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ANALYZING ACCELERATOR OPERATION DATA WITH NEURAL NETWORKS*

F.Y. Wang†, X. Huang#, Z. Zhang
SLAC National Accelerator Laboratory, Menlo Park, CA, USA

Abstract

Accelerator operation history data are used to train neural networks in an attempt to understand the underlying causes of performance drifts. In the study, injection efficiency of SPEAR3 [1] over two runs is modelled with a neural network (NN) to map the relationship of the injection efficiency with the injected beam trajectory and environment variables. The NN model can accurately predict the injection performance for the test data. With the model, we discovered that an environment parameter, the ground temperature, has a big impact to the injection performance. The ideal trajectory as a function of the ground temperature can be extracted from the model. The method has the potential for even larger scale application for the discovery of deep connections between machine performance and environment parameters.

INTRODUCTION

SPEAR3 is a 3rd generation storage ring based light source. It operates in the top-off mode with frequent fills at the 5-minute interval, keeping the stored beam current within 1.2% percent from 500 mA. It's very import to keep a high injection efficiency in order to minimize the disturbance to the storage beam and the radiation due to the lost beam. Injection efficiency is sensitive to many parameters that affect the injected beam and the storage ring. For SPEAR3, the injected beam is mostly stable as it comes from a 3 GeV Booster, which shields upstream jitters. The injection performance is mainly determined by the Booster-to-SPEAR (BTS) transport line and the storage ring due to mis-steering of the injected beam, optics matching at septum, dynamic aperture and physical aperture in the ring, longitudinal phase space, and so on.

The BTS trajectory is controlled by a feedback that correct the trajectory every 5 minutes during operation. While the trajectory is kept stable, the injection efficiency still varies over time as shown in Fig. 1. During a run, the target trajectory needs to be updated in accelerator physics shifts from time to time.

To understand the cause of the injection performance variation, we are motivated to exam the operation history data. A fully-connected NN model was built to successfully extract the complex dependence of injection efficiency with steering as well as the environment variables.

DATA PREPARATION

We investigated operation history data of SPEAR3, which include injection efficiency, BPM readings, and steering magnet currents in BTS, insertion device gaps, and ambient air and ground temperatures. These parameters are archived at the different time intervals and there were occasionally missing data points. Therefore, some efforts were necessary to clean up the data and align the data points.

Data from three recent runs were used in the analysis, including the 2017, 2018 runs and a fraction of the 2019 run. There are about 60,000 data points in each full run and about 10,000 data points from the 2019 run.

Injection Efficiency

There are three injection efficiency measurements, differing in the monitor used to measure the average intensity of the injected beam (see Fig. 1). Among them, the Booster Q-meter based data are the least noisy and were thus used as the target of NN model. There are still some unrealistic data points due to diagnostic issues. To ensure only valid data enter the analysis, we filtered out data points with injection efficiency above 200%, below 50%, or periodic large fluctuation (~20%) in 5 minutes interval. About 3% of all data sets were removed from the study.

BTS Trajectory

The beam trajectory has very large shifts between different runs, with some BPM readings change by more than 10 mm, as shown in Fig. 2. Accordingly, the downstream steering magnets had to be tuned to compensate. The vertical orbit at two BPMs and the currents on two vertical steering magnets are shown in Fig. 2 as examples.

Environment Parameters

Two of the SPEAR3 insertions devices (ID) can have particularly large effect on the injection efficiency, including the BL5.elliptical polarized unduator (EPU) and BL15 ID, an in-vacuum undulator (IVU). The EPU is a major source of perturbation to the dynamic aperture. The IVU gap changes the physical aperture and could affect the injection beam loss. The gap changes of two devices for the three runs are shown in Fig. 3. The EPU phase is also included in the analysis.

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† fywang@slac.stanford.edu
# xiahuang@slac.stanford.edu

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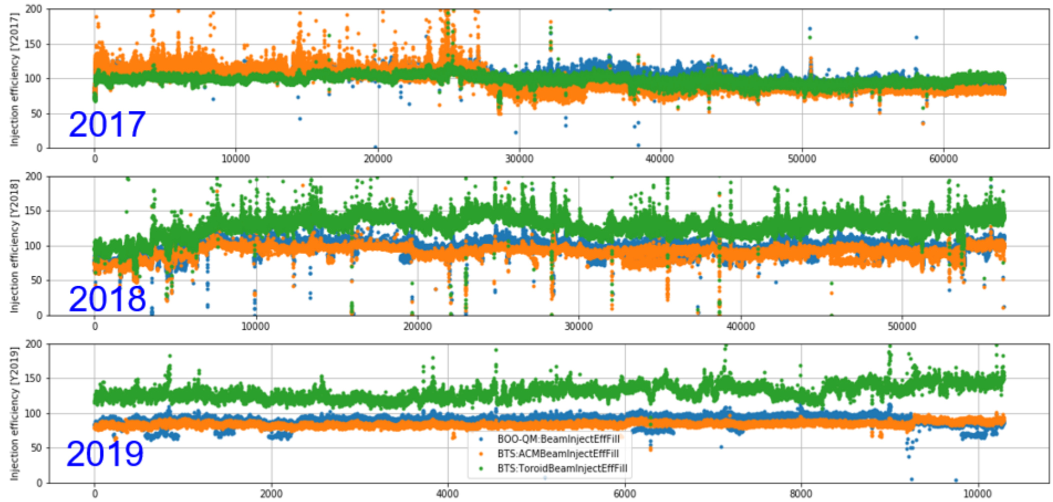

Figure 1: The history data of BTS to SPEAR3 injection efficiency for three runs, where the orange, green and blue dots are the three different measurement by the average current monitor (ACM), Toroid, and Booster Q-meter, respectively.

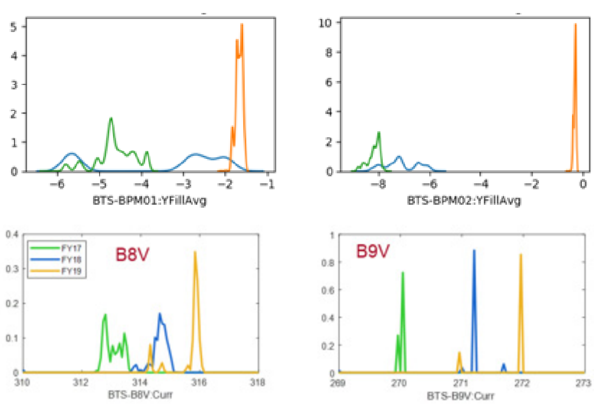

Figure 2: Histograms of the vertical BPM readings on BPM 1 and 2 (top row) and the last two vertical steering magnets (B8V and B9V) for the three runs (2017, 2018, and 2019). Areas under each curve are normalized to 1.0.

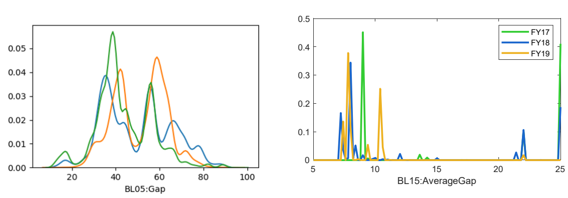

Figure 3: Histogram of BL5 EPU (left) and BL15-IVU (right) gaps (in unit of mm). Areas under each curve are normalized to 1.0.

The ambient air temperature and ground temperate are included in the analysis as they could drive trajectory shifts in various ways. In the course of a 9-mon run, the ground temperature varies for about 10 °C, while the air temperature changes by up to 40 °C (see Fig. 4). The 2019 run data cover 42 days, starting from late October, 2018.

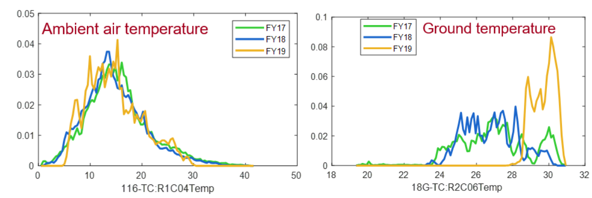

Figure 4: Histogram of ambient air and ground temperature (horizontal axis in unit of °C).

NN MODEL

An NN model was built to map the monitor and control parameters and the environment parameters with the performance measures. The predictive model could be used for performance stabilization and the discovery of root causes for any observed performance drifting.

The fully connected forward NN has a single output, which is the injection efficiency, and 22 input variables, which include the horizontal and vertical readings of 5 upstream BPMs in the BTS (10 variables), horizontal and vertical steering magnets in the downstream end of the BTS (7 variables), the temperatures (2), and the undulator gaps and EPU phase (3). The upstream BPMs determine the initial conditions of the trajectory, which, combined with the downstream steering magnets give the launching orbit of the injected beam into the storage ring. The results are similar if the downstream BPMs are included as input parameters.

About 63.8% of all data points are used for the training of the NN. Another 27.4% are used for the validation of the model. The rest of the data points are used for testing. The test data contain 20 blocks of history data, each block is 2 days of continuous of operation. The blocks are evenly distributed. Thus, we have 40 days of data for test and exclusive from training.

The NN model consists of 5 layers of networks. The first layer being a Recurrent NN (RNN). The 2nd through the 4th layers are Convolutional NN (CNN). The 5th layer is the

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output. There are a total of 5611 training parameters. A finite drop rate is adopted to improve the model reliability in some layers.

The trained NN model fits the data very well. The standard deviation of prediction errors for the validation data is 3.4%. For the test data the standard deviation is 4.4%. Fig. 5 shows the comparison of the model predicted injection efficiency and the history data for the test data set.

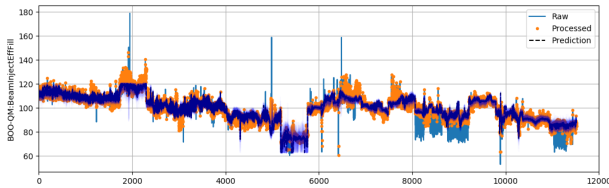

Figure 5: comparison of the injection efficiency predicted by the model and the history data, where the light blue, blue, and orange lines are for the raw data, processed data, and model prediction, respectively.

APPLICATION

The ability to use the trained NN model to make predictions of the performance measure with a given set of input parameters is useful in many scenarios. One application is to discover the hidden connections between the environment parameters and the performance measures. In our case, the goal is to find out how the injection efficiency depends on the environment variables, such as ID gaps and temperatures.

The approach we took is essentially to calculate the partial derivative of the output parameter of the NN with respect to the environment parameters. Figure 6 shows the change of the injection efficiency predicted by the model when an environment parameter is changed by 10% and all other parameters are fixed. The three curves represent the partial derivative for the air temperature, ground temperature, and BL5 EPU gap, respectively. The ground temperature causes the biggest variation to the output parameter, up to 30% in the injection efficiency.

The environment variables typically vary slowly and their impact to the performance measure could be small compared to that of the other parameters. In addition, the performance measure parameter, such as the injection efficiency data, can be noisy. Therefore, it would be difficult to detect the small dependence on the environment parameters directly from the data.

After the ground temperature is identified to be an environment parameter with a large impact, we studied the dependence of the ideal trajectory on the parameter. The ground temperature is first divided into 1°C zones. Within each zone, we used to the NN model to find the data points with the top 10% injection efficiency. The distribution of the corresponding trajectory readings on each BPM can then be used to determine the ideal trajectory.

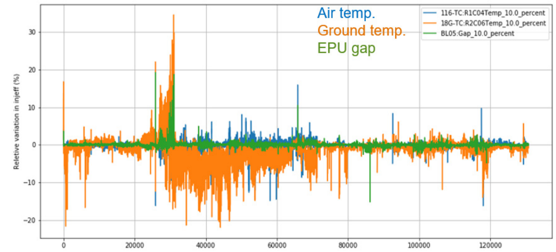

Figure 6: The relative output variation by the NN model with a 10% variation of an individual input, including the air temperature (blue), ground temperate (orange), and EPU gap (green).

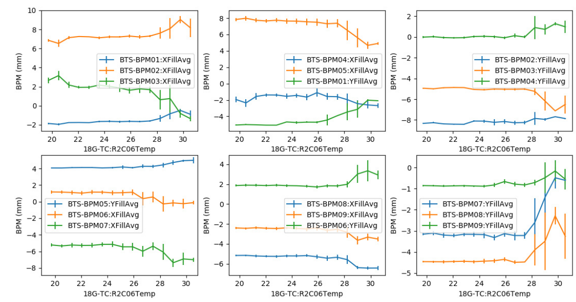

Figure 7: the dependence of the ideal BTS trajectory on the ground temperature.

Figure 7 shows the variation of the ideal BTS trajectory vs. the ground temperature at the 9 BPMs.

CONCLUSION

An NN model has been successfully used to analyze the injection efficiency history data of a storage ring and its dependence on the transport line steering and the environment variables. From the analysis, it is discovered that the ground temperature drives the slow drift of injection efficiency. The ideal orbit as a function of the ground temperature is also determined. The method may be integrated with the transport line trajectory feedback to stabilize the injection performance. The method of data analysis with NN model may be extended to more complex application scenarios.

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