ISBN: 978-3-95450-201-1 doi:10.18429/JACoW-IBIC2018-MOPC18

DEVELOPMENT OF AN EXPERT SYSTEM FOR THE HIGH INTENSITY NEUTRINO BEAM FACILITY AT J-PARC

K. Nakayoshi*, K. Sakashita, Y. Fujii, T. Nakadaira,
High Energy Accelerator Research Organization (KEK), Tsukuba, Japan

Abstract

A high intensity neutrino beam is utilized by a long-baseline neutrino oscillation experiment, T2K at J-PARC. To generate a high intensity neutrino beam, a high intensity proton beam is extracted from a 30GeV Main Ring Synchrotron (MR) to the neutrino primary beamline. In the beamline, one mistaken shot can potentially do serious damage on the beamline equipment. To avoid such a consequence, many beamline equipment interlocks to stop the beam operation are implemented. Once an interlock is activated, prompt and proper error handling is necessary. We are developing a beamline expert system for prompt and efficient understanding of the status to quickly resume the beam operation. The beamline expert system consists of three components such as a data collection component, inference engines and a result presenting component. The data collection component continuously collects the beamline information and the inference engines infer beamline status from the beamline monitor data. Finally the result presenting component presents the inferred results. The inference engines are a key component in the expert system. We are developing a Machine-Learning(ML) based inference engine for our expert system. ML is one of the most active research fields in computing, we adopt the technology from it. We report the progress of development of the expert system, especially the prototype of ML based inference engine.

INTRODUCTION

The T2K (Tokai-to-Kamioka) experiment [1] is a long-baseline neutrino oscillation experiment at J-PARC (Japan Proton Accelerator Research Complex). A high intensity neutrino/anti-neutrino beam is produced and propagates 295 km from J-PARC to Super-Kamiokande. In August 2017, T2K excluded CP-conservation at 95% confidence level using the data until April 2017. In order to keep generating interesting physics, steady operation of the facility is very important.

Figure 1 shows a layout of the neutrino experimental facility (neutrino facility). The neutrino facility is composed of the primary/secondary beamline and a near detector (ND280). In the primary beamline, the high intensity proton beam is extracted from the Main Ring synchrotron (MR) and guided through super/normal conducting magnets to the target station. In the secondary beamline, the proton beam hits a graphite target and produces pions. These pions decay into muons and muon neutrinos in a decay volume. The high intensity proton beam reached 485 kW in 2018. The MR plans to upgrade the beam power up to 1.3MW.

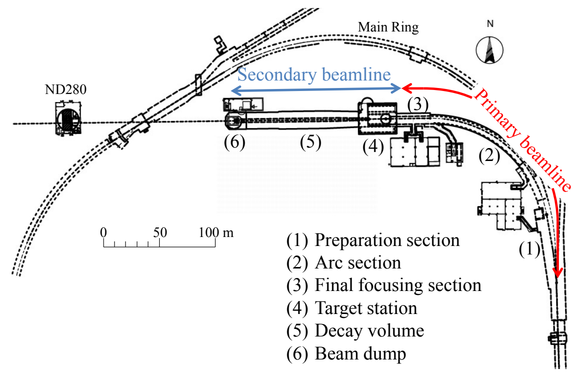

Figure 1: Layout of the T2K experimental facility.

MOTIVATION

We handle a high intensity proton beam at the neutrino facility. In the beamline, one mistaken shot can potentially do serious damage to the beamline equipment. To avoid such a consequence, a lot of beamline equipment interlocks, called MPS (Machine Protection System) to stop the beam operation are implemented. We have more than 800 interlock sources. Multiple sources can cause an interlock at the same time. For example, many BLM (Beam Loss Monitors) sometimes issue an interlock simultaneously. In that case, it is difficult for the beamline operators to understand quickly what happened in the beamline and these can lead to a time loss of the beamline operation.

When an essential beamline equipment fails, it may take a long time to restore the beam operation. For example, a helium compressor in the helium circulation system at the target station was broken in January 2017. We lost about two weeks of the beam time due to this trouble.

To improve these situations, we plan to introduce a beamline expert system to the neutrino facility.

BEAMLINE EXPERT SYSTEM

Figure 2 shows a schematic diagram of the beamline expert system. The beamline expert system consists of three components such as a data collection component, inference engines and a result presenting component. The data collection component continuously collects beamline information and the inference engines infer the beamline status from

* kazuo.nakayoshi@kek.jp

ISBN: 978-3-95450-201-1 doi:10.18429/JACoW-IBIC2018-MOPC18

beamline monitor data. Finally the result presenting component presents the inferred results.

The **inference engine** is a key component of the expert system. Although a typical expert system inference engine is rule-based [2], we adapt machine-learning(ML) based inference engine in our expert system. We studied two types of inference engines:

- a supervised trained engine for classification of MPS events
- an unsupervised trained engine for detection of equipment anomalies

The beamline expert system runs during the beam operation of the neutrino facility. If MPS is activated at the neutrino facility, the expert system infers the MPS reason and presents a recovery procedure. For detection of equipment anomalies, the expert system continuously collects the status of the beamline equipment and informs the abnomality to a beamline operator if it detects a sign of a equipment anomaly.

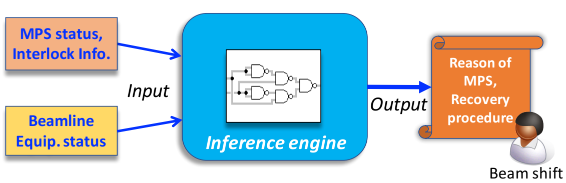

Figure 2: Schematic diagram of the beamline expert system.

MPS CLASSIFICATION BY SUPERVISED TRAINING

Actual Examples of MPS Events

Here we introduce some actual examples of MPS events. A failure of the fast extraction magnets of the MR, such as the septum magnets (FX septum) and/or kicker magnets (FX kicker), cause simultaneous BLM interlocks at the primary beamline. And it has some possibility of doing serious damage to the beamline. It is also difficult to quickly understand the source of the MPS just looking at these BLM interlock patterns. We carried out the initial evaluation of the ML-based inference engine considering the following cases:

- A case where the simultaneous BLM interlocks occur at the primary beamline. This is caused by either a failure of the FX septum or FX kicker magnets.
- A case where there is an MPS from a source other than a BLM, such as the normal-conducting magnets, etc.

Our initial evaluation is to classify the MPS events into three labels, which are (0) FX septum, (1) FX kicker or (2) others, using the ML-based inference engine.

Model and Supervised Training

We evaluated the following procedure:

1. We built a model using **TensorFlow™** [3], which is a famous open-source library for ML developed by Google.
2. Training was performed using training data which simulates the real MPS events. The model parameters were optimized by a supervised training.
3. Finally we used the trained model as an expert system inference engine, as well as to evaluate it using actual MPS events.

We used a 2-layer neural network model for the evaluation [4]. Figure 3 shows a schematic diagram of the 2-layer model. The MPS bit stream is put into the input layer. The output layer is 3 nodes and it is taken to represent the classification of FX septum, FX kicker or other.

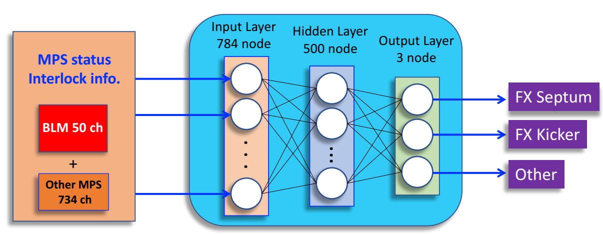

Figure 3: 2-layer neural network model.

Performance Evaluation by Actual MPS Events

We evaluated the performance of MPS classification of the inference engine by actual MPS events during about six months beam operation. Table 1 shows the results of MPS classification. The inference engine predicted two FX kicker events although there were no FX kicker misfire MPS events during this period The accuracy was 98.3%. We investigated two mis-predicted MPS events in Table 1. One of them was an event where a beam instability in the MR occurred and a lot of BLM in the primary beamline were activated. On the other hand, it was found that another event was similar to the FX kicker misfire event by analyzing the beam monitor data. The horizontal position of the extracted beam in the primary beamline was shifted by about +0.2mm and the extracted horizontal angle was quite large. Figure 4 shows the horizontal orbit for that spill shown in red line, as well as two normal spills shown in blue and black. This result suggests that even if a prediction fails, the expert system can suggest to investigate the beam condition carefully to the beam operator in order to reduce the risk of potential for unknown failure condition.

ISBN: 978-3-95450-201-1 doi:10.18429/JACoW-IBIC2018-MOPC18

Table 1: Results of the Actual MPS Classification (Oct. 2017 - Dec. 2017, Mar. 2018 - May 2018)

	True	**Prediction**
FX septum	0	0
FX kicker	0	**2**
Other	120	118

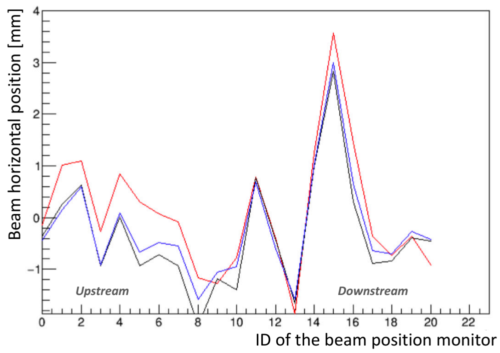

Figure 4: The graph shows horizontal beam orbit which extracted in the primary beamline. The red line shows the horizontal beam orbit corresponding to the mis-prediction MPS event. The blue and black lines show normal events.

ANOMALY DETECTION BY UNSUPERVISED LEARNING

We also investigated a method of anomaly detection for the beamline equipment using ML. Figure 5 shows a schematic diagram of the anomaly detection scheme in the bemline expert system. An inference engine, which is different from the MPS classification one, infers anomaly of the beamline equipment.

Autoencoder and PCA

We found that Autoencoder (AE), a model of NN, can predict the anomaly. The essential part of the AE is a dimension reduction [5]. The anomaly can be detected by comparing the input data with the predicted data which is calculated from a restoration from the dimension reduced data. We also studied PCA (Principal Component Analysis). The PCA can be used as a tool of the dimension reduction. The PCA is also mathematically equivalent to AE with some restrictions. For our initial study, we used the PCA in our inference engine.

First, a matrix for the dimension reduction (F) is calculated by PCA. PCA can calculate the matrix by an eigenvalue decomposition of the covariance matrix of the input data during the normal condition of the beamline equipment. A matrix for the restoration (G) is also calculated as the transposed matrix of F. Second, the predicted data $\hat{\boldsymbol{y}}$ is calculated from the input data $\boldsymbol{y}$ and those matrices, $\hat{\boldsymbol{y}} = GF\boldsymbol{y}$. Finally, a *Loss* defined by $\|\boldsymbol{y} - \hat{\boldsymbol{y}}\|^2$ is calculated as a metric for the anomaly detection since it could be large value if the predicted data is not consistent with the input data.

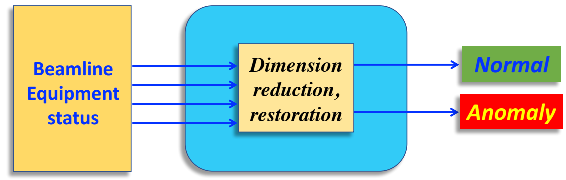

Figure 5: Anomaly detection by beamline expert system.

Initial Evaluation Using Three-Dimensional Normal Distribution

We performed an evaluation of the inference engine using PCA for the anomaly detection. One hundred sets of a three-dimensional normal distribution data $\{\boldsymbol{x}_1, \boldsymbol{x}_2, ..., \boldsymbol{x}_{100}\}$ (dataset-A) and another ten set of three-dimensional normal distribution data $\{\boldsymbol{y}_1, \boldsymbol{y}_2, ..., \boldsymbol{y}_{10}\}$(dataset-B) are generated as shown in Fig. 6. Dataset-A and dataset-B emulates the data in normal and anomaly condition, respectively. We calculated the *Loss* for those data. Figure 7 shows the distribution of the *Loss*. The *Loss* of the dataset-B is larger than one of the dataset-A and therefore it is possible to detect the anomaly condition from the *Loss* values.

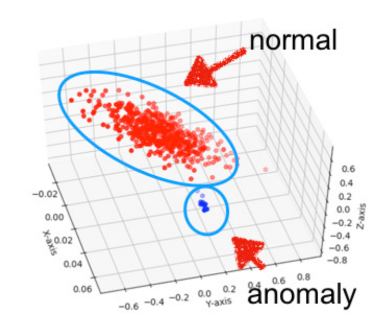

Figure 6: Three-dimensional normal distribution emulating a normal condition and emulating an anomaly data.

Actual Monitor Data of the Beamline Equipment

We also studied to use the PCA based inference engine to the actual beamline data. Our challenge is to detect a sign of the failure of the helium compressor happened in January 2017. Figure 8 shows a schematic view of the helium circulation system for the helium vessel. We utilized seventeen relevant monitor data, such as the supply pressure and temperature of helium gas. Figure 9 shows the distribution of each monitor data during a certain one hour when the helium compressor system was normally running. It looks that the distribution of those data are almost similar to the normal distribution. On the other hand, some of the variances was changing over the time, as shown in Fig. 10. Therefore, it is necessary to predict the present covariance

ISBN: 978-3-95450-201-1 doi:10.18429/JACoW-IBIC2018-MOPC18

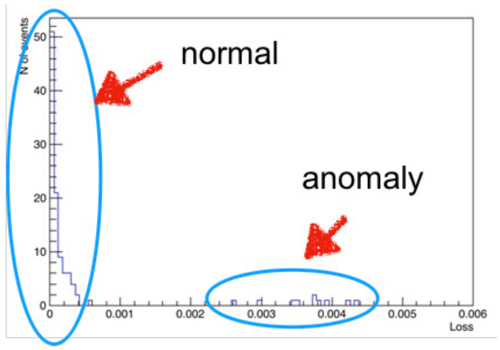

Figure 7: The distribution of the reconstruction error (*Loss*). By calculating the value of *Loss*, we know if the anomaly occurs in the equipment.

matrix from the past data in order to utilize the PCA based inference engine because the PCA assumes that the input data follow a normal distribution which is constant over the time.

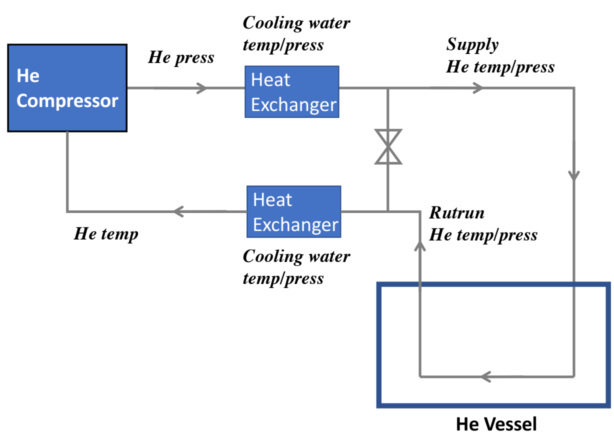

Figure 8: Schematic diagram of the helium circulation system for the helium vessel.

SUMMARY AND FUTURE PROSPECT

We are developing ML-based beamline expert system for efficient beamline operation. We developed a prototype inference engine for the classification of MPS events and performed initial evaluation using actual MPS events during six months beam operation. The accuracy of the inference engine was 98.3%. There were two mis-prediction during the evaluation period. We investigated two mis-prediction MPS events and found that one of MPS events was similar to FX kicker misfire event by analyzing the beam monitor data. The results indicate that the inference engine in the supervised training is promising. We also studied anomaly detection of the beamline equipment using the unsupervised training. We confirmed the performance for anomaly detection by PCA using three-dimensional normal distribution data. However, the variance of helium compressor data varied with time. As a solution to this, we will develop another engine which infers the present variance of data using the past variance. We show possibility of efficient beamline operation using ML-based expert system in this study.

REFERENCES

[1] K. Abe, *et al.*, "The T2K experiment", Nucl. Instr. and Meth. **A659**, Issue 1, 11 Dec. 2011, pp106-135.

[2] A. Kazarov, *et al.*, A rule based verification and control framework in ATLAS Trigger-DAQ, IEEE Trans. Nucl. Sci. **54** 604-608, 2007.

[3] TensorFlow™, `https://www.tensorflow.org`.

[4] K. Nakayoshi, Y. Fujii, T. Nakadaira and K. Sakashita, “Development of an Expert System for the High Intensity Neutrino Beam Facility at J-PARC,” doi:10.18429/JACoW-ICALEPCS2017-THCPA07.

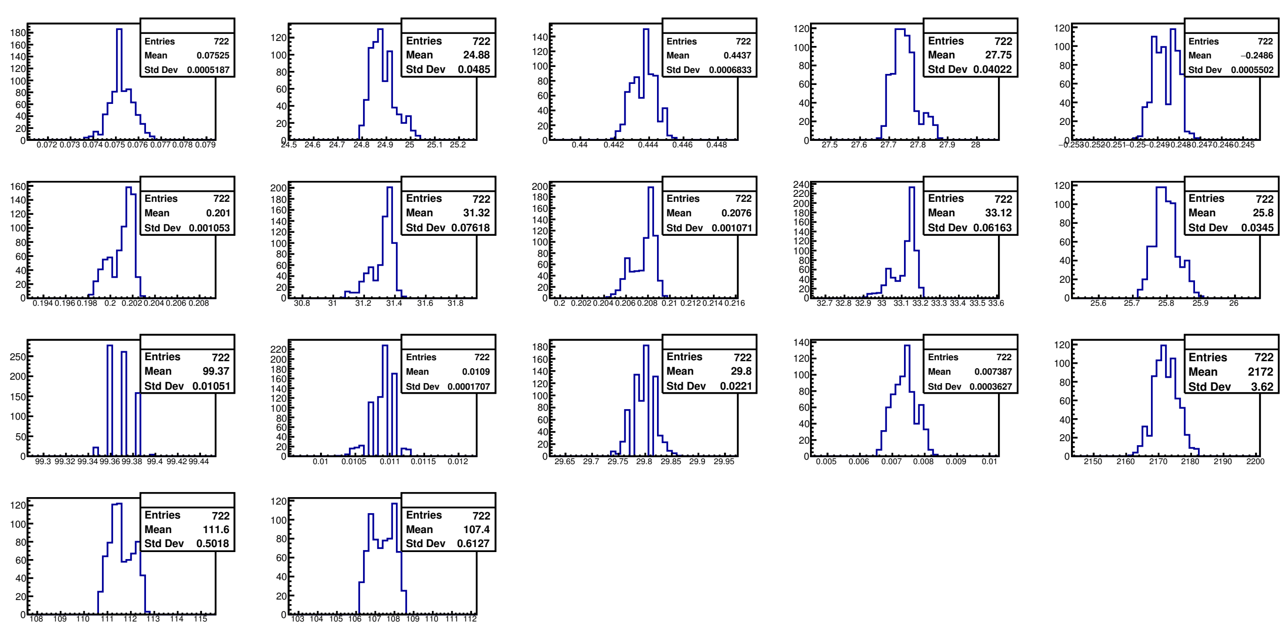

Figure 9: The distribution of the data for 1 hours. The horizontal axis shows the hour.

ISBN: 978-3-95450-201-1 doi:10.18429/JACoW-IBIC2018-MOPC18

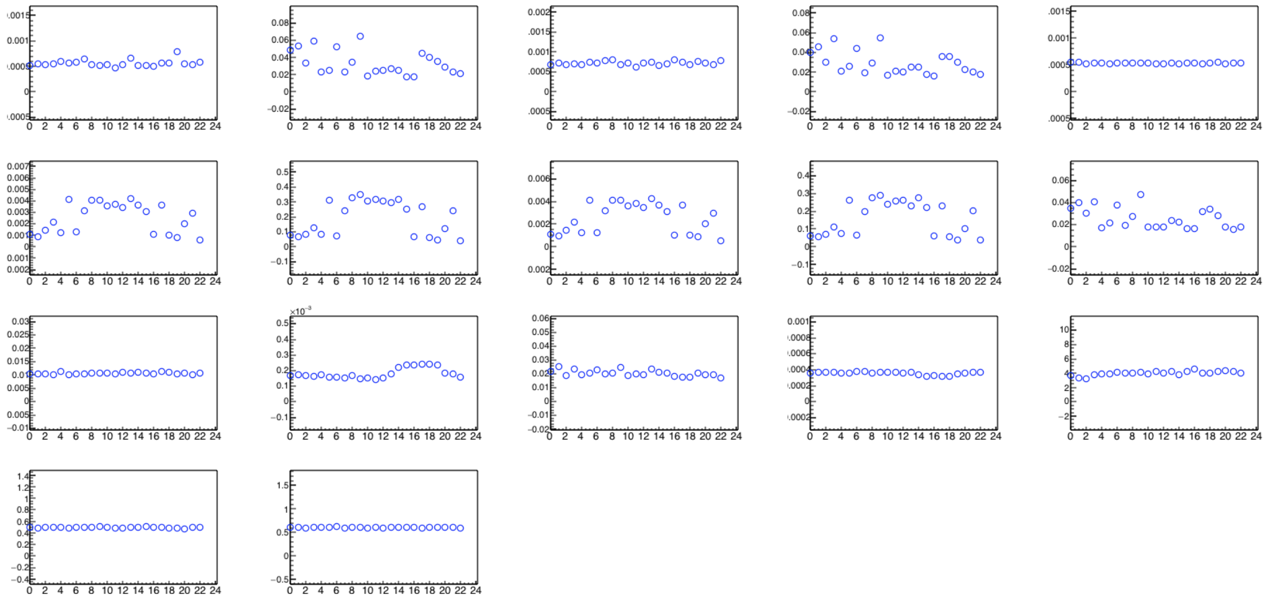

Figure 10: Time variation of the variance of each data for 24 hours. The horizontal axis shows the hour. The vertical axis shows standard deviation.

[5] M. Sakurada and T. Yairi, Dimensionality Reduction with the Autoencoder for Anomaly Detection of Spacecrafts, The 28th Annual Conference of the Japanese Society for Artificial Intelligence, 2014.