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USING LINEAR REGRESSION TO MODEL THE PARAMETERS OF THE FLAT WIRES IN TLS-EPU56

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Abstract

Although a theoretical calculation might predict the set currents of the flat wires, which are used to compensate the deviation in the Betatron tune caused by the elliptically polarized undulator (EPU), those set currents must still be tuned in reality. To approach this reality, a strategy of Machine Learning was adopted, which included collecting real-condition data and using a linear-regression model to adjust the parameters of the flat wires. After training the model, the predictions in variables tune *x*, tune *y* and beam size *x* were compared with the required amount of correction of the EPU at various gaps and phases. To prove the feasibility of this method, a test was performed under the real conditions of accelerator Taiwan Light Source (TLS).

INTRODUCTION

Beginning with studies of flat wires [1] of the elliptically polarized undulator (EPU) magnet in Taiwan Light Source (TLS) in 2016 [2, 3], we theoretically calculated the distribution of the magnetic field of an EPU; we then tried to utilize the local magnetic field of the flat wires to compensate the variation of the Betatron tune working point [4, 5] and the electron beam size [6], which was produced when the EPU magnet altered its gap or phase. If we could use the flat wires to solve the problem of the working point shift, it could not only diminish the burden on other feedback systems, for example the Tune Feedback System [7], but also improve the beam injection issue, which had much difficulty when the EPU worked in its minimal gap condition. The picture of the installing of the flat wires is shown in Fig. 1.

When we applied the theoretically predicted set currents in the flat wires for a test in the real machine, we found that, because of the differences between the real and theoretical conditions (such as the installation position or the electron-beam trajectory), the theoretically predicted values still had to be tuned. We hence decided to use a Machine Learning strategy to find the proper set currents of the flat wires, i.e. training a model with real-condition data. As the parameters of this model are determined by data, all effects of the reality have become reflected in the parameters.

Although there are many applications of Machine Learning in the field of accelerators [8, 9], as our purpose is to predict continuous values of the output variables, and as the contribution of the flat wires is the superposition of each wire's magnetic field, a linear-regression model [10] suffices for this study. The code of the model is provided by the Python open-source scikit-learn [11].

One benefit of this method is that it is easy to begin, even for operators who have little knowledge of the magnetic field calculation of an insertion device (ID); so they can easily use set currents of the flat wires to maintain the working point constant while the gap and phase of the EPU are moving.

This paper is organized as follows. The influence of each pair of flat wires; the collection of data used to train the model; the performance and prediction of the trained model; the result of test under real conditions of the accelerator; and a conclusion.

Figure 1: Picture of twenty-eight flat wires installed in EPU 56 of storage ring TLS. Fourteen wires lie on the top side of the vacuum chamber; the other fourteen wires are sticking on the bottom side.

INFLUENCE OF THE FLAT WIRES

To understand the influence of the flat wires qualitatively, we examined the effect of each flat wire first. For the flat wires, the present way of the hardware setting was for each two flat wires (for example, the wires shown in Fig. 2(b) or (c)) to have the same current; so 14 pairs were available for us. The results of adjusting the current in each flat-wire pair are shown in Fig. 2(a). As four pairs have positive slopes whereas the other ten have negative slopes in the Betatron tune in the x-direction (tune x), one can see that the influences of the four pairs in the middle are similar to the focus quadrupole (FQ), whereas the influences of the outer ten pairs are similar to the defocus quadrupole (DQ). Schematic diagrams of FQ and DQ are shown in Fig. 2(b) and 2(c), respectively.

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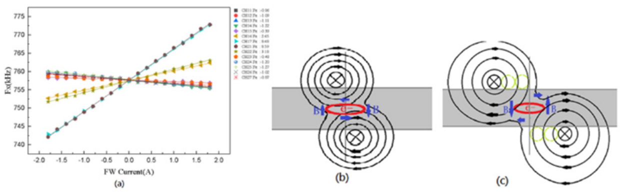

Figure 2: (a) Results of adjusting the current in each flat-wire pair in tune x. The legend at the right shows the number and slope of each pair of flat wires. (b) and (c) are schematic diagrams of FQ and DQ respectively. The direction of the electron beam is opposite to the currents in the flat wires.

DATA COLLECTING AND FILTERING

To learn the relations between input and output variables of the flat wires quantitatively, we randomly scanned all possible current settings in the range ±2.0 A to collect the data for model training. The current settings of 14 pairs of flat wires were taken as input variables; the corresponding variations of the tune (x, y) and beam size (x, y) were taken as four output variables. There were 4200 events in the learning data; the distributions in the three output variables are shown in Fig. 3, where one can see, for tune x, tune y and size x, that the distributions of their variations are symmetric and peaked at zero. The measurement of size y had problem during the data-taking so it was hence not considered in this study.

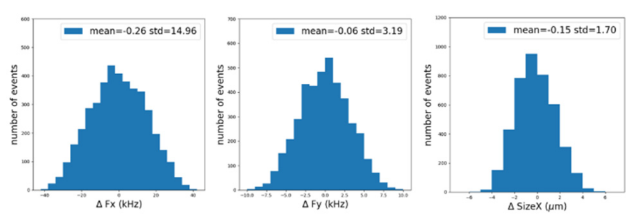

Figure 3: Histograms of learning data in three output variables: variations of tune x (left), tune y (middle), and size x (right).

In addition to the 1-D distribution, we could also monitor two variables together in the same time as a 2-D scatter plot, shown in Fig. 4. One can see that correlations exist between each two of all variables (the variations of tune x, tune y and size x). These correlations mean that, when the value of one variable increases or decreases, the trend of how another variable alters is certain (becoming larger or smaller) in the present way of the hardware setting.

One can also see that some data points locate far from the mainstream data in Fig. 4. The reason for these abnormal points could be some unknown factors interfering with the acquisition of our output variables. As those factors were not taken into account as input variables, these abnormal points must be excluded from the learning data to avoid misleading in the model training. We thus retained only the data in the easier-learning region (between two red lines in Fig. 4); 7% of the total amount of data was lost in this filtering.

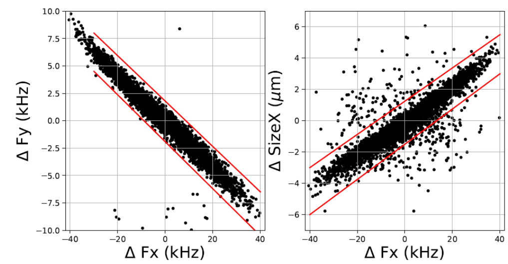

Figure 4: 2-D scatter plot of learning data in three output variables. Each black dot represents one input-output event. The red lines in the plots are for the easier-learning region filter.

MODEL TRAINING AND PREDICTION

In the model training, the learning data were randomly separated into two parts. The part used to train the learning model was called training data; the other part used to test how well the model could describe the data was called validation data. Once the model had been trained using the learning data, we would then use the validation data to compare the model-predicted value with the true value in each event.

In the linear-regression model, the output variables (x) are connected with the input variables (y) according to this equation:

$$\hat{y}(w,x) = w_0 + w_1x_1 + w_2x_2 + \cdots + w_{14}x_{14}. \quad (1)$$

Parameters (w) are decided on minimizing the residual sum of squares (RSS), defined as

$$RSS \equiv \sum_i (y_i - \hat{y}_i)^2, \quad (2)$$

in which y_i is true value and $\hat{y}_i$ is predicted value for event i in the training data.

The performance of the linear-regression model for the validation data is shown in Fig. 5. The model is thought to learn the data successfully in an output variable if the coefficient of determination (R^2-score) is near one. The R^2-score is defined as

$$R^2\text{-score} \equiv 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y})^2}. \quad (3)$$

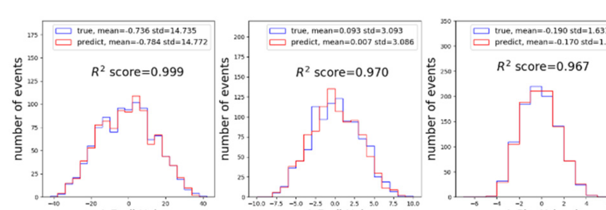

Figure 5: Performances of the linear-regression model with validation data in output variables. The histograms are predicted values (red) and true values (blue).

After training the model, we could compare the possible distribution of the flat wire (black dot) with the required amounts of correction of the EPU at varied gap and phase (colored dot) in the 2-D scatter plot, as shown in Fig. 6.

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The possible distribution was generated with the trained model with 10,000 random events, for which the input currents had the same input constraints (within ±2.0 A). One can see that the colored dots do not necessarily fall into the black dot region, which means that for some gaps and phases the flat wires can satisfy the requirement of multiple variables at the same time, whereas for other gaps and phases it can satisfy only one variable at one time.

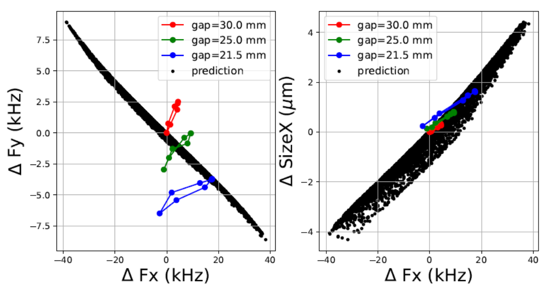

Figure 6: Possible distribution of the flat wire (black dot) and required amounts of correction of EPU at varied gaps and phases (colored dot) in the three output variables. The colored dots with the same color belong to the same gap but different phases.

RESULTS OF TESTING IN THE REAL ACCELERATOR

To prove the feasibility of this method, the trained model and its predictions must be tested in the real accelerator. As the biggest deviation in tune *x* occurred when the condition of the EPU was gap 21.5 mm and phase 28 mm, we chose this EPU condition to test ten current settings of the flat wires, which were predicted with the model to compensate the deviations of the EPU in both tune *x* and tune *y*. A constraint that the current distribution of 14 pairs of the flat wires must be symmetric (left and right), which was inspired from the theoretical calculations [2, 3], was added to these 10 settings to avoid severe beam loss. The test was performed under the "top-up mode", in which an electron beam was injected once a minute.

During the test, the monitoring variables versus time are shown in Fig. 7; the five steps in the testing are described as follows:

1. Before testing the flat wires, the EPU conditions were gap 30 and phase 0. The tune feedback system had been turned ON. The EPU condition began to change to gap 21.5 and phase 28.
2. Once the EPU conditions had arrived at gap 21.5 and phase 28, the tune feedback system turned OFF.
3. The test of the 10 settings of the flat wires began. Each setting was maintained for 10 min.
4. Once the 10 settings were done, another setting was tested, which was derived from the theoretical calculation and used in the 2016 test, also kept for 10 min.
5. The current of the flat wires was turned OFF.

As the result of testing, one can see that a partial beam loss occurred when the EPU began to alter its condition to gap 21.5 and phase 28 (step (i)), although tune *x* and tune *y* were still fixed about 758 kHz and 439 kHz respectively (the original values) because of the working of the tune feedback system. After applying the current setting of the flat wires, not only tune *x* and tune *y* could be corrected to their original values, but also beam current was restored gradually, which means that the flat wires have the ability to correct tune *x* without disturbing the beam injection. One might notice that there were a few instances of small beam loss in step (iii), which were then caused by instability in the booster ring. A few drops (about 600 kHz) in tune *x* occurred because the tune measurement and the beam injection occurred at the same time.

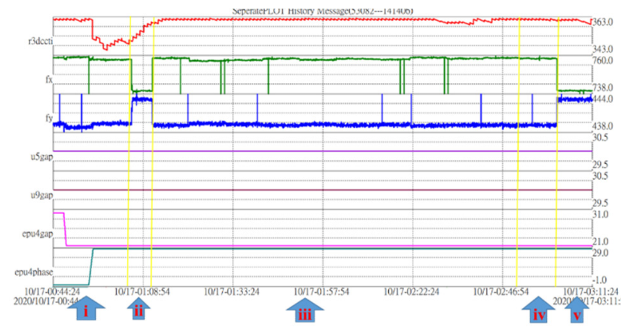

Figure 7: Monitoring variables vs time in the testing. The r3dccti is the beam current in the storage ring. F_x and F_y denote tune *x* and tune *y*. EPU4gap and EPU4phase are the gap and phase of the EPU. U5gap and U9gap are the gaps of another two undulators that remained unchanged during the test.

CONCLUSION

The test in accelerator TLS shows that, although both the flat wires and the tune feedback system could compensate the deviation in tune caused by the EPU, it seems that the flat wires impose less disturbance on the beam injection. As the beam injection issue seems to involve more than one factor (the tune shift), further studies are required to discover the true reasons for the beam loss.

The parametric modeling of the flat wires indicates the possibility of fixing multiple variables, which includes tune *x*, tune *y* and beam size *x*, with one current setting. This possibility has been confirmed in a test using gap 21.5 mm and phase 28 mm, at which both tune *x* and tune *y* have been corrected to their original values. Although for all gaps and phases it is not always achievable under the present mechanism of hardware setting, we plan to adjust the hardware setting to expand the multi-variable region of the flat wires in the 2-D scatter plot.

All above experience of the TLS flat wire might inspire the operation of TPS to solve similar issues such as beam-size shifts, which are significant for the nano-scale light-source experimental station.

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