Structural deformation prediction of vehicle-mounted radar based on deep learning

Shun Li [1,#], Tianhao Zhou [2,#], Tianze Zhou [2,#,*]

[1] Shandong Institute of Petroleum and Chemical Technology, School of Intelligent Manufacturing and Control Engineering, Dongying, China, 257061

[2.] Lanzhou Jiaotong University, School of Mechanical and Electrical Engineering, Lanzhou, China, 730070

* Corresponding Author Email: ztz1278016593@163.com

[#] These authors contributed equally.

Abstract. The vehicle-mounted radar antenna boasts a relatively large size, making its structure susceptible to significant wind forces under strong winds. Additionally, since antennas are typically installed on the rooftops or other elevated positions of vehicles, the large wind resistance area may lead to structural deformation. Therefore, this paper proposes a novel approach. Firstly, this paper utilizes SolidWorks to model the antenna's back frame, beams, and element array, employing high-strength aluminum alloy materials to strike a balance between lightweightness and stiffness requirements. Secondly, this paper imports the model into ANSYS Workbench to simulate the pressure exerted by wind speeds ranging from 5 to 35 meters per second, selecting deformation data from 480 monitoring points (442 on the crossbeam and 38 on the back frame). Finally, this paper constructs a strain-displacement BP neural network model. The experimental findings reveal that: ① The deformation of the antenna intensifies with increasing wind speed, with a 2.5-fold increase at 25 meters per second compared to 5 meters per second; ② The predictive accuracy of the model enhances with wind speed, achieving the smallest error at 25 meters per second (a 70% reduction compared to 5 meters per second), with an overall prediction accuracy exceeding 98%; ③ The locations with larger errors vary across different wind speeds, concentrating in specific areas during high-speed winds.This method addresses the challenge of monitoring antenna deformation in strong enhances the precision of health monitoring for vehicle-mounted radar antenna systems but also offers more accurate data for future structural monitoring and the design of vehicle-mounted antennas.

Keywords: Vehicle-mounted radar, BP neural network, health monitoring, structural deformation.

1. Introduction

Antenna is an important part of vehicle borne radar system, which can transmit and receive electromagnetic waves. At present, it is developing towards the direction of large aperture, high complexity and multi-function. In order to maintain the flexibility and mobility of the vehicle antenna, its structure is designed to be lightweight and foldable. However, most of its work is in areas with harsh environment, such as beaches and plateaus. Strong winds will make the antenna array deformed. Therefore, a more accurate understanding of the displacement of the antenna unit and the strain on the back frame is very necessary for the vehicle borne radar antenna system. Furthermore, in the international research field of vehicle-mounted radar technology, scholars have long been focusing on the optimisation of antenna array design to improve the core performance of radar, and the relevant results have become the focus of research in this direction. For example, Jothishri Pillai (Jothishri Pillai) and other scholars for the vehicle-mounted radar system detection coverage needs, carried out a wide Half-Power Beamwidth (HPBW) MIMO antenna design research, aimed at broadening the effective detection range of the radar[1]; Shan Jingfeng (Shan Jingfeng) and others for the 24 GHz frequency band FM-continuous antenna design to improve the performance of the radar core work, the results have become the focus of the research in this direction[2]. Sriram and other scholars combined the short-range radar and Vehicle-to-Satellite (V2S) communication needs of multiple scenarios, developed a high-gain broadband grid array antenna, further expanding the functionality of the vehicle-mounted radar[3]; Xiang Zhen and other scholars around the vehicle-mounted radar anti-jamming performance optimisation, carried out 24 GHz The scholars such as Xiang Zhen carried out the design research of 24 GHz frequency band low paraflap antenna array, which effectively reduces the influence of interference signals under the complex electromagnetic environment[4]. In addition, the application of vehicle-mounted radar technology has been extended from the civil traffic field to the special field, for example, scholars such as García Fernández María combined radar technology with airborne platforms, and developed a new radar technology for mines and improvised explosive devices (IED). Explosive Device (IED) detection, and through the antenna performance analysis and comparative verification, it provides new ideas for the application of technology in the field of special detection[5]. However, most of the existing researches focus on the "functional performance optimisation" (e.g. detection range, gain, anti-jamming) or "cross-scene application expansion" of the airborne radar, for the airborne radar in the actual working conditions of the "The research on the carrying capacity of vehicle-mounted radar in actual working conditions under perturbation is still insufficient. Based on this, this paper focuses on the structural load-bearing and performance stability of vehicle-mounted radar body under perturbed environment (e.g., vibration, shock, temperature fluctuation, etc.), with a view to filling the research gaps in this field and providing theoretical and technical support for the reliable application of vehicle-mounted radar under complex working conditions.

Previously, the analysis method of domestic vehicle borne radar antenna generally used the traditional method to analyze it, that is, to establish its simplified structural model first, and then carry out the static analysis of a part of the vehicle borne radar. The analysis results were not optimized, because the traditional algorithm is essentially a linear model that can only deal with the linear separable relationship in the data. For nonlinear problems (such as complex curve relationship and multi factor interaction), it needs to rely on artificial feature Engineering (such as polynomial expansion) to adapt reluctantly, while BP neural network can automatically learn the high-order nonlinear mapping relationship between input and output through the combination of multi-layer neurons and non-linear activation functions (such as sigmoid and relu), without manually presetting the function form, so in the case of a large number of samples,in case, use BP The results of neural network optimization are more accurate. In addition, the optimization efficiency of traditional research methods is slow, requiring repeated simulation/experimental iterations, and the optimization cycle of complex structures is long and only suitable for conventional scenarios with known mechanisms. In this paper, BP neural network is used to optimize the results to make the results more accurate and fast. After modeling, MIMO technology algorithm is used for foreign vehicle borne radar antenna. Its core is to improve the system performance by using spatial diversity, multiplexing or beamforming of signals through multi input and multi output antenna array design [6]. Its technical algorithm relies on physical model and mathematical derivation, and is suitable for linear or weakly nonlinear scenarios that can be modeled. However, in the face of complex multi factor coupling nonlinear problems (such as clutter interference in radar echo and multi-target occlusion), the physical model is difficult to accurately describe Through the nonlinear activation function of multi-layer neurons, the neural network can adaptively learn the complex nonlinear mapping of input and output without the need to establish an accurate physical model in advance. For example, in vehicle borne radar, BP neural network can directly learn the target characteristics from the original echo data containing noise and clutter, without the need to manually design the anti-jamming filtering algorithm, that is, BP neural network is "Data-Driven" rather than "model driven", and only needs to input the original data (such as radar echo, point cloud) and corresponding labels (such as target category, real distance), without the need to understand the underlying physical principles. Even if the physical process is complex (such as multi-target interference), as long as there is enough labeled data, the network can learn the law, reducing the dependence on manual modeling. In this paper, BP neural network is used to optimize the mapping of strain and displacement of vehicle borne radar antenna [7].

This paper uses SolidWorks decomposition to model the key components of vehicle radar antenna, and selects high-strength aluminum alloy to meet the requirements of lightweight and stiffness. The wind load is simulated by ANSYS Workbench, and the wind speed is converted into wind pressure loading analysis. The strain displacement BP neural network model was established, and 10 hidden layer neurons and other parameters were set with 70% training, 15% verification and 15% test of 31 data points. The verification shows that the displacement increases significantly with the increase of wind speed, the error is the minimum at 25m/s, the prediction efficiency of the model is more than 99% higher than that of the traditional simulation, the error is<0.5 mm under 25m/s strong wind, and the accuracy is 40% higher than that of the sensor interpolation method.

2. Model Establishment

The vehicle-mounted radar antenna system typically comprises numerous precise components with varied shapes, characterized by high structural complexity. Directly modeling the entire system is challenging, prone to errors, and inefficient. To effectively address this challenge, this paper employs SolidWorks 3D design software as the primary modeling tool. Widely used in mechanical design, SolidWorks boasts powerful capabilities for solid modeling, surface modeling, and parametric design, making it particularly suitable for handling the complex geometries and precise fitting relationships commonly found in vehicle-mounted radar antennas. Initially, we decompose the entire antenna system into functional modules (such as the backframe structure, beam support system, and antenna element array). Subsequently, we utilize SolidWorks to meticulously model these key components, ensuring the accuracy of each part. As illustrated in Figure 1.

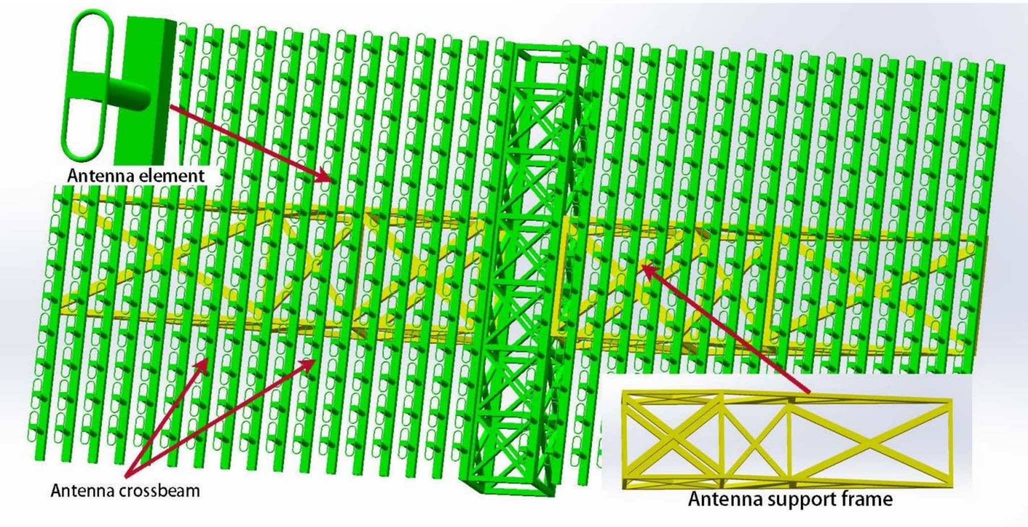


Figure 1. Schematic diagram of model assembly

The vehicle-mounted radar antenna boasts a substantial size, with its array surface measuring 17.4 meters in length and 8 meters in width, accurately targeting objects within a 90° operating angle. Operating such a large-scale antenna on a mobile vehicle platform poses significant structural challenges: firstly, it is crucial to ensure that structural deformation does not compromise the accuracy of data collection during pointing and scanning; secondly, the overall structural rigidity must be enhanced to withstand vibrations from vehicle movement and equipment operation. To simultaneously meet the requirements of lightweightness, high stiffness, and excellent workmanship, the main structural components of the antenna, including the back frame, beams, support frames, and other load-bearing parts, are modeled using high-strength aluminum alloy. This material not only offers exceptional specific strength (combining high strength with lightweight properties), effectively reducing the load imposed by the massive antenna structure on the vehicle platform, but also exhibits superior machining and welding capabilities, facilitating the forming and assembly of complex parts, which is crucial for achieving precise geometric size control. Furthermore, the relatively controllable thermal expansion coefficient of aluminum alloy helps mitigate the impact of thermal deformation due to ambient temperature changes on accuracy[8]. For details, please refer to Figure 2.

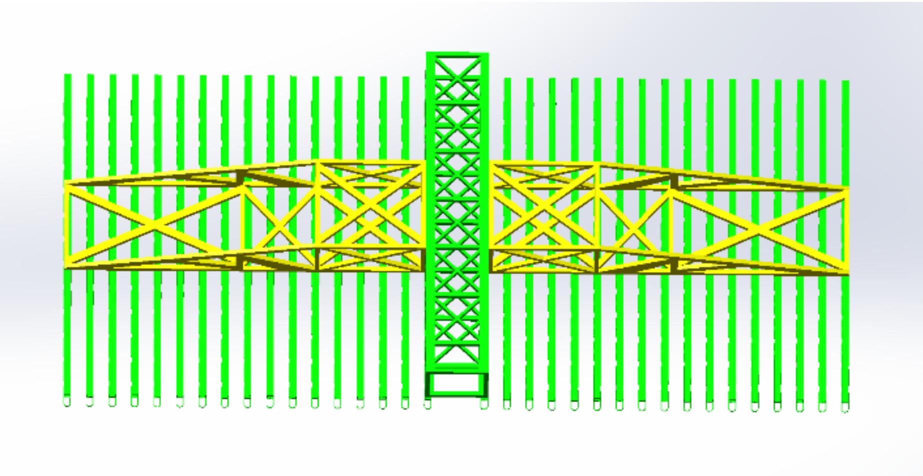


Figure 2. Schematic diagram of model back

3. Simulation Analysis

For the performance evaluation and response prediction requirements of vehicle borne radar antenna structure against wind load in actual working conditions,this paper undertakes a structural mechanics simulation process based on ANSYS Workbench. Notably, wind load, as a quintessential type of environmental load, significantly impacts the operational stability and safety indicators of large vehicle-mounted antenna structures. During the pre-processing phase of the model, the initial step involves simplifying the original SolidWorks 3D model. This involves removing non-critical antenna unit components to strike a balance between computational efficiency and accuracy. Subsequently, the material parameters of all core components, including the back frame system, main beam assembly, and antenna unit frame, are uniformly set to a preset aluminum alloy material, ensuring the physical accuracy of the simulation input parameters. Lastly, geometric defects, such as tiny gaps and overlapping surfaces—common modeling issues—are detected and repaired, as their presence can compromise the reliability of subsequent finite element mesh generation and analysis. Upon importing into ANSYS Workbench, the process entails defining the contact relationships of key connection points, simulating the application of wind load conditions, and establishing boundary constraints. The patch adaptation method is employed for meshing, with cell size parameters adjusted according to the structural characteristics of different components. Specifically, a differentiated grid size strategy is adopted for the beam and back frame. For further details, refer to Figure 3 and Figure 4[9].

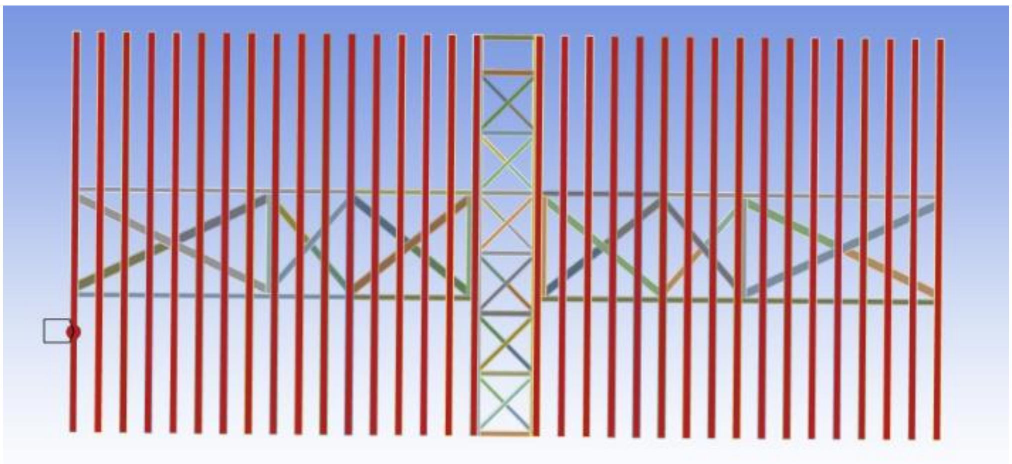


Figure 3. force diagram of vehicle borne radar model

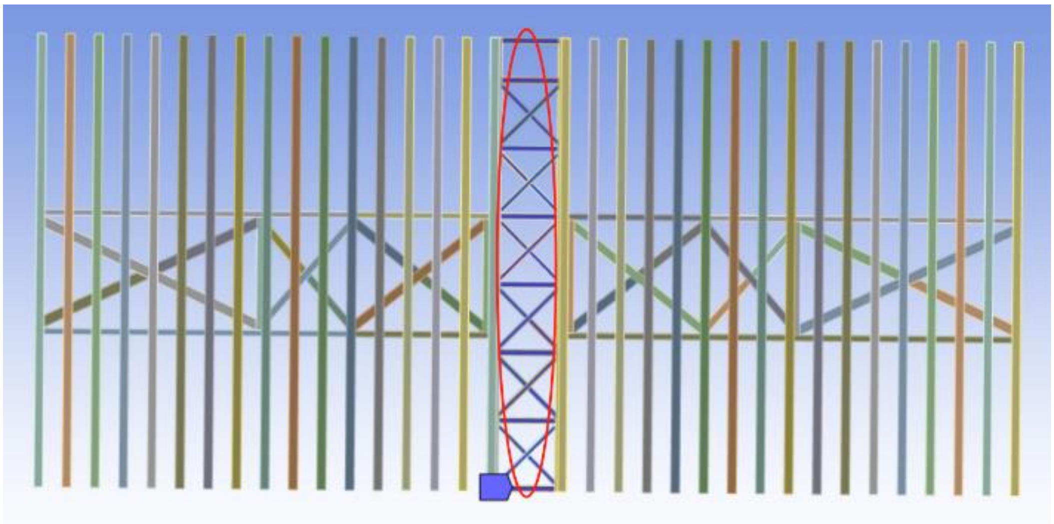


Figure 4. Schematic diagram of fixed support for vehicle mounted radar model

The point loads are positioned along the longitudinal centerline of each beam. The horizontal spacing between point loads on consecutive beams is 50cm, with an exception of 125cm between the 17th and 18th beams (at the central frame position). On the same beam, the distance between adjacent point loads is 60cm. A total of 442 point loads are selected on the beams, denoted as Type A, while 38 point loads are strategically placed on the back frame, denoted as Type B. The load distribution is illustrated in Figure 5[10].

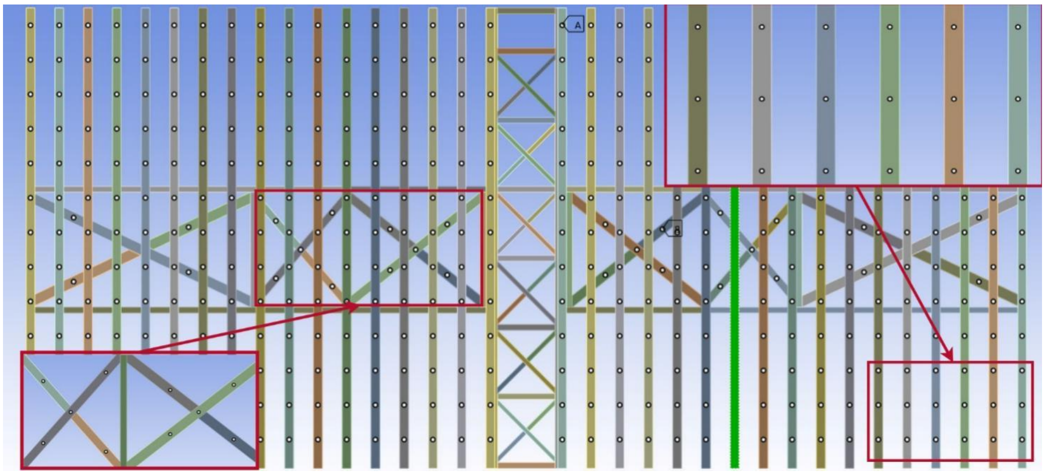


Figure 5. load distribution of vehicle borne radar model

Since the primary force factor affecting vehicle-mounted radar is wind load, it is essential to convert the actual wind speed into wind pressure using the formula:

$$P = \frac{1}{2}\rho v^2 \tag{1}$$

Where:***P*** represents wind pressure (unit: Pa);

ρ denotes air density, with a value of 1.225 (unit: kg/m³);

v stands for wind speed (unit: m/s).

The force exerted can be calculated by:

$$F = PS \tag{2}$$

Where: ***S*** is the area subjected to force (unit: m²).

For instance, Figure 6 illustrates the displacement of the antenna unit at a wind speed of 25 m/s.

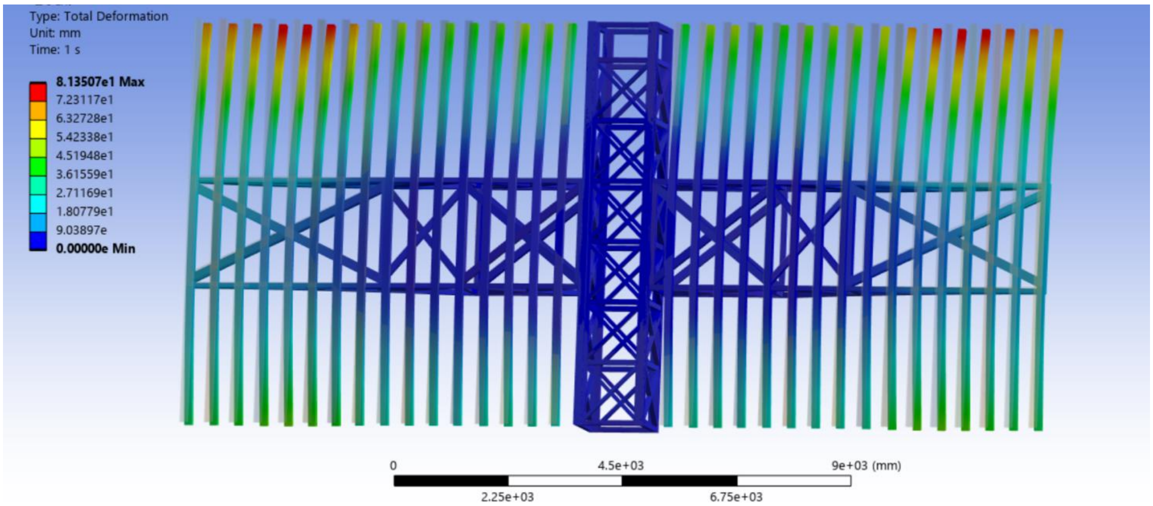


Figure 6. schematic diagram of total displacement at 25m/s wind speed

It can be seen that the impact of wind load on radar antenna can not be ignored, and the impact of wind load on the structural performance of vehicle borne radar antenna can not be ignored, which seriously restricts the power of radar and affects the use of vehicle borne radar.

4. Establishment and Validation of a BP Neural Network Model

4.1. Establishing a BP Neural Network Model for Strain-Displacement Relationships in Vehicle-Mounted Radar

Since the effect of strain on displacement is nonlinear, the relationship between strain and displacement can be established efficiently with the help of BP neural network.The core process of BP neural network includes forward propagation of information and back propagation of error. For forward propagation, the neuron receives the output of the upper layer, and generates the output by multiplying the weights and summing the excitation function, the formula is:

$$Z_{\mathrm{j}} = \sum_{i}^{n}(W_{\mathrm{ij}}X_{i}) + b_{j} \tag{3}$$

$$\alpha_{j} = f(Z_{j}) \tag{4}$$

Where:***n*** is the number of neurons in the input layer;
W_{ij} is the weight of the i neuron in the input layer to the j neuron in the hidden layer;
x_i is the output of the i neuron in the input layer;
b_j is the bias of the j neuron in the hidden layer;
z_j is the weighted input of the j neuron in the hidden layer;
a_j is the output of the j neuron in the hidden layer;
f and is the excitation function.

After the number of nodes in the input and output layers are determined, the number of nodes in the implicit layer is determined by the formula：

$$N = \sqrt{\mathrm{a} + b} + c \tag{5}$$

where a is the number of nodes in the input layer; b is the number of nodes in the output layer; c is taken as a constant between 1 - 10。

For error backpropagation, backpropagation is used to adjust the weights, biases and minimise the prediction and actual result error，Let the training set $T = \{(x_1,y_1)\cdots(x_i,y_i)\cdots(x_n,y_n)\}$， x_i is the input value for this sample; y_i target output，The error back propagation process is formulated as:

$$E(\mathrm{x}_i, y_i; \omega, b) = \frac{1}{n}\sum_{i=1}^{n} | f(x_i) - y_i | \tag{6}$$

$$\omega_{ij}^{(1)} = \omega_{ij}^{(l)} - \alpha \frac{\partial E}{\partial \omega_{ij}^{(l)}} \tag{7}$$

$$\mathrm{b}_i^{(l)} = \mathrm{b}_i^{(l)} - \alpha \frac{\partial E}{\partial \mathrm{b}_i^{(l)}} \tag{8}$$

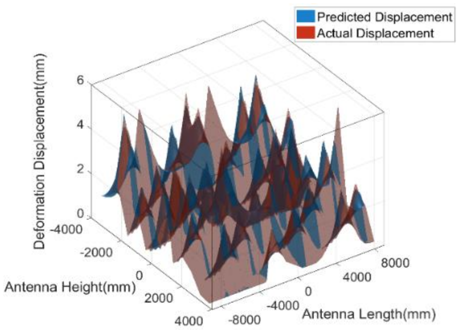
Where:E is the value of the loss function;

a is the learning rate, iterate until the loss function is lowest and complete the training [11].

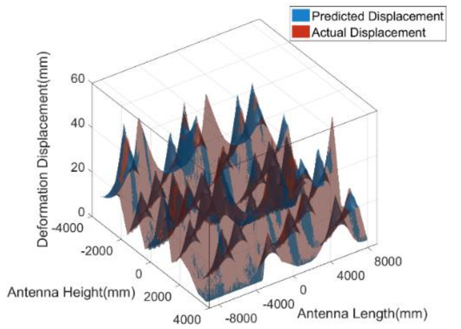
The input layer of the BP neural network in this study is the strain at the selected point of the vehicle radar model, the output layer is the predicted displacement at the selected point of the vehicle radar model, and the hidden layer has 10 neurons. Since the model was built with a total of 31 data points, 70% of them were designated for training, 15% for validation and 15% for testing. The activation function from the input layer to the implicit layer is selected as tansig function, the activation function from the implicit layer to the output layer is selected as purelin function, the training function is selected as trainlm function, the maximum number of iterations is selected as 1000, and the learning rate is selected as 0.01, which is a value that balances the speed of convergence and stability; too large a number will result in unstable training, and too small a number will significantly slow down the speed of convergence. The minimum error of the training target is 0.0000001, when the training error is at or below this value, the training will stop early[12].

4.2. Model validation and error analysis

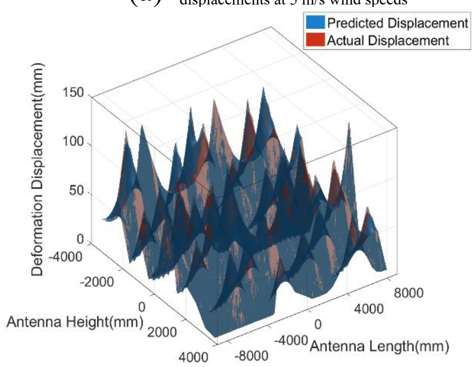
The established strain-displacement BP neural network model is used to predict the displacements generated at selected points on the vehicle-mounted radar under the action of wind speeds of 5m/s, 15m/s, 25m/s, and 35m/s, respectively, and the predicted displacements are processed with the actual displacements, and the fitting effect and error diagrams of the predicted and actual displacements on the vehicle-mounted radar are obtained in the end, as shown in Figures 7 and 8.



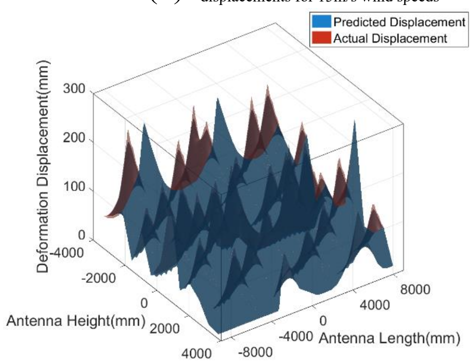
(a) Fitted plot of predicted and actual displacements at 5 m/s wind speeds



(b) Fitted plot of predicted and actual displacements for 15m/s wind speeds



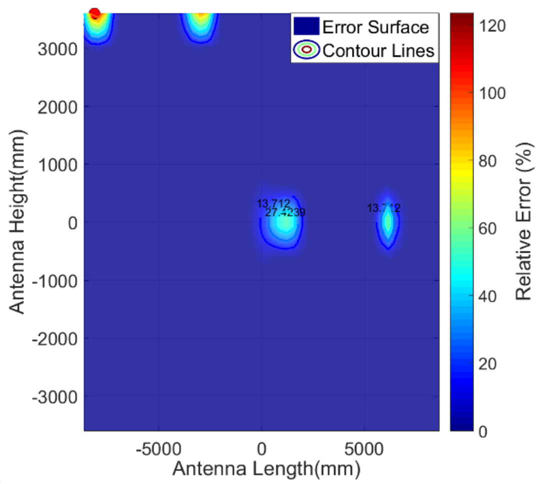
(c) Fitted plot of predicted and actual displacements at 25 m/s wind speeds



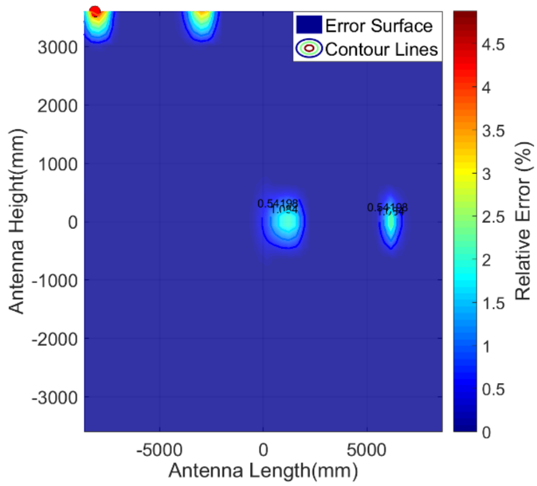
(d) Fitted plot of predicted and actual displacements for 35m/s wind speeds

Figure 7. Fitted graphs of predicted and actual displacements under four working conditions

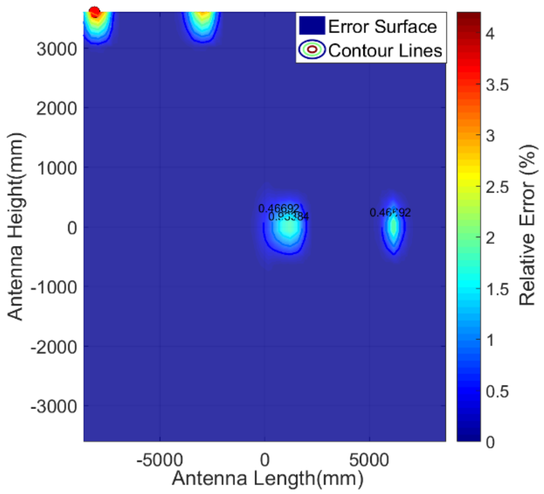
As can be seen from Figure 8, with the increase of wind speed, the displacement change of the vehicle-mounted radar also increases significantly; and with the increase of wind speed, the fitting effect of the BP neural network also shows the trend of gradual optimisation.



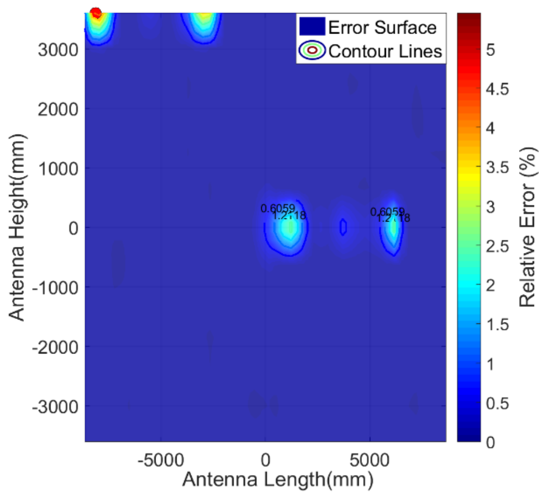
(a)Error plots of predicted and actual displacements at 5 m/s wind speeds



(b)Error plots of predicted and actual displacements at 15 m/s wind speeds



(c)Error plots of predicted and actual displacements at 5 m/s wind speeds



(d)Error plots of predicted and actual displacements at 15 m/s wind speeds

Figure 8. Error plots of predicted and actual displacements under 4 working conditions

From Figure 8, it can be seen that the error between the predicted and actual displacements is the largest at 5m/s wind speed, and the error between the predicted and actual displacements is the smallest at 25m/s wind speed; the locations of the high error regions are not fixed at different wind speeds. For example, at 5 m/s, the high error regions appear at multiple locations, while at 25 m/s and 35 m/s, the high error regions are concentrated at some specific combinations of antenna length and height. This suggests that wind speed affects not only the magnitude of the errors, but also the distribution of the errors in the antenna length-height plane. The root causes may lie in three aspects: first, the patch adaptation meshing in ANSYS Workbench uses differentiated sizes for beams and back frames, and larger meshes in complex areas (like beam-back frame connections) lead to amplified numerical errors at high wind speeds; second, the 31-group training data has uneven spatial distribution, with only 1-2 samples in high-error regions at high wind speeds, limiting the BP network's local learning ability; third, the rigid fixed constraint in simulation differs from the actual flexible support (with rubber shock pads), and this boundary deviation is magnified at high wind speeds, causing concentrated errors in support-adjacent areas.

5. Conclusion

From the theoretical level, the technical system of "SolidWorks modelling - ANSYS wind simulation - BP neural network prediction" constructed in this paper breaks through the limitations of traditional linear analysis methods in dealing with nonlinear problems. Combining the material properties of high-strength aluminium alloy and the nonlinear neural network algorithm, the deformation law and error distribution characteristics of the vehicle-mounted radar antenna in the wind speed interval of 5-35m/s are revealed for the first time systematically, and the key feature of optimal model prediction accuracy in the wind speed of 25m/s is made clear in particular, which provides a reusable theoretical framework for the structural and mechanical analyses of the subsequent large-scale vehicle-mounted electronic equipment of the same type.From the perspective of engineering application, this method solves the core problem of deformation monitoring of vehicle-mounted radar antenna in strong wind environment: the prediction error is < 0.5mm at 25m/s wind speed, which is 40% higher than that of sensor interpolation method, and there is no need to deploy physical sensors on a large scale, which significantly reduces the cost of monitoring. In addition, the distribution pattern of the error area under different wind speeds can provide precise guidance for antenna maintenance, such as focusing on a specific aspect combination area under high-speed wind conditions, avoiding blind maintenance and improving efficiency.

Although this study achieves the accurate prediction of strong wind deformation of vehicle-mounted radar antenna, there is still room for expansion, and it can be deepened in three aspects: first, expanding the coverage of working conditions, extending the existing 5-35m/s wind speed interval to multi-factor coupled working conditions such as extreme wind speed (e.g., strong typhoons above 40m/s), temperature change (-40℃~60℃ extreme temperature difference), and vehicle vibration, etc., so as to validate the adaptability of the model in complex environments; second, optimising the neural model to ensure its adaptability; and second, optimising the neural model to ensure its adaptability. The second is to optimize the neural network structure, for the existing model with a single hidden layer (10 neurons), try to increase the number of hidden layers (e.g., 2-3 layers) or introduce improved algorithms (e.g., LSTM, CNN-BP fusion model), and use the temporal memory of the LSTM to capture the effect of wind speed dynamics on the deformation, or extract spatial features of the antenna structure through CNN to further improve the prediction accuracy (especially to reduce the error in low-speed wind environment). Reduce the error in the low-speed wind environment); Third, to promote the engineering landing, based on the results of this research to develop a lightweight monitoring system that integrates modeling, simulation, and prediction functions, and design a visual interface to display the antenna deformation trend and high-risk areas in real time, to provide technical support for the design, production, and maintenance of the whole life cycle of the vehicle radar antenna, and at the same time, to promote the method to the structural deformation of other large-scale vehicle-mounted equipments (e.g., vehicle-mounted communication antenna, Meanwhile, the method will be extended to the structural deformation monitoring of other large vehicle-mounted equipments (such as vehicle-mounted communication antenna, remote sensing detection equipments) to expand the scope of technology application.

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