Research Article

In-Orbit Temperature Prediction of Alpha Magnetic Spectrometer Based on the Neural Network Model

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The Alpha Magnetic Spectrometer (AMS) is a high-precision particle detector deployed on the International Space Station (ISS) to look for the origin of dark matter, antimatter’s existence, and the origin and features of cosmic rays. Analyzing and forecasting the thermal status of electric equipment of AMS is of great significance to ensure that they operate within acceptable temperature limits. In this study, the orbital parameters of the AMS and thermal data of the main radiators are analyzed. Artificial neural network models are established for predicting the temperatures of AMS in orbit under the ISS normal and special operating conditions. The mean squared errors (MSE) of the predictions after the model training show that the established neural network models can accurately predict AMS temperatures. Comparison results between the recorded telemetry data and the predicted temperature obtained from the established neural network models show that the proposed models are precise enough for predicting AMS temperatures with the minimum MSE being 0.006. This work offers a reference for the thermal control of AMS and other spacecraft in orbit.

1. Introduction

Alpha Magnetic Spectrometer (AMS) is a large acceptance particle detector mounted on the International Space Station (ISS) to investigate the existence of antimatter and dark matter, the origin and features of cosmic rays, and novel phenomena in space [1]. An active thermal control system (TCS) is crucial for the safe and normal operation of AMS [2]. The AMS is made up of a permanent magnet and a series of particle detectors that monitor the velocity and charge of passing particles and nuclei. The transition radiation detector (TRD) is positioned at the top of the AMS, silicon tracker planes are located inside the magnet bore, higher and lower time-of-flight (H/LTOF) counters are positioned above and below the magnet bore, and electromagnetic calorimeter and ring image Cherenkov counter are located below the LTOF counters [3].

According to the recorded data, temperature anomalies have occurred on five components of AMS so far, especially the frequently low-temperature warnings at the gas circulation box (BOX-C) of the TRD [4]. To solve the low-temperature warnings at BOX-C, a thermal blanket was installed on the AMS port side with the consent of NASA in 2015 [5]. Since then, the internal and external thermal environment of AMS has been changed [6]. As a result, it is critical to understand AMS’s new thermal environment with the thermal blanket to update the associated thermal control techniques.

In time of AMS operating, several key factors, such as direct solar radiation, infrared radiation of the Earth, solar radiation reflected by the Earth, the angle \(\beta\), the ISS flight attitude, and positions of the ISS solar arrays and radiators, affect its thermal environment [7]. The complicated environmental factors and ISS special operations make it difficult to figure up the temperatures of AMS.

Artificial neural networks (ANNs) have become popular in recent years for forecasting the characteristics of complicated thermal management systems, such as performance prediction and load forecasting [8]. Backpropagation (BP) neural networks are typical multilayer feedforward neural network models and have been extensively used in various research fields, including aerospace, due to their outstanding
efficiency in data analysis [9]. Investigation of the TCS based on the in-orbit status is conducted by many scholars. Zhang et al. [10] established a BP neural network model to predict the temperature of a nanosatellite in orbit. Their study considered the major thermal environmental factors for nanosatellites, including solar radiation, infrared radiation by the Earth, and reflected radiation by the Earth which are similar to those for AMS. Li et al. [11] proposed an autonomous mission planning mechanism for spacecraft based on BP neural network models. Simulation results proved that the artificial neural network models are more efficient than the method provided by the extensible universal remote operations’ planning architecture. Ning [12] built BP neural network models to predict the temperature of the equipment installed on a satellite. The prediction error after training was approximately 1%, which shows the high precision and stability of the BP neural network models. In addition, BP neural network models are also used in space exploration to achieve the following research targets: determination of spacecraft orientation [13], stochastic tuning of spacecraft controller [14], and attitude control of spacecraft. Marco Molina et al. [15] presented techniques for TCS confirmation of the payload of the AMS and examined the entire system for the space setting in sequence. Cui et al. [3] provided an overview of the TCS and AMS and its thermal surroundings based on the analysis and correlation of the external parameters with the thermal status of various components. In terms of AMS thermal control, Shao et al. [16] applied artificial neural network models to predict the temperatures of AMS main radiators, and the errors are about 0.2°C. Although the study implies that ANN may have very good applicability to AMS, there has not been any study that applied ANNs to comprehensively forecast the temperature of different AMS surfaces or the key components where temperature anomalies frequently occurred.

To fill the knowledge gap, this study developed BP neural network models for forecasting AMS temperatures. To this aim, ISS orbital parameters and operating conditions that affect the external heat fluxes of AMS are used in the BP neural network models. The model structure and hyperparameters are optimized using the telemetry data. The contribution of the study is the development of a statistic model at high accuracy for the prediction of temperatures on various AMS surfaces and the key components with anomalies.

The remainder of the paper is ordered as follows. Section 2 analyses the thermal environment of AMS to determine the key influencing factors. The methods and data of established BP neural network models are presented in Section 3. Predicted results of the BP neural network models are discussed in Section 4, and the conclusion is presented in Section 5.

2. Analysis of AMS Thermal Environment

The thermal environment of AMS is affected by ISS orbital parameters and operating conditions. The key influencing factors that should be included in BP neural network models are determined in this section.

2.1. ISS Orbital Parameters. The main ISS orbital parameters influencing AMS external heat fluxes are ISS orbital altitude, angle β, and solar radiation intensity. The ISS orbital period and exposure time within an orbital period are determined by the ISS orbital altitude, which varies from 370 km to 460 km. Normally, the ISS orbital altitude is maintained at 400 km. The angle β represents the relative position between the sun and the ISS orbital plane, and it varies periodically between −75.1° and +75.1°. Solar radiation intensity varies with the distance between the Earth and the sun, which is 1322 W/m² at the apogee and 1414 W/m² at the perihelion. The present study is based on the solar radiation intensity of 1367 W/m². Figure 1 shows the AMS on the ISS.

2.2. ISS Operating Conditions. ISS operating conditions can considerably affect the thermal surroundings of AMS and three operations, i.e., adjusting ISS flight attitude, adjusting the fixed angle of ISS starboard radiator, and locking the ISS solar arrays, have significant effects on AMS. Since the ISS, in most cases, flies at the +XVV&+ZLV attitude, +X is aligned with the velocity vector of the ISS and +Z directs to the core of the Earth. Figure 2 shows the ISS Flight altitude, where the yaw, pitch, and roll (YPR) are −4.0°, −2.0°, and +0.7°, respectively; with the ISS starboard radiator being fixed at +25° and the ISS solar arrays operating in the automatic light tracing mode, it is referred to as the ISS normal operating condition, and other operating conditions are called ISS special operating conditions. There are two main radiators on the ISS, i.e., the port radiator and the starboard radiator. Since the ISS port radiator is far from AMS, this study mainly focuses on the impacts of the ISS starboard radiator. The rotation angle of the ISS starboard radiator is defined as STRRJ, which varies between −90° and +90°. The ISS starboard radiator is usually fixed at +25°, i.e., the normal operating condition. When the ISS conducts special missions, the ISS starboard radiator may be adjusted to other positions and STRRJ varies accordingly. When STRRJ is positive, the starboard radiator reflects solar radiation to AMS, while there is no solar radiation reflected to AMS by the ISS starboard radiator when STRRJ is negative. A total of eight solar arrays are installed on the ISS. They automatically trace the sunlight under the normal operating condition, while they can be locked at specific positions when the ISS performs special missions. Based on the ISS mission logs, the solar arrays were locked vertically when angle β was near the extreme values. The locked ISS solar arrays might block or reflect radiation to AMS and thus change its thermal environment. SA is defined to represent the operating mode of the solar arrays, where 0 stands for the automatic light tracing mode and 1 represents the locking mode.

In summary, since the present study aims to develop ANN models that can accurately predict the temperature on all AMS surfaces and at the key positions with anomalies, angle β yaw, pitch, roll, STRRJ, and SA are the factors impacting the AMS thermal environment under the ISS special operating conditions.
3. Method and Data

The neural network models of AMS under the ISS normal and special operating conditions were constructed and used for predicting temperatures. Based on the models, the temperature variations of seven parts of AMS were examined, and the predicted temperatures of AMS under the ISS normal and special operating conditions were given. Figure 3 shows the schematic outline of the research.

3.1. Data Preparation. Among 1118 temperature sensors of AMS, five sensors (1N-5, LVCR4, LVCR2, RR4, and WR2) were selected to represent the top, port, starboard, RAM (front), and WAKE (back) side of AMS surfaces, respectively. Considering the frequent temperature warnings that occurred at BOX-C and the power distribution system (PDS) of AMS, one sensor at each of the two parts was also selected. Figure 4 shows the location of these sensors. Telemetry data from January 1, 2016, to December 31, 2017, of these selected sensors were used for neural network models training in this study.

According to the ISS operating condition, the recorded telemetry data were classified into ISS normal operating condition and ISS special operating condition. Orbital average temperature data were calculated and used for model training. Finally, 1974 groups of data under ISS normal operating conditions and 8723 groups of data under ISS special operating conditions were obtained. Among them, 95% of the data were randomly divided to form the training dataset for model training and the rest 5% data were utilized for testing, i.e., model validation. All data were normalized and mapped to the interval [0, 1].

3.2. Neural Network Structure. Based on the traditional BP neural network model, the dropout algorithm was employed to avoid the problem of overfitting [17]. The ReLU activation function was adopted to avoid the problem of gradient disappearance in the training process [18]. Moreover, the Adam optimizer was used to optimize the loss function and improve the efficiency of model training [19]. In addition, by applying the minibatches’ learning algorithm, the whole training dataset was divided into small groups and the loss function was calculated using only a small group of data each time. Therefore, the iterations required for convergence are significantly reduced and the efficiency of parallelization operation is improved [20].

The hidden layers, the number of neurons inside each hidden layer, the dropout rate, and the training batch size are collectively considered to obtain the optimum prediction accuracy of the neural network models. Mean squared error (MSE) was used to measure the accuracy of the established neural network models.

4. Neural Network Models of AMS

After training, the neural network models achieved good prediction performance and the main outcomes are reported as follows.

4.1. Models of AMS under the ISS Normal Operating Condition. The neural network models of AMS under the ISS normal operating condition were established, as shown in Figure 5. The input layer is the angle $\beta$, and the output layer contains the orbital average temperatures of seven selected sensors. There are 100 neurons in each of the two hidden layers with the dropout rate being 0.2. After 100 training epochs, the MSEs of the neural network models were calculated with the batch size being 32. Table 1 lists the detailed results of the models, and the comparison between the recorded telemetry data and the predicted results by the established models are shown in Figure 6. Given that the data in the testing dataset were randomly selected, it does not cover a full range of angle $\beta$ and the data are not in the same orbital period. In general, predicted results using the established neural network models are in good agreement with the recorded telemetry data.

4.2. Models of AMS under the ISS Special Operating Condition. According to the analysis in Section 2, seven factors affect the thermal environment of AMS under the ISS special operating condition. Neural network models of AMS under the ISS special operating condition were established with six neurons ($\beta$, yaw, pitch, roll, STRRJ, and SA) in the input layer, and 100 neurons in each of the four hidden layers with the dropout rate being 0.2. After 100 training epochs, the MSEs of the neural network models under the ISS special operating condition were calculated with the batch size being 32. Table 2 lists the detailed results of the models, and Figure 7 shows the comparison between the recorded telemetry data and the predicted results for four of 436 groups.
2. Analysis of AMS thermal environment
3. Method and data
Selection, processing and normalization

Influencing factors
Model construction
Training dataset
Testing dataset

4. Neural network models of AMS
ISS normal operating condition
ISS special operating condition

Temperature prediction

Figure 3: Schematic outline of the research.

Figure 4: Location of the selected sensors.

Figure 5: Neural network models of AMS under the ISS.
Table 1: Results of the neural network models under the ISS normal operating condition.

| Sensor | 1N-5 | LVCR4 | LVCR2 | RR4  | WR2  | BOX-C | PDS-D |
|--------|------|-------|-------|------|------|-------|-------|
| MSE    | 0.013| 0.031 | 0.037 | 0.006| 0.029| 0.021 | 0.032 |

Figure 6: Continued.
Figure 6: Comparison between the recorded telemetry data and the predicted results by the neural network models under the ISS normal operating condition. (a) 1N-5. (b) LVCR4. (c) LCVR2. (d) RR4. (e) WR2. (f) BOX-C. (g) PDS-D.

**Table 2: Results of the neural network models under the ISS special operating condition.**

| Sensor | 1N-5 | LVCR4 | LVCR2 | RR4 | WR2 | BOX-C | PDS-D |
|--------|------|-------|-------|-----|-----|-------|-------|
| MSE    | 0.012| 0.016 | 0.024 | 0.007| 0.013| 0.009 | 0.013 |

Figure 7: Comparison between the recorded telemetry data and the predicted results by the neural network models under the ISS special operating condition. (a) Condition 1. (b) Condition 2. (c) Condition 3. (d) Condition 4.
The results verify the accuracy of the established neural network models well, which means the neural network models of AMS in orbit established in this study can be used to predict the temperature of AMS different parts under both the ISS normal and special operating conditions.

4.3. Temperature Predictions of AMS

4.3.1. Temperature Predictions of AMS under the ISS Normal Operating Condition. Figure 8 shows the predicted temperatures of AMS different surfaces with angle $\beta$ under the ISS normal operating condition. (a) 1N-5. (b) LVCR4. (c) LCVR2. (d) RR4. (e) WR2. (f) BOX-C. (g) PDS-D.

Figure 8: Predicted results by the neural network models under the ISS normal operating condition. (a) 1N-5. (b) LVCR4. (c) LCVR2. (d) RR4. (e) WR2. (f) BOX-C. (g) PDS-D.
ISS normal operating condition based on the established neural network models. Table 3 lists the predicted temperature ranges and the corresponding warning limits of AMS.

| Sensor  | Predicted temperature range (°C) | Warning limits (°C) |
|---------|---------------------------------|--------------------|
| 1N-5    | −12.38~−4.34                   | −15~+45            |
| LVCR4   | +2.69~+14.24                   | −15~+45            |
| LVCR2   | −9.75~+29.43                   | −15~+45            |
| RR4     | −4.06~+4.50                    | −15~+45            |
| WR2     | +0.44~+24.16                   | −15~+45            |
| BOX-C   | +10.39~+20.06                  | +10~+35            |
| PDS-D   | +18.56~+40.40                  | −20~+43            |

The results show that the orbital average temperature of each selected sensor of AMS is within the temperature range required by the thermal control, that is, there is no temperature warning of AMS under the ISS normal operating condition after installing the thermal blanket. Even if the transient temperature of AMS at some orbital positions will exceed the temperature limited range and trigger the temperature warning, the warning can be released automatically without additional human interventions as the ISS moves forward. The predicted results by the established neural network models under the ISS special operating condition (part). (a) Condition 1. (b) Condition 2. (c) Condition 3. (d) Condition 4.

![Graphs showing temperature distributions](image-url)
neural network models further confirm the effectiveness of the existing thermal control system of AMS after adding the thermal blanket.

4.3.2. Temperature Predictions of AMS under the ISS Special Operating Condition. The special operations of ISS make the periodic thermal environment of AMS more complex. Since the special operations plan of the ISS is made according to the mission requirements, there are amount of combination possibilities for the adjustment of factors mentioned in Section 2. We take four kinds of ISS special operating conditions as an example; Figure 9 shows the predicted temperatures of AMS different parts based on the established neural network models.

The results show that the temperatures of the different parts of AMS are different under the same operating condition. Among them, the temperature of the AMS top part (sensor 1N-5) is usually the lowest, and its orbital average temperature is generally no more than 0°C. The temperature of AMS PDS (sensor PDS-D) is the highest, and its orbital average temperature exceeds 25°C.

5. Conclusions

The AMS is an advanced particle physics detector that was installed on the ISS to measure the spectra of primary charged cosmic rays with a high statistic and for a long time. The TCS offers a suitable thermal environment for the subdetectors to function normally. In this study, the ANN models of four layers were constructed by evaluating the orbital parameters and previous thermal data to anticipate the thermal condition of the primary radiator. The BP neural network models were established for predicting the temperatures of AMS under the ISS normal and special operating conditions. The angle -semibold math notation  is selected as the only input data under the ISS normal operating condition, while six factors including angle -semibold math notation  yaw, pitch, roll, STRRRJ, and SA were used in the neural network model input layer under the ISS special operating condition. Comparison results between the recorded telemetry data and the predicted temperature obtained from the established neural network models show that the models established in this study are precise enough for predicting AMS temperatures with the minimum MSE being 0.006. The temperatures of different parts of AMS under the ISS normal and special operating conditions were predicted based on the BP neural network models. Furthermore, the method and findings of this work can be used to evaluate and anticipate periodic temperature variations in complicated temperature fields in space.

Data Availability

The data used to support the findings of the study can be obtained from the corresponding author upon request.

Conflicts of Interest

The author declares that there are no conflicts of interest.

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