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BEAM ORBIT SHIFT DUE TO BPM THERMAL DEFORMATION USING MACHINE LEARNING*

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Abstract

Stabilizing beam orbit is critical for advanced synchrotron radiation light sources. The beam orbit can be affected by many sources. To maintain a good orbit stability, global orbit feedback systems (OFB) has been widely used. However, the BPM thermal deformation would lead to BPM misreading, which can not be handled by OFB. Usually, extra diagnostics, such as position transducers, is needed to measure the deformation dependency of BPM readings. Here, an alternative approach by using the machine operation historic data, including BPM temperature, insertion device (ID) gaps and corrector currents, is presented. It is demonstrated at Hefei Light Source (HLS). The average orbit shift due to BPM thermal deformation is about 34.5 µm/°C (horizontal) and 20.0 µm/°C (vertical).

INTRODUCTION

Synchrotron radiation source has many advanced characteristics such as high brightness, transverse coherence, good time structure, etc, which is developed as one of the most powerful scientific tools over decades [1]. The beam orbit stability is required to be better than 10% of the beam size for modern light sources [2, 3]. Many sources could lead to beam orbit shifts. Global orbit feedback system has been widely used to suppress them. However, the BPM thermal deformation would lead to BPM misreading, instead of direct orbit disturbance, which could not be effectively corrected by OFB. Significant beam orbit shift due to BPM misreading has been observed in sources like APS [4], KEKB [5], and HLS [6].

Dedicated diagnostics is needed to measure and correct BPM thermal deformation, for example, the work carried out at HLS [6]. It is a straight forward method and generally provides good results. However, few downsides are there like the cost of hardwares and the need of machine study time, which actually make it difficult for wide implementation. In this paper, we will present an alternative approach by using machine learning, which is successfully demonstrated at HLS-II by predicting effective beam orbit shift accompanied by direct corrector current. It could be integrated to orbit feedback system to improve beam orbit stability.

In the following, we first introduce the theoretical model of beam orbit change due to BPM vacuum chamber thermal deformation, then a surrogate model built using a neural network (NN). Finally results from the surrogate model are presented.

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THEORETICAL MODEL

Thermal effects from synchrotron radiation, parasitic heat induced by machine impedance and tunnel temperature variation can cause BPM vacuum chamber mechanical deformation, which leads to its geometric center shift in global reference coordinate and results in BPM misreading. BPM reading, $\vec{u}$, can be written as

$$\vec{u} = \vec{R} - \vec{r}, \tag{1}$$

where $\vec{r}$ and $\vec{R}$ are BPM center and beam position respectively in global coordinate.

In principle, BPM center shift does not affect beam orbit directly, except when OFB is functioning, where the beam experiences extra kicks from correctors. Accordingly, a BPM reading changes as,

$$\Delta\vec{u}_i = \Delta\vec{R}_i - \Delta\vec{r}_i = (\frac{\partial\vec{R}_i}{\partial\vec{r}_i} - \bar{\bar{I}}) \cdot \Delta\vec{r}_i, \tag{2}$$

where $\Delta\vec{r}_i$ is BPM center shift due to heating, $\Delta\vec{R}_i$, beam position change at BPM due to OFB, $\partial\vec{R}_i/\partial\vec{r}_i$, Jacobian matrix and $\bar{\bar{I}}$, a unit 2 by 2 tensor.

With an ideal OFB, beam orbit is corrected back to its original, it then yields

$$\Delta\vec{u} = (\Delta\vec{u}_1, ..., \Delta\vec{u}_N) = 0, \tag{3}$$

$$\Delta\vec{r} = \Delta\vec{R}|_{\Delta\vec{u}=0} = \mathcal{M} \cdot \Delta\Theta, \tag{4}$$

where $\Delta\Theta$ is corrector kick strength change, and $\mathcal{M}$ is machine orbit response matrix (ORM), which ideally depends only on machine optics and is given by

$$\mathcal{M}_{ik} = \frac{\partial u_i}{\partial\theta_k} = \frac{\sqrt{\beta_i\beta_k}}{2\sin\pi\nu}\cos[\nu(\phi_i - \phi_k + \pi)], \tag{5}$$

where (β_i, ϕ_i) and (β_j, ϕ_j) are the beta function and phase advance at position i and k and ν is the betatron tune.

The Θ only responses to the BPM readings, which depends on the beam reference orbit and real beam orbit change. The change of reference orbit is caused by the BPM misreading. The real beam orbit shift can be generated by the gap variation of IDs. The physics model of the corrector strength can be described as a function of the ID gaps and BPM temperature by

$$\Theta(\vec{g}, \vec{T}) \approx \Theta(\vec{g}, \vec{T}_0) + \frac{\partial\Theta}{\partial\vec{T}_0}\Delta\vec{T}, \tag{6}$$

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where $\vec{T}$ is the BPM vacuum chamber temperature, $\Delta\vec{T}$ is the BPM temperature variation and $\vec{g}$ is the ID gap.

Therefore, beam orbit shift due to BPM thermal deformation is

$$\Delta\vec{r} = \mathcal{M}\frac{\partial\Theta}{\partial\vec{T}_0}\Delta\vec{T} = \mathcal{M}\mathcal{N}\Delta\vec{T}, \tag{7}$$

where $\mathcal{N}$ is the temperature response matrix (TRM) of corrector strength at given ID gaps.

Technically, TRM could be obtained with implementation of dedicated diagnostics [6], which is difficult for a large storage ring with hundreds of BPMs. Alternatively, we will use a neural network model to obtain the TRM.

NEURAL NETWORK SURROGATE MODEL FOR TRM

Neural networks could efficiently find the function between inputs and outputs, which handles regression and classification problems very well, especially for nonlinear problems with large quantity data [7]. Therefore, a neural network is applied to this work.

According to theoretical analysis above, the BPM temperature, IDs gap and correctors current data from the historic data for the entire year of 2019 are used to study the thermal effects. We take ID gaps (see Fig. 1) and temperature (see Fig. 2) as inputs and corrector currents (see Fig. 3) as outputs, and use the about 80% of the processed data as training dataset to train NN models and the rest data as testing dataset to test models. Then get an NN surrogate model which describes the mapping function,

$$\Theta(\vec{T},\vec{g}) = f(\vec{T},\vec{g}). \tag{8}$$

The TRM can be obtained using this surrogate model, while the ID gaps are fixed. This process is similar to the measurement of the ORM in a real storage ring. A disturbance of the BPM temperature ΔT (0.1 °C) is applied to each BPM in turn. The new temperature $\vec{T}'$ is used as the inputs to the model to get the corresponding corrector currents

$$\Theta'(\vec{T}',\vec{g}) = f(\vec{T}'(T_1,...,T_i+\Delta T,...,T_N),\vec{g}). \tag{9}$$

Finally, the TRM is calculated as

$$N_{ij} = \frac{\partial\theta_j}{\partial T_i} \approx \frac{\theta'_j - \theta_j}{\Delta T}, \tag{10}$$

where N_{ij} is the term of TRM $\mathcal{N}$, θ_j is the j-th term of Θ and T_i is the i-th term of $\vec{T}$.

For more accurate results, the predictions with NN multiple models are combined, which is called the model ensemble. Averaging usually works well for a wide range of problems. Here we train several different single models by changing the activation function, the number of layers and the number of neurons in each layer. The results from different models are averaged as the ensemble result in this work.

DATA PREPARATION

The orbit feedback system of the HLS-II storage ring is composed of 32 sets of BPMs and 32 sets of correctors [8]. There are two temperature sensors attached to each BPM, for a total of 64. The raw data are needed to be processed properly before training as following.

1. Select the data of user mode (the data with beam current at 355 mA -360 mA). This is because the factors that affect the beam orbit are relatively fewer in the user mode.
2. Discard the data which are out of the normal range.
3. Remove 4 sets of BPM temperature related to broken sensors.
4. Apply interpolation to form consistent data frequencies.
5. Normalize the data.

Comparing the data (see Figs.1, 2, and 3), we can see that they have a strong correlation, especially at positions 1 and 2 in the figures, which is consistent with theoretical analysis above.

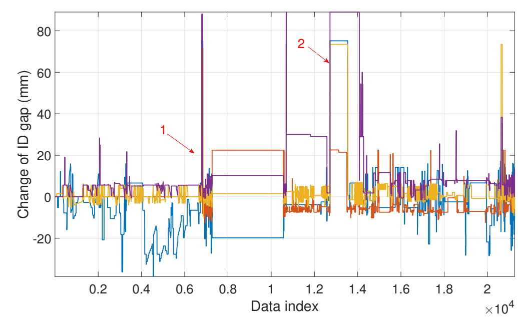

Figure 1: Change of ID gaps.

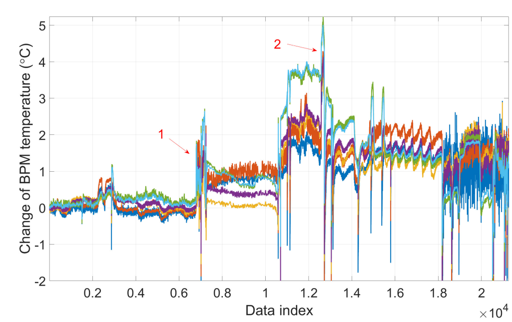

Figure 2: Change of BPM vacuum chamber temperature. Temperature of six BPMs are shown.

RESULTS

After training, several single models and an ensemble model are obtained. The Fig. 4 shows the predictions of one horizontal corrector current from testing dataset. From the results, we can see that the prediction of the ensemble model is better than that of a single model, and the real values are almost within the error range of its predicted values, which indicates good performance of this neural network model.

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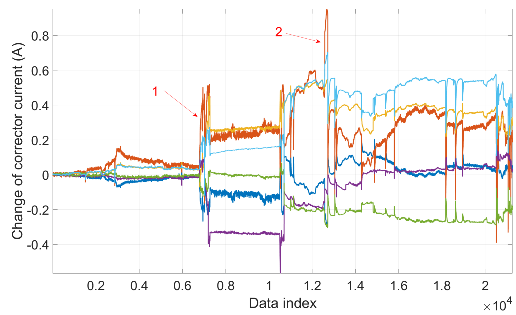

Figure 3: Change of corrector currents. Currents of six correctors are shown.

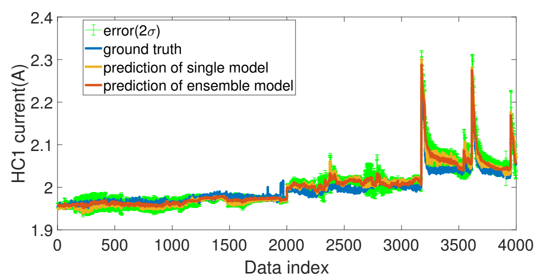

Figure 4: Predictions of the models. The result of one corrector current is shown in the figure, and the rest of the results are similar. The real values are almost within the error range of its predicted values.

By changing the BPM temperature sequentially, the beam orbit shift due to BPM thermal deformation could be obtained using the NN model and the Eqs. 7, 9, and 10. From the results (see Fig. 5 and Fig. 6), the BPM temperature variation has a great impact on the beam orbit, especially in some locations, which is related to the lattice optics and the BPM mechanical structure.

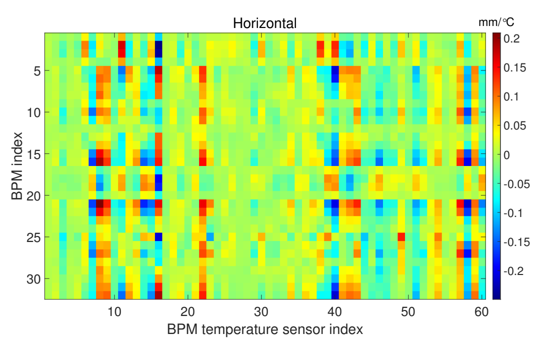

Figure 5: Response of horizontal BPM readings to BPM temperature. The average orbit shift due to BPM temperature is about 34.5 µm/°C.

SUMMARY

In this paper, we report our study on the beam orbit dependency of BPM temperature. An NN surrogate model is introduced using the historic operation data of the HLS-II

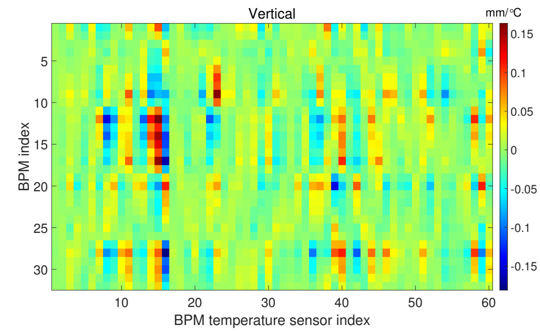

Figure 6: Response of vertical BPM readings to BPM temperature. The average orbit shift due to BPM temperature is about 20.0 µm/°C.

storage ring. The average orbit shift due to BPM thermal deformation is about 34.5 µm/°C and 20.0 µm/°C in horizontal and vertical plane respectively.

The neural network only needs machine data, which is easy to implement for storage ring based light sources. Besides, this model could be used for the compensation of beam reference orbit to improve beam orbit stability.

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