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MACHINE LEARNING USING BEAM LOSS MONITORS FOR DIAMOND-II

C. Lehmann*[,1,2], L. Bobb[2], P. N. Burrows[1]
[1]John Adams Institute, University of Oxford, Oxford, UK
[2]Diamond Light Source, Oxfordshire, UK

Abstract

The slow losses measured by Beam Loss Monitors (BLMs) at synchrotron light source facilities offer useful but indirect insight into the state of the beam. Patterns arise across the set of BLMs depending on the movement of insertion devices, beam current, temperature, humidity, and other contributors. A variety of neural network models were designed and evaluated to model this behaviour under user beam operation. By applying an anomaly detection algorithm, a set of known disturbances were successfully detected.

INTRODUCTION

With the upcoming Diamond-II upgrade [1] new BLMs are being installed. The Libera BLMs from Instrumentation Technologies [2] are scintillator-based and capable of measuring losses in both the fast regime (125 MHz, approaching bunch-by-bunch speeds) and slow regimes (5 Hz averaging). The same systems are already in use at several other light sources such as Soleil [3] and ESRF [4]. The data from BLMs is commonly used to identify where and when high loss rates occur for decision making around the Machine Protection Systems (MPS) [5]. However, there is untapped potential to analyse their data to gain diagnostics about the beam itself.

Machine Learning methods are well suited to this problem since a change in the measured loss rate can originate from a variety of sources, often with complex non-linear relationships [6]. Unlike colliders such as the LHC which have quite stable beam conditions, synchrotron light sources such as Diamond have a constantly changing beam state primarily due to beamlines adjusting the gap size or phase of their Insertion Devices (IDs). Beamlines and users adjust these parameters to meet the needs of their experiment sporadically throughout the day, causing subtle changes to the lattice and beam dynamics. Feed-forward tables [7] and feedback systems [8] are heavily used to minimise these effects, but aren't perfect. With sufficient data and appropriate design, a Machine Learning model can predict the effects of these loss rate changes under normal beam conditions, allowing abnormal behaviour to be identified.

Abnormal changes in the losses can come from many sources outside of the knowledge of the model [5]. The difference between the measured beam losses and those predicted by the model can be used to identify these abnormalities. Some abnormalities can have severe consequences for accelerator operations, causing beam degradation or leading to a beam dump. This paper describes the early design and performance of such a BLM anomaly detection system to analyse the slow losses (on the order of seconds) to identify these anomalies and alert an operator to provide corrective action.

* corey.lehmann@physics.ox.ac.uk

EXPERIMENTAL SETUP

Diamond Light Source is a synchrotron light source facility. Electrons are accelerated to 3 GeV energy and stored in the Storage Ring providing synchrotron radiation for users at the beamlines. The facility is receiving a major upgrade to Diamond-II starting in December 2027 [1], including a new set of Beam Loss Monitors from I-Tech [2].

Diamond-II will have a BLM placed in each of its 24 cells, and more in areas of interest. The term BLM refers to the digitisation and controls box, which each controls and receives data from 4 Beam Loss Detectors - a scintillator with photomultiplier tube [2]. As such, Diamond-II will be able to monitor losses from over 100 detectors simultaneously.

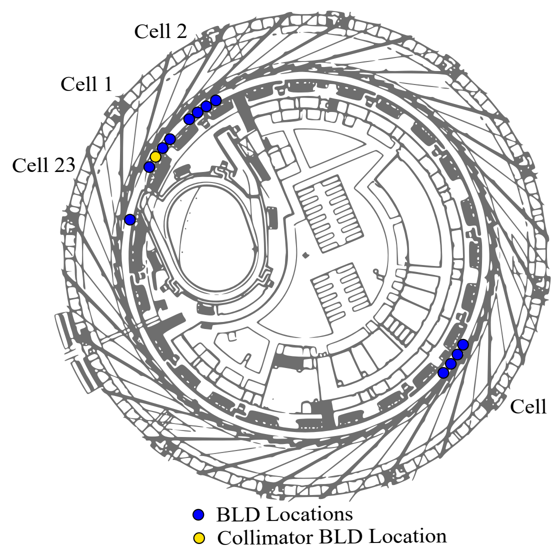

Figure 1: Positions of BLDs for initial testing in the Diamond Light Source storage ring, modified from [9]. The Collimator BLD is shown in yellow.

In preparation for this upgrade, 13 BLDs across 4 BLMs have been deployed in the Diamond storage ring for testing. The locations of these BLDs are shown in Fig. 1, also highlighting the Collimator BLD which has the strongest signal. All BLDs have been calibrated using LED methods similar to those at Soleil [3].

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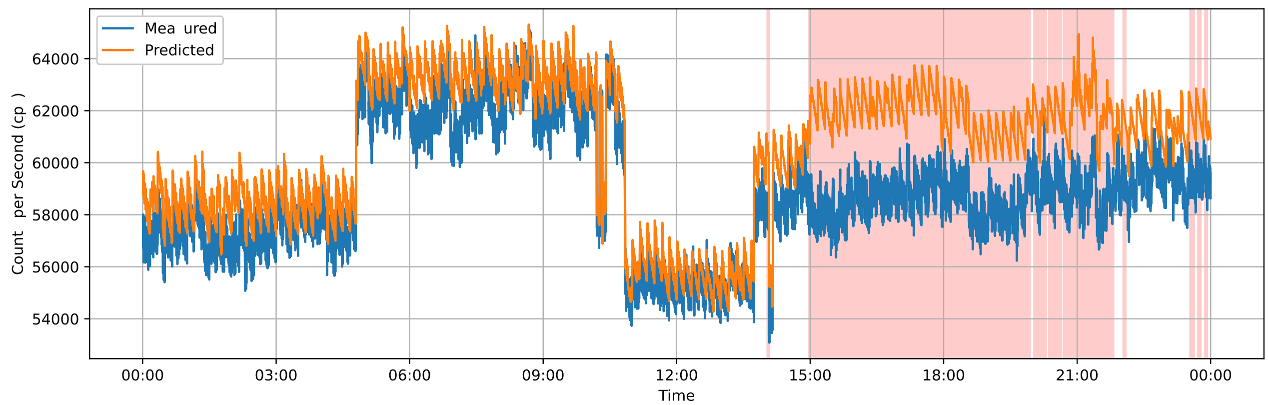

Figure 2: Example of a 24-hour period of Test data for the Collimator BLD, comparing the true measured values (Blue) with the values predicted by the 1x32 NN model (Orange). Red shaded areas indicate where anomalies are detected from the measured and predicted data being sufficiently diverged.

Each BLM offers several digitised data streams for each BLD. Testing showed the best signals were the counts per second (cps), triggered by a static threshold on the differential data, using the 50 Ω (Fast) input impedance. Average cps for each BLD are calculated at a 5 Hz rate and stored in the Diamond Archiver [10].

MACHINE LEARNING INPUT PARAMETERS

The gap movements of the IDs at Diamond are tracked via 28 PVs stored in the archiver. Early studies showed these are the dominant contributors to the loss rate changes. The beam current was also included as an input variable. Many other loss contributors are known, but excluded to create the simplest effective model.

In total, 55 days of data were passively collected during user beam. Data with the machine in abnormal conditions such as low current, machine top-up or during Machine Studies were removed. Although the analysis of the injection fast losses from this will be a topic of further research, this data is omitted for this study.

For training and fair evaluation of the model, the 55 days of data are split with a cyclic partition into 28 days of training data, 13 days of evaluation data, and 14 days of test data (with the example day fixed). The machine learning model used the training data to learn, used the evaluation data to stop training early preventing over-fitting, and the test data was used only for the final evaluation [6].

MACHINE LEARNING MODEL DESIGN

A simple neural network (NN) was chosen as the model due to its continuous multi-input multi-output capabilities. Using the set of 29 input variables, the model was trained to predict the values of 15 output variables - the count rates of 13 Beam Loss Detectors (BLDs) and the 30-second average lifetime measured by the DC Current Transformer (DCCT) and Electron Beam Position Monitors (EBPMs).

Several different architectures were designed and tested, stepping up in complexity to find a model which best suits this purpose. The simplest model design is effectively a linear regression between the input variables and output variables with 0 hidden layers. Capability for more complex relationships was increased by adding a hidden layer with 8, 16 or 32 nodes, then expanding to a second hidden layer [6]. For convention, the models will be referred to with the notation NxM, indicating N hidden layers of M nodes each.

MODEL EVALUATION

The evaluation function which best represents the purpose of this model is the Mean Average Error (MAE) Loss, aka L1 Loss [6]. However, some of the output data streams have a much wider operational range than others, from 100 000 cps to 10 cps. Higher values would have its errors prioritised much higher than a BLD with lower losses. To have the model act evenly across the output variables, a standard scaler is applied first to both input and output data variables based on the distribution of data in the training dataset.

Table 1 shows the prediction of each model evaluated using the MAE over the Training, Evaluation and Test datasets respectively. A low MAE indicates a highly accurate model.

Table 1: Standard-Scaled MAE Scores of Various Neural Network Architectures Over Each Dataset

Model	**Training**	**Evaluation**	**Test**
Linear NN	0.181	0.218	0.387
1x8 NN	0.163	0.209	0.237
1x16 NN	0.154	0.204	0.234
1x32 NN	0.143	0.195	0.216
2x8 NN	0.177	0.214	0.223
2x16 NN	0.167	0.229	0.229

The results from the Test dataset are best to evaluate the performance of the model in a real scenario. In this case, the 1x32 NN model performed best with a MAE of 0.216.

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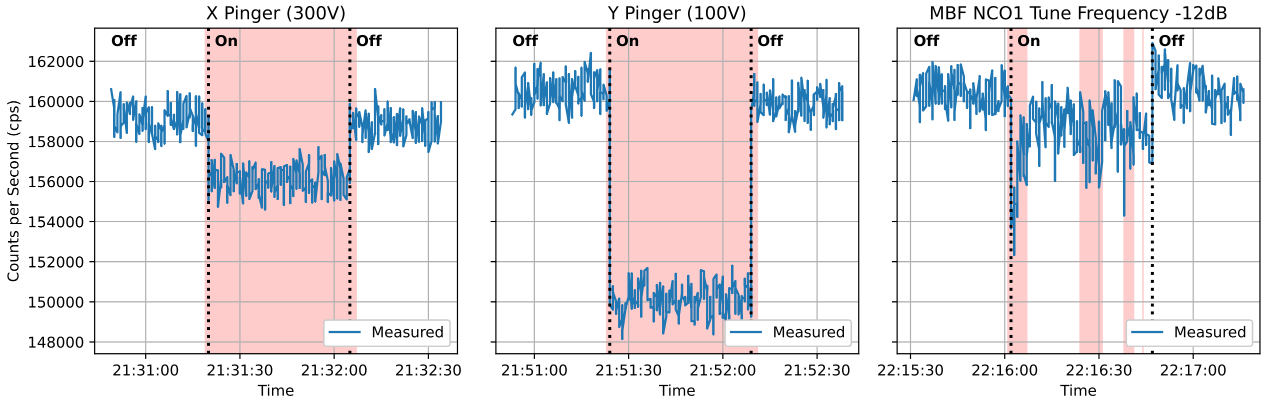

Figure 3: Examples of raw data from the Collimator BLD showing the effects on the loss rate of turning on and off various disturbances. The shaded red sections show where the anomaly detection indicates an anomaly for a correctly predicting model.

To demonstrate the effectiveness of the models, an example was chosen of the 1x32 NN model operating on a 24-hour period of Test data which is representative of the Training data, and is shown in Fig. 2. The model can be seen to predict most of the changes in the beam losses with considerable accuracy, and scored a scaled MAE of 0.040 in this time period, equivalent to an unscaled MAE of 1745 cps.

This example was chosen due to its interesting features, and the effectiveness with which the model correctly predicts them despite never seeing this data before. The model's predictions deviate slightly between 15:00 and 22:00 due to an arrangement of IDs that is not represented in the training data. The model performs quite well despite this.

ANOMALY DETECTION DESIGN

With the 1x32 NN chosen as the best current model based on its low MAE in the test dataset, this can now be used for anomaly detection. Anomalies of interest include ones which have occurred during operation before, can be easily missed by an operator, will have consequences in beam degradation or potential beam loss, and have a signature expected to be detectable by the BLMs. Some of these are difficult to replicate, but others can easily be recreated under controlled circumstances. The disturbances investigated for demonstration are the X Pinger Magnet being left on, the Y Pinger Magnet being left on, and the Multi-Bunch Feedback (MBF) with extra excitation from the Numerically Controlled Oscillator (NCO) being left on.

A detection trigger system also needed to be chosen - a differential threshold that triggers when the difference between the measured data and the predicted data exceeds a set value. This threshold is chosen based on the accuracy of the model, chosen to be at 2 standard deviations based on the MAE, as measured over an average of 5 seconds (25 data points). Filtering was then used to smooth this over a longer time period. This anomaly detection is shown as the shaded red sections in both Fig. 2 and Fig. 3.

EXPERIMENTAL ANOMALY DETECTION RESULTS

To measure how effectively this anomaly detection would identify disturbances such as the X Pinger Magnet, Y Pinger Magnet or MBF Excitation, each was tested in a Machine Shift and the data measured by the Collimator BLD is shown in Fig. 3. A variety of disturbance strengths were measured, with results shown in Table 2.

All data was taken with the vertical emittance feedback and orbit feedback off. For the MBF measurements, NCO1 was set to the betatron tune frequency with standard settings.

Table 2: Averaged Signal From the Collimator BLD for Each Disturbance and Strength

Disturbance	Collimator BLD Avg Signal
X Pinger 100 V	−617 cps
X Pinger 200 V	−1283 cps
X Pinger 300 V	−3118 cps
Y Pinger 25 V	−1033 cps
Y Pinger 50 V	−4577 cps
Y Pinger 100 V	−10 585 cps
MBF NCO1 −24 dB	−312 cps
MBF NCO1 −12 dB	−2317 cps

CONCLUSION

The use of BLMs as a beam diagnostic tool was investigated. A machine learning model was designed to accurately predict beam losses for a given machine state to a scaled Mean Average Error of 0.216, allowing for confident anomaly detection. Using this model, some anomalies from the X Pinger magnets, Y Pinger magnets and MBF were able to be recreated and shown to be correctly detected.

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