Short-wave communication link prediction algorithm based on deep learning

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Abstract. In view of the shortcomings that the accuracy of the existing ionospheric models is not enough to reflect the local real-time changes, this paper uses the time series prediction tool of deep learning to obtain the model of a specific communication link, and combines it with the ionospheric theoretical calculation model to improve the accuracy of communication link prediction. The main work is to analyze and compare the international broadcasting data and the model calculation data, summarize and sort out the characteristics of the link data, and then on this basis, look at the change of the difference between the two, and carry out link prediction, which achieves the goal of improving the calculation effect of the link model, which is of great significance to the short-wave frequency management.

Keywords: Shortwave； frequency management,；time series； deep learning.

1. Introduction

Short-wave communication has the advantages of long-distance communication, strong resistance to destruction, and low cost, and has always been the backup means of communication[1]. It is also an important guarantee for broadcast rescue and long-distance communication in wireless communication. Long-distance short-wave communication mainly propagates through the sky wave, so the effect of short-wave communication is related to the changing characteristics of the ionosphere. The reflection characteristics of the ionosphere are constantly changing with time, location, frequency, season, and year, and belong to a time-varying dispersive channel. Due to the influence of the solar activity cycle, even the changes within a day are very large. It has three types of selective fading in time, frequency, and space, which brings great uncertainty to the scheduling and use of shortwave communication resources[2]. Due to the time-varying dispersive characteristics of the shortwave channel, its availability and reliability are greatly affected by changes in shortwave frequency, so shortwave frequency selection has become an important means of effectively utilizing shortwave communication for transmitting information.

Frequency prediction based on ITS model is one of the important means for short-wave frequency selection. The ITS short-wave communication channel model is a communication link prediction model established by the American Telecommunication Science Association through years of ionospheric information statistics over 30 years ago. It is obtained by statistical simplification of the ionosphere after being established, and its accuracy is not enough to reflect the local real-time changes[3]. In addition, there are many factors affecting the short-wave communication effect, including the performance of transmitter and receiver equipment and antenna performance, so there will be deviations in the prediction of working frequency in actual short-wave communication, and sometimes there are considerable differences.

In this paper, the deep learning method is used to construct the corresponding time series prediction model, which improves the prediction accuracy of the shortwave traditional ionospheric model and better predicts the available frequency bands of shortwave, which also has a certain guiding role in real-time link analysis, and can improve the frequency selection efficiency of frequency tube equipment to a certain extent.

2. Communication link prediction

2.1 Algorithm selection and short-wave propagation model selection

2.1.1 GluonTS time series prediction algorithm

Deep learning is a method of machine learning that aims to uncover underlying patterns and representation levels within initial sample data. The knowledge acquired through this process not only facilitates the generalization of various types of data, such as text, images, and sound, but also enables the rational interpretation of these datasets and the extraction of potential information from them[4]. With advancements in computer technology, particularly in the deepening research on artificial neural networks, deep learning has demonstrated remarkable capabilities[7]. Given the substantial volume of data processed by deep learning algorithms, there is a need to enhance storage utilization efficiency, which has spurred further exploration into neural network learning algorithms. By emulating memory principles and storage mechanisms inherent in neural networks, deep multi-layer neural network-based deep learning algorithms exhibit high proficiency in both learning and processing capabilities[8].

GluonTS is a deep learning-based toolkit that operates within the Python programming environment. The integrated GluonTS toolkit offers convenient functionality for straightforward data prediction and evaluation. Built on the MxNet deep learning framework, GluonTS provides trained predictive models (i.e., predictors) that return predictions along with representations of time indices (start, end, and granularity) and probability distributions of values at these time indices. To date, time series forecasting has found applications in various domains within scientific research[5], with deep neural networks demonstrating numerous successful applications in this field. As a comprehensive toolkit incorporating a wide range of deep learning methods, GluonTS is particularly well-suited for handling large volumes of data.

2.1.2 VOACAP

The short-wave skywave propagation model used in this study is VOACAP, which uses global ionospheric data collected from 1950 to 1960, including free-space transmission loss, ionospheric absorption, reflection absorption, and additional loss. One of its advantages is that the predictive mathematical model used is a smooth function between short-range and long-range models, which has better predictive effects than models such as ICEPAC in the distance range of 7,000 to 10,000 kilometers. However, there is a large gap between the model's predictions and actual received data. Analyzing the reasons for this, the first is that the performance of the receiving antenna is not clear, the second is that the randomness of skywave propagation is relatively large, and the third is that the ionospheric data used has temporal discontinuity. Because some time-varying effects of shortwave skywave communication links are difficult to fully consider, using time series prediction methods can be used to predict such changes and ultimately improve the model's predictive effect.

2.2 Data processing and model training

The program designed in this paper analyzes and predicts huge communication data. The first problem encountered is that there are certain problems in data recording, such as the data recorded every second is 0 or not collected in the first ten seconds of every minute in the time period. Therefore, the first step is to carry out simple comparison and screening processing of the data. The programming environment used in this design is built based on python[6], which has certain advantages in convenience and processing, mainly because it has many open source function libraries to facilitate the realization of the purpose. The main idea of data processing is to first compare the richness of the data recorded between different stations, and then determine the combination of several groups of sending and receiving messages as an alternative, and then use python's pandas library to read and write and process the data, so as to further eliminate abnormal data, and then calculate the size of the received signal every minute. Finally, the median of one hour is calculated to replace the calculated value of each hour VOACAP model, so as to facilitate data comparison and processing.

In the final results, as shown in Figure 1, the relationship between the predicted signal strength changes and the actual signal can be clearly seen. There are two curved stripe areas in the figure, which represent the predicted probability distribution. That is, the probability of the image falling in the narrower region is 50% (dark green area), and the probability of falling in the wider region is 90% (light green area). This shows that the model's prediction results will fluctuate with the adjustment of parameters, but the trend of predicting the signal's increase or decrease will not change. By comparing the changes in the predicted signal and the actual signal, it can be seen that predicting the signal strength directly is not accurate enough. Therefore, this paper proposes an improved prediction model.

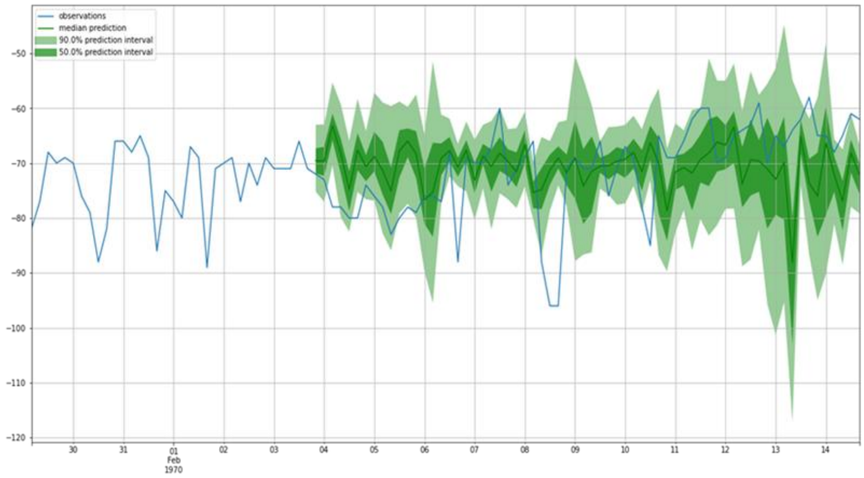

Fig. 1 Model prediction output

2.3 Model evaluation

The accuracy of the GluonTS prediction model in this paper was evaluated using goodness of fit and MAPE. Goodness of fit refers to the degree to which the regression equation fits the observed values. The statistic that measures goodness of fit is the decision coefficient R2. The value of R2 ranges from 0 to 1. The closer the value of R2 is to 1, the better the regression equation fits the observed values. Conversely, the closer the value of R2 is to 0, the worse the regression equation fits the observed values. MAPE is the mean absolute percentage error, which measures the offset of the predicted value relative to the measured value. The value ranges from [0,+]. The closer to 0, the better the model fits.

The formula for goodness of fit:

$$R^2 = 1 - \frac{RSS}{TSS} \quad (1)$$

RSS is the sum of squares of deviation, representing the sum of squares of deviation between the actual value and the predicted value, representing the unknown degree of change of the variable:

$$RSS = \sum_{i=1}^{n} (y_i - \widehat{y_i})^2 \quad (2)$$

TSS is the total sum of squares, representing the sum of squares of the deviation between the actual value and the expected value, representing the total degree of change of the variable:

$$\mathrm{TSS} = \sum_{\mathrm{i}=1}^{\mathrm{n}} (\mathrm{y_i} - \bar{\mathrm{y}})^2 \quad (3)$$

MAPE is the mean absolute percentage error, which measures the offset of the predicted value relative to the measured value:

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{\widehat{y_i} - y_i}{y_i} \right| \quad (4)$$

3. Improvement of HF communication prediction model

3.1 Comparative analysis of VOACAP predicted value and measured value

According to the sorting of all broadcast data, the two sets of data records from Kashgar, China - Kirov, Russia, and Qiqihar, China - Chengdu, China are relatively unified, which is conducive to data analysis. The data of Kashgar, China and Kirov, Russia were selected for analysis.

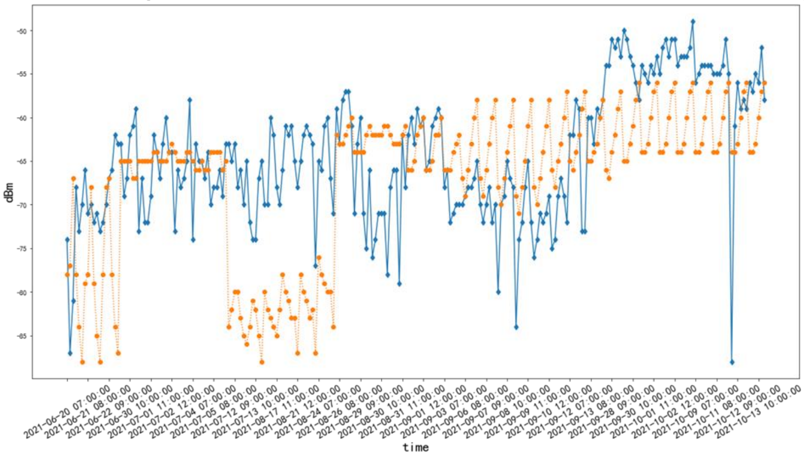

Fig. 2 Kashgar, China - Kirov, Russia communication data

As shown in Figure 2, the prediction of communication effect using VOACAP model is not reliable, and there is a big gap between them.The VOACAP model has strong regularity, and the signal randomness in the actual communication is strong. The correlation between the two sets of data is calculated, and the probability of the two being irrelevant is about 0.0019. Therefore, it is believed that there is a certain connection between the two, and the correlation between the two can be fitted and predicted.

3.2 Signal strength prediction of communication link

The MXNet module of GluonTS is used for deep learning based on LSTM neural network. This model has a relatively good processing effect on time series data, and only needs to predict the rule of the gap between the actual received signal and the predicted signal strength of VOACAP.

In the analysis and prediction of the signals of Kashgar International Broadcasting in China and Kirov International Broadcasting in Russia, the trained model can predict the future period of time within a certain error range, which can be considered to have achieved a relatively good prediction effect, as shown in Figure 3.

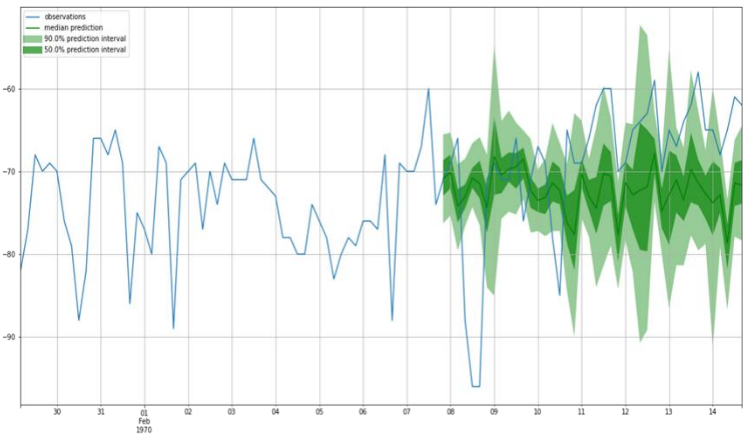

Fig. 3 Kashgar, China - Kirov, Russia GluonTS prediction

By checking and evaluating the predicted results, it can be found that GluonTS 'prediction model has a good effect on short-wave skywave propagation. By calculating the goodness of fit of the model, it can be obtained that the goodness of fit of the model is 88.5%, which means that the law predicted by the model reaches 88.5% of the law of the data.In order to verify the accuracy of the conclusion, another communication link was analyzed and predicted to verify the feasibility of using GluonTS for communication link transmission prediction.Here is the forecast for Qiqihar, China - Chengdu, China:

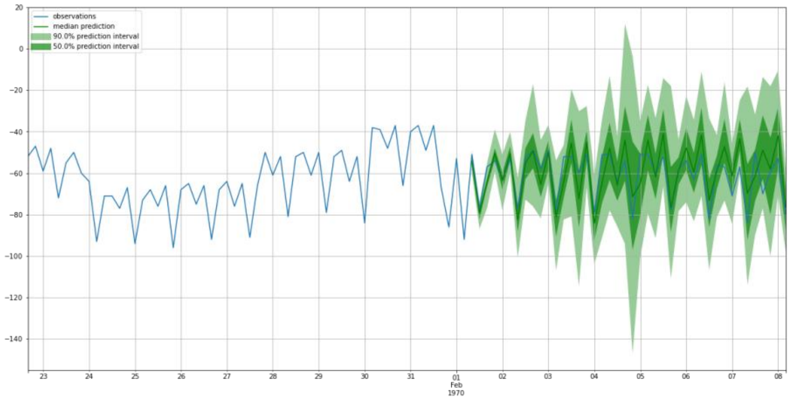

Fig. 4 Qiqihar, China - Chengdu , China GluonTS prediction

Through the analysis of these two links, it can be seen that the GluonTS model prediction has basically achieved the expected results. The prediction effect of the model is above 80% for both links, which means that the model can reflect the规律 of more than 80% of the data. This indicates that GluonTS can accurately predict data of this type, and it is possible to further analyze and predict the data using GluonTS. By studying the changes in the signal of a specific communication link, it is possible to investigate how to improve the prediction results of the communication link.

3.2 Improvemnet of forecast results

First, the difference between the calculated results of the shortwave sky-wave ionospheric model and the actual received values is calculated, and then the GluonTS is used to train the model and forecast, and then the improved values are added to the calculated results of the shortwave sky-wave ionospheric model, and the accuracy of the prediction is compared with the actual received values. The following is the improvement of each link.

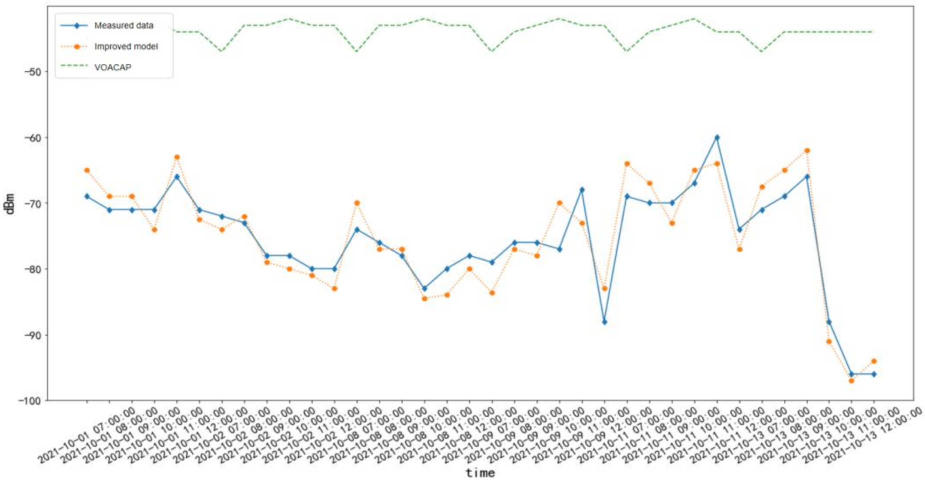

Fig. 5 Improvement of Communication Link Between Qiqihaer, China and Kirov, Russia

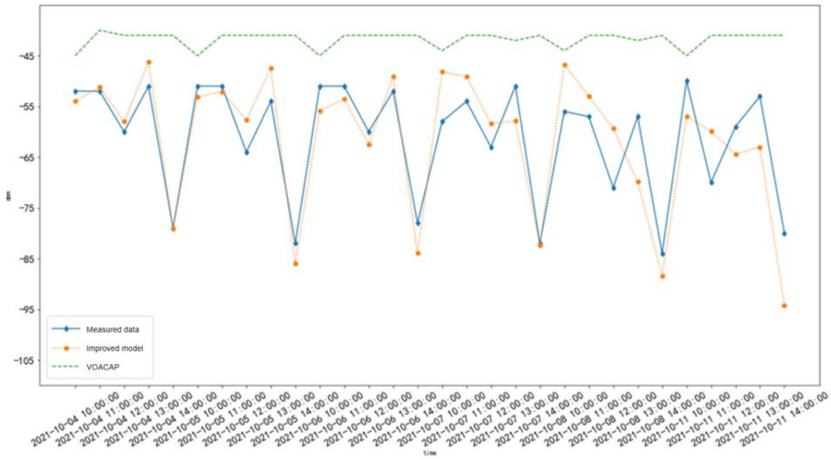

Fig. 5 Improvement of communication link between Qiqihar, China and Chengdu, China

As shown in the figure above, by using the coefficient of determination for evaluation, we can obtain the degree of fitting between the predicted signal using VOACAP and the actual received signal on the communication link between Kashgar, China and Kirov, Russia, which is 16.8%, while the improved prediction using the GluonTS model can reach 89.4% with a MAPE of 0.09. For the communication link between Qiqihar, China and Chengdu, China, the prediction using VOACAP cannot describe the features of the actual received signal, while the improved prediction using the GluonTS model can reach 81.5% with a MAPE of 0.0815.

From the above results, it can be found that the prediction is effective, and the prediction for a certain communication link can be improved to some extent by using deep learning algorithms. Although the data used in this problem is not sufficient, not all links have achieved the target, the main reason is that the data volume collected is not enough to cause poor model training effect. There is still a long way to go to accurately predict the shortwave tropospheric transmission effect, but using time series prediction methods can effectively improve the accuracy of the prediction, making the improved predicted value closer to the actual received signal in terms of trend and amplitude.

4. Summary

In this paper, the prediction results obtained by predicting the communication links in both directions are basically consistent with the actual measurement results, indicating that Gluonts' time series prediction can indeed meet the requirements of ontology. GluonTS 'prediction model was able to predict about 90% of the signal changes in the work in this paper, and it is feasible to use it to improve communication links. Then, the difference between the calculated results of the shortwave sky-wave ionospheric model and the actual received values was calculated, and GluonTS was used to train the model and forecast, and the improved values were added to the calculated results of the shortwave sky-wave ionospheric model, and the accuracy of the prediction was compared with the actual received values. The results obtained from the analysis were that the GluonTS model predicted that the improved results could reach more than 80%, and the MAPE was below 0.1. It can be said that the time series prediction has achieved the effect of improving the mathematical calculation results of the short-wave sky-wave ionospheric model.

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