Prediction of Radio Telescope Backup Structure Temperature Field Distribution Based on EVSC Unsupervised Feature Selection and MIMO-BP Neural Network: A Postprint

Authors:

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Abstract

Non-uniform temperature effects on the backup structure constitute one of the important factors causing precision degradation of the main reflector surface of radio telescope antennas. For antennas operating in the field, the complex topological structure of the backup structure leads to mutual shading, heat conduction, and thermal radiation among structural members, making it difficult to accurately obtain and predict the temperature field of the backup structure through thermodynamic simulation. By deploying temperature measurement sensors on the backup structure of the Nanshan 26,m radio telescope antenna, a temperature dataset of the antenna backup structure was obtained. Three different unsupervised feature selection methods were utilized to select 16 temperature-sensitive points from 66 measurement points, which were then used as inputs to a multi-input multi-output BP (Back Propagation) neural network model trained to output the predicted temperature values for the corresponding 66 measurement points, thereby achieving temperature prediction for continuous points throughout the entire backup structure through an interpolation algorithm. Through computational comparative analysis, it was concluded that the unsupervised feature selection method based on the eigenvalue sensitivity criterion yielded the best results for selecting temperature-sensitive measurement points. The combination of the BP neural network and Barnes interpolation algorithm enabled the prediction of the continuous temperature field distribution throughout the entire backup structure of the Nanshan 26,m radio telescope antenna using only 16 measured temperature points, with a predicted root mean square error of approximately 0.707 { }C. The research findings provide an optional method for the arrangement of temperature acquisition points and the acquisition and prediction of temperature fields for the backup structures of large-aperture radio telescope antennas.

Full Text

Preamble

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Predicting the Temperature Field Distribution of Radio Telescope Back-Up Structure Based on EVSC Unsupervised Feature Selection and MIMO-BP Neural Network

ZHANG Shi-jiao[1,2], XU Qian[1,3,4,5]†, WANG Hui[1,2], XUE Fei[1,2], CAO Xiao-man[1]

(1 Xinjiang Astronomical Observatory, Chinese Academy of Sciences, Urumqi 830011)
(2 University of Chinese Academy of Sciences, Beijing 100049)
(3 Key Laboratory of Radio Astronomy, Chinese Academy of Sciences, Urumqi 830011)
(4 Key Laboratory of Xinjiang Radio Astrophysics, Urumqi 830011)
(5 Shaanxi Key Laboratory of Antenna and Control Technology, Xi' an 710065)

Abstract

Non-uniform temperature effects on the back-up structure (BUS) constitute a significant factor causing degradation of the main reflector surface accuracy in radio telescope antennas. For antennas operating in the field, the complex topological structure of the BUS leads to mutual shielding, heat conduction, and thermal radiation among members, making it difficult to accurately obtain and predict the structural temperature field through thermodynamic simulation. By deploying temperature measurement sensors on the BUS of the Nanshan 26-meter radio telescope (NSRT), we obtained a temperature dataset for the antenna back-up structure. Three different unsupervised feature selection methods were employed to identify 16 temperature-sensitive points from 66 measurement points. These three distinct sets of temperature-sensitive points were then used as inputs to train a Multiple Input and Multiple Output Back Propagation (MIMO-BP) neural network model to predict the temperature values at the corresponding 66 measurement points. Temperature prediction for continuous global points on the BUS was subsequently achieved through interpolation algorithms. Comparative analysis demonstrated that the unsupervised feature selection method based on the eigenvalue sensitive criterion (EVSC) yielded the best results for selecting temperature-sensitive points. By combining the BP neural network with the Barnes interpolation algorithm, we successfully predicted the temperature field distribution of continuous global points on the

NSRT BUS using only 16 measured temperature points, achieving a root-mean-square error of approximately 0.707 °C. This research provides an alternative method for the arrangement of temperature collection points and the acquisition and prediction of temperature fields in the BUS of large-aperture radio telescopes.

Keywords: telescopes, instrumentation: back-up structure, methods: unsupervised feature selection, methods: neural network

Introduction

Reflector surface accuracy and pointing accuracy are two critical indicators reflecting radio telescope antenna performance, and temperature-induced deformation of the antenna back-up structure represents an important factor affecting reflector surface accuracy. Currently, extensive research on radio telescope thermal analysis has been conducted both domestically and internationally, primarily employing two approaches: thermodynamic simulation and measured data analysis. For instance, Nikolic et al. [?] used holographic measurement techniques on the 100 m Green Bank Telescope (GBT) to demonstrate that thermal deformation effects typically exceed gravitational deformation during daytime. Greve et al. [?] deployed 156 temperature sensors on a 30 m radio telescope antenna to obtain actual thermal conditions, analyzed the antenna' s thermodynamic characteristics using measured temperature data, and calculated errors caused by temperature gradients through structural finite element methods. Yi et al. [?] used finite element thermodynamic modeling and simulation analysis to show that the temperature distribution of the NSRT back-up structure under solar radiation follows an approximately linear pattern. Li et al. [?] used a total station to measure displacement errors caused by thermal deformation at selected points on the Shanghai 65 m Tianma Radio Telescope (TMRT) back-up structure, and analyzed the impact of solar temperature variations on surface accuracy based on the thermal deformation patterns. Fu et al. [?] combined infrared thermal imagers and Pt100 temperature sensors with a distance-angle correction formula to achieve precise temperature measurement of the TMRT back-up structure.

Based on existing research progress in related fields, numerical simulation methods cannot set real-time antenna operating parameters and can only obtain antenna performance under extreme operating conditions by setting boundary conditions for such scenarios. For methods using measured data to obtain telescope temperature information, the optimal number of measurement points requires further investigation. Additionally, due to the complex antenna structure, contact temperature sensors are difficult to install and maintain, while non-contact temperature sensors have measurement limitations and cannot achieve complete structural measurement. Currently, there is no efficient and feasible method for obtaining temperature distribution data of telescope back-up structures.

This study proposes a method for predicting temperature distribution in telescope back-up structures based on unsupervised feature selection combined with neural network models. A data-driven approach is used to establish a predictive model as an alternative to solving complex mathematical and physical equations, thereby achieving temperature field distribution prediction for structural components. Using measured temperature data from the NSRT back-up structure, three different unsupervised feature selection methods were applied to identify three sets of 16 temperature-sensitive points each. These different sensitive point sets were used as inputs to establish corresponding MIMO-BP (Multiple Input and Multiple Output - Back Propagation) neural network models, and interpolation algorithms were subsequently employed to achieve real-time prediction of the overall temperature field distribution on the back-up structure. This method provides theoretical support for the arrangement of temperature collection points on telescope back-up structures and offers a feasible solution for predicting the temperature field of continuous global points using fewer measured temperature points while maintaining measurement accuracy.

Data Acquisition and Processing

Temperature measurement sensors based on Fiber Bragg Grating (FBG) technology were deployed on the 26 m NSRT back-up structure to obtain actual temperature data, while multi-parameter sensors were installed around the telescope to collect various environmental data for establishing a data-driven neural network prediction model. The data collection period spanned from November 15, 2021, to July 19, 2022, with a sampling frequency of 10 seconds per measurement. The collected data included ambient temperature, humidity, atmospheric pressure, wind direction, wind speed, telescope azimuth and elevation angles, solar azimuth and elevation angles relative to the NSRT, and temperature values from 66 measurement points on the NSRT back-up structure.

[Figure 1: see original paper] shows the schematic diagram of the 66 temperature sensor installation positions on the antenna back-up structure. The top view of the 66 temperature sensor locations is illustrated in Figure 1(a), where A-P represent 16 measurement channels distributed on 16 main radial beams of the 26 m NSRT antenna back-up structure in a centrally symmetric pattern. Since the main radial beams are the core load-bearing components of the antenna back-up structure, focusing temperature measurement on these beams facilitates analysis of the overall thermal deformation of the back-up structure. Sensors on each main radial beam were installed at the middle of connecting rods, using the temperature at the rod' s central node to represent the average temperature of the entire rod. Figure 1(b) shows a cross-sectional side view of a single radial beam, with dots indicating temperature sensor installation positions. As shown, all temperature sensors were deployed at equally spaced points on the lower chord beams. The field installation of temperature sensors is shown in [Figure 2: see original paper], where Figure 2(a) depicts a spider lift carrying personnel to install sensors on the lower chord beams of the radio telescope back-up structure, Figure 2(b) shows the global layout of sensors on the back-up structure members, and Figure 2(c) provides a detailed local view of sensors and fiber lines secured with moisture-proof, waterproof, heat-insulating, and wear-resistant gray polytetrafluoroethylene film tape. [Figure 3: see original paper] illustrates the temperature acquisition equipment inside the NSRT high-frequency cabin, where Figure 3(a) shows the transmission of Bragg wavelength information from each temperature sensor via fiber lines to the high-frequency cabin, and Figure 3(b) presents the overall FBG fiber grating temperature measurement system data processing equipment.

In selecting the temperature sensor type, we comprehensively considered measurement accuracy, electromagnetic compatibility, service life, and installation and maintenance difficulty, ultimately choosing FBG temperature sensors to obtain actual back-up structure temperatures. The measurement principle of FBG temperature sensors [?] involves detecting temperature at measurement points by measuring Bragg wavelength shifts. The Bragg wavelength (cid:21)B is defined by Equation (1):

(cid:21)B = 2N Λ

where N is the effective refractive index of laser propagation within the fiber, and Λ is the period of the Bragg grating. The reflected wavelength (cid:21)B is affected by changes in the physical or mechanical properties of the grating region, with temperature variations causing changes in N. For unconstrained fibers, Λ is affected by thermal expansion and contraction. Equation (2) describes the temperature effect on (cid:21)B:

Δ(cid:21)B = (cid:21)B ((cid:13) + (cid:16)) ΔT

where Δ(cid:21)B is the change in Bragg wavelength, (cid:13) and (cid:16) represent the thermal expansion coefficient and thermo-optic coefficient respectively, and ΔT denotes the temperature change.

Selection of Temperature-Sensitive Points Based on UFS

To achieve prediction using fewer temperature sensors without reducing measurement accuracy, selecting sensitive temperature measurement points from the 66 available points is essential, and unsupervised feature selection methods can achieve this goal. Feature selection can be divided into supervised and unsupervised categories: supervised methods are applied when class information is known, while unsupervised methods are used when such information is unknown. Since different back-up structure temperature measurement points exhibit varying sensitivity to temperature changes, unsupervised feature selection (UFS) methods should be employed for feature screening.

In UFS theoretical research, Solorio-Fernández et al. [?] comprehensively introduced various UFS methods, providing structured classification and comparative analysis of their advantages and disadvantages. Xu et al. [?] proposed an unsupervised feature selection method based on mutual information, using unsupervised minimum redundancy maximum relevance to evaluate feature importance, and theoretically proved the effectiveness of this approach. Ding et al. [?] proposed a novel unsupervised feature selection method based on improved ReliefF (an algorithm commonly used for multi-class sample classification problems by leveraging inter-sample differences), termed UFS-IR (Unsupervised Feature Selection based on Improved ReliefF). By improving the sampling strategy, this method avoids the low sampling probability for small-class samples and the inability to remove redundant features inherent in ReliefF-type algorithms, achieving effective data dimensionality reduction while ensuring maximum relevance and minimum redundancy of the feature subset. This study employs three unsupervised feature selection methods to obtain 16 temperature-sensitive points, subsequently analyzing the prediction results to determine the optimal UFS method. The three UFS methods are: Eigenvalue Sensitive Criterion (EVSC), Laplacian Score (LS), and Spectral Feature Selection (SPEC).

The EVSC method [?] performs feature selection by exploiting the relationship between similarity matrices and covariance matrices, using the common Gaussian kernel function as the similarity measurement:

SEVSC(i;j) = exp − xi − xj 2=2(cid:14)2 (cid:128)

where SEVSC(i;j) represents the similarity between features i and j, xi and xj are the data samples corresponding to features i and j in the dataset, and (cid:14) is the width parameter of the Gaussian kernel. The importance score for each feature is calculated using the EVSC criterion:

(cid:138) ScoreEVSC(i) = (cid:21)n(i) vn(i) n (cid:21)n(i) (cid:12) (cid:12) (cid:12) (cid:12) (cid:12) (cid:12)

where ScoreEVSC(i) denotes the importance score of feature i calculated using the EVSC method, vn(i) is the eigenvector of feature i, and (cid:21)n(i) is the eigenvalue of feature i. A higher importance score indicates greater feature significance, so the feature subset with the highest scores is selected as the final feature set.

Laplacian Score [?] primarily constructs an undirected graph model to understand the geometric structure of data, based on the principle that a feature is more important if it exhibits more uniform behavior on the data manifold. The basic procedure is as follows: (1) Construct an affinity matrix S using similarity between features, where S(i;j) representing the affinity between features i and j can be expressed by Equation (5):

S(i;j) = exp − xi − xj 2=t (cid:128) (cid:138)

where t is a constant; otherwise S(i;j) = 0. (2) Define a diagonal matrix D and calculate the Laplacian matrix, where diagonal matrix D(i;i) is defined by Equation (6):

D(i;i) = S(i;j)

Then obtain the Laplacian matrix L = D − S. (3) Calculate the Laplacian score for each feature using Equation (7):

ScoreLS(i) = i L˜xi i D ˜xi

where ˜xi = xi − xT iDE, with T representing transpose and E being the unit vector E = [1; ・・・; 1]T. As shown in Equation (7), a feature' s Laplacian score consists of two parts: the numerator represents the feature' s variation degree on the data manifold structure, while the denominator represents the dispersion degree of the feature' s values across all samples. Therefore, a lower score indicates better preservation of the data' s geometric structure.

Spectral Feature Selection [?] can be applied to both supervised and unsupervised feature selection. For UFS applications, the algorithm proceeds as follows: (1) Construct a feature graph based on input data: for the input dataset, calculate pairwise feature similarities to form an affinity matrix. For the SPEC algorithm in unsupervised feature selection scenarios, this study uses the common radial basis function Gaussian kernel to express the affinity matrix S(i;j), with the specific calculation formula identical to Equation (5). (2) Calculate the Laplacian matrix L: after obtaining the affinity matrix S(i;j), define the degree matrix D as a diagonal matrix where the degree of the ith node is Dii, calculated using the same formula as Equation (6), then derive the Laplacian matrix L = D − S. (3) Calculate Laplacian scores and rank features. Before scoring, compute the normalized Laplacian matrix Lnorm:

Lnorm = D− 1 2 (D − S) D− 1

After obtaining the normalized Laplacian matrix Lnorm, the Laplacian score ScoreSPEC(i) for feature i is calculated as:

ScoreSPEC(i) = ˆH i Lnorm ˆH i

where ˆH i = . Although SPEC' s basic idea is similar to Laplacian Score in that features consistent with the data manifold should assign similar values to close instances, and both use the Laplacian matrix, it should be noted that their scoring calculation methods differ.

presents the ranking of the top 16 features from the 66 temperature measurement points using the three unsupervised feature selection methods EVSC, LS, and SPEC. The first two columns show the sensor numbers and corresponding feature importance scores for the sensitive temperature measurement points calculated using the EVSC method. Figure 4: see original paper illustrates the spatial distribution of the top 16 sensitive points selected by EVSC on the back-up structure. Columns 3-4 show the sensor numbers and scores from the LS method, with the spatial distribution shown in Figure 4: see original paper. Columns 5-6 present the results from the SPEC method, with distribution shown in Figure 4: see original paper.

In summary, the three unsupervised feature selection methods (EVSC, LS, and SPEC) successfully selected three different sets of 16 sensitive temperature measurement points from the original 66 points. While these three UFS methods are not inherently superior or inferior to one another, their applicability varies across different data processing scenarios. Based on subjective experience, the authors speculate that EVSC may yield better results due to its more dispersed selection positions. However, to more objectively and accurately validate the three UFS selection results and achieve back-up structure temperature field prediction, the following section employs a multiple-input multiple-output MLP-BP neural network model using the 16 sensitive temperature measurement points as inputs to predict temperature values at all 66 measurement points.

Temperature Prediction of BUS Based on MIMO-BP Neural Network Model

The relationship between temperature distribution and prediction in telescope back-up structures essentially constitutes a complex system of multivariate nonlinear equations that is difficult to solve analytically using traditional methods. However, multi-layer artificial neural networks [?] can solve complex equations by continuously training and optimizing network models with large amounts of data. [Figure 5: see original paper] illustrates the MIMO neural network structure designed in this study, where the input layer is X = [x1; x2; x3; ⋯], the output layer is Y = [y1; y2; y3; ⋯], and the intermediate layer contains two hidden layers, forming a four-layer structure where df represents the fth neural node in the nth hidden layer.

Each circle in the diagram represents a neural node, with full connections between layers but no connections between neurons in the same layer or across layers. This structure is commonly known as a "multi-layer feedforward neural network." In forward propagation, the computation for each layer to obtain zn is as follows:

zn = wnan−1 + bn

where zn = [z1 n; z2 n; ⋯; zf n]T, an−1 = [a1 n−1; a2 n−1; ⋯; af n−1]T represents the activation values corresponding to nodes zf n−1, a0 is the original input X, wn is the weight matrix (connection coefficients) of the nth layer, and bn = [b1 n; b2 n; ⋯; bf n]T is the bias of the nth layer. The activation value an corresponding to node values is calculated by:

an = gn(zn)

where an = [a1 n; a2 n; ⋯; af n]T, af n is the activation value corresponding to node df n, and gn is the activation function selected for the nth layer [?]. Considering the large dataset and the fact that temperature values do not exhibit sudden numerical changes, the Tanh function was selected as appropriate for this model.

Given the complexity of the network structure, selecting a more efficient training method is necessary to improve training efficiency. The BP (Error Back Propagation) algorithm is a commonly used training method consisting of forward propagation and backward propagation processes: the former calculates the loss, while the latter backpropagates the error. The forward propagation algorithm was described above; essentially, it prepares input values for backpropagation, which is an efficient gradient calculation method. The loss value from forward propagation is obtained through the loss function E in Equation (12):

$$E = (t(p) - y(p))^2$$

where p represents all possible neural nodes in the current layer (i.e., layer n), t(p) is the true value corresponding to all neural nodes in layer n, and y(p) is the forward propagation output value of all neural nodes in layer n. The local loss of each neuron is calculated through this equation, and the loss gradient is computed by derivation. The weight and bias parameters are then iteratively updated using:

wn = wn − (cid:11) E/ wn
bn = bn − (cid:11) E/ bn

where (cid:11) represents the learning rate, empirically set within the range (0, 1]. After iterative updates, the loss function E continuously decreases, ultimately achieving the goal of machine learning model optimization.

Data Results Analysis

To ensure model generalizability, 80% of the data was randomly extracted as the training set, with 10% each allocated as validation and test sets before each training session. A Python-based MLP-BP network model with a structure of two hidden layers [50, 96] was built and trained using the TensorFlow framework.

Various metrics can evaluate model performance. Considering the practical application scenario and dataset characteristics, this study employs the R^2 coefficient (coefficient of determination) and RMSE (Root Mean Squared Error) to assess overall model generalization capability. The coefficient of determination R^2 is an important metric for measuring regression model fit, with values closer to 1 indicating better fit quality. Generally, a goodness-of-fit above 0.8 indicates excellent performance, calculated as:

$$R^2 = 1 - \text{mean}[\ (yt - \hat{y}t)^2] \ /\ \text{mean}[\ (yt - \bar{y}t)^2]$$

where mean denotes the averaging operation, t is the current prediction point, $\hat{y}t$ is the predicted value at point t, $\bar{y}t$ is the mean of predicted values at point t, yt is the true value at point t, and m is the number of prediction points. RMSE measures the absolute difference between predicted and true values, with smaller values indicating higher precision, calculated as:

$$RMSE = \sqrt{}[(yt - \hat{y}t)^2]$$

The three different sets of sensitive temperature measurement points were used as inputs for model training, and the predicted results were compared with true values. presents the model training results using different UFS methods.

The results in indicate that the model using EVSC-selected sensitive points achieved the best prediction performance, with the coefficient of determination R^2 closest to 1 (indicating the strongest explanatory power of output values by input values) and the smallest RMSE among the three methods. Since the predicted data represents temperature and RMSE shares the same unit as the dataset, the overall prediction error using the EVSC method is approximately 0.707 °C, demonstrating excellent model training and test set generalization performance. Given that measurement devices at different locations have varying stability and accuracy, error analysis for different measurement positions is necessary. [Figure 6: see original paper] uses box plots to analyze the RMSE and R^2 coefficients for 66 measurement points at different locations, thereby determining the skewness and tail weight of the overall data.

Figure 6: see original paper shows the RMSE values for 66 different positions predicted using different UFS methods, while Figure 6: see original paper displays the R^2 coefficients for these positions. Box plot analysis reveals that the RMSE and R^2 distributions for all three methods are relatively concentrated, though some outlier anomalies exist in R^2 coefficients. Analysis of overall distribution positions shows that both RMSE and R^2 error ranges follow the pattern: EVSC method smallest, LS method intermediate, and SPEC method largest.

To verify the stability of EVSC method model prediction accuracy under various extreme operating conditions and quantitatively evaluate its robustness, this study categorized NSRT working environments into eight extreme conditions [**?**, **?**]: relatively strong wind (wind speed $> 4\ \mathrm{m \cdot s^{-1}}$) versus windless, high temperature (ambient temperature > 25 °C) versus low temperature (below -15 °C), rainy/snowy versus sunny, and strong sunshine versus nighttime. It should be noted that wind speeds at the NSRT site are mostly within $3\ \mathrm{m \cdot s^{-1}}$ throughout the year, so periods with wind speeds exceeding $4\ \mathrm{m \cdot s^{-1}}$ were defined as relative strong wind conditions. During the actual measurement period (November 15, 2021, to July 19, 2022), the minimum temperature was -19.7 °C and the maximum was 28.1 °C, so data from periods above 25 °C were defined as high-temperature condition datasets, and data from periods below -15 °C as low-temperature condition datasets. The test dataset was classified according to these conditions for separate prediction. presents the prediction accuracy under various working conditions.

The results in demonstrate good prediction performance under all extreme conditions, though relatively poorer performance occurs under strong wind and strong sunshine conditions. Strong wind conditions lead to complex and diverse backup structure orientations and wind angles, resulting in different wind-cooling heat dissipation patterns across the temperature field, while strong sunshine conditions cause complex and variable temperature field changes due to different solar azimuth/elevation angles and irradiated regions. However, overall analysis of shows that prediction errors under all conditions are similar and remain within 1 °C, indicating considerable prediction accuracy. This confirms that using the EVSC method with the MIMO-BP model exhibits strong robustness and good prediction performance under complex extreme conditions.

To achieve temperature prediction for continuous positions from discrete points, we referenced Wang et al. [**?**] on temperature field reconstruction using interpolation algorithms and employed the Barnes interpolation algorithm [?, ?] to obtain and predict the overall back-up structure temperature field. This algorithm is widely used in atmospheric and oceanic sciences due to its small computational requirements and high stability. Interpolation was performed on both the 66 actual measured sensitive points and the 66 predicted temperature points to calculate RMSE for evaluating the error precision of continuous position temperature prediction on the back-up structure. presents the prediction accuracy errors for continuous-domain temperature fields on the back-up structure. The data show that prediction errors increase through multiple transmissions from MIMO-BP model prediction to Barnes interpolation. However, the combination of EVSC method with model prediction and interpolation algorithm still achieves superior performance, with a prediction accuracy of approximately 1.912 °C.

For more specific and intuitive analysis of the interpolation prediction accuracy in continuous domains of the back-up structure temperature field from a spatial perspective, [Figure 7: see original paper] displays the RMSE heat maps of the overall back-up structure temperature predicted by the three UFS methods (EVSC, LS, and SPEC), where deeper red indicates higher temperature prediction error and deeper blue indicates lower error.

[Figure 7: see original paper] demonstrates that EVSC prediction error is superior to LS, which in turn is superior to SPEC, consistent with previous results. Since the continuous-domain temperature field prediction is achieved through neural network prediction of 66 sensitive points followed by interpolation, errors undergo multiple transmissions and accumulations requiring re-statistics and evaluation. Both [Figure 7: see original paper] and show that using the EVSC feature selection method combined with MLP-BP neural network and Barnes interpolation achieves back-up structure continuous global point temperature prediction errors within 2 °C, with relatively concentrated distribution and no abrupt anomalies. This study employs multiple validation methods and evaluation metrics to comprehensively demonstrate from global to local perspectives that EVSC is the most suitable unsupervised feature selection method for this scenario. Furthermore, the combination of EVSC feature selection with MLP-BP neural network and Barnes interpolation successfully achieves temperature distribution prediction for continuous global points using fewer measured temperature points.

This study successfully selected 16 sensitive temperature measurement points from 66 points using multiple unsupervised feature selection methods. Comparative analysis demonstrated that the EVSC unsupervised feature selection method achieved the best results for selecting sensitive measurement points, with robust prediction accuracy under various extreme conditions and overall prediction error of approximately 0.707 °C. However, due to the complex and variable field conditions at NSRT, particularly under strong wind and strong sunshine conditions, prediction accuracy for the back-up structure temperature field is relatively poorer. Therefore, further research is needed for temperature field prediction of antenna back-up structures under extreme conditions. Ultimately, this study achieved continuous global point temperature prediction for the back-up structure using the EVSC feature selection method combined with MIMO-BP neural network and Barnes interpolation, with a prediction accuracy of approximately 1.912 °C. This method provides theoretical reference for temperature sensor placement on radio telescope back-up structures and offers an alternative solution for temperature measurement and prediction of continuous temperature field distribution in antenna structural components.

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Note: Figure translations are in progress. See original paper for figures.