple CEDM failures including control element assembly CEA drop, CEA position deviation (group & bank), CEA slippage, CEA insertion delay, and CEA full insertion failure during scram. One of these events occurred in South Korea in Hanbit unit 1 in May 2019. During the reactor characteristic test, positional deviation occurred between two groups, during position deviation adjustment operation it was found that the control rod cannot be withdrawn. When the maintenance engineer tries to restore the operability by forcing the CEDM to move up and down, this human action led to exceeding the limiting conditions of operation (LCO) of the CEDM so violating the LCO during this event.[2]

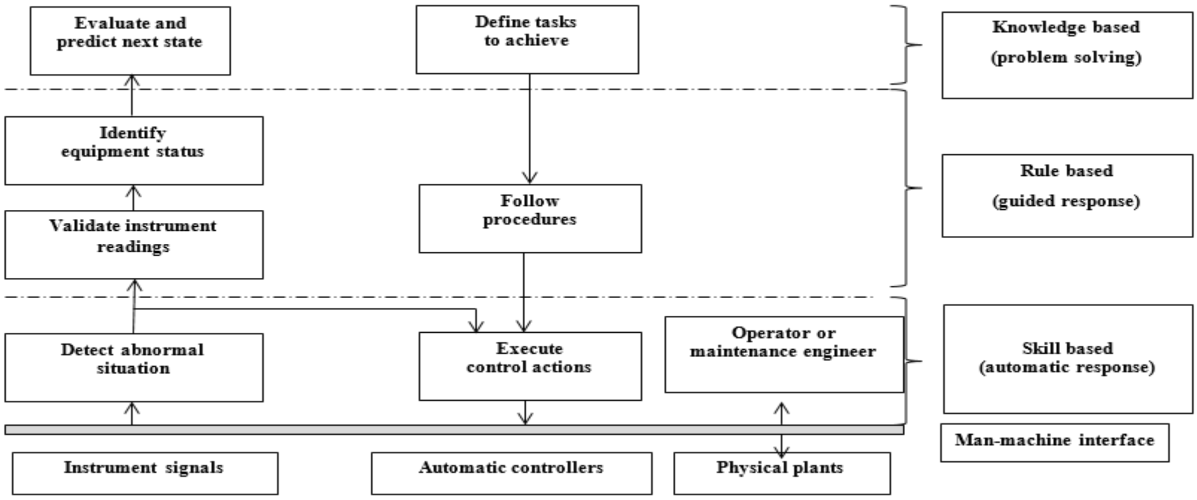
In such abnormal situations or transient, the operator or maintenance engineer must follow and manage information from procedures and operation limits. Due to disturbance or misunderstanding of procedures, information management may be confusing for the operator under these situations. So, the presence of an advisor or recommender system that can process input data and provide appropriate or necessary action to be taken according to the procedures and LCO will be helpful and provide an additional layer of confidence to the operator in decision making.

To develop a recommender or support system, it is important to understand the interaction process of the operator with information and signals in the control room or maintenance engineer in dealing with faults.

The operator control action can be illustrated by the information model shown in Figure 1. The control process is divided into three modes:

1) Skill-based(automatic response)
2) Rule-based (guided response)
3) Knowledge-based (problem-solving)

The operator monitors the instrument signals and the automatic controllers that control the plant and apply safety actions required when exceeding the predefined safety limits. When the operator detects the abnormal situation, automatically will provide necessary control actions to restore the plant to its normal state. This is considered Skill-based control. When the situation is more complex,




[Figure 1] Information model of the control action process

the operator first validates instrument readings then follows procedures to restore the plant to its normal state. This is referred to as Rule-based control. If the situation is not obvious and much more complex, the operator first evaluates the plant state and predicts the next state then defines the appropriate tasks to restore the plant to its normal state (Knowledge-based control).[3]

Improved Digital control systems and refined computer algorithms are currently fit for analysis, diagnosing, and proposing alleviations to even the most perplexing and quick-moving situations. Such systems could help the operator in accomplishing quick and accurate response to failures and plant transients. To implement such a diagnosis or recommend corrective actions, predictive models should be developed based on historical failure data and processing current real-time plant data. An example of this improving technology is Digital twin which is a virtual replica of complex component, which collect component operating information in addition to historical data to monitor, control, and improve its functionality. To improve and achieve good performance of operators, digital twin with a recommender system can be used to provide fast recommendations in abnormal situations.

This paper proposes the operational concept of a digital twin with a recommender system that would provide recommendations according to the LCO.

System engineering approach (SE) is applied here to guide the engineering work of such complex systems and enable the realization of a successful system [4],[5] which is developing a digital twin to CEDM to support operator actions in the control room.

## 2. Requirements Identification

The well-known systems engineering V-model, as seen in Figure 2, represents the primary engineering activities in a logical flow of the balances development activities with their corresponding testing activities.[4]

### 2.1 Developed Mission Requirement

Systems engineering focuses on reducing uncertainty and reducing risk early in project development by defining good requirements. The requirements of this work can be categorized into three groups: mission requirements, originating requirements, and system derived requirements.[4]

The mission requirement represents the general need from a system gotten from stakeholders. The stakeholders considered starting from the designer who designs the nuclear power plant and its instrumentation and control systems, the utility (for example KHNP) that is responsible for the whole plant and would propose new plants including the new system, operation and maintenance teams that have a direct contact with the system, the regulatory body to see if the new system maintain the safety and respect its regulations and the public also as designing such support system may increase the people confidence in nuclear power plants and decrease the nuclear fear that calling for plants shutdown that has an economic impact.

The mission requirement for developing a CEDM digital twin

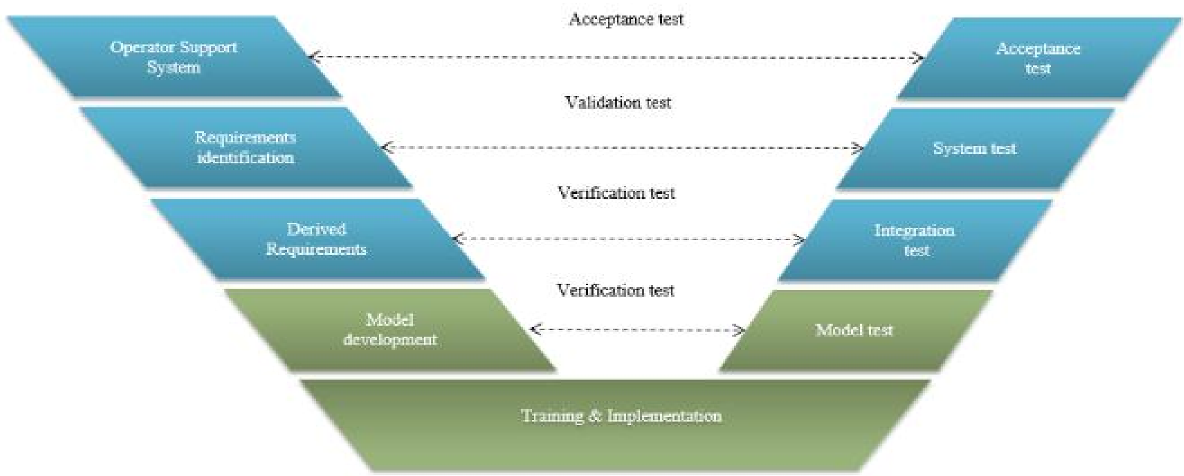
1) Supporting the operator in decision making related to the CEDM system.
2) Reducing operator temporal and mental workload
3) Reducing human error related to CEDM system

### 2.2 Developed Originating Requirements

The originating requirements are developed from stakeholders' needs and mission requirements. This is about the system's capabilities from stakeholders' points of view that define the constraints and performance parameters which the system should meet.

1) The CEDM digital twin should maintain and improve plant operational safety and performance.
2) It should improve operation management by adding more layers of confidence to operators in transient and time-critical situations.

In these situations, fast operator actions are




[Figure 2] Systems Engineering V-Model

quickly diagnosed as the cause of the situation and perform mitigation action that maintains the safety margin without taking conservative actions from the plant protection system (PPS).

### 2.3. Developed Derived Requirements

Derived requirements consist of system and component requirements. Systems requirements are the first level of derived requirements. System and component requirements translate the originating requirements into “engineering language”. Much more detailed than originating requirements that deeply describe system capabilities. The derived requirements are:

1) System should provide a better presentation of plant information and produce reliable information about plant and process status according to data collected from instrumentation and control (I&C) systems.
2) System should have the ability to identify abnormal situations and diagnose and define the root cause of the event.
3) System should predict how the process going to help the operator in mitigation abnormal situations.
4) System should follow the operation procedures and limiting conditions for operation (LCO) in supporting operator decision making.
5) The system should reduce the time taken by operator in detection, diagnosis, prognosis, and decision making as it reduces the time and pressure to bring the appropriate procedure and technical specification and follow the diagnosis steps to reach the correct action.

## 3. Methodology

### 3.1 Digital twin general concept

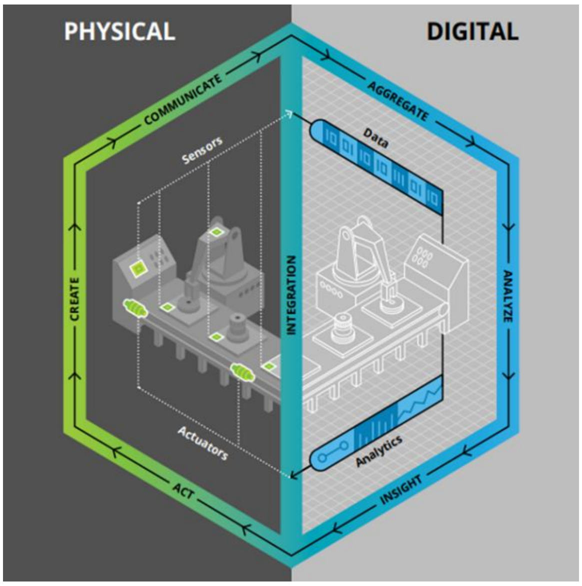
There are many definitions for Digital Twin (DT). According to (NASA) definition [6] “A Digital Twin is an integrated multi-physics, multi-scale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin.”. Also, the definitions of digital twin differ based on the level of integration.[7] In Digital Twin, data and information exchange is bidirectional and fully integrated which means any change in physical object directly changes the digital object and vice versa.

Most Digital Twin applications were for diagnostics and prognostics purposes, but advanced technologies enabled using it for new tracks. Smarslok et al [8] proposed DT to support decision-making in condition-based maintenance. Also, J. Ríos et al [9] used the DT concept to support the design of the Aircraft mock-up. In the manufacturing field, M. Abramovici et al [10] introduced the DT concept in information management for developing and continuous reconstruction of smart products and systems. DT is also used to digitally mirror the behavior and predict the performance of the physical system. DT concept is used to digitally mirroring of the physical object life to predict early alerts of micro-cracks in aero-structures.[11]

Digital Twin technology application in the nuclear field is still in the beginning, A. Oluwasegun et al [12] proposed the application of the Digital Twin concept for prognostics and health management (PHM) of the CEDM. They used coil current data for optimizing system predictive maintenance to improve plant safety and availability.

The general digital twin conceptual architecture is shown in Figure 3 [13] and described as follows:

**Create:** At first, creating a model of the physical object using a modeling tool such as MATLAB, ANSYS, etc., to create the model for the digital twin. The data produced from sensors, actuators, or other devices are collected and can be transmitted. There are two kinds of data that can be obtained from this stage. The first is operational measurements that measure the physical performance of the component or system and environmental measurements that measure the external or environmental factors that affect the system.




[Figure 3] General Digital Twin Architecture

**Communicate:** This communication step ensures the bidirectional connection between physical and the digital objects to ensure that the data generated or obtained are transmitted real-time and changes are made as the data or input changes.

**Aggregation:** This deals with data storage, which deals with the preprocessing of data to be ready for the next step. The large amount of data that would be generated from sensors, data preprocessing should be stored and processed to be used as database for the twin. The better the datasets generated the easier processing in the next stage.

**Analyze:** in this part data from the previous step is analyzed. This step makes a data-driven model to analyze the data to generate insights needed to support decision making. The use of Artificial Intelligence (AI) and Machine Learning (ML) play major roles in the context of a digital twin. ML is a subset of artificial intelligence which is a method of data analysis that automates analytical model building.[14] The use AI and ML algorithms is to understand and extract useful features from the data being analyzed.

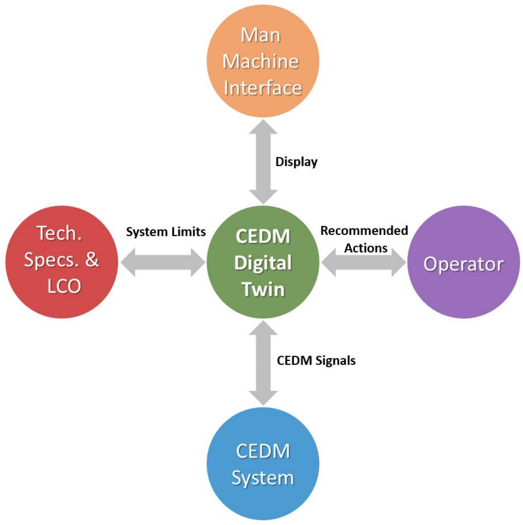
**Insight and Act:** The insights from the previous analysis step can be visualized and utilized to provide required actions that can be fed back to the physical object. The output can be connected to a display unit that can serve as an interface between humans and the machine.

### 3.2 CEDM Digital Twin

From the general concept of Digital Twin, it can be applied to a complex system like the CEDM system in a nuclear power plant. The sensed data such as CEDM step counter data, digital rod position indicator (DRPI) data, temperature, vibration, and coils current can be collected using advanced and smart sensors technology. These sensed data is transmitted to be used in the digital layer of the twin. The sensors data with information regarding the design, technical specifications, and the plant status collected to form the Digital Twin as shown in Figure 4. The CEDM sensors data continuously update the digital layer to reflect CEDM operation conditions, so it will help in the diagnosis of any abnormality and predict the future situation by using historical data.

As the information about CEDM technical specifications and limiting conditions for operation (LCO) is included in the database for the CEDM Digital Twin. This can quickly provide recommendations to support operator action to restore the situation within LCO without violation. The digital twin data analysis -using ML algorithms-will predict the future state and improve operator performance in decision making. The model also can learn from similar systems to increase its accuracy in prognosis to the physical object.

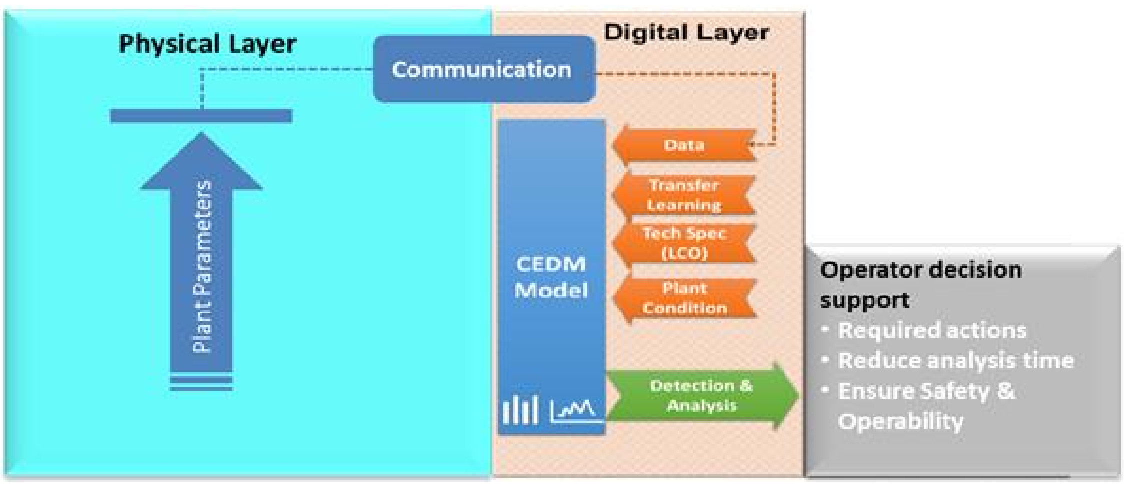
So, the digital twin analysis provides an additional layer of confidence to the operator in transient and time-critical situations related to plant safety, sustainability, and accident mitigation.




[Figure 5] CEDM Digital Twin context diagram

## 4. Misalignment detection

For supporting the operator in decision-making related to the CEDM system, the LCO related to CEDM deviation is analyzed to

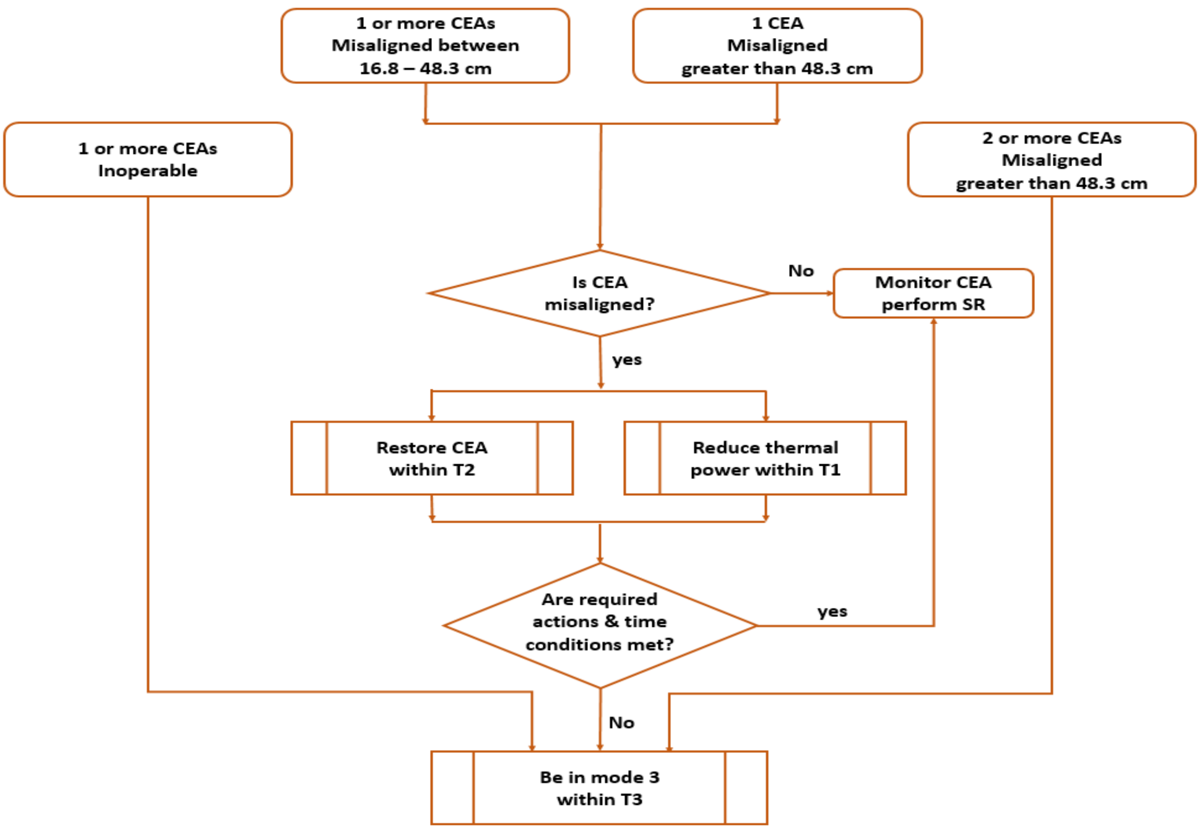



[Figure 4] General CEDM Digital Twin Architecture develop an advisory support system to avoid abnormal events as a part of the CEDM Digital Twin.

Figure 6 shows the logic for the LCO when CEA deviation occurs. It shows four possible states for CEA deviation at the start of the flow diagram. The technical specification describes the limiting conditions for operations of CEA which is All CEAs shall be operable and be aligned to within 16.8 cm of their groups.[15]

There are two major conditions for CEA misalignment, which have other conditions under them. Condition one explains that one or more CEAs are misaligned from its 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. The action required is that the thermal power is reduced within an hour and the restore the CEA alignment within two hours.

Condition two includes three conditions in which any one of them occurred, the required action should be applied. These conditions are that if required actions of condition one are not executed or one or more full−strength CEAs are inoperable or two or more CEAs are misaligned by more than 48.3 cm. if any of these conditions are met, the plant should be put in mode 3 which is the hot standby mode. The required time for this action is 6 hours. The state's description and the required actions are explained in terms of a logic and flow diagram and were modeled for the ML




[Figure 6] LCO logic for CEA deviation

algorithm for developing the recommender system.

Different supervised ML algorithms; support vector machine, K-nearest neighbor and decision tree algorithms were utilized in this study for classifying the misalignment states. The data-driven modeling using ML algorithms is considered as part of the analysis step of developing the DT.

The CEDM positions data were extracted from APR1400 simulator as physical layer in the DT. In order to apply CEDM data on different algorithms, data preprocessing is mandatory. Data should be prepared in such a way that many algorithms can work on it to compare the results. At first, rescaling technique is applied to match the varying scales of the data. Also, encoding technique is used to convert the categorical data labels; that represent the different CEDM misalignment states, into numerical values in the form of binary vectors. Python programming language is used for data preprocessing and ML modeling in this study.

## 5. Verification and Results

Using a ML algorithm for misalignment detection and text mining code for information extraction from the LCO, the system could provide the correct recommendation according to CEDM data.

The extracted CEDM positioning labeled data is used for training and testing the ML model. Data is divided into 75% for training and 25%for testing and validation.

The K-Nearest Neighbors algorithm gives the best performance in classifying the CEDM positions for the misalignment detection in terms of prediction accuracy.

<Table 1> Classification algorithms validation accuracy

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

By comparing the analysis results from ML modeling to the limiting conditions in the LCO, the system is able to provide the operator with the required action. Figure 7 shows the action required for condition one as extracted from the technical specification by using the text extraction python code.

```
ACTION 1:   A.1 Reduce THERMAL
POWER in accordance with

Figure 3.1.4-1.

AND

A.2 Restore CEA Alignment.


1 hour


2 hours
```

[Figure 7] action extracted from LCO

Also, by applying the code to extract the required action from another document in case of violating the limits in procedures, Figure 8 shows the required action to be extracted in the case of Hanbit unit 1.

If the heat output exceeds 5% during the reactor characterization test,

the reactor must be stopped "immediately"

[Figure 8] action extracted from event report

From the results obtained, the system could have the ability to provide the operator with the required action during abnormal situation for example in our case “CEDM misalignment” . The fast analysis of the ML model make it able to detect the abnormality and the system could provide the decision in a very short time. So, the system will help to reduce operator temporal and mental workload and human error related to CEDM system.

## 6. Conclusion

This paper introduced a systems engineering approach for applying Digital Twin technology concept to the CEDM complex system in a nuclear power plant to support operator actions. Systems engineering V-model is used to represent the stepwise development of a new system by addressing the requirements and balances development activities with their corresponding testing activities. General concept of the digital twin is introduced. By applying this concept on the CEDM system, CEDM digital twin with a recommender system is developed to support operator or maintenance engineer actions in case of a transient, time-critical, or abnormal situation. To achieve the reason for this study machine learning algorithm with a text mining technique is applied to extract the appropriate action or recommendation to support operator in decision making.

## Acknowledgement

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