TRANSIENT ORBIT OF INJECTION IN TAIWAN LIGHT SOURCE STORAGE RING

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Abstract

Top-up operation has been started since many years ago at Taiwan Light Source Storage Ring (TLS-SR). For this operation it is important to reduce the beam injections should not excite the oscillation of stored beams. For further reduction of these oscillations, corrections with injection kicker-magnets are used.The details of the study will be reported in this paper.

INTRODUCTION

This study aimed to minimize injection transverse beam oscillation of the Taiwan Light Source Storage Ring (TLS-SR). Artificial neural network (ANN) design software, known as computer-aided formula engineering (CAFE) [1], was used to analyze and optimize the injection kicker-magnets parameters of the storage ring. We aimed to identify the main influential the injection kicker-magnets parameters of the storage ring and, through optimization, develop the injection kicker-magnets parameters of the storage ring adjustment program that best stability and minimizes injection transverse beam oscillations.

RESEARCH PROCESS

Artificial Neural Network

ANNs are construction methods for nonlinear models. Among which, back-propagation networks (BPNs) are currently the most representative and commonly applied of the ANN learning models [2] [3].

Data Collection

The equipment that affects the injection transverse beam oscillations includes injection kicker-magnets(1~4). Each device has a tuning knob for the magnet voltage and timing settings with 8 values. The beam injection oscillations is determined by the turn-by-turn Beam Position Monitor (BPM) system data for the 40~340 turns integral value. Using MATLAB programming to establish the effective operating range of each quality factor, we employed a random number setting every minute to intercept different settings and response values. In total, 134 pieces of data were obtained.[4]

ANN Train- and -Test Analysis

After calculating the ANN model construction, we obtained the "train- and -test" error convergence curve, as shown in Fig. 1. They appear to converge after approximately 60 computations.

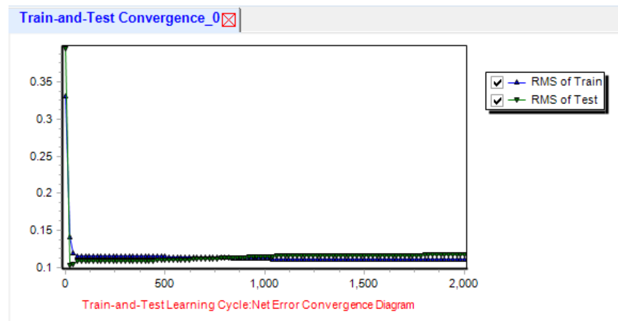

Figure 1: The "train- and -test " error convergence curve.

The "train- and -test " scatter plots for the training and test samples are shown in Figs. 2 and 3, respectively.

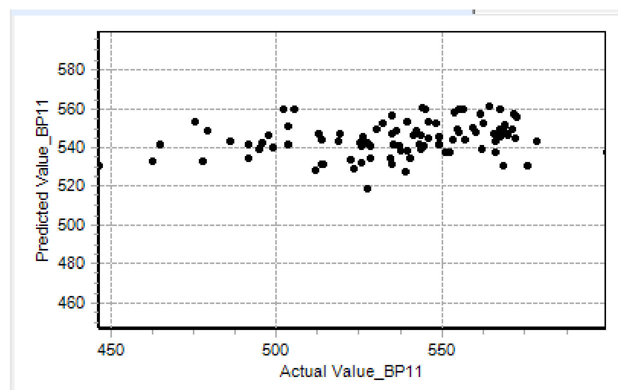

Figure 2: The "train- and -test " scatter plot of the training samples.

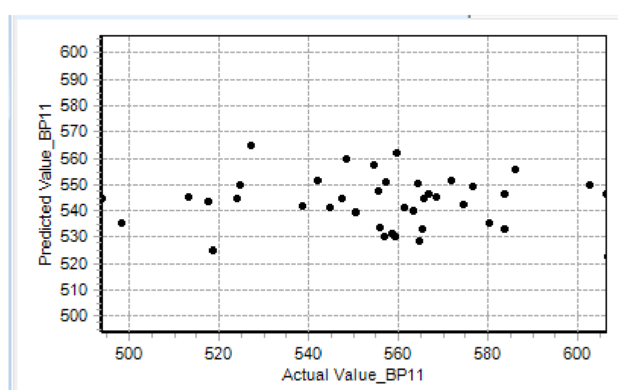

Figure 3: The "train- and -test " scatter plot of the test samples.

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Analysis of the experimental results included sensitivity analysis and influence line analysis. Sensitivity analysis was conducted using weight value analysis graphs, and influence line analysis was conducted using a main effect diagram with status. [4] The sensitivity analysis results revealed the significance of quality factors, are shown in Figs. 4 and 5. We found the kicker2(KV) and kicker4(KV) quality factor had the highest significance.

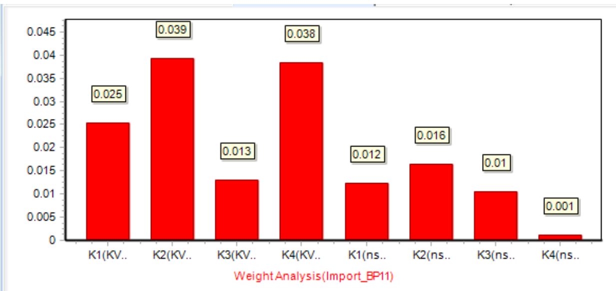

Figure 4: A bar graph of Y significance.

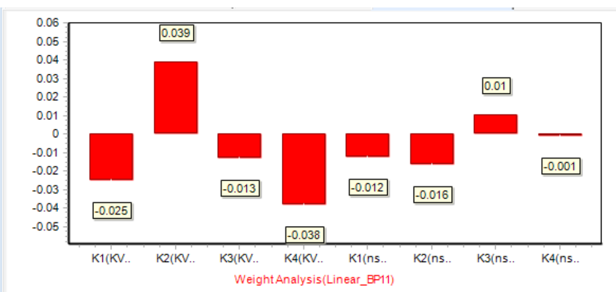

Figure 5: A bar graph of Y linear sensitivity.

Analysis of the results clearly showed the curved figure and significance of the quality factors, as shown in Fig. 6.

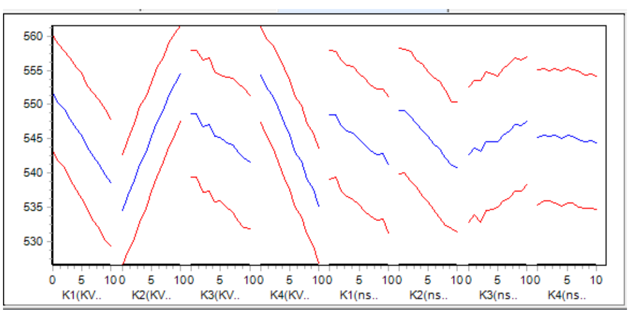

Figure 6: Status effect diagram.

The ANN-optimized parameter solution as shown in Fig. 7. The turn-by-turn Beam Position Monitor (BPM) system data for the 40~340 turns integral value was estimated as 510.47.

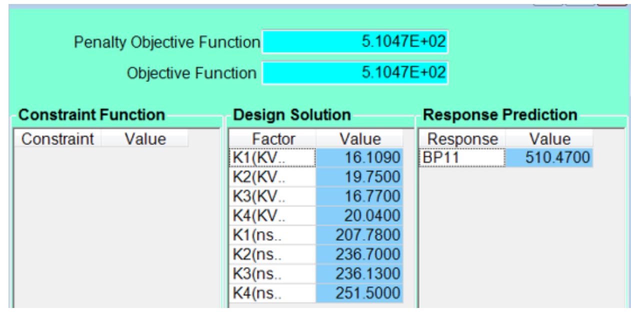

Figure 7: Optimal solution settings for ANN-optimized quality factors.

ANN Cross- and -Validation Analysis

After calculating the ANN model construction, we obtained the "cross- and -validation" error convergence curve, as shown in Fig. 8. They appear to converge after approximately 30 computations.

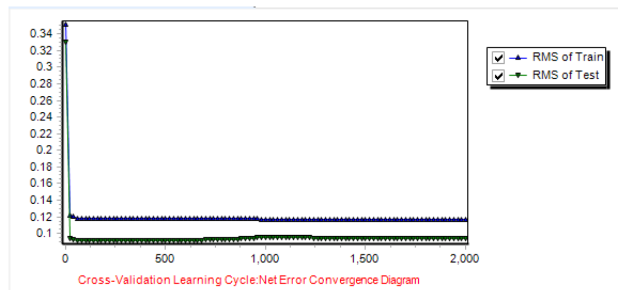

Figure 8: The "cross- and -validation " error convergence curve.

The "cross- and -validation " scatter plots for the training and test samples are shown in Figs. 9 and 10.

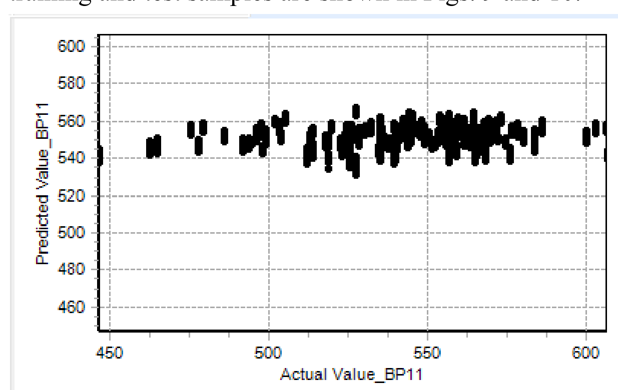

Figure 9: The "cross- and -validation " scatter plot of the training samples.

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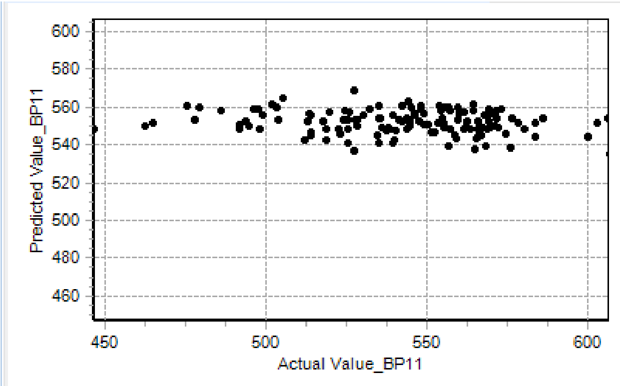

Figure 10: The “cross- and -validation ” scatter plot of the test samples.

The sensitivity analysis results revealed the significance of quality factors, are shown in Figs. 11 and 12. We found the kicker2(KV) and kicker4(KV) quality factor had the highest significance.

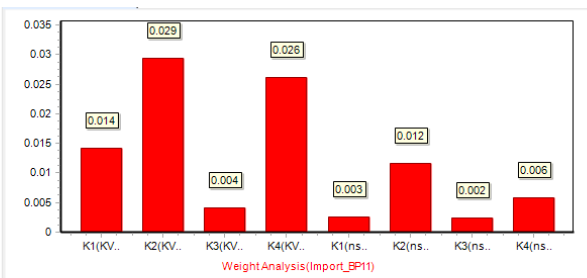

Figure 11: A bar graph of Y significance.

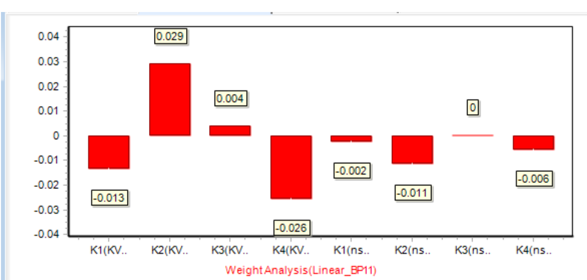

Figure 12: A bar graph of Y linear sensitivity.

Analysis of the results clearly showed the curved figure and significance of the quality factors as shown Fig. 13.

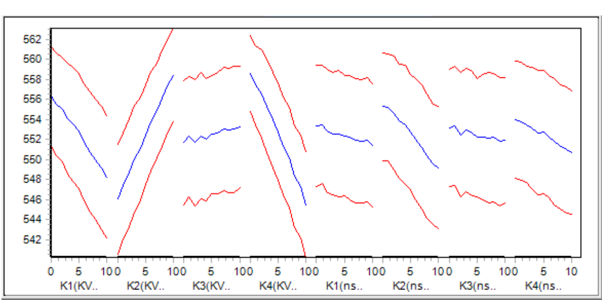

Figure 13: Status effect diagram.

The ANN-optimized parameter solution as shown in Fig. 14. The turn-by-turn Beam Position Monitor (BPM) system data for the 40~340 turns integral value was estimated as 531.30.

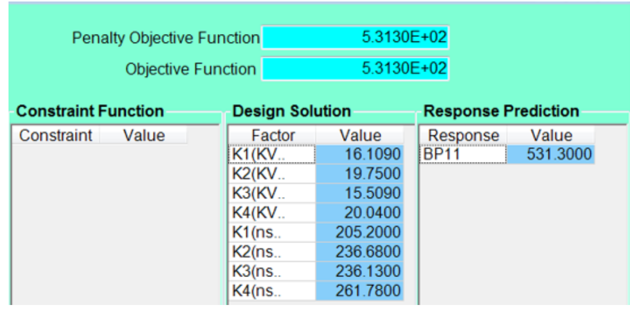

Figure 14: Optimal solution settings for ANN-optimized quality factors.

CONCLUSIONS

This study aimed to minimize injection transverse beam oscillations of the Taiwan Light Source Storage Ring (TLS-SR). Using ANN experiment methods to analyze and optimize the injection kicker-magnets parameters of the storage ring. Analysis of the experimental results. The ANN- “train- and -test”optimized the turn-by-turn (BPM11X) system data for the 40~340 turns integral value was estimated as 510.47. The ANN-“cross- and -validation ” optimized the turn-by-turn (BPM11X) system data for the 40~340 turns integral value was estimated as 531.30. The current that turn-by-turn (BPM11X) system data for the 40~340 turns integral value was estimated as 548.81. Only 0.38% improvement can be achieved excluding the prediction error. Current operating parameters had been set nearby to the optimum value , are shown in Figs. 15 and 16.

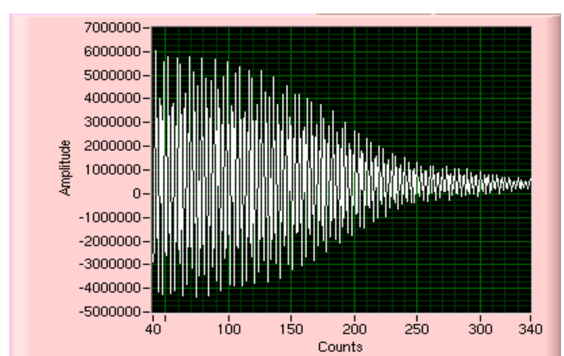

Figure 15: Current turn-by-turn (BPM11X)

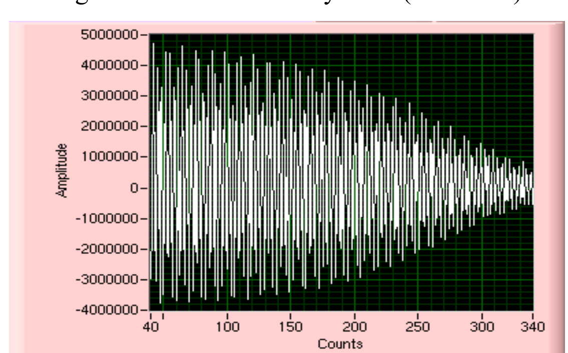

Figure 16: Optimal turn-by-turn (BPM11X).

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