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Research Article

Navigation Signal Radio Frequency Channel Modeling and Predistortion Technology Based on Artificial Intelligence Technology and Neural Network

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Digital predistortion technology is widely used in wireless communication. As a vital part of wireless communication system, the predistortion technology of radio frequency power amplifier has always been a hot and difficult topic. This paper will research and explore the key technologies of radio frequency channel construction and predistortion of navigation information through artificial intelligence technology and neural network. The article first conducts a simple research on a new generation of artificial intelligence systems--artificial intelligence is an engineering technology scientific research that develops theories, methods, skills, and application systems for modeling, scaling, and amplifying collective human knowledge. Then, the article combines neural network algorithms. BP network is not only a part of synthetic neural network but also a multiple layer fed-forward network. Finally, a neural network method is proposed to model and predistort the load channel model. Then, the RF channel distortion model can be constructed, and the RF channel modeling simulation experiment and the RF channel predistortion simulation experiment are carried out. The experimental results of this paper showed that compared with the situation without predistortion, the two indicators of the zero-crossing slope distortion and the zero-crossing offset of the discriminant function of the output signal of the channel with predistortion had been greatly improved. Overall, the neural network-based model outperformed the RVTDNN model by 30% on these two metrics. It also indicated that the neural network model could model and predistort the cascade model well, and the new model had better modeling accuracy and predistortion effect than the RVTDNN model.

1. Introduction

For an accurate location service, a navigation payload must provide continuous, accurate, and high-quality navigation signals. However, in the actual satellite payload, due to the influence of nonideal devices, the navigation information is distorted, the information quality is degraded, and the positioning accuracy is also affected. The information loss caused by satellite payload can be mainly divided into two categories: nonlinear distortion caused by power amplification, and linear distortion caused by equipment such as filters and multiplexers. In order to ensure that the signal at the ground receiving end can have a sufficiently large signal-to-noise ratio, the onboard power amplifier generally needs to work near the saturation point, so that the signal will form a relatively strong nonlinear distortion when it is amplified by the power. For large-bandwidth signals, the band-limiting effect of the onboard filter will cause obvious intersymbol interference when the signal passes through the filter. Digital predistortion technology is widely used in wireless communication. As an vital part of wireless communication system, the predistortion technology of RF power amplifier has always been a hot and difficult topic.

Many scholars have proposed various models for power amplifiers based on measurement data, and these models are used for power amplifier modeling and predistortion. At present, most studies on the nonideal characteristics of onboard payloads are conducted independently on filters and high-power amplifiers, and there are few studies on the modeling and predistortion of satellite payload RF channels as a whole. However, in practice, when the components of the onboard radio frequency channel are assembled and integrated, it will be difficult to study each component separately. Especially, when the channel characteristics change due to environmental factors, it is tedious and impractical to measure and analyze each device separately. Therefore, it is meaningful to study the nonideal characteristics of the satellite payload radio channel as a whole and to compensate for it. At the same time, this paper studies and explores the key technologies of radio frequency channel construction and predistortion for navigation information through artificial intelligence technology and neural network, in order to make certain contributions to the research in this area.

According to the research progress abroad, different researchers have also conducted corresponding cooperative research in the modeling of the RF channel of the navigation signal: Chen et al. presented manifold and nonsighted range (NLOS) tunnel patterns for GPS L1CA and BDS B1I signatures. In addition, a method for estimating multipath elements and NLOS satellite particles in a static tunnel situation had been developed [1]. Inspired by the idea of vector tracking, and referring to the principle that the Taylor-extended pseudorange observations in the location domain can be positioned by the least squares method, Wang et al. proposed a novel multichannel combined particle estimation (MPJE) approach based on the least squares method. In the signal domain, the benefits of channel convergence are retained while maintaining the versatility and adaptability of the positioning algorithms [2]. Yang et al. developed a global signature pattern for mobile targets using multiple-input multiple-output radar based on any transmit waveshape and any dish configuration. The results showed that the available signature model was a particular case of the presented signature model [3]. However, these scholars lack certain technical research on the modeling of the radio frequency channel of the navigation signal. In this regard, we will conduct research on the modeling and predistortion technology of the radio frequency channel of the navigation signal on the basis of synthetic technology and neural networks, so we refer to some literature on artificial intelligence technology and neural networks.

Some scholars have also conducted corresponding research in artificial intelligence technology. Mamoshina et al. outlined the next generational human intelligence and blockchain technologies and proposed creative resolutions that could be applied to speed up biomedical studies, giving patients the ability to control and monetize their individual data through new tools. Continual health surveillance incentives had also been adopted [4]. Zhang et al. attempted to present an artificial intelligence medical network framework based on a wide range of artificial intelligence skills and approaches. The architecture utilized artificial intelligence techniques to monitor, diagnose, and treat patients quickly and effectively. Finally, the rational analysis of the technical challenges and real issues that may be facing the implementation of the framework was presented [5]. Rakšnys et al. explored the strengths and weaknesses of big data, data gathering problems, dependability, and usage. Big data could be useful for analyzing and modeling public governing and phenomena related to social policies [6]. Zhao and Cai combined computer study skills to evaluate critical competencies in ELT subjects and constructed an assessment matrix relative to the thresholds [7]. Zhao analyzed the main functions, features, and characteristics of virtual reality sensory management system in virtual reality environment with virtual reality health club sensory management system as the research background. He also proposed to use the Kinect device as a visual capture facility to obtain the user's physical sensory business actions and perform physical sensory operations through depth information [8]. However, there are many kinds of algorithms in artificial intelligence technology, which are not analyzed and studied by these scholars.

A neural network algorithm is a basic method in artificial intelligence technology, and a few academics studied neural network algorithm accordingly. Goh investigated the feasibility of using neural networks to simulate complex relationships between seismic and soil parameters and liquefaction potential. The information processing control system of the neural network was basically modeled after the biological control system of the human brain. A very simple backpropagation neural network algorithm was used [9]. Perna and Rocca proposed a policy for selecting the size of the covert lamina in a feedforward network model. This process was based on a comparison of the out-of-sample predictive power of different models for a given loss factor. In order to get over the issue of spying on the figures, the solution was extended using reality checks and modified to compare nested models [10]. However, these scholars did not research or discuss the radio frequency channel modeling and predistortion technology of navigation signals based on artificial intelligence technology and neural network, but only discussed its significance unilaterally.

The innovation of this paper is reflected in: (1) A brief introduction to artificial intelligence systems; (2) The neural network algorithm is given. A BP network is a multilayer feedforward network based on an algorithm trained on error backpropagation. It is considered to be one of the most broadly available neural network models; and (3) Finally, the method of neural network is proposed to model and predistort the load channel model. The RF channel distortion model is constructed, and the RF channel modeling simulation experiment and the RF channel predistortion simulation experiment are also carried out.

2. Artificial Intelligence Technology and Neural Network Algorithm

The nonideal characteristics of the core components of the satellite payload make the navigation signal distorted, causing the attenuation of the relevant amplitude of the navigation signal, which lead to the distortion of the shape of the correlation function. It ultimately affects the tracking accuracy and tracking deviation of the navigation system. To evaluate the impact on the navigation signal, a load channel model needs to be established. Since the parameters of the proposed load channel model are difficult to extract, a neighborhood approach to model and predict the load channel model in this paper is presented.

2.1. Artificial Intelligence. Artificial intelligence was born mainly from the upgrading, manufacturing, and application exploitation of software in human society. In past years, the application of "new generation human intelligence" has also sprung up, permeating all aspects of life. There are more and more channels for people to know about it, from the conceptual description in Hollywood sci-fi movies to the production mode of real manufacturing, to the use of products in life. Its development once led to the trend of electronic intelligence in this era. Robots, expert intelligence, driverless cars, integrated smart home appliances, smartphones, etc. are all examples of artificial intelligence, which is affecting our daily behavior. The rapid development of technology has brought us into the age of human intelligence. Figure 1 shows the application of human intelligence technology. How is artificial intelligence defined?

General reference book defines artificial intelligence as an engineering technology scientific research that develops theories, methods, skills and application systems for modeling, scaling, and amplifying collective human wisdom. It is an important branch of computer technology and a frontier field of computer technology [11]. Although it is only a branch of computer science, it includes brain science and technology, neurophysiology, psychology, linguistics, logic, cognitive (thinking) science and technology, action research and mathematics, information systems science technology, management science and technology, and other fields of science and technology. It can be said that it is an interdisciplinary subject. For many experts, they hope to have a unified interpretation of the concept of "artificial intelligence." However, from the perspective of technological development, its definition is still not unified.

Most of us have a vague understanding of artificial intelligence under different mindsets. When people are talking about artificial intelligence, high-tech equipment like robots will come into their minds. The major distinction between the two, however, is that artificial intelligence is the functional equivalent of a robot's brain and is not confined to its brain. Its nature is an automatic imitation of the human mind and awareness of the human device. It can reflect autonomously and has the ability to surpass human intelligence. After the downturn, artificial intelligence has now moved into a new phase. As the need for future smart applications grows, artificial intelligence with more versatility will present itself [12].

2.2. Neural Network Algorithm. The artificial neural network is an algorithm that realizes distributed data processing by simulating the behavioral characteristics of neurons. The network realizes data processing through system complexity and by adjusting the interconnection relationship between nodes in the network [13]. Human neural networks also have an initial capacity for adaptation and self-organization. During learning or training, the weight values of synapses change in response to changes in the surrounding environment. The same network can have various capabilities as a result of various learning approaches and contents. BP network is also a part of artificial neural nets, which is a multilayer feedforward network. BP neural network algorithm uses a given target as an algebra of the linear equation, thereby establishing a linear equation. It can learn the pattern mapping relationship between input and output. The algorithm is practical and easy to understand.

Classification of neural networks: Some factors of the neural network model must also be emphasized, such as network topology, learning rules, and neuron characteristics. So far researchers have created more than forty neural network models, among which the more well-known ones are backpropagation networks, self-organizing maps, and Boltzmann [14]. Psychologists and cognitive scientists study the purpose of neural networks to explore the mechanisms by which the human brain processes, stores, and searches for information, to understand the mechanisms by which the human brain functions and to develop a microstructural theory of human epistemic processes. According to different topological structures, neural networks roughly include the following:

Forward neural network: A forward network is also called a feedforward network. The neurons of this neural network can only receive the injection of the previous neuron, which cannot be reflected in the network. The main method of realizing constitutive nonlinearity in this network is the multiple repetitions of the simplest nonlinear function [15]. The more classic feedforward neural networks include BP neural network and RBF neural network. BP neural network is a typical feedforward network.

Feedback network: It performs very well on the dynamic characteristics of nonlinear dynamical systems. There are some stable equilibrium states in the feedback neural network, and these equilibrium states can be adjusted and saved in the network through the set network weights. The most classic feedback network is the Hopfield-type neural network.

BP neural network algorithm: Neurons are the basic units of neural networks. The model of the neuron is shown in Figure 2. After the addition of the external input value A and the weight U, the threshold D is summed as the input of the neuron, and then the output B of the neuron is obtained according to the activation function $g(A)$ of the neuron. The more common activation functions are logsig(a) and tansig(a), and sometimes purelin(a) is also used as the activation function.

The expression for logsig(a) is as follows:

$$\operatorname{logsig}(a) = \frac{1}{1 + \operatorname{esp}(a)}. \tag{1}$$

The expression for tansig(a) is as follows:

$$\operatorname{tansig}(a) = \frac{2}{1 + \operatorname{esp}(2a)} - 1. \tag{2}$$

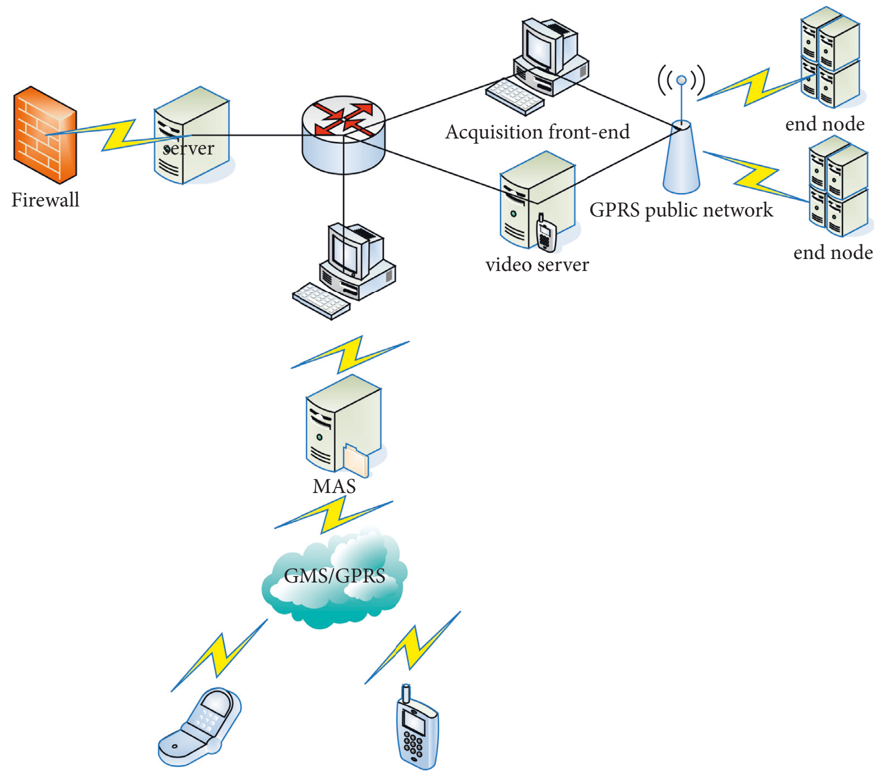

Figure 1: Application of artificial intelligence technology.

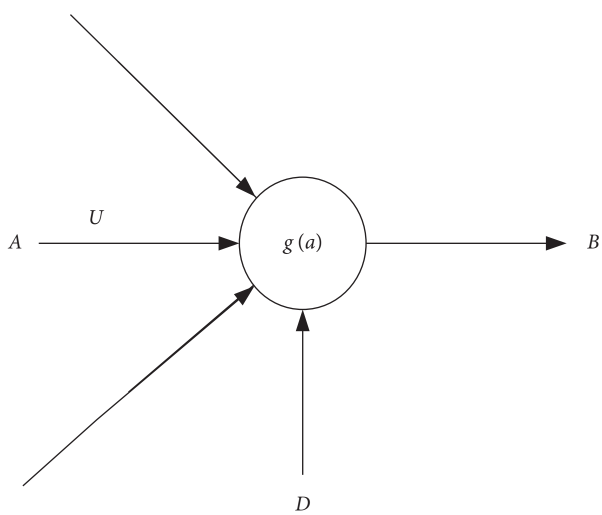

Figure 2: Neuron structure diagram.

The expression for purelin(a) is as follows:

$$\mathrm{purelin}(a) = -a. \tag{3}$$

The BP algorithm is a monitored study algorithm whose key idea is to input study samples, use a backpropagation algorithm to iteratively adapt the weights and biases of the network to make the output vector as near as possible to the desired vector, and then save the weights and biases of the network. BP neural network refers to a type of feedforward neural network that is connected by multiple neurons. It contains three layers, namely, input and output layer, hidden layer, and input and output layer. Figure 3 shows a classic three-layer BP network system. The BP neural network adopts a form of complete interconnection on the bottom layer and between layers, that is, each neuron on any level is connected with all neurons on the previous level. Cells are connected, but there is no mutual connection between neurons within the same level. The signal passes layer by layer, propagating from left to right.

BP network transmission mode is divided into two stages:

(1) *Forward Pass Stage*. Pass the input information step by step until the output layer. In the forward transmission stage, the values of the weights and limits of the network are constant. In the forward transmission stage of the neural network, the transmission of the input signal from the input signal to a hidden layer is the beginning of the forward transmission, and the message is transmitted from left to right. The output layer calculates the error of each neuron in this layer as a sign of the end of forward propagation.

For a three-layer BP neural network, first enter the forward propagation stage. a_q is taken as the entry of the neural network to transmit the signal to the hidden lever, and then the input w_n of the nth neuron in the hidden layer is as follows:

$$w_n = \sum_{q}^{p} \phi_{mn} a_q + \tau_n. \tag{4}$$

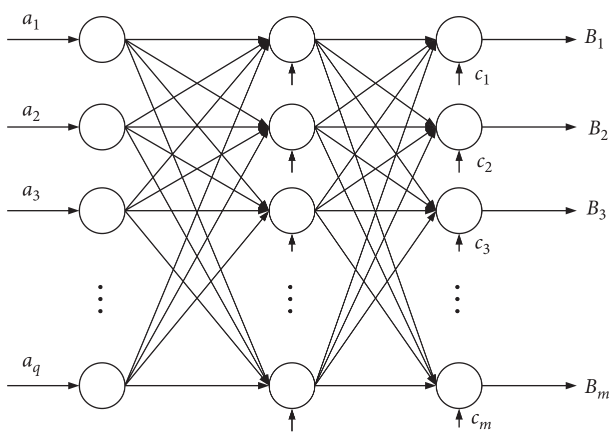

Figure 3: BP neural network structure diagram.

Then, according to the working principle of neurons, the output b_n of the nth neuron can be expressed as follows:

$$b_n = \gamma(w_n). \tag{5}$$

The input of the mth neuron in the output lever is as follows:

$$W_n = \sum_{n}^{l} \phi_{mn}\gamma(w_n) + c_m. \tag{6}$$

According to the working principle of neurons, the output B_{m} expression of the mth neuron in the output layer is as follows:

$$B_{\mathrm{m}} = \alpha(W_m). \tag{7}$$

By integrating the formulas, the output B_{m} of the mth neuron can be obtained as follows:

$$B_m = \alpha\left[\sum_{n}^{1} \phi_{mn}\gamma\left(\sum_{q}^{p} \phi_{mn}a_q + \tau_n\right) + c\sum m\right]. \tag{8}$$

Finally, the difference K_{m} between the output of the neural network and the standard response can be calculated through formula (9), that is, the total instantaneous error μ:

$$u = \frac{1}{2}\sum_{m}^{1} (K_m - B_m)^2. \tag{9}$$

So far, the forward propagation process of the BP algorithm ends. The algorithm ends if u meets the error requirement. Otherwise, the BP algorithm enters the backpropagation stage.

(2) *Reverse Transfer Process*. When the reverse process is carried out, the error information is reversely transferred from the output layer to the input layer step by step. At the same time, the local gradient of each neuron is calculated recursively, and the direction of change of the weights of each level is modified, from right to left, recursively calculated layer by layer. The backpropagation method adapts the weights and thresholds of each connection layer. The weight correction Δu is defined as formula (10):

$$\Delta u = -\beta\frac{\partial u}{\partial u}, \tag{10}$$

$$\delta_q = \frac{1}{2}\log\frac{1 - h_q}{h_q}. \tag{11}$$

It can be known from formula (11) that β is the learning rate parameter. The negative sign indicates gradient descent in the weight space. The ratio of ∂u and ∂u represents the sensitivity factor, and its value determines the search direction of the weight value in the weight space. The correction to the output layer weights is slightly distinct from the correction to the hidden layer weights, and they need to be derived separately. First, the modification of the weights of the output layer is derived. For the mth neuron in the output layer, its sensitivity factors are as follows according to the chain rule:

$$\frac{\partial u}{\partial u_{mn}} = \frac{\partial u}{\partial R_{mn}} \bullet \frac{\partial R_{mn}}{\partial B_{mn}} \bullet \frac{\partial B_{mn}}{\partial W_{mn}} \bullet \frac{\partial W_{mn}}{\partial u_{mn}}. \tag{12}$$

R_m is the difference between the expected response and the output of the mth neuron, which is expressed as follows:

$$R_m = K_m - B_m, \tag{13}$$

$$\mathrm{l}_n = g\left(\sum_{m=1}^{M-1} s_{mn}a_{mn} - O_n\right). \tag{14}$$

By integrating these formulas, the correction amount of the output layer weight can be obtained as follows:

$$\partial u_{mn} = -\beta\frac{\partial u}{\partial u_{mn}} = \beta R_{mn}\alpha^{\cdot}(W_m)b_n. \tag{15}$$

The hidden layer weight correction is slightly more complicated. For the hidden layer neuron n, the sensitivity factor can also apply the chain rule, but the false signal of the hidden layer is computed based on the false signal R_{mn} of all neurons connected to the neurons of the hidden layer, which is different from the output layer. Therefore, the sensitivity factor to the hidden layer neurons satisfies the new chain rule as follows:

$$\frac{\partial u}{\partial u_{nq}} = \frac{\partial u}{\partial b_n} \bullet \frac{\partial b_n}{\partial w_n}\frac{\partial w_n}{\partial u_{nq}} \tag{16}$$

b_n is the output of the hidden layer neurons. The derivative of all instantaneous errors to the hidden layer neuron output b_n is as follows:

$$\frac{\partial u}{\partial b_n} = \sum_{m}\frac{\partial u}{\partial R_m} \bullet \frac{\partial R_m}{\partial B_m} \bullet \frac{\partial B_m}{\partial W_m} \bullet \frac{\partial W_m}{\partial b_m} = -\sum_{m} R_m\alpha^{\cdot}(W_m)u_{mn}. \tag{17}$$

The hidden layer error correction value is as follows:

$$\Delta u_{nq} = \beta\left(\sum_m R_m \alpha'(W_m) u_{mn}\right) \bullet \gamma'(w_m) a_{nq}. \tag{18}$$

The correction amount of the threshold is the same as that of the weight correction amount. The threshold correction amount for the output layer is as follows:

$$\Delta\tau_n = -\beta \frac{\partial u}{\partial \tau_n} = \beta W_m \alpha'(W_m). \tag{19}$$

The threshold correction amount for the hidden layer is as follows:

$$\Delta c_m = -\beta \frac{\partial u}{\partial c_m} = \beta\left(\sum_m R_m \alpha'(W_m) u_{mn}\right) \bullet \gamma'(w_m). \tag{20}$$

After modifying the weight threshold of each layer, the backpropagation algorithm is completed.

Steps of BP neural network calculation:

Figure 4 is a flowchart of neural network training. The specific steps are as follows:

(1) *Neural Network Initialization.* During the initialization phase of the neural network, the weights and thresholds of each layer will be assigned.

(2) Enter training samples.

(3) *Forward Propagation Process.* The signal is forward propagated from the input layer from left to right.

(4) *The Output Layer Computes the Error.* It will stop the program if the error meets the accuracy. If the accuracy is not met, the algorithm will enter the backpropagation stage.

(5) *Backpropagation Process.* The local gradient of the network will be calculated to modify the weights of each layer.

(6) Enter the forward propagation process again.

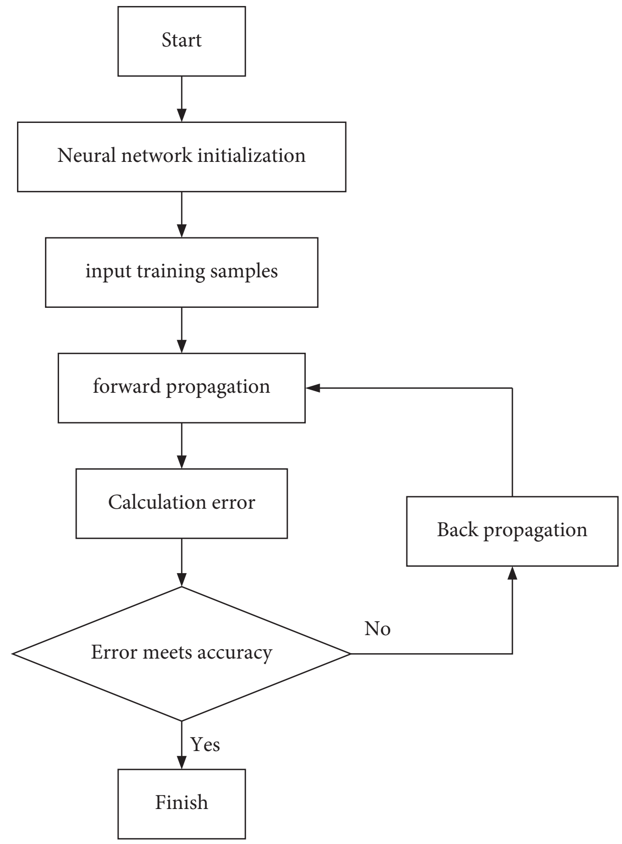

Figure 4: Neural network training flow chart.

3. Experimental Results of Channel Modeling and Predistortion Technology

3.1. Radio Frequency Channel Distortion Model. Figure 5 shows a general block diagram of the satellite navigation payload, which is mainly divided into a navigation information generation unit, a spectrum generation and upconversion devices, a high power amplifier, and a low-output power multiplicators and aerials.

The system shown in the figure has five components, each of which causes the signal to distort one of the following situations: distortions that are linearly time-invariant, for example, amplitude distortion and group-delay fluctuations, are primarily caused by information generators, filters, multiplexers, and antennas.

3.2. Radio Frequency Channel Modeling and Simulation. For verifying the modeling ability of the neural network model to the baseband equivalent model of the radio frequency channel of the satellite payload, simulation verification is carried out. The channel model is shown in Figure 6.

The input signal was an AltBOC(15, 10) digital baseband signal which was ideally filtered according to the single-sideband emission bandwidth of 35.805 MHz, and the saleh model was selected as the memoryless power amplifier model. The prefilter and postfilter were designed by Fdatool tool of MATLAB platform. The pre/postfilters were simulated as FIR filter and IIR filter, respectively. The FIR filter was a 3rd-order low-pass Equiripple filter, the sampling rate was 500 MHz, Fpass = 35 MHz, Fstop = 36 MHz, Wpass = 1, and Wstop = 0.1. The IIR filter was a 3rd-order low-pass Chebyshev filter, the sampling rate was 500 MHz, Fpass = 35.805 MHz, Apass = 1 dB.

Both prefilter and postfilter were FIR filters: The output of the neural network model obtained through training was very close to the output of the cascade model, and the modeling effect of the neural network model on the cascade model was very impressive. The neural network model was more accurate than the RVTDNN neural network model in the modeling accuracy of the cascade model. For the AltBOC signal with a duration of 1 ms and a sampling rate of 500 MHz, that is, the number of signal points was 500,000, the normalized mean square errors of the neural network model and the RVTDNN model were calculated, which were −55.9680 dB and 50.6864 dB respectively. Since the LMBP training algorithm has a certain randomness, the method of

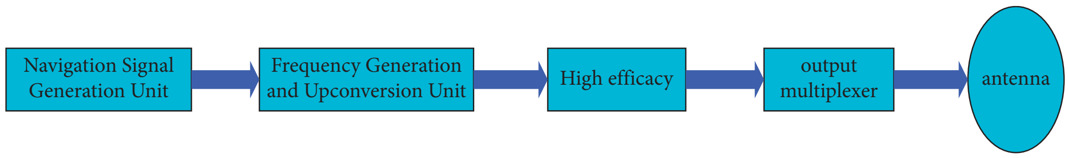

Figure 5: Navigation payload structure diagram.

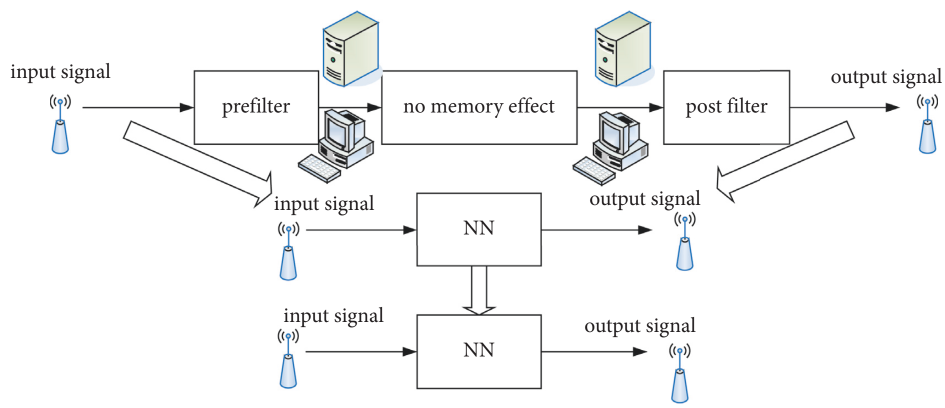

Figure 6: Simulation channel model.

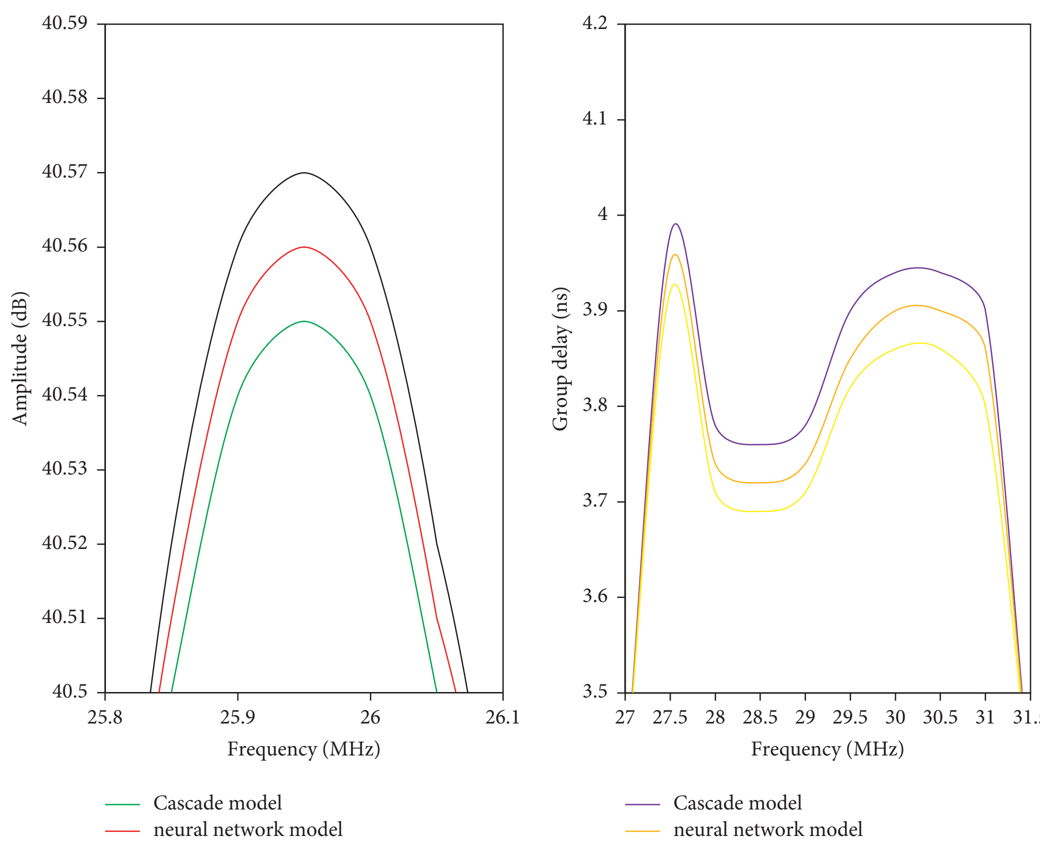

Figure 7: Amplitude-frequency response and group delay comparison.

averaging multiple trials was used to reduce the influence of this randomness on the test results.

Figure 7 shows the magnitude-frequency reaction and group delay of the lanes. The neural network model in this paper is more accurate than the RVTDNN model in the modeling accuracy of the FIR filter-memoryless power amplifier-FIR filter cascade model. The parameters of each model are adjusted through simulation, and the number of

Table 1: Model parameters and corresponding NMSE 1.

Type of model	Total number of parameters	NMSE (dB)
Neural network model	261	−56.03021
RVTDNN model	339	−51.01203
Cascade model	351	−49.87326

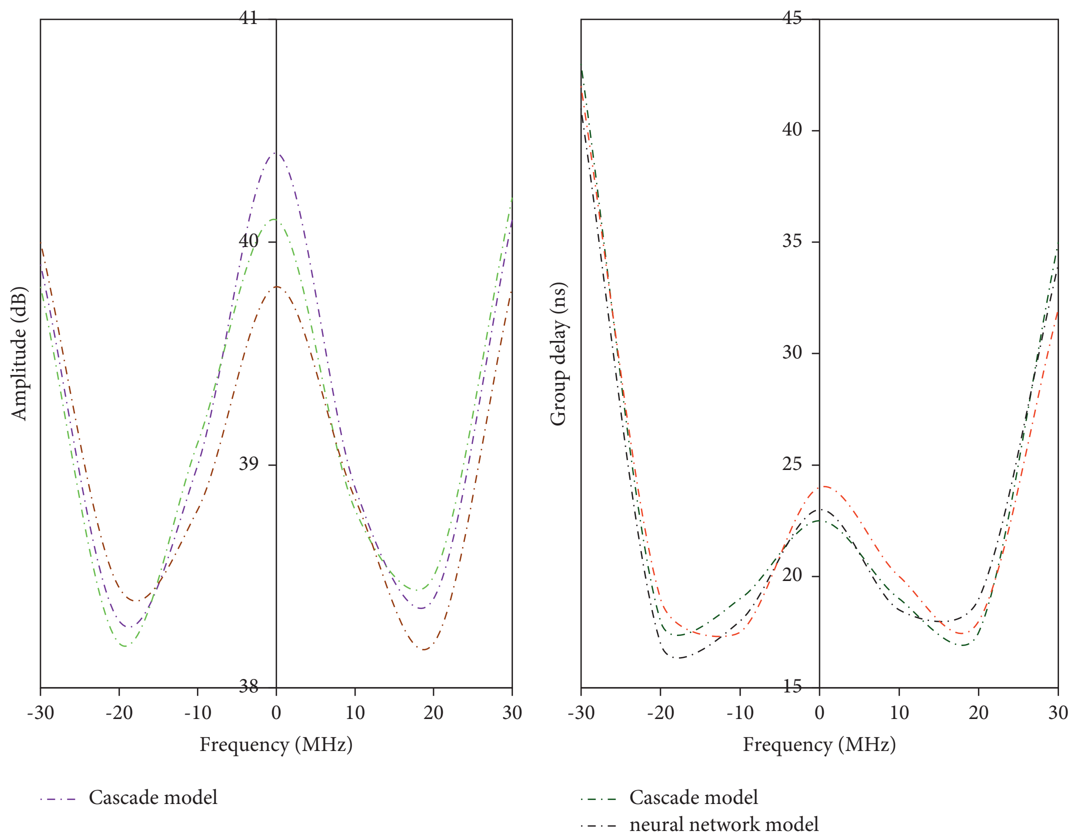

Figure 8: Amplitude-frequency response and group delay.

parameters is minimized while ensuring the modeling accuracy. The number of parameters of each model obtained is shown in Table 1.

As can be observed from the table, the neural network model has fewer parameters than the RVTDNN network model, and from the obtained NMSE results, the neural network model has a higher fitting accuracy than the cascade model. When adjusting the model parameters, it is found that when the number of delay taps and the quantity of neurons per layer is small, appropriately increasing the number of delay taps and the number of neurons per layer can improve the modeling accuracy. However, when a suitable value is exceeded, continuing to increase the number of delay taps and neurons will degrade the modeling accuracy. This is because when the number of parameters exceeds the minimum suitable number, continuing to increase the number of parameters will easily lead to overshooting. The fitting and convergence rate will also decrease.

Both prefilter and postfilter were IIR filters: For the case where the cascaded model filter was an IIR filter, the modeling accuracy of the neural network model was also higher than that of the RVTDNN model. Meanwhile, compared with the case where both the pre/post were FIR filters, when both pre/post were IIR filters, the modeling precision of the two neural network models decreased. The calculated NMSEs of the neural network model and the RVTDNN model were −45.5387 dB and −41.4719 dB, respectively, both of which had dropped by about 10 dB. In the meantime, to better fit the strong memory influence brought by the IIR filter, the delay taps of both models were increased. This phenomenon could be explained by the structure of the neural network.

Figure 8 shows the prefilter (IIR)-memoryless power amplifier-postfilter (IIR) cascade model and the magnitude-frequency reaction and group delay of the neural network model obtained by training fit. It is verified from the

Table 2: Model parameters and corresponding NMSE 2.

Type of model	Total number of parameters	NMSE (dB)
Neural network model	941	−46.02312
RVTDNN model	1698	−40.9795
Cascade model	1706	−39.8921

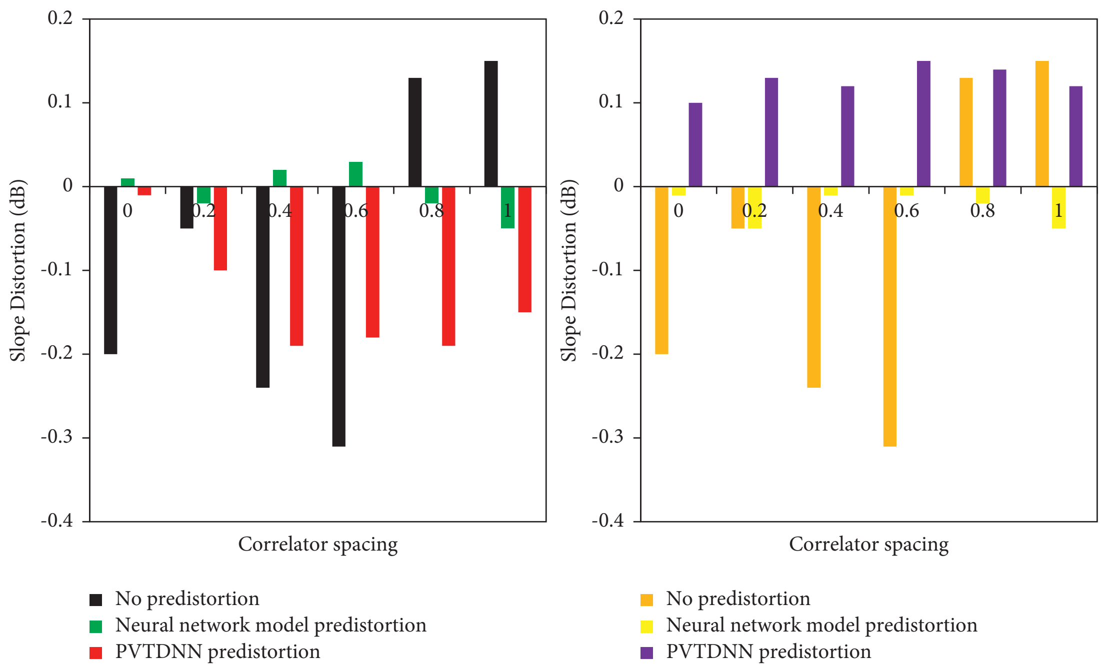

Figure 9: Slope distortion at the zero-crossing point of the upper and lower sideband discrimination function of the AltBOC signal.

frequency domain that the modeling accuracy of the neural network model for the IIR filter-memoryless power amplifier-IIR filter is higher than that of the RVTDNN model. Likewise, the parameters of the two models and the corresponding NMSE are given, as shown in Table 2.

As can be seen from the table, compared with the RVTDNN model, the neural network model has fewer parameters and achieves better NMSE performance.

3.3. Radio Frequency Channel Predistortion Simulation. The neural network model can also be used to predistort the baseband equivalent model of the RF channel of the navigation signal. The input signal will go through the neural network predistortion model for predistortion processing before going through the prefilter, and then it will go through the radio frequency channel baseband equivalent model represented by the prefilter-memoryless power amplifier-postfilter. Since the characteristics of the neural network predistortion model and the radio frequency channel baseband equivalent model are inverse, the neural network predistortion model can compensate the input signal in advance to reduce the distortion of the signal. The prefilters and postfilters were FIR filter and IIR filter, respectively. After experiments, it is found that when the quantity of parameters of the neural network predistortion model is the same as the number of parameters in modeling, better predistortion effect can be achieved.

Both prefilter and postfilter were FIR filters: When the pre/postfilters were both FIR filters, the predistortion effect could be evaluated by comparing the energy profile of the output signal with/without the pre-true channel model, the zero-crossing offset of the discriminant function, the ramp distortion of the discriminant function, the correlation loss, the out-of-band power loss, and other indicators.

Figure 9 illustrates the zero offset of the discriminant function and the ramp distortion of the zero of the discriminant function for the output signal. It can be observed that after predistortion compensation, the zero-crossing offset and slope distortion indicators are significantly improved.

The calculation results of correlation loss and out-of-band power loss are shown in Table 3. After predistortion, both the correlation loss and out-of-band power loss are reduced by about two orders of magnitude. By comparison, it can also be found that the predistortion influence of the neural network model is greater than that of the RVTDNN model.

Both prefilter and postfilter were IIR filters: When both pre/post filters were IIR filters, the predistortion effect is

Table 3: Correlation losses and out-of-band power losses 1.

Indicator	Correlation loss (dB)	Out-of-band power loss (dB)
No predistortion	−0.0182	−0.0301
Neural network model predistortion	$-6.8996e-04$	$-8.5201e-05$
RVTDNN predistortion	−0.0024	$-1.7002e-04$

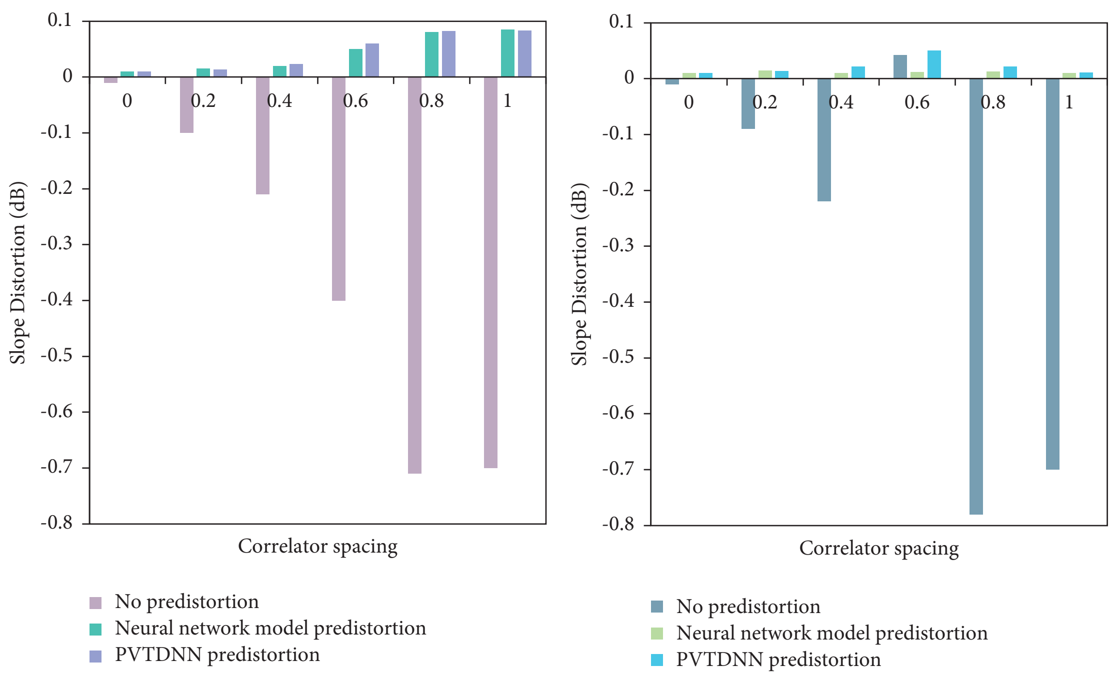

Figure 10: Zero-crossing offset of the upper and lower sideband discrimination functions of the AltBOC signal.

Table 4: Correlation losses and out-of-band power losses 2.

Indicator	Correlation loss (dB)	Out-of-band power loss (dB)
No predistortion	−0.0391	−0.0081
Neural network model predistortion	−0.0021	$-4.9796e-04$
RVTDNN predistortion	−0.0022	$-6.9669e-04$

evaluated by comparing the power spectrum of the output signal of the channel model with and without pre-warning, the zero-crossing offset of the discriminant function, the ramp distortion of the discriminant function, the correlation loss, and the out-of-band power loss.

Figure 10 shows the zero-crossing offset and zero-crossing slope distortion of the upper and lower sideband discrimination functions of the output signal with and without predistortion when the pre/post filters were both IIR filters. As can be seen from the figure, compared with the case without predistortion, the two indicators of the discrimination function zero-crossing offset and zero-crossing slope distortion of the output signal of the predistorted channel have been significantly improved. On the whole, the neural network model outperformed the RVTDNN model slightly on these two metrics by 30%.

When both pre/postfilters are IIR filters, the correlation loss and out-of-band power loss of the output signal in the channel are shown in Table 4. As you can see from the chart the predistortion reduces both the correlation loss and the loss of out-of-band power by an order of magnitude, and the predistortion influence of the neural network model is slightly greater than that of the RVTDNN model.

4. Discussion

High-quality navigation signal broadcasting is an important assurance for the high accuracy of navigation signal applications, and the nonideal characteristics of onboard payload components lead to nonlinear and linear distortions in navigation communication, which in turn reduces the efficiency of navigation communication. Irregular misalignment is primarily induced by powerful amplifiers, while irregular misalignment is primarily induced by filters, upconverters, multiplexers, and antennas. At present, most of the research studies on the nonideal characteristics of onboard payloads focus on the filter and high power amplifier respectively, and there are few studies on the modeling and predistortion of the satellite payload RF channel as a whole. In real practice, there is a need to study the nonideal characteristics and predistortion of the radio frequency channel of the satellite payload as a whole.

5. Conclusions

For verifying the modeling and predistortion capability of the neural network model to the baseband equivalent model of the radio frequency channel of the satellite payload, a simulation experiment was carried out. The FIR filter-saleh model-FIR filter cascade model and the IIR filter-saleh model-IIR filter were modeled and predistorted with the suggested neural network model, respectively. The proposed neural network model can effectively model and predict the cascade model, as shown by the simulation results. Compared with the RVTDNN model, the new model has higher modeling accuracy and better predistortion effect with fewer numbers. The simulation of this paper is based on the MATLAB platform, and the simulation of the channel model is on the basis of the outcomes of the mathematical model. However, due to the influence of noise and other environmental factors in practical applications, the situation will be more complicated, and the effectiveness and stability of the modeling and predistortion methods need to be further verified.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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