Length Analysis of Training Data for F10.7 Prediction Method Based on Deep Learning

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Abstract

The F10.7 solar radiation index is of great significance for the calculation of atmospheric density in low-Earth orbit. In recent years, a variety of neural network methods, especially the LSTM method, have been used for the modeling and forecasting of the F10.7 index, but the research on the length selection of historical data in the LSTM method is still very lacking. In this manuscript, the influence of different historical data lengths on the F10.7 index modeling and forecasting accuracy are studied in the F10.7 solar radiation index modeling and forecasting method based on LSTM. The reasonable selection interval of historical data length is given when applying LSTM method to forecast F10.7 index.

Keywords: *F10.7 index; atmospheric model; LSTM method*

1 INTRODUCTION

In recent years, with the continuous development of low-orbit constellations such as Starlink and OneWeb, the research on atmospheric density modeling and forecasting methods for precise orbit determination and forecasting of low-orbit constellations has also continued to heat up. For low orbit satellites, atmospheric resistance is one of the main perturbation factors, and the model accuracy of atmospheric density in low earth orbit directly affects the calculation accuracy of low earth orbit [4]. At present, the accuracy of mid- and long-term orbit forecasts of near-Earth satellites is not high. One of the important reasons is that the ability of the academic community to predict the density of the space atmosphere that seriously affects the mid- and long-term orbit changes of near-Earth satellites is very weak. The F10.7 index is closely related to the solar activity cycle, but currently there is no strict law restriction, so its prediction is very difficult. In the two most commonly used atmospheric compaction models, namely the DTM model [1] and the MSIS model [7], the solar radiation flux index is used as the key input parameter. The MSIS model uses the F10.7 index as an eigenvalue of solar radiation. The DTM model before DTM2013 used the F10.7 index as the characteristic value of solar radiation. So the enhance of forecasting ability of the F10.7 index is of great value for improving the orbit determination and forecasting ability of low-Earth orbit satellites.

The solar radiation index is a time-varying physical quantity, and its variation has a large period of 11 years and a small period of 81 days according to the solar activity cycle. Currently, the prediction of F10.7 parameters can be divided into modeling based on traditional mathematical methods and modeling based on artificial intelligence methods. Before the emergence of artificial intelligence algorithms, people mainly tried to use various mathematical methods to model and predict them. Robert L. Holland et al. proposed an improved statistical prediction method for estimating the intermediate-term (months) and long-term (years) behavior of solar flux F10.7 in 1984 [5]. R. Cameron et al. proposed a simple flux transport model which contains a source term describing the emergence of new flux based on observational sunspot data in 2007 [2]. C Xiao et al. applied a Back Propagation (BP) neural network technique to forecast the daily F10.7 based on the trial data set from 1980 to 2001 [10]. Cong Huang et al. applied support vector regression (SVR) to forecasting daily values of F10.7 to examine the feasibility of SVR in short-term F10.7 forecasting in 2009 [6]. WEN Jing et al. proposed a new 27-day forecast model of F10.7 based on the observation and general evolution of the solar active regions to improve the Auto-Regress (AR) method. The area and longitude of an active region has been used as control parameters in the new model [9]. Wang X et al. proposed a neural network based on the classical multi-layer perception model for the mid-term forecast of daily F10.7 in 2016 [8]. T Guo et al. first proposed novel

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method that utilize RNNs, especially long short-term memory (LSTM) for solar radio spectrum classification [3]. YANG X et al. proposed a new method for F10.7 observation forecasts over a 27-day period through the LSTM method [12].

This maniscript mainly analyzes the length setting of historical data when using LSTM for F10.7 index prediction. For the modeling and prediction of time series data, historical data of different lengths can be used in RNN. The length of historical data is not as long as possible. In order to distinguish the influence of different time data on the current data, the LSTM method sets forget gate to reduce the influence of old data on the current prediction. For the prediction of F10.7 data, a variety of intelligent methods has been studied, such as LSTM and RNN. However, the length of historical data had never been studied as a issue, and the length of historical data have a decisive impact on how well an LSTM or RNN method performs. Therefore, the focus of this study is the length of historical data can be used for prediction to achieve the best results.

2 F10.7 DATASET AND LSTM METHOD

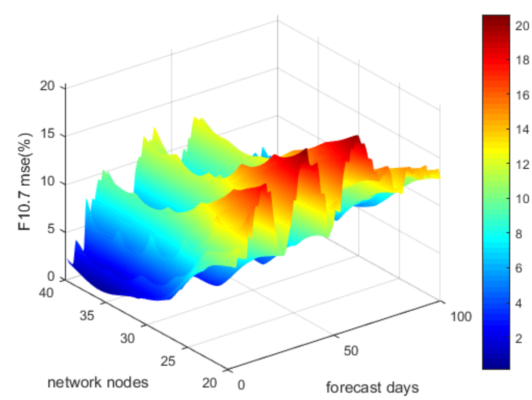
Currently, F10.7 data from 1947 to the present is available. But the F10.7 dataset from 1947-1956 has a large number of missings. Considering that the completion of missing datasets may lead to bias in deep learning, the F10.7 data studied in this maniscript are from 1956 to 2018.

LSTM (Long Short-Term Memory) is a time cyclic neural network, which is specially designed to solve the long-term dependence problem of general RNN (Recurrent Neural Network). All RNN have a chained structure of repeating neural network modules. The LSTM method was first published in 1997. Due to the unique design structure, LSTM are suitable for processing and predicting important events with very long intervals and delays in time series. LSTMs generally perform better than temporal recurrent neural networks and hidden Markov models (HMMs), such as for non-segmented continuous handwriting recognition. In 2009, the artificial neural network model built with LSTM won the ICDAR handwriting recognition competition. LSTM is also widely used in autonomous speech recognition, and in 2013, the TIMIT natural speech database was used to achieve a record of 17.7% error rate. As a nonlinear model, LSTM can be used as a complex nonlinear unit to construct larger deep neural networks. When the LSTM block is set, the error is also calculated backwards, affecting each gate from the output back to the input stage, until this value is filtered out. Therefore, the normal BP DNNs is an efficient way to train LSTM blocks to remember long-term values.

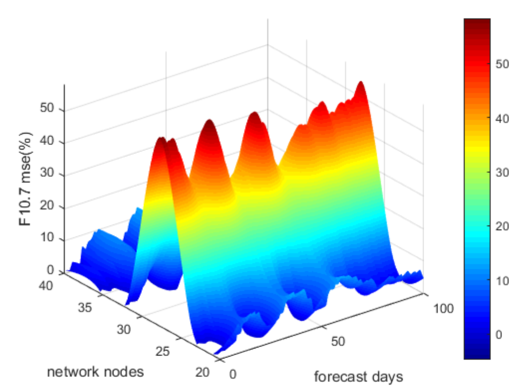
3 ANALYSIS OF THE IMPACT OF DIFFERENT HISTORICAL DATA LENGTHS ON F10.7 PREDICTION BASED ON LSTM

In the experiment of this maniscript, the measured data of F10.7 from 1956 to 2018 are taken as the basic dataset. n days data are taken as the training data. The LSTM method was used to predict the data of F10.7 on the n+1th day, and the predicted MSE (Mean Square Error) of the LSTM method was determined by comparing with the actual observed value. The values of n are 5, 6, 7, 8, 9, 10, 20, 30, 40, 50, and 60, respectively.

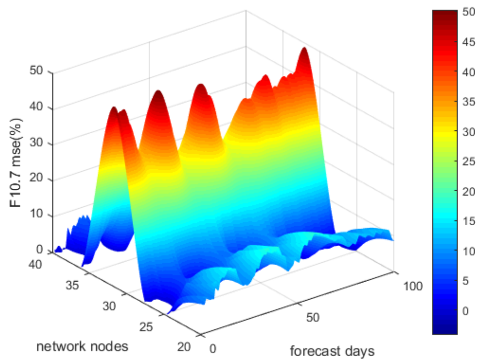
For different historical data lengths, the prediction results of F10.7 are as follows:



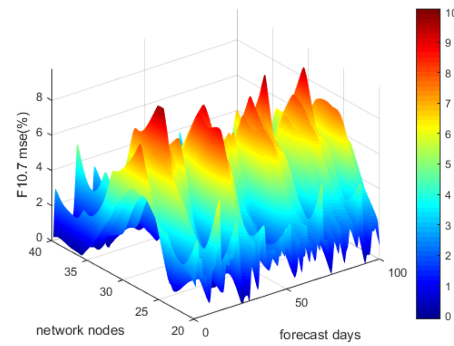
5-day F10.7 data forecast results



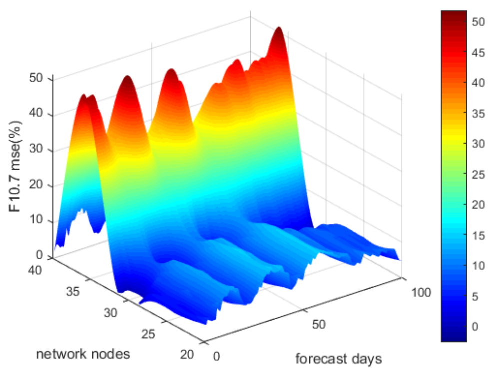
6-day F10.7 data forecast results



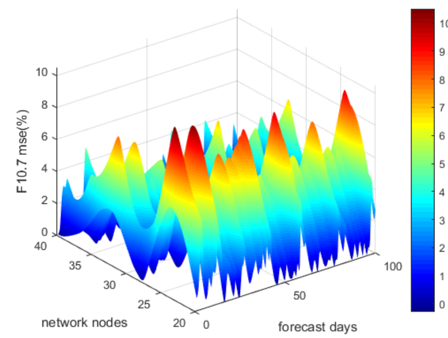
7-day F10.7 data forecast results



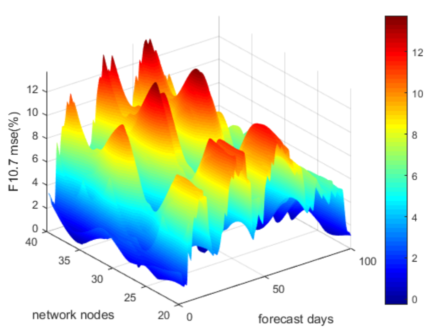
20-day F10.7 data forecast results



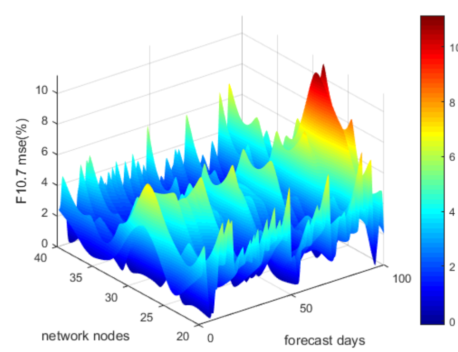
8-day F10.7 data forecast results



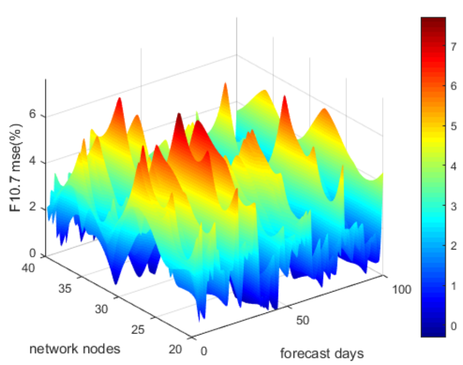
30-day F10.7 data forecast results



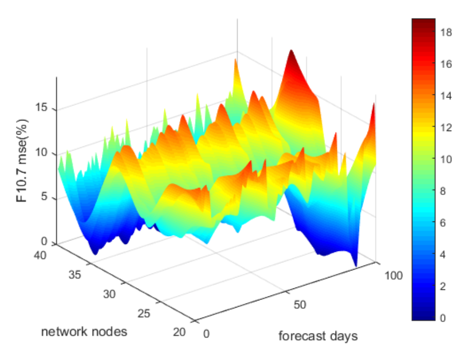
9-day F10.7 data forecast results



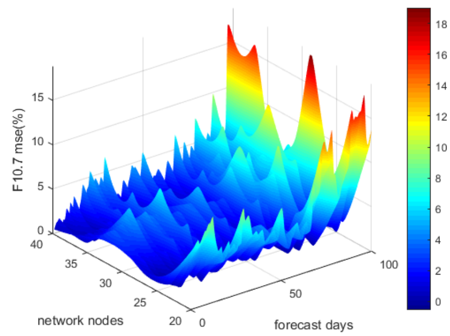
40-day F10.7 data forecast results



10-day F10.7 data forecast results



50-day F10.7 data forecast results



60-day F10.7 data forecast results

Figure 1 F10.7 prediction results under different historical data

It can be seen from the figures that the errors in different network node number models have obvious consistency. The reason for this phenomenon is: the initial value of the LSTM model is randomly generated in this maniscript, so the error rate of the model presents a certain randomness when it finally ends the iteration. This phenomenon does not prove that an LSTM model with a certain number of nodes has definite advantages and disadvantages.

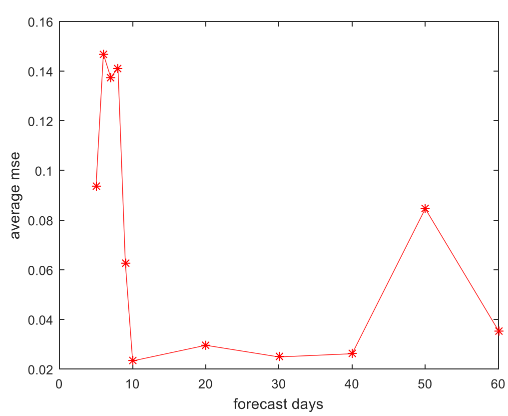


Figure 2 The Relationship between Prediction Accuracy and Historical Data Length

It can be seen from the above analysis that the prediction effect of F10.7 based on LSTM is relatively fine. The error rates range of F10.7 prediction is about 2.3%-14.69%. When the length of the historical data are 5-8 days, the average prediction error increases rapidly, and then gradually shrinks to the extreme value when the length of the historical data is 10 days. The average prediction expands expands to the extreme value when the length of the historical data is 50 days. In general, the prediction effect of using historical data with a length of 10 days and 40 days is significantly precise than other lengths.

4 CONCLUSIONS

From the analysis of the algorithm characteristics of LSTM, the effect of longer historical data on data prediction is not linear because LSTM has a unique forget gate mechanism. The effect is also related to the neural network layers and weight values of LSTM. At the same time, the length of historical data is not as long as possible. From the results of simulation calculations, the LSTM method with a data length of 10 days or 40 days has the highest prediction accuracy. The prediction effect will have a large deviation when the value range of historical data is too long or too short. Therefore, it is recommended to choose a historical data length of 10 days or 40 days for F10.7 data modeling and prediction based on the LSTM method.

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