OPTIMIZATION OF THE ELECTRON BEAM EXTRACTION EFFICIENCY IN A BOOSTER FOR TLS

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Abstract

Response surface methodology (RSM) was used to explore the optimization of electron beam extraction efficiency for the Taiwan Light Source (TLS) at the National Synchrotron Radiation Research Center (NSRRC). A study model was constructed based on artificial neural network (ANN) theory, using selected beam extraction tuning knobs as the variables. An optimization procedure was also developed by setting extraction efficiency as the objective function and the selected beam tuning knobs as the variables. Furthermore, the theoretical model and optimization procedure were practically implemented to verify the effectiveness of the model. By appropriately applying the constructed optimization procedure to examine electron beam extraction, the efficiency was effectively improved. The results of this research are discussed in this study.

INTRODUCTION

This study endeavored to improve the booster ring electron beam extraction efficiency in the National Synchrotron Radiation Research Center (NSRRC) using the basic theory of response surface methodology (RSM). Employing the artificial neural network (ANN)-constructed experiment design software known as Computer-Aided Formula Engineering (CAFE) [1] to analyze and optimize the parameters of the booster ring electron beam extraction efficiency, we aimed to identify the main influencing parameters and, through optimization, develop a parameter adjustment program that maximizes the efficiency of electron beam extraction.

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 booster ring electron beam extraction efficiency includes Bumper 1, Bumper 2, Bumper 3, a kicker, and a septum. Each device has a tuning knob for the magnet voltage (or current) and timing settings with 10 values. These values formed the quality impact factors in this study (Fig. 1). The electron extraction efficiency is determined by the size of the electric current detected by integrated current transformers (ICTs) (Fig. 2). 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, 460 pieces of data were obtained.

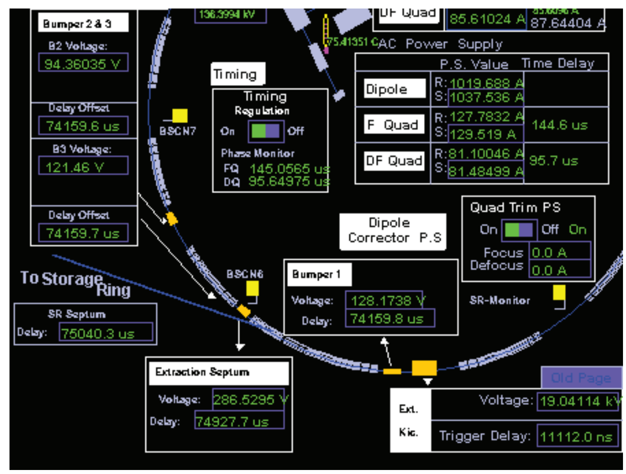

Figure 1: Electron beam extraction efficiency parameters [4].

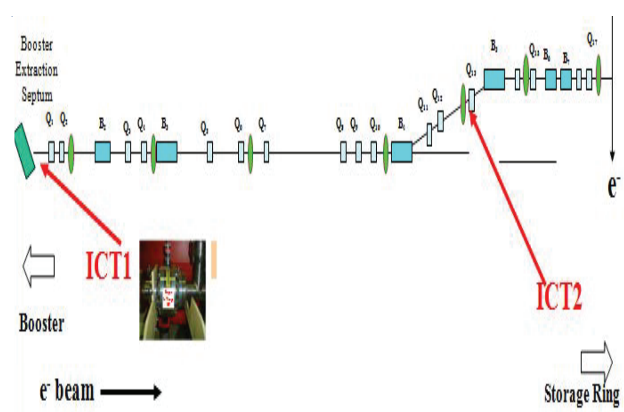

Figure 2: Positions of integrated current transformers [5].

Experimental Analysis

After calculating the ANN model construction, we obtained the "cross-validation" error convergence curve, as shown in Fig. 3. The representative model construction

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was ideal because they appear to converge after approximately 1,100 computations.

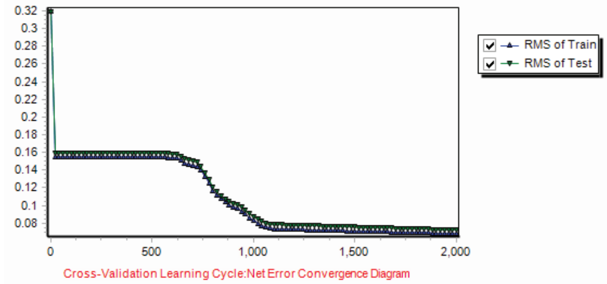

Figure 3: The "cross-validation" error convergence curve.

The "cross validation" scatter plots for the training and test samples are shown in Figs. 4 and 5, respectively. The predictive ability of the representative model was also ideal.

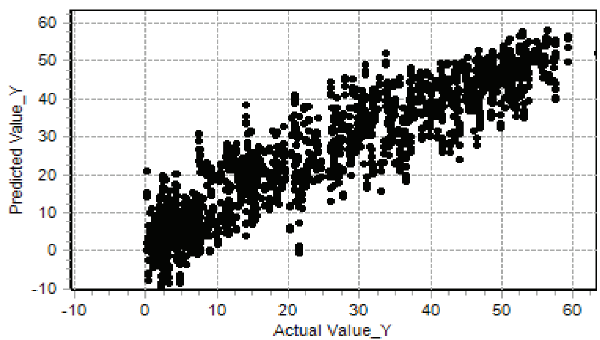

Figure 4: The "cross-validation" scatter plot of the training samples.

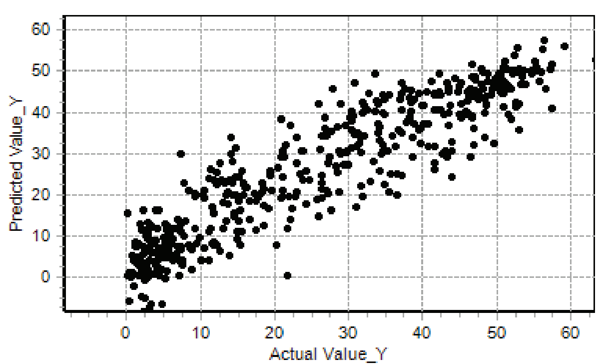

Figure 5: The "cross-validation" scatter plot of the test samples.

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. The sensitivity analysis results revealed the significance of quality factors, as shown in Figs. 6 and 7. We found that three quality factors had the highest significance, of which, the kicker voltage setting (X3) was the most significant.

- The weight of the kicker voltage setting (X3) was 0.338.
- The weight of the Bumper 1 current setting (X5) was 0.203.
- The weight of the Bumper 2 current setting (X7) was 0.263.

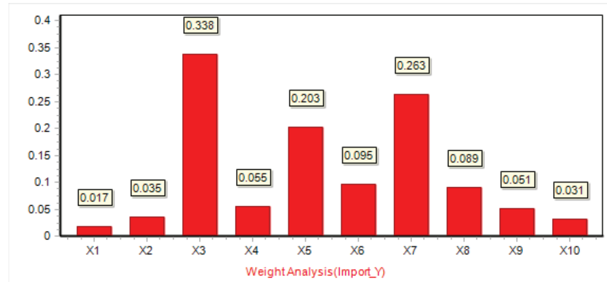

Figure 6: A bar graph of Y significance.

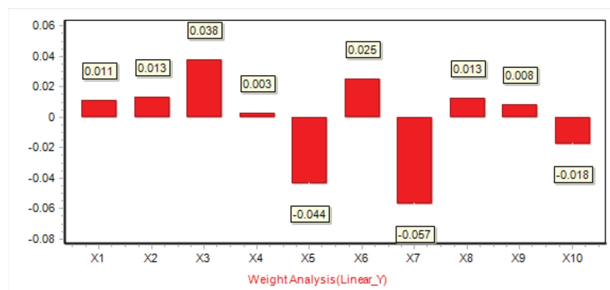

Figure 7: A bar graph of Y linear sensitivity.

Analysis of the results clearly showed the curved figure and significance of the quality factors (Fig. 8).

- Kicker voltage settings (X3)
- Bumper 1 current settings (X5)
- Bumper 2 current settings (X7)

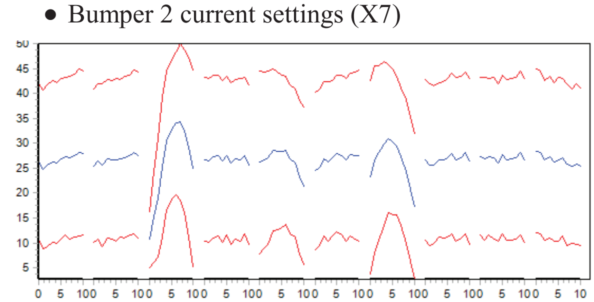

Figure 8: Status effect diagram.

After programming the quality factors for optimization, the ANN-optimized parameter solution was found. The quality factor optimization convergence process showed that convergence occurred after approximately 90 searches (Fig. 9). The ANN-optimized parameter solution is shown in Fig. 10. The booster ring electron beam extraction efficiency was estimated as 63.31%.

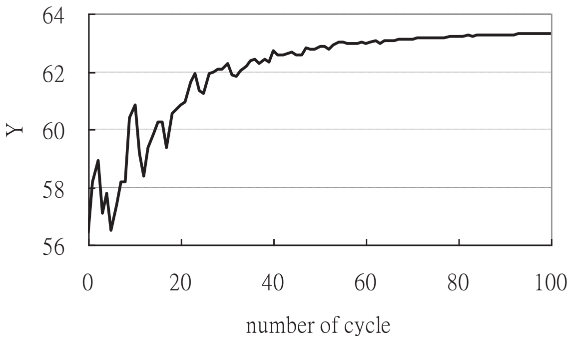

Figure 9: Convergence process diagram.

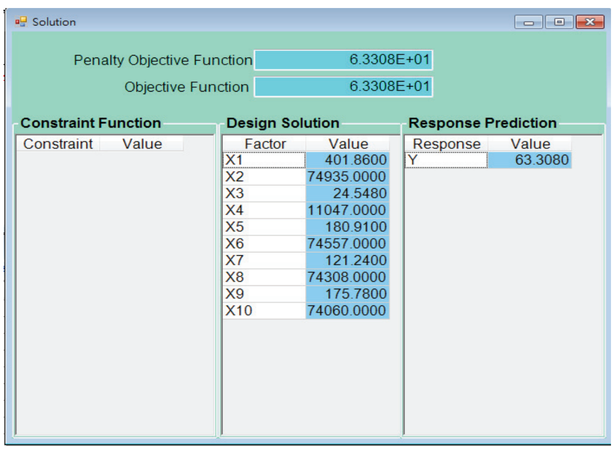

Figure 10: Optimal solution settings for ANN-optimized quality factors.

Using the ANN-optimized quality factor setting combination, actual machine tests showed that the booster ring electron beam extraction efficiency could be increased from an average of approximately 40% to approximately 73%.

Result Verification

Using the ANN-optimized quality factor setting combination, actual machine tests showed that the booster ring electron beam extraction efficiency could be improved from an average of approximately 40% to approximately 73%.

Based on the analysis results, appropriate adjustments were made for the three most significant quality factors, namely, the kicker voltage value (X3), Bumper 1 current value (X5), and Bumper 2 current value, and an actual test was conducted. The electron beam extraction efficiency was further improved to 83%. The procedure for the entire empirical experiment is shown in Fig. 11. In the graph, the Y axis represents the electron beam extraction efficiency, and the X axis represents the electron beam extraction time. The electron beam extraction achieved a maximum of 85.5%, a minimum of 37.1%, and an average of 67%. From right to left, the curve changes from the original machine parameter settings, where the electron beam extraction efficiency averaged approximately 40%, to the ANN-optimized parameter settings, where the electron beam extraction efficiency averaged approximately 73%, to the adjusted optimal settings, where electron beam extraction efficiency averaged approximately 83%.

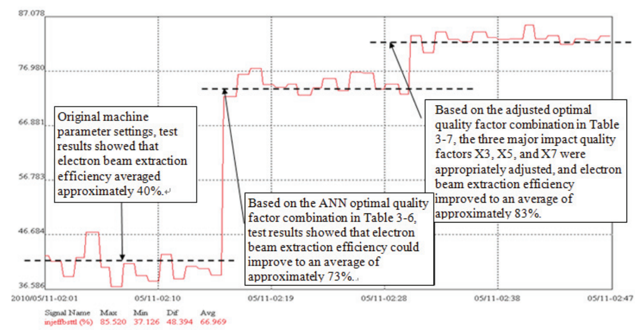

Figure 11: The optimization process of the electron beam extraction efficiency.

CONCLUSIONS

This study endeavored to improve the extraction efficiency of a booster ring electron beam at the NSRRC. Using BPN for analysis and the cross-validation experiment method to effectively estimate the generalization error, we developed an electron beam extraction efficiency estimation method using beam tuning knobs as the variables. Through experiment verification, the efficiency of electron beam extraction increased to an average of 83%. These results demonstrate the significant benefits of using ANN parameter optimization theory to enhance accelerator operation quality.

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