BP Neural Network for Temperature Prediction of Alpha Magnetic Spectrometer on Orbit

Fei Yang¹, Qie Sun¹, Lin Cheng²

¹ Institute of Thermal Science and Technology, Shandong University, 250061 Jinan, PR China
² Shandong Institute of Advanced Technology, 250100 Jinan, PR China

qie@sdu.edu.cn (Qie Sun), cheng@sdu.edu.cn (Lin Cheng)

Abstract. A BP neural network combined with the Adam optimization algorithm and the Mini-batches Learning algorithm was established for predicting the temperature of BOX-C on Alpha Magnetic Spectrometer (AMS) in this paper. After training, the Mean Squared Error (MSE) of the prediction results under the normal operating condition is 0.14 and this shows that the model can be used to predict the temperature of BOX-C with a satisfying accuracy. The model paves the ground for AMS thermal control on orbit.

1. Introduction

Alpha Magnetic Spectrometer (AMS) is a particle physics detector installed on the international space station (ISS) (Figure 1) [1]. Effective thermal control is quite essential for the operation of AMS. There are over 1100 sensors on AMS to monitor the temperature of different components in real time.

Figure 1. AMS on the ISS

So far, low temperature anomalies occurred mainly at the gas circulation box (BOX-C) of the transition radiation detector (TRD) (Figure 2), of which the low temperature warning limit is 10°C. To solve warnings, a thermal blanket was installed with the consent of NASA. Since then, the thermal environment for the covered area have been changed. Therefore, it is necessary to understand the new thermal environment in order to update the corresponding thermal control strategies.

During the operation of AMS, many factors such as solar radiation, angle β, ISS flight attitude, affect its thermal environment. These factors plus special operations of the ISS make it difficult to calculate temperature field of each component in space using traditional thermodynamic models.

BP neural network is a multi-layer feedforward network trained by the error back propagation algorithm and it has been widely applied to various research areas, including aerospace studies. However, most existing research adopted full connection between layers [2,3]. This kind of structure has a common...
problem of overfitting. In terms of activation function, Sigmoid activation function is the most widely used method and it is subject to the problem of gradient disappearance [4]. In addition, most traditional optimization algorithms used a single learning rate with low computational efficiency. To fill the knowledge gaps, this paper aims to establish an improved BP neural network for predicting the temperature of AMS. The specific focus is on the temperature changes of the BOX-C after the installation of the thermal blanket when the ISS is under the normal operating condition on orbit.

2. Dynamic characteristics of AMS thermal environment
AMS flies with the ISS on a low Earth orbit at the height of 370–460 km. The thermal environment of AMS is jointly affected by the external heat fluxes and other components on the ISS. External heat fluxes include solar radiation, solar radiation reflected by the Earth and infrared radiation of the Earth.

2.1. Solar radiation
Solar radiation received by the ISS mainly depends on its relative position to the sun, which can be characterized by three parameters: angle β, angle θ and Sunlight Exposure Factor (SEF).

Angle β is the angle between sunlight and orbital plane. For ISS, angle β varies from -75.1° to +75.1°. Angle θ represents the position of the ISS relative to the nearest point to the sun on its orbit. When ISS enters the shadow area of the Earth, AMS cannot receive direct solar radiation. SEF indicates the proportion in a single orbital cycle, where ISS can receive solar radiation (Equation 1).

\[
SEF = 1 - \frac{1}{180} \cos^{-1} \left( \frac{1 - \frac{R_E^2}{(R_E + h)^2}}{\cos \beta} \right)
\]

Therefore, the heat flux from solar radiation received by the ISS can be calculated as:

\[
q_{solar} = \begin{cases} 
S \max(\cos \beta_s, 0) & \theta \not\in [\theta_i, \theta_o] \\
0 & \theta \in [\theta_i, \theta_o]
\end{cases}
\]

where S is the solar constant and 1367 W/m² is used in this study; θ varies in the range [θ_i, θ_o] according to position of the ISS; β_s is the angle between the sunlight and the normal direction of the exposed area, which can be derived from:

\[
cos \beta_s = \sin \delta \sin \beta + \cos \delta \cos \beta \cos \alpha
\]

For BOX-C, heat flux from solar radiation is related to angle β and SEF. Since SEF is dependent on angle β, heat flux to BOX-C can be expressed as a single-variable function of angle β.

2.2. Solar radiation reflected by the Earth
It is assumed that the solar radiation reflected by the Earth is diffuse and the albedo of the Earth (ρ) is 0.27. The heat flux of the reflected solar radiation can be approximately calculated as:

\[
q_{albedo} = \Phi_{IR} \rho \max(0, \cos \theta \cos \beta)
\]

where \(\Phi_{IR}\) is the angular coefficient of the Earth’s infrared radiation on AMS surface.

2.3. Infrared radiation of the Earth
The infrared radiation of the Earth on a certain part of the ISS can be calculated as:

\[
q_{IR} = \Phi_{IR} E_{IR} = \Phi_{IR} \frac{1 - \rho}{4} S
\]

For the port side of the AMS, where BOX-C is located, \(\Phi_{IR}\) is calculated as:

\[
\Phi_{IR} = \frac{1}{2\pi} \left[ \pi - 2k \sqrt{1 - k^2} - 2 \sin^{-1} \sqrt{1 - k^2} \right]
\]

\[
k = \frac{R_e}{R_e + h}
\]

where \(R_e\) is the equatorial radius of the Earth, i.e. 6378.14 km; h refers to the orbital altitude of the ISS, which is assumed to be 400 km in this study.

2.4. Other components on the ISS
Two main radiators are respectively installed on the port side and the starboard side of the ISS and they can be rotated by adjusting the ISS thermal radiation rotation joints (TRRJ). Adjusting port side TRRJ (PTRRJ) and starboard side TRRJ (STRRJ) can reflect solar radiation to the port side of AMS and thus increase external heat flux.

According to the above analysis, β, PTTTRJ and STTRJ will be involved into the BP neural network for predicting the temperature of BOX-C.

3. Method and data

3.1. BP neural network
To improve the generalization ability of the BP neural network, dropout algorithm was adopted. Some neurons are randomly discarded with a certain dropout rate in the training procedure in order to reduce the problem of overfitting and inter-dependence between neurons.

Common activation functions used are Sigmoid function and Tanh function, which have the problem of gradient disappearance. By contrast, ReLU activation function has the advantage of biological rationality. The present study thus employs the ReLU activation function to introduce nonlinear features into the BP neural network.

Mini-batches learning algorithm calculates the loss function of a small portion of the training data every time, called a batch. This can greatly reduce the number of iterations required for convergence and thus save computational effort without affecting training accuracy. Batch size will affect the speed and performance of model optimization. This study searched for the optimal batch size by comparing the training performance of different batch sizes. The test started from 2 to 1024.

Commonly used optimization algorithms include stochastic gradient descent (SGD), adaptive gradient (AdaGrad), AdaDelta, Ada Max, root mean square propagation (RMSProp), adaptive moment estimation (Adam) and Nd Dam [5]. In this paper, various optimization algorithms are compared to determine the most accurate one.

3.2. Data collection and adoption
The temperature of AMS under the normal operating condition were applied to the BP neural network for training and prediction. 80% of the data were randomly selected for model training and the rest 20% data were used for validation.

3.3. Model training
To obtain the optimal structure of the BP neural network, the number of hidden layers (1-5 layers), the number of neurons in each hidden layer (100-140 neurons), dropout rate of neurons (0-0.9) and batch-size of training (2-1024) are jointly considered. A total of 2500 model structures, i.e. 5 (layer) * 10 (dropout rate) * 10 (batch-size) * 5 (number of neuron in each hidden layer), were tested and the optimal structure was obtained to achieve the highest prediction accuracy.

4. Results
After training, the BP neural network model and the main findings are report as follows.

4.1. The optimal structure of the neural network
In the total 2500 model structures, the optimal structure of the neural network is: 3 hidden layers, 120 neurons in each hidden layer, dropout rate being 0.2 and batch-size being 32, i.e. the smallest MSE, i.e. 0.161, is obtained under this model structure in all combinations of the parameters.

The influences of number of hidden layers on prediction accuracy were calculated with dropout rate being 0.2, batch-size being 32 and training epoch being 100. The MSEs of the model with three hidden layers can be reduced to about 0.161 with more neurons and the approximate interval of the number of neurons in each hidden layer is 100 to 140.

Figure 3 shows the influences of dropout rate and batch-size on prediction accuracy, where the number of neurons in each hidden layer was 100 (Figure 3(a)) and 120 (Figure 3(b)).
4.2. The impact of optimization algorithm

Different optimization algorithms were used to train the BP neural network and the MSEs of the training processes are shown in Figure 4. The results show that the BP network with the Adam optimization algorithm has significant advantage in convergence speed and prediction accuracy over the other models. The MSE of the BP neural network with the Adam optimization algorithm decreased to 0.161, which is the smallest in all models.

4.3. The impact of training epoch

Training epochs can greatly affect the prediction accuracy of neural networks and the time required for computation. Regarding the prediction of AMS temperature, the effects of training epochs are shown in Figure 5. 600 epochs of training achieved the most accurate prediction results.

4.4. Validation of the BP neural network model

Validation of the BP neural network model was implemented by comparing the prediction results with the measured data. To achieve this objective, 120 predicted temperature values were randomly selected and compared with corresponding measurements (Figure 6).
Since the predicted temperature for validation was randomly selected, the data do not cover a full range of angle $\beta$. In general, predicted temperature is in good agreement with measured temperature, with the MSE being 0.14. The result indicates that the BP neural network with the improved structure is accurate for predicting the temperature of AMS BOX-C under the normal operating condition. The prediction accuracy is relatively low when angle $\beta$ is near the extremes. The ISS usually performs special operations when angle $\beta$ approaches the extreme and thus the amount of measured data under normal conditions (without special operations) becomes smaller. The decrease in the amount of data for training affects the prediction accuracy.

4.5. Temperature prediction for AMS BOX-C

The BP neural network model determined from previous steps was utilized for predicting the temperature of AMS BOX-C under the normal operating condition. According to statistics, the starboard side radiator of the ISS is ported at $+25^\circ$ in 93.68% of all working conditions, while the port side radiator is ported at $-40^\circ$ in 70.79% of all working conditions. Therefore, temperature was predicted according to the variation in angle $\beta$ when STRRJ is ported at $+25^\circ$ and PTRRJ is ported at $-40^\circ$.

Figure 7 shows the temperature prediction for AMS BOX-C in a full range of angle $\beta$ under the normal operating condition. The temperature of BOX-C varies between 13.84°C and 17.01°C and this satisfies the requirements for thermal control. In addition, the prediction results imply that the installation of the thermal blanket eliminates the low temperature warnings at BOX-C under the normal operating status [6]. The remaining low temperature warnings were mainly due to the special operations of the ISS [7].

5. Conclusions

A BP neural network was established for predicting the temperature of BOX-C on AMS. To achieve high prediction accuracy, the study implemented several steps to determine the structure of the BP network, including: (1) the model includes one input layer with three neurons, three hidden layers with 120 neurons on each layer and one output layer with one neuron; (2) the dropout rate 0.2 was adopted; (3) the batch-size 32 was used in the mini-batches learning; (4) the Adam optimization algorithm was adopted to minimize the loss function; (5) 600 epochs of training were implemented; and (6) a total of over 100,000 measured data from October 29, 2015 to February 1, 2018 were used in this study. With the BP neural network, the MSE is 0.14, which is accurate enough for predicting the temperature of AMS BOX-C under normal operating conditions.

With the BP neural network model, the temperature variations of AMS BOX-C can be accurately understood. Plus the influences of ISS special operations, the strategies on AMS thermal control can be developed. In addition, this study also provides a reference for analysing and predicting periodic temperature changes in complex temperature fields in outer space.

6. References

[1] Ting S 2013 The alpha magnetic spectrometer on the international space station *Nucl. Phys. B* - *Proc. Suppl.* 243–244 12–24

[2] Li Z, Xu R, Cui P and Zhu S 2018 Artificial Neural Network Based Mission Planning Mechanism for Spacecraft *Int. J. Aeronaut. Sp. Sci.* 19 111–9

[3] Leeghim H, Choi Y and Bang H 2009 Adaptive attitude control of spacecraft using neural networks *Acta Astronaut.* 64 778–86

[4] Amari S I 1998 Natural Gradient Works Efficiently in Learning *Neural Comput.* 10 251–76

[5] Duchi J, Hazan E and Singer Y 2010 Adaptive subgradient methods for online learning and stochastic optimization *COLT 2010* - 23rd Conf. Learn. Theory 12 257–69

[6] Yang F, Sun Q and Cheng L 2020 Effects of the thermal blanket on AMS-02 *Nucl. Instruments Methods Phys. Res. Sect. A Accel. Spectrometers, Detect. Assoc. Equip.* 962 163608

[7] Wang K, Sun Q, Song L, Cui Z, Wang N and Cheng L 2015 Investigations on the temperature warnings of the Alpha Magnetic Spectrometer on the International Space Station *Nucl. Instruments Methods Phys. Res. Sect. A Accel. Spectrometers, Detect. Assoc. Equip.* 791 69–79