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

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Abstract

A high intensity neutrino beam produced at J-PARC is utilized by a long-baseline neutrino oscillation experiment. To generate a high intensity neutrino beam, a high intensity proton beam is extracted from the 30 GeV Main Ring synchrotron to the neutrino primary beamline. In the beamline, one mistaken shot can potentially do serious damage to 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 an expert system for prompt and efficient understanding of the status to quickly resume the beam operation. An inference engine is one key component in the expert system. Although a typical inference engine of the expert system is rule-based, we adapt a Machine-Learning (ML) based inference engine in our expert system. We will report the initial evaluation of our 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). Figure 1 shows the overview of the T2K experiment. A high intensity neutrino/anti-neutrino beam is produced and propagates 295 km from J-PARC to Super-Kamiokande (SK). In July 2013, muon neutrino to electron neutrino transformation was firmly established [2]. In August 2017, T2K excluded CP-conservation at 95% confidence level using the latest data. In order to keep generating interesting physics, steady operation of the facility is very important.

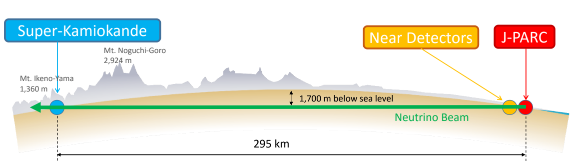

Figure 1: Overview of the T2K experiment.

Figure 2 shows a layout of the neutrino experimental facility (neutrino facility) at J-PARC. The neutrino facility is composed of two beamlines and a near detector (ND280). The beamline consists of the primary and secondary beamlines. In the primary beamline, the high intensity proton beam is extracted from the Main Ring synchrotron (MR) and guided through super and 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 470 kW in 2017 and ready to the design power of 750kW with a few years.

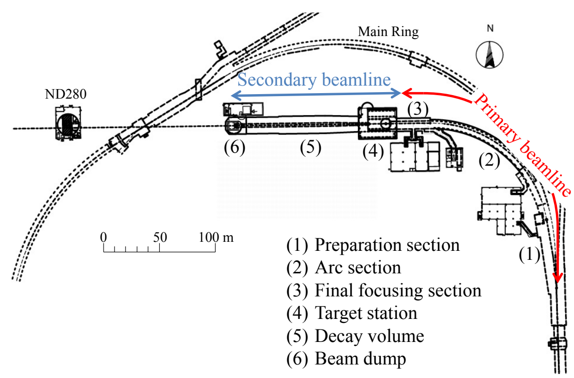

Figure 2: Layout of the T2K experimental facility.

MOTIVATION

We handle a high intensity proton beam at the J-PARC neutrino facility. If an interlock is activated, prompt and proper error handling is necessary. However it is not easy because of the following reasons:

- There are many interlock sources (~800)
- Multiple sources of interlock can happen at the same time

It is difficult for the beamline operators to understand the beamline status and recovery procedure and resume beam operation correctly and rapidly. To improve this situation, we plan to introduce a beamline expert system.

MPS IN THE NEUTRINO FACILITY

MPS, Machine Protection System, is an interlock designed to protect beamline equipment from the high intensity beam. If an MPS occurs, the beam in the MR is aborted and next beam spill is inhibited. The MPS is critical in a high intensity proton beam facility because one off-orbit beam spill potentially can do serious damage to the beamline equipment.

The number of MPS source channels at the neutrino facility is approximately 800. These contain interlock signals from each beam loss monitor (BLM), as well as the magnet power supplies, etc.

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Some Actual Examples of MPS Events

Here we introduce some actual examples of MPS events. Figure 3 shows the primary beamline of the neutrino facility and the fast extraction magnets of the MR. A failure of the fast extraction magnets, such as the septum magnets (FX septum) and/or kicker magnets (FX kicker), causes simultaneous BLM MPS events at the primary beamline (shaded region).

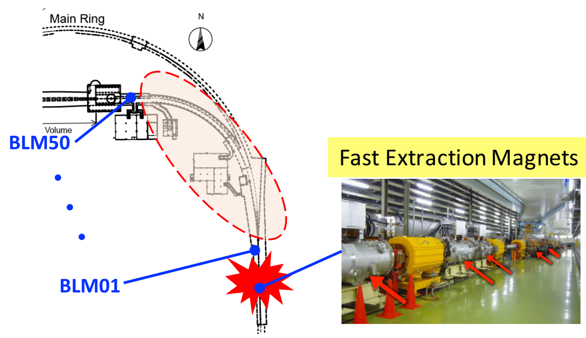

Figure 3: The primary beamline and fast extraction magnets.

Figure 4 shows the BLM MPS events caused by the FX septum or kicker for February 2016 to March 2017. Each row shows the BLM number, BLM#1 to #50. The orange cells represent the activation of each BLM MPS. The columns show each MPS event. There are 10 events. It is difficult to quickly understand the source of the MPS just looking at these BLM MPS patterns.

	2016/2/11	2016/2/17	2016/2/23	2016/2/25	2016/5/15	2016/11/14	2016/12/11	2016/12/25	2017/2/27	2017/3/20
	SEPTUM	SEPTUM	SEPTUM	SEPTUM	FXKM	FXKM	FXKM	FXKM	FXKM	FXKM
BLMP01	1	1	1	1	1	0	1	1	1	1
BLMP02	1	1	1	1	1	0	1	1	1	1
BLMP03	1	1	1	1	1	0	1	1	1	1
BLMP04	1	1	1	1	1	0	1	1	1	1
BLMP05	1	1	1	1	1	1	1	1	1	1
BLMP06	1	1	1	1	1	1	1	1	1	1
BLMP07	1	1	1	1	1	1	1	1	1	1
BLMP08	1	1	1	1	1	1	1	1	1	1
BLMP09	1	1	1	1	1	1	1	1	1	1
BLMP10	1	1	1	1	1	1	1	1	1	1
BLMP11	1	1	1	1	1	1	1	1	1	1
BLMP12	1	1	1	1	1	1	1	1	1	1
BLMP13	1	1	1	1	1	1	1	1	1	1
BLMP14	1	1	1	1	1	1	1	1	1	1
BLMP15	1	1	1	1	1	1	1	1	1	1
BLMP16	1	1	1	0	0	1	0	1	0	1
BLMP17	1	1	1	1	1	1	1	1	1	1
BLMP18	1	1	1	1	1	1	1	1	1	1
BLMP19	1	1	1	1	0	1	0	1	0	1
BLMP20	1	1	1	1	1	1	1	1	1	1
BLMP21	1	1	1	1	1	1	1	1	1	1
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BLMP28	1	1	1	1	0	1	0	1	0	1
BLMP29	1	1	1	1	0	1	0	1	0	1
BLMP30	0	1	1	1	0	1	0	1	0	1
BLMP31	1	1	1	1	0	1	0	1	0	1
BLMP32	1	1	0	0	0	1	0	1	0	1
BLMP33	1	1	1	0	0	1	0	0	0	0
BLMP34	0	0	0	0	0	1	0	1	0	1
BLMP35	0	0	0	0	0	0	0	0	0	1
BLMP36	0	0	0	0	0	1	0	1	0	1
BLMP37	0	0	0	0	0	1	0	0	0	0
BLMP38	0	0	0	0	0	1	0	1	0	1
BLMP39	0	0	0	0	0	1	0	0	0	1
BLMP40	0	0	0	0	0	1	0	1	0	1
BLMP41	0	0	0	0	0	0	0	0	0	0
BLMP42	0	0	0	0	0	0	0	0	0	0
BLMP43	0	0	0	0	0	0	0	0	0	0
BLMP44	0	0	0	0	0	0	0	0	0	0
BLMP45	0	0	0	0	0	1	0	0	0	0
BLMP46	0	0	0	0	0	1	0	0	0	0
BLMP47	0	0	0	0	0	0	0	0	0	0
BLMP48	0	0	0	0	0	1	0	0	0	1
BLMP49	0	0	0	0	0	1	0	1	0	1
BLMP50	0	0	0	0	0	1	0	1	0	1

Figure 4: BLM MPS patterns caused by FX septum or kicker.

BEAMLINE EXPERT SYSTEM

Overview of Beamline Expert System

Figure 5 shows a schematic diagram of the beamline expert system. The beamline expert system continuously collects the MPS status. If MPS is activated at the neutrino facility, expert system infers the MPS reason and presents a recovery procedure.

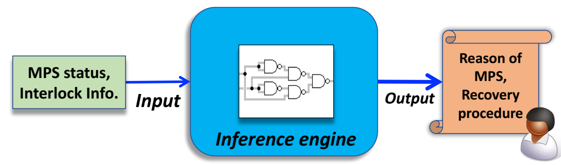

Figure 5: Schematic diagram of the beam line expert system.

New Idea of Inference Engine Based on Machine Learning

The “inference engine” is a key component of the expert system. It infers the cause of MPS. Although a typical expert system inference engine is rule-based [3], we adapt a machine-learning(ML) based inference engine in our expert system.

ML is a method of optimization for the model constructed by a neural network. We evaluated the following procedure:

1. We defined a model using **TensorFlow**™ [4], which is a famous open-source library for machine learning developed by Google.
2. Training was performed using training data generated by bit-manipulation of the real MPS events. The model parameters were optimized by supervised training.
3. Finally we used the trained model as an expert system inference engine, as well as to evaluate it using a test dataset.

We will discuss the initial evaluation of the ML-based inference engine in the following section.

Index of Learning Degree

There are two indexes of the progress degree of training. One is "cross-entropy" and the other is "accuracy". Cross-entropy function (E) is defined as in equation (1).

$$E(t, y) = -\sum_{i}^{M} \sum_{j}^{N} t_{i,j} \log y_{i,j} \tag{1}$$

where $t_{i,j}$ is the true label distribution by one-hot encoding, which is a group of bits and contains a single one and all the others zero, $y_{i,j}$ is a prediction from the model. M is the number of the training datasets, and N is the number of the labels. As in the equation, cross-entropy is positive

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and it tends toward zero as the model gets better at training. Accuracy (Acc) is the correct answer rate of prediction from the model and it is defined the equation (2).

$$Acc = \frac{Number\ of\ correct\ predictions}{Number\ of\ input\ data} \tag{2}$$

If the results of the prediction are correct, the model can classify perfectly, and in this case the accuracy is 1.

INITIAL EVALUATION OF MACHINE LEARNING BASED INFERENCE ENGINE

Testbed

We used the following hardware and software for the evaluation.

- MacBook Pro (2.7 GHz Intel Core i5)
- Tensorflow™1.2.0 with Python 2.7.12

Method of the Initial Evaluation

We carried out the initial evaluation of the ML-based inference engine considering the following cases:

- A case where interlock signals from many BLMs placed along the primary beamline fire simultaneously: This is caused by either a failure of the FX septum or 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 (1) FX septum, (2) FX kicker or (3) others, using the ML-based inference engine.

A Model for the Initial Evaluation

We used a 2-layer neural network model for the evaluation. Figure 6 shows a schematic diagram of the 2-layer model. The MPS bit stream is put into the input layer in our case. The output layer is 3 nodes and it is taken to represent the classification of FX septum, kicker or others.

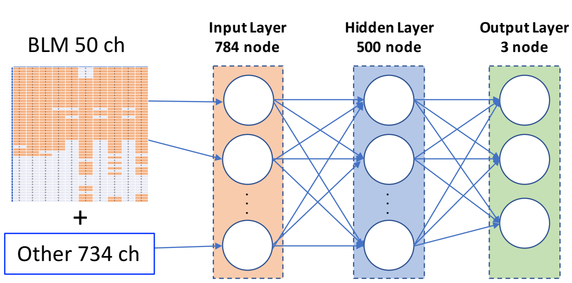

Figure 6: 2-layer neural network model.

Supervised Training of the Model

We performed a supervised training of the model. Figure 7 shows the schematic diagram of the supervised training. First we prepared training data which consists of input data with its correct label and 30000 training datasets (10000 of each label as shown in table 1) generated based on the actual past MPS events. Then we performed training to optimize the model to get the correct label.

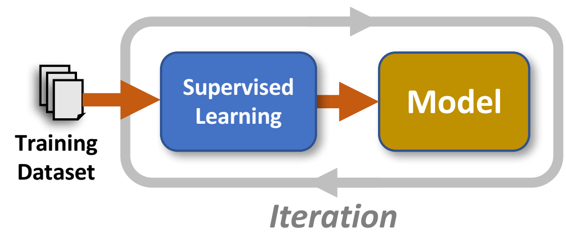

Figure 7: Supervised training.

Table 1: Training Dataset

MPS source	Label	Number of data
FX septum	0	10000
FX kicker	1	10000
Other	2	10000

Results of Initial Evaluation

Figure 8 shows the cross-entropy as a function of the number of training. The vertical axis shows cross-entropy and the horizontal axis shows the number of training. The cross-entoropy is reduced rapidly and became flat. Figure 9 shows a graph of the accuracy of training. The accuracy improved rapidly and became 1 at about twenty training. After the training, we also evaluated the model using a set of data which is independent of the training data, and the result of accuracy was 1. It means the model can classify the MPS into the three classes, FX septum, kicker and others, perfectly.

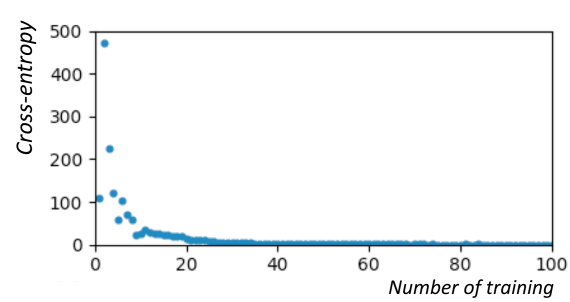

Figure 8: Cross-entropy of the 2-layer model in the training.

We also performed a study with an other model case, CNN (Convolution Neural Network), which is particularly

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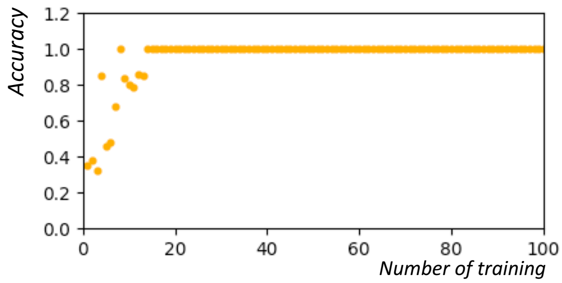

Figure 9: Accuracy of the 2-layer model in the training.

well-adapted to classify images. Figure 10 shows the cross-entropy of the 2-layer model, as shown in Figure 8 but with a reduced vertical axis. Figure 11 shows the cross-entropy of the CNN model. From this initial study, it is found that the CNN model also shows 100% accuracy, while the learning speed seems faster than the 2-layer model.

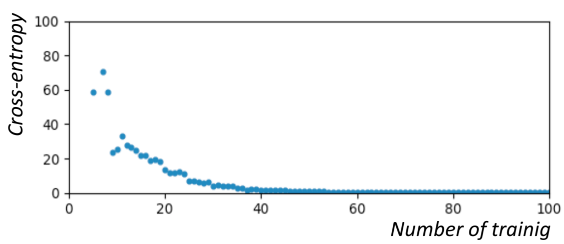

Figure 10: Cross-entropy of the 2-layer model in the training. The graph is as same as Fig 8 and verical axis is up to 100 instead of 500.

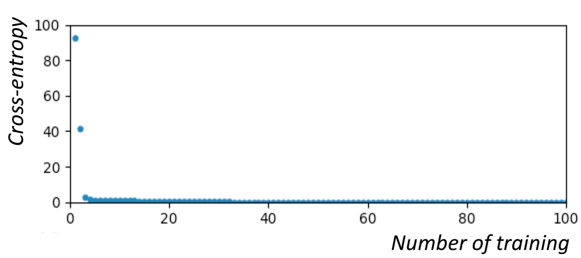

Figure 11: Cross-entropy of the CNN model in the training.

SUMMARY AND FUTURE PROSPECT

We are developing a ML-based beamline expert system for the J-PARC neutrino facility. We performed initial evaluation and the results indicate that a ML-based inference engine is promising. We also evaluated other model scheme (e.g. Convolution Neural Network) . We plan to study further details of the ML-based inference engine and evaluate the expert system with future actual interlock events during the next beam operation (from mid-October 2017). As a next step of our development, to detect a sign of beamline equipment abnormality using the ML-based expert system, we plan to use various monitor data of the beamline equipment in addition to MPS data.

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