NUMERICAL METHODS FOR THE ORBIT CONTROL AT THE KEK 12 GEV-PS

Y. Hitaka, M. Shirakata, H. Sato, KEK, Ibaraki, Japan

M. Yokomichi, M.Kono, Miyazaki University, Miyazaki, Japan

Abstract

At the KEK 12GeV-PS main ring (PS-MR), when the least square method is applied to correct whole beam orbit all at once, it remains unacceptable beam loss and it is necessary to adjust the local positions of the beam orbit by hands with the beam loss monitors until the beam loss is suppressed under an acceptable level. However, the orbit generated by this way doesn't always satisfy the minimum-loss condition. In this paper, a new method is proposed. It focuses a fact that the beam loss distribution depends on the shape of the beam orbit, and formulates this relationship to a functional approximation by using a neural network algorithm. Then, solving an optimization problem for generated network system, data of the beam shape which is more suitable for the beam loss of the accelerator can be obtained. The description of the system construction and experimental results are presented.

INTRODUCTION

For the orbit tuning about the synchrotron accelerator, it is deficient to correct the COD (Closed Orbit Distortion) from the beam position signal. There are measurement errors at the beam position monitors and the setting errors of the vacuum chambers. Then, the beam touches the wall of the beam pipes and losses. Thus, the orbit tuning is necessary from the point of view of beam loss monitors in order to minimize the beam loss.

At the PS-MR, the beam orbit is adjusted at each measured point of beam position data by the local bump method with the beam steering magnets. The operators correct the beam orbit with the beam loss monitors until the beam loss is suppressed under an acceptable level. However, this strategy depends on the traditional history of the orbit tuning and operator's experience. Besides, the beam orbit tuned by this way doesn't always satisfy the minimum-loss condition for the accelerator.

Note a fact that the beam loss distribution depends on the shape of the beam orbit. If this relationship can be formulated in some way, it is expected that the minimum loss condition can be obtained by using some kind of the optimization methods.

In this paper, a new strategy is proposed for the beam orbit tuning. It formulates the relationship between the shape of the beam orbit and the beam loss distribution by using a neural network algorithm. The neural network creates a vector map from some of the data sets called "training data". A training data set consists of an input vector and a reference vector. The neural network receives the input vector and generates a corresponding output vector. This map is characterized by a process called "training" which adjusts the internal parameters of the network. Then, solving an optimization problem for the trained neural network, the orbit data which is more suitable for the beam loss of the accelerator can be obtained. This method will be more systematic and efficient than the previous method.

In this paper, we introduce an overview of the neural network. And then, as the PS-MR is an applicable example, we show a concrete network training strategy about the relationship between the shape of the beam orbit and the beam loss distribution. Next, we just refer about the optimization method and show the experimental results for our approaches. Conclusion and challenges for the future are finally shown.

NEURAL APPROACH FOR THE FORMULATION OF THE RELATIONSHIP BETWEEN THE BEAM POSITION AND BEAM LOSS

Backpropagation Neural-Network

There are various types of neural network algorithms. In this paper, the Backpropagation (BP) method [1] is used to formulate the relationship between the shape of the beam orbit and the beam loss distribution. BP method has generated a lot of good results for many actual problems whose relationships between their inputs and outputs are nonlinear or higher order correlation. Figure 1 shows the structure of a feed-forward network for the BP method.

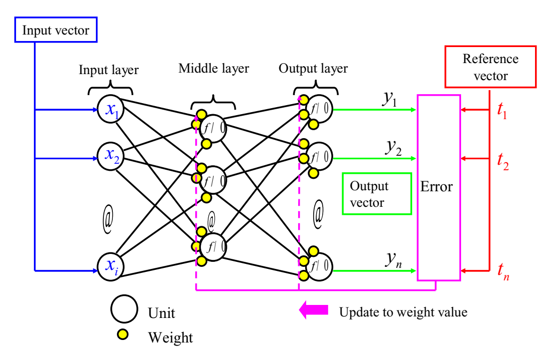

Figure 1: Feed forward neural network.

The BP network consists of an input layer, middle layers (not always one layer) and an output layer. Each layer is a set of the units, and each unit in a layer is connected to each unit in the succeeding layer via a weighted link. When an input vector is presented to the BP network, each input unit is assigned to one of the input vector component values. The units in the next layer receive the input unit values through links and compute output values to pass to the next layer. In each unit of the middle layers or the output layer, the sum of input values is restricted between 0.0 and 1.0 by a sigmoid transfer function (1).

$$f(x) = 1/(1+e^{-x}) \qquad (1)$$

This process continues until the output layer produces an output vector for the BP network. After an input vector propagated forward to the output layer through the middle layers, the reference output vector for the input vector is used to compute an error value for each unit in the output layer. These error values are reduced by adjusting the weight value of the links. This operation is called "training". At the output layer, each weight value for a unit is adjusted to minus partial differential orientation for the corresponding error value. On the other hand, for the update weights at each middle layers unit, a composite function of all error values in the succeeding layer have to be used. Because weight values in a layer affect all units of a succeeding layer. This is why the sigmoid transfer function is used by each unit in the middle layers or the output layer.

The BP network which is well trained by a real problem must has a generalization property. It means that when this network is given an input vector which is different from the training input, the network can output the appropriate result for the problem. In general, the network training with higher generalization property depends on the amount of training data.

Training Data Acquisition and Application of the Neural Network for the PS-MR

There are two periods for the beam orbit tuning in order to reduce the beam loss. One is the injection period, and the other is the several ten milliseconds after the beam acceleration at which the orbit shape transforms significantly. The orbit tuning is divided into two works; one is for the horizontal direction and the other is for the vertical direction. A precise orbit tuning is not necessary for horizontal direction, because the dimensions of the beam pipes are landscape and there are enough clearance for the beam and the pipe's wall. Thus, the BP network of the orbit tuning is trained for the relationship between the vertical beam position and corresponding beam loss at the injection period. The training data for the BP network is acquired by following way. A certain beam orbit is transformed by some random local bumps. And then, a set of the training data which consists of the beam position data and beam loss data at that time is acquired.

Here, we assume that the BP network finished the successful training about the relationship between the beam position and loss and also, we could know the best shape of the beam orbit by the optimization. To actualize this best orbit shape for the PS-MR, the local bump method will be suitable. In theory, this method can move one of a beam position which is measured by a beam position monitor to the desired displacement and direction without any effect at other positions of the beam orbit. The local bump method is executed by using the steering magnets in three combinations. But in actual, this manipulation generates a few errors and gives undesired displacement to any other beam positions. It is cause that each parameter which decides the input of the steering magnet for the local bump has a little error. Then it may be difficult to actualize the best orbit shape by using this method. There is another problem that the orbit control system of the PS-MR will not acquire the training data with sufficient quantities to success the network training. Because this system is old, and the ability of the data processing or the data transmission speed cannot satisfy our demands.

To get the optimal solution which is applicable for the actual beam tuning, we use "a virtual beam orbit" to the input pattern of the BP training data. This orbit is generated at random from the ordinal beam orbit. Then, the input of the steering magnet which corresponds to this variation is calculated based on the local bump method. After this calculation, the ordinal beam is moved and changed beam loss data is acquired. The relationship between the virtual beam orbit and the beam loss can be restated the relationship between the input variation of the steering magnets and the beam loss. Although there are several differences between the shape of the virtual beam orbit and the shape of the actual beam orbit due to the previous problem of the local bump method, we expect the BP network to train within those errors.

There are two advantages for above operation. The first is that the actual beam position data doesn't need and the training data can be acquired effectively. The second is that the optimal solution by this way can be use to the actual beam tuning directly.

OPTIMIZATION TECHNIQUE

Though the optimization problem about the shape of the beam orbit realizes the minimum beam loss, it has many local minimum solutions. Avoiding these local minima and deriving a global optimal solution, we apply the Simulated Annealing (SA) which is one of the heuristic optimization methods. The detail of SA algorism is shown in [2].

EXPERIMENTAL RESULT

In this section, the experimental results for our approaches are shown. The training data of the BP network was acquired by following methodology on ground of the data acquisition ability of current the PS-MR orbit control system and limited data acquisition time.

Nine steering magnets out of twenty eight were chosen to give local bumps at the points of quarter range (2-1D~2-7D) of an arbitrary ordinal orbit. At this range, the shape of the virtual beam orbit was decided at random (maximum ± 4.0 mm from position zero, step 1.0 mm) and corresponding input of steering magnets was calculated. Then, the ordinal orbit was transformed and the amount of beam loss was changed. Figure 2 shows these operations.

The virtual orbit data and the changed beam loss data were bound to a set for training data to the BP network. Hence, the BP network for this experiment was constructed from 7 input units and 56 output units. Also the amount of middle layer units was decided 56.

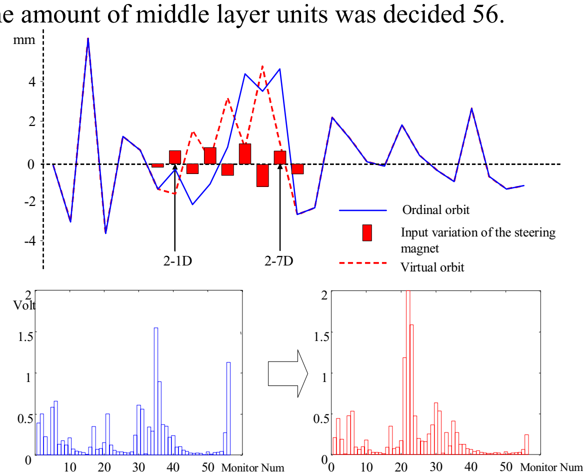

Figure 2: The beam loss variation by the random local bump.

At the experiment in June14, 2004, thirty sets of the training data could be obtained for 1 hour of beam tuning time. The training for the BP network finished about 50 minutes, where the error tolerance of the network outputs for training data was configured 0.002. For the optimization of the trained network, the best input pattern was searched by using normal random numbers (average 0, dispersion 0.2). The performance criterion for the evaluation of the solution was 1-norm of the network output vector. Figure 3 shows the expectation from optimization result and Figure 4 shows actual result in June 21, 2004.

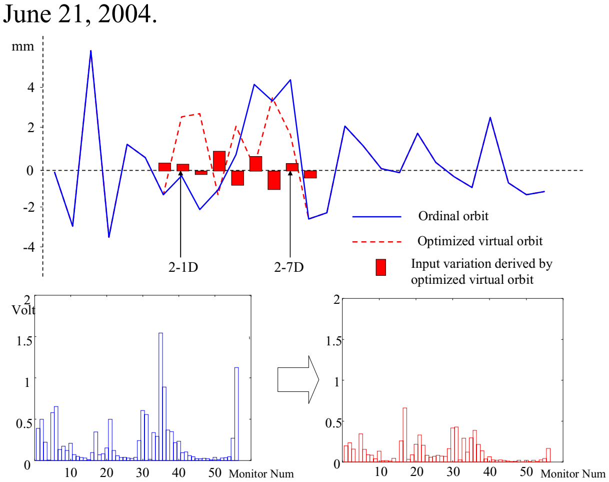

Figure 3: Expected result by optimization.

Figure 4 shows the total beam loss decrease slightly. However, expected result from optimization for the trained network was not obtained. There are two reasons. First, we didn't have time to obtain enough amount of the training data set in there experiments. We will update each devices of orbit control system to enable more high-speed data acquisition. The second reason, as shown in Figure 4, was the variation of the orbit shape due to the passage of time. In other words, the property of the accelerator changes as time advances. For this problem, online training will be necessary for the neural network to adapt the change of the accelerator's property.

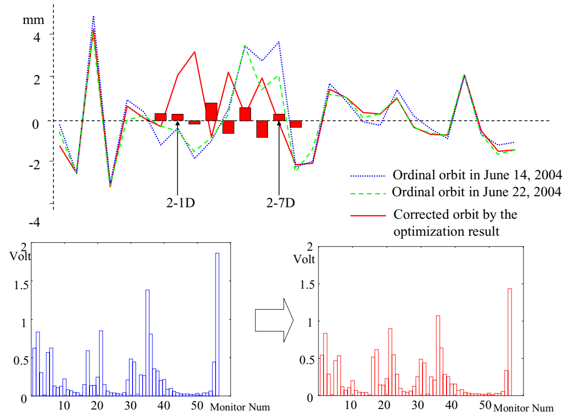

Figure 4: Experimental result.

CONCLUSION

Although the experimental result figured out some problems for our beam tuning approach, our approach performed to reduce beam loss. The neural network is effective for the orbit tuning operation because witless orbit correction causes huge beam loss.

In the future, we'll achieve the neural network training with higher order precision and then, our method will be practical for actual beam orbit tuning of the accelerator.

REFERENCES

[1] Philip D. Wasserman, "ADVANCED METHODS IN NEURAL COMPUTING", Van Nostrand Reinhold, 1993.

[2] Colin R. Reeves, "Modern Heuristic Techniques for Combinational Problems", Blackwell Scientific Press, 1993.