Neural Network Data Analysis in the Large Helical Device Thomson Scattering System

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In Thomson scattering diagnostics systems, a combination of the lookup table and the minimum χ² methods has been widely used to determine electron temperature. The concept of the minimum χ² method is based on clearly defined mathematical statistics. However, the minimum χ² method calculation requires a large amount of time because all χ² values have to be calculated at all temperatures included in the lookup table. Thus, this method is unsuitable for the real-time data analysis required for the next generation of fusion devices, e.g., the International Thermonuclear Experimental Reactor in France. To establish real-time data analysis for Thomson scattering diagnostics, we have developed a neural network program for the large helical device (LHD) Thomson scattering (TS) system. First, we systematically studied the number of nodes and training cycles required to obtain satisfactory results, and then applied them to the LHD TS system. The calculation time was successfully reduced by approximately 1/50 - 1/100 of the χ² method calculation time. In addition, experimental error estimation has been performed according to the concept of the neural network method used in this study.

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1. Introduction

In forthcoming thermonuclear fusion plasma research, real-time plasma diagnostics is an important issue. In current Thomson scattering (TS) diagnostics, the combined method of using a lookup table and the χ² method has been widely used to determine electron temperature (Tₑ). The concept of the traditional minimum χ² method is based on clearly defined mathematical statistics. However, this method requires a relatively long calculation time because all χ² values have to be calculated at all temperatures included in the lookup table. For example, the Tₑ range and the number of Tₑ points in the large helical device (LHD) TS lookup table are Tₑ = 0.1 eV - 50 keV and 7000 points respectively [1, 2]. Therefore, this method is likely unsuitable for real-time data analysis.

To establish real-time data analysis in TS diagnostics, we applied the neural network (NN) method to determine Tₑ. In the Korea Superconducting Tokamak Research (KSTAR) and Huan-Liuqi-2A (HL-2A) TS systems, this method has already been successfully applied [3, 4]. We developed a new program for the LHD TS system that can be applied to the KSTAR and HL-2A TS systems [5–8]. Section 2 describes the developed NN program, which includes an error estimation procedure according to the concept of the NN method. The application of the developed program in the LHD TS diagnostic is presented in Section 3.

2. The Neural Network Method for Large Helical Device Thomson Scattering Diagnostics

2.1 Fundamentals

NN methods have been widely applied in various scientific fields. Once the training process has been completed in the NN method, calculation time is expected to be reduced even for complicated processes such as nonlinear processes with many input and output parameters. Although the basic concepts of the χ² method and the NN method are quite different, it is expected that the NN method will provide good results through proper training. Figure 1 shows a diagram of the NN program used in this study. In the LHD TS system, Tₑ is determined by five signals experimentally measured using a polychromator with five wavelength channels [1, 2]. Accordingly, the number of input parameters is five and the number of final results Tₑ is one. In this study, the depth of the hidden layer is fixed at one. The sigmoid function, $y = 1/[1 + \exp(-x)]$, is used as the activation function.

In the NN program, input and output parameters are normalized to be non-dimensional values. The exper-
Eqs. (4) and (5): 

\[ t = \frac{\log(T_e/T_{e\text{min}})}{\log(T_{e\text{max}}/T_{e\text{min}})} \]  

where \( t \) means the temperature inside the program, and \( T_{e\text{min}} \) and \( T_{e\text{max}} \) are the minimum and maximum values of \( T_e \) in the used lookup table, respectively. The output from the \( j \)-cell in the hidden layer is given as follows:

\[ \alpha_j^B = \frac{1}{1 + e^{-\alpha_j^B}}, \quad \alpha_j^B = \sum_i w_{ij}^B \alpha_i^B + th_j^B, \]  

where \( w_{ij} \) is the weight and \( th_j \) is the bias parameter. Similarly, the final output, \( o_i \), is given as follows:

\[ \alpha_i^C = \frac{1}{1 + e^{-\alpha_i^C}}, \quad \alpha_i^C = \sum_j w_{ij}^C \alpha_j^C + th_i^C. \]  

Once the training process is completed, \( T_e \), can be easily calculated using the NN parameters determined in the training process.

In addition to determining \( T_e \), estimating experimental error (\( \Delta T_e \)) is also important in experimental studies. \( \Delta T_e \) is calculated using the same NN parameters shown in Eqs. (4) and (5):

Error in the final output:

\[ (\Delta \alpha_i^C)^2 = \sum_j \left( \frac{\partial \alpha_i^C}{\partial \alpha_j^B} \Delta \alpha_j^B \right)^2 = \sum_j \left( (\alpha_i^C (1 - \alpha_i^C) W_{ij}^C) \Delta \alpha_j^B \right)^2. \]  

Error in the hidden layer output:

\[ (\Delta \alpha_j^B)^2 = \sum_i \left( \frac{\partial \alpha_j^B}{\partial \alpha_i^A} \Delta \alpha_i^A \right)^2 = \sum_i \left( (\alpha_j^B (1 - \alpha_j^B) W_{ij}^B) \Delta \alpha_i^A \right)^2, \]  

where \( \Delta \alpha_i^C \) is the error of the final output, \( \alpha_i^C \), and \( \Delta \alpha_j^B \) is the error of the hidden layer output, and \( \Delta \alpha_i^A \) is the error of the input layer, i.e., the experimental errors included in the raw experimental signals. The error in the raw data propagates through Eqs. (4) and (5) to the error in the final result.

Based on the above results, we performed the training.
procedure for all polychromators. Figure 4 shows an example of the results for $N_{\text{nodes}} = 10$ and 50. The number of trainings was $N_t = 1 \times 10^5$. The horizontal and vertical axes show the target temperature, $T_0$, and the calculated temperature, $T$, respectively. As seen in the Fig. 4, the agreement of $T_0$ and $T$ is worse in low and high $T$ ranges. This deviation is due to the LHD polychromators are optimized to the temperature range $10 \, \text{eV} \leq T \leq 10 \, \text{keV}$. As expected (see Figs. 2 and 3), no clear difference was observed between the cases of $N_{\text{nodes}} = 10$ and 50. In low- and high-temperature regions, slight deviations between $T_0$ and $T$ are observed. However, a positive agreement was indicated in the intermediate region. In regard to the normalization of $T$, a logarithm-type approach (Eq. 1) was used in this study. The KSTAR NN program uses a simple and linear normalization, i.e., $t = T / T_{\text{max}}$, where $T$ is the electron temperature and $T_{\text{max}}$ is the maximum temperature in the lookup table [3]. We compared results using the two normalization methods for the LHD TS. No clear or significant difference was observed between the results from the two methods.

3. Application in the LHD TS System

Using the NN parameters determined in the previous section, we calculated $T_e$ and $\Delta T_e$ and compared them to those obtained by the traditional minimum $\chi^2$ method. Figures 5(a) and (b) show examples of the $T_e$ profile and the temporal history of $T_e$ at the plasma center, respectively. In both figures, $\Delta T_e$ values are also plotted (lower curves). As shown in the figures, the two $T_e$ values derived using the NN and $\chi^2$ methods show good agreement. For the $\Delta T_e$, small deviations are observed near the center high-temperature region. However, the overall agreement is good. Therefore, we consider that the accuracy and reliability of the NN method is as good as those of the $\chi^2$ method.

With regard to calculation time, we first divided the total calculation time, $t_T$, into four elements: data reading time from an analog-to-digital converter to a personal computer, $t_R$; preprocessing time (e.g., background signal subtraction), $t_P$; data analysis time, $t_A$; and the data writing time to a hard disk drive, $t_W$; $t_T = t_R + t_P + t_A + t_W$. In the case of the LHD TS system, the ratio is typically $t_R : t_P : t_A : t_W \approx 3:20:30:2$. The NN method was significantly faster than the $\chi^2$ method, $\sim 1/50 - 1/100$ of $t_A$. The typical total calculation time of a $T_e$ profile including 144 spatial points was $\sim 30$ msec and $<\sim 1$ msec for the $\chi^2$ and
NN methods, respectively. The other three factors, $t_R$, $t_P$, and $t_W$ were the same for both $\chi^2$ and NN data analyses. In future work, we aim to reduce the preprocessing time, $t_P$, which is the most time-consuming process of the three factors, to further decrease total calculation time.

4. Conclusion

The NN method is one of the candidates for reducing data analysis time in TS diagnostics. We have developed a new program for the LHD TS system. The $T_e$ and $\Delta T_e$ values calculated by the NN and minimum $\chi^2$ methods show very good agreement. We consider that the accuracy and reliability of the NN method are as good as those of the $\chi^2$ method. Data analysis time was reduced when the NN program is used for 1/50 - 1/100 that of the $\chi^2$ method. This is an attractive feature for real-time data analysis in TS diagnostics. In addition to this merit, the data memory size required for the NN method is much smaller than that of the lookup table method. The NN method is thus suitable for calculation using a mini-board computer and GPU based system, in which memory size is limited [9].

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