A Prediction Model of Relativistic Electrons at Geostationary Orbit Using the EMD-LSTM Network and Geomagnetic Indices

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Abstract In this study, the Empirical Mode Decomposition algorithm (EMD) and the Long Short Term Memory neural network (LSTM) are combined into an EMD-LSTM model, to predict the variation of the >2 MeV electron fluxes 1 day ahead. Input parameters include the Pc5 power, AP, AE, Kp, >0.6 MeV, and historical electron flux values, are used for predictions. All the time resolution of parameters are daily integral values. As compared to the prediction results of the EMD-LSTM model with other classical prediction models, the results show that the 1 day ahead prediction efficiency of the >2 MeV electron fluxes possesses a prediction efficiency of 0.80, and the highest prediction efficiency can reach 0.93. These results are superior to the prediction accuracy of more previous models. Using two high-energy electron flux storm events for validation, the results indicate that the performance of the EMD-LSTM model in the period of the high-energy electron flux storm is also relatively good, especially for the prediction of high-energy electron fluxes at extreme points, and the predictions are closer to actual observations.

Plain Language Summary During the main phase of a high-energy storm, the relativistic electron fluxes level at MeV energy from the outer radiation belt will be enhanced at geosynchronous orbit. In particular, the >2 MeV electrons could penetrate the surface of satellites and accumulate on their insides. After a long period, the effect of these electrons could result in satellites being unable to operate or being damaged beyond recovery. To mitigate against this damage by accurate forecast to take protective measures, we combine the empirical mode decomposition (EMD) and long short-term memory (LSTM) algorithms to predict >2 MeV electrons flux values. The EMD-LSTM model results show that the model can accurately predict the rapid changes in data series and extreme data points with little time offset.

1. Introduction

Geosynchronous orbit (GEO, ~6.6 Earth's radii) is located in the region of the outer radiation. At GEO, hundreds of satellites operate in this region, during the main phase of a high-energy storm, the relativistic electrons rise in count from 10 up to 10¹⁰ electrons Sr⁻¹ s⁻¹ (Sakaguchi et al., 2013). The deep-dielectric charging by relativistic electrons could damage satellites at GEO and poses a risk for space security (Wrenn et al., 2002). According to the statistics of faults, more than 50% failure rate of GEO satellites were caused by the accumulation of high-energy charged particles from March 1992 to April 1994 (He et al., 2013). Therefore, the prediction of >2 MeV electron fluxes has important scientific and application value, which is the necessary measure to be taken in advance to reduce the harm of relativistic electrons to space instruments.

The sudden acceleration of relativistic electrons is responsible for the increased fluxes. Summers et al. (1998) proposed a model which account for the observed variations in the flux and pitch angle distribution of relativistic electrons during geomagnetic storms. Presently, two types of acceleration mechanisms of relativistic electrons have been proposed: the mechanism of radial diffusion (Li et al., 2001), and the local interaction of wave-particles (Simms et al., 2018). Based on the radial diffusion mechanism, Li et al. (2001) proposed a radial diffusion model that took solar wind parameters and the interplanetary magnetic field as input parameters to predict the relativistic
electron fluxes of the 1–2 days ahead. The prediction efficiency (PE, the fraction of accurate predictions within 1 standard deviation of the model) of the radial diffusion model is up to 0.64, however, that is not ideal during the solar maximum period. Jaynes et al. (2015) demonstrated that two distinct electron populations resulting from magnetospheric substorm activity are crucial elements in the ultimate acceleration of highly relativistic electrons in the outer belt. Turner and Li (2008) developed the LOW-E model, which used the low-energy electron fluxes as an input parameter to predict the relativistic electron fluxes of the 1 day ahead, and the PE of up to 0.73. The Space Weather Prediction Center of the National Oceanic and Atmospheric Administration (NOAA), developed a prediction model of the relativistic electron fluxes (REFM, Relativistic Electron Forecast Model | NOAA/NWS Space Weather Prediction Center). The REFM model uses solar wind speed as an input parameter and provides forecasting values of the >2 MeV electron fluxes of 1–3 days ahead. The prediction efficiency of the first day is 0.71, but that of the next day is poor because the outer radiation belt varies rapidly through a magnetic disturbance period (Baker et al., 1990).

Based on the wave-particle interaction mechanism, He et al. (2013) took geomagnetic pulsation parameters as input parameters and combine linear filter technology and Kalman filter to establish the relativistic electrons prediction model at GEO. The model PE for 2004 is about 0.73, which is equivalent to the imitation REFM model. However, for 2005 the He et al. (2013) prediction results are lower than other models, with PE of about 0.62. Potapov et al. (2014, 2016) combined the mechanisms of radial diffusion and wave-particle interaction to establish a daily prediction model using a multivariate regression method. This model takes the amplitude of Pc4–5 oscillation, the daily maximum of seed electron flux, and the IMF as input parameters to establish the model. The model is significantly characterized by prediction extreme values preceding the measured values.

Horne and Thorne (1998) pointed out that whistler mode waves and highly oblique magnetosonic waves have the potential to contribute to the stochastic acceleration of electrons up to relativistic energies during magnetic storms. Elkington et al. (1999) found that electrons can be adiabatically accelerated through a drift-resonant interaction with the waves. Mathie and Mann (2000) presented that significant electron flux increases at geosynchronous orbit are only observed in response to ULF wave power which is sustained at high levels over a number of days following storm onset. ULF Pc5 waves can migrate inward to lower L-shells and may accelerate low and medium-energy electrons to relativistic energies via several proposed mechanisms (Simms et al., 2018). So, the Pc5 wave may be the key to electronic excitation at GEO. Many studies demonstrated that Pc5 power has a good correlation with relativistic electrons fluxes (Lam, 2017; Regi et al., 2015), with a clear relationship between solar wind and Pc5 amplitude (Takahashi & Ukhorskiy, 2008). In addition, the importance of relativistic electron diffusion process attributable to Pc5 waves, and precipitations of energized particles in the atmosphere at high latitudes with consequence modifications on chemical and electrodynamics processes is emphasized (Rycroft et al., 2012; Seppälä et al., 2014). Regi et al. (2016) also found that there is some correlation between atmospheric parameters change in the high latitude atmosphere and Pc5 fluctuations at 27 days. In this work, Pc5 power is used to predict the >2 MeV electron fluxes.

Since the relationship between the relativistic electron fluxes and each parameter is not completely linear, the variation of relativistic electrons is too complex to describe by the functional relationship between the input parameters and the output of electron fluxes. However, neural network methods have good learning abilities and represent a better approach to solving nonlinear problems. Fukata et al. (2002) and Ling et al. (2010) established a neural network model to predict the relativistic electron fluxes. The PE of the Fukata et al. (2002) model is approximately 0.6. The Ling et al. (2010) model is more efficient than the former, and the PE of the model is close to 0.7. There, input parameters are the indices of geomagnetic disturbance including 7 consecutive days of daily summed values of the planetary Kp index, but no solar wind parameters. For the sudden enhancement and loss of high-energy electron fluxes, Qian et al. (2020) combined the EMD algorithm and Kalman filter algorithm to establish the EMD-KLM model for high-energy electron prediction. The average PE of >2MeV electron fluxes can reach up to 0.8. In particular, the accuracy forecasting is excellent for the sudden decline of electron fluxes, but the accuracy forecasting needs to be improved during sudden electron flux enhancements.

With the development of machine learning, deep learning neural networks are also used to predict the high-energy electron flux values. Wei et al. (2018) established a prediction model based on the deep learning algorithm LSTM network, called the LSTM-FRK model. The prediction efficiency of Wei’s model is in the range of 0.83–0.91, and it verifies the good effects of the LSTM network in predicting high-energy electron fluxes. Zhang et al. (2020) constructed a probabilistic approach by using the neural network and the quantile regression
method to predict the daily flux of relativistic electrons (>2 MeV) 1 day ahead, with the average PE reaching up to 0.91 during the periods of 2011–2017. In addition, intelligent algorithms, including radial basis functions and support vector machines, were also used to predict relativistic electrons flux values (Guo et al., 2013; Xue & Ye, 2004).

Although these models have achieved great success in predicting electron fluxes, there is still much room for improvement in accuracy prediction during the relativistic electrons storm period and the prediction of the minimum inflection point of the >2 MeV electron fluxes. Therefore, using geomagnetic pulsation parameters and related geomagnetic indices, the EMD-LSTM model is used to predict the >2 MeV electron fluxes. The EMD-LSTM model can solve the nonstationary and nonlinear problems of high-energy electron fluxes data (Qian et al., 2020), and geomagnetic pulsation parameters are easier to obtain and more stable than solar wind parameters.

2. Data

2.1. Data Source and Processing

In this work, we use a daily value of the >2 MeV electron fluxes to eliminate the local time effects. The fluxes data derived from the relativistic electron fluxes at a temporal resolution of 5 min are obtained from the GOES10-13 satellites and are available from NOAA (https://satdat.ngdc.noaa.gov/sem/goes/data). The daily Pc5 power datasets are derived from ground magnetic data collected by Canadian Magnetic Observatory System (CANMOS) observatories located in the auroral zone proximal to footprints of field lines. The detail of the datasets is shown in Table 1. To extract Pc5 wave power from magnetic data, the method of Lam (2017) is followed. A band pass filter is first used to filter the tiny data to extract the variation of the Pc5 band. A Hanning window is used to calculate the Fast Fourier Transform to obtain the Pc5 power spectrum estimation based on hourly data. Finally, the hourly power is integrated to obtain daily Pc5 power (Lam, 2017).

The >2 MeV electron fluxes data is obtained from the GOES10, GOES11 and GOES13 satellites. The electron fluxes with different locations at GEO orbit are different. If the training set and the testing set are from different satellites, the prediction result analysis may be inappropriate. So we calibrated the datasets of the GOES satellites based on the calibration equation derived from the strong linear correlation between satellite overlapped time in the article by Wei et al. (2018). In Equations 1 and 2, the reference frame of observed electron flux \( x \) is represented by the GOES 11 satellite. The calibration equation of the logarithm of >2 MeV electron fluxes between GOES10 and GOES11 is:

\[
y = 1.057997x - 0.876159
\]

And the calibration equation of the logarithm of >2 MeV electron fluxes between GOES13 and GOES11 is:

\[
y = \begin{cases} 
4.506723x - 21.896771, & x \in [5.8, 6.2] \\
1.106844x - 0.718085, & x \in [0, 5.8) \cup [6.2, 11) 
\end{cases}
\]

where \( x \) is the raw value of the logarithm of >2 MeV electron fluxes, and \( y \) is the calibrated value (the unit is \( \text{cm}^{-2}\text{d}^{-1}\text{sr}^{-1} \)).

Figure 1 shows the result calibrated data of the electron fluxes as a function of time. The black line represents observations from different satellites from 2001 to 2013, and the orange line represents calibrated values based on the GOES11 satellite.

| Code | Station       | Geographic latitude | Geographic longitude | Geomagnetic latitude | Geomagnetic longitude | L  |
|------|---------------|---------------------|----------------------|----------------------|-----------------------|----|
| FCC  | For Churchill | 58.8°N              | 94.1°W               | 68.8°N               | 94.1°W                | 8.18 |

Table 1

Coordinates of Canadian Magnetic Observatory System Auroral Zone Observatories
2.2. Selection of Input Parameters

Previous studies indicated that Pc5 waves have a strong correlation with energy electron fluxes increase at GEO (Borovsky & Deton, 2014; Lam, 2017; O’Brien et al., 2003; Regi et al., 2015; Simms et al., 2018). Simms et al. (2018) suggested that Pc5 waves are the main waves that drive electron acceleration. Lam (2017) analyzed the relationship between Pc5 wave and >2 MeV electron fluxes in two solar cycles and proposed that strong ground Pc5 is a precursor of enhanced relativistic electron fluxes at GEO by 2–3 days ahead for all phases. On the other hand, solar wind parameters are usually used in the prediction model of relativistic electron fluxes.

Regi et al. (2015) proposed that the Pc5 power correlates highly with solar wind pressure fluctuations and with the solar wind speed by several hours offset. Comparison with solar wind parameters, the Pc5 power is derived from ground magnetic data, so it costs lower and is more stable than satellite data. So, we use the Pc5 power as one of the input parameters to predict >2 MeV electron fluxes.

In this work, we also use the >0.6 MeV electron fluxes (Potapov et al., 2016), geomagnetic indices (Ap, Kp, AE) (Sakaguchi et al., 2013; Yousrfi et al., 2009), and the historical >2 MeV electron fluxes as other input parameters to predict the >2 MeV electron fluxes 1 day ahead (all the time resolution of parameters are daily integral values). First, we analyze the correlations between each input parameter and output result of >2 MeV electron fluxes, shown in Figure 2. The results are shown in Figure 2. We can conclude that the best correlation between each input parameter and the >2 MeV electron fluxes is no more than 5 days, because the correlation coefficient values are lower than 0.3 when time offset greater than 6 days.

The feature of offset time is an important factor of setting the time step in modeling to determine the number of consecutive days to be used as inputs to the model (Wei et al., 2018). We can see in Figure 3 that the validation error decreases as the time step increases and then reaches the minimum value when the time step is five. The form of input sequence of a sample set that combines multiple parameters such as the training and testing data sets can be expressed as \([f_{T-i}, A_{T-i}, (i = 0,2,\ldots,4)]\) and the output form of the model is \(f_{T+1}\). Here, \(f\) is the logarithm of daily >2 MeV electron fluxes, and \(A\) represents other input parameters.

![Figure 1. Comparison of the calibrated data and observations.](image1)

![Figure 2. The correlations between input parameters used and the logarithm of daily >2 MeV electron fluxes with different offset times in days.](image2)
3. Method

3.1. EMD Algorithm

Due to the external compression by the solar wind, the high-energy electrons fluxes during a magnetic storm can change very dramatically. The nonstationary and nonlinear characteristics of the $\geq 2$ MeV electron fluxes data series are easily observed, which introduces great difficulties to accurate forecasting. Previous models used statistical methods to deal with the impact of nonlinear problems on the forecast (Xiao et al., 2012), but the nonstationary problem of data series was not strongly considered. EMD is well suited to handle nonstationary high-energy electron flux data series. The basic idea is that all complex signals are composed of simple intrinsic mode functions (IMF) (Huang et al., 1998). The termination condition of EMD is decided by the restricted standard deviation proposed in Rilling et al. (2003). These IMFs are arranged in the order of from high frequency to low frequency, where each IMF is independent of the other (Sain & Stephan, 1997). The components of different scales in the high-energy electron flux data sequence are decomposed by the EMD algorithm, and several data sequences with different characteristic scales are generated. These components of different characteristic scales are more regular than the original high-energy electron flux data sequence. This fact helps to improve the prediction accuracy. Qian et al. (2020) introduced the EMD algorithm to process and forecast the $\geq 2$ MeV electron fluxes, called the EMD-KLM model, and found that the forecasting results are greatly improved in comparison with the prediction results without employing EMD.

3.2. LSTM Network

The high-energy electron flux usually increases significantly during the main phase of a high-energy electron storm, and sometimes it suddenly increases by 3–4 orders of magnitude. Most of the existing forecasting models are difficult to accurately follow the event of a sudden increase in high-energy electron fluxes. However, with the development of machine learning (ML), deep learning neural networks are also used in the prediction of the $\geq 2$ MeV electron fluxes. Wei et al. (2018) used the LSTM network to predict the daily integral values of the high-energy electron fluxes 1 day ahead at GEO, and get a great result.

The LSTM network is a type of Recurrent Neural Network (RNN). RNNs have input, hidden, and output layers, whose nodes between the hidden layers are connected, which is different from traditional neural networks. The iterative function loops are used by RNNs to store information (Graves, 2012). Information is allowed to pass from one unit of the network to the next. This feature means RNN can remember historical information (Tan et al., 2018). However, if the information needed is too far in the past, the standard RNN is unable to learn how to connect the information. This problem is because of the vanishing gradient problem occurring during the training phase of RNN (Hochreiter & Schmidhuber, 1997). The LSTM is designed to avoid the vanishing gradient problem, which can remember information for long periods by three gates (input, forget, and output gate) to control the flow of information. The detailed algorithm is described in the following and shown in Figure 4.

**Step 1.** How much information is forgotten by forgetting gate function calculation? The formula is represented by the following:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

(3)

where $f_t$ is the forgotten gate function, $x_t$ is the input at the current moment $t$, $h_{t-1}$ is output at moment $t-1$, $W_f$ and $b_f$ are the weight and bias, respectively.

**Step 2.** What information should be stored in the cell state at moment $t$? That is decided by input gate function, $i_t$ and the new candidate value, $\tilde{C}_t$. The formulas are represented by the following:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

(4)
where $W_f, W_c$ and $b_f, b_c$ are the weights and biases.

**Step 3.** The old cell state $C_{t-1}$ is updated into the new cell state $C_t$ by the forget gate and input gate layers. The formula is represented by the following:

$$ C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t $$

(6)

**Step 4.** What the cell output at moment $t$ is decided by the output gate based on output gate function, $o_t$, and output function $h_t$. The formulas are represented by the following:

$$ o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) $$

(7)

$$ h_t = o_t \cdot \tanh(C_t) $$

(8)

where $W_o$ and $b_o$ are the weight and bias. Two activation functions are the sigmoid function ($\sigma(x)$) and tanh function ($\tanh(x)$). The operators “$\cdot$” and “$\cdot$” are the convolution operator and vector operator, respectively.

The LSTM networks can memorize for a long time and store useful information, and the role of three doors is critical. They determine how much useful information to store, then add information to renew cells and update the hidden layers. The LSTM network can more easily learn useful information from the historical data series of high-energy electron flux to predict the $>2$ MeV electron fluxes more accurately.

### 3.3. EMD-LSTM Model

The LSTM network is effective in dealing with the nonlinear problem of data sequences. It has a memory function and can capture more complex nonlinear relationships in the data sets, which is more suitable for the prediction of the data sequences. At the same time, the EMD algorithm is very effective in dealing with the nonstationary problem of high-energy electron flux data series. Therefore, we combine the EMD algorithm and the LSTM network to predict the $>2$ MeV electron fluxes at GEO. The combined forecasting model is named the EMD-LSTM model, which uses ultralow frequency Pc5 power as one of the input parameters to predict the $>2$ MeV electron fluxes 1 day ahead.
Figure 5. The flow chart of the Empirical Mode Decomposition algorithm-Long Short Term Memory neural network (EMD-LSTM) model.

Figure 5 shows the main process of the combined forecast. The main steps are following:

1. Use the EMD algorithm to decompose the observed data series of the >2 MeV electron fluxes to obtain $N$ ($N = 9$) IMF components and one margin;
2. Add the input data into the LSTM network. The input data is a vector ($V_{input}$) that contains the input parameters (Ap, Kp, AE, >0.6 MeV electron flux, and Pc5 power daily integral values of 5 days) and IMFi ($i = 1, ..., 10$);
3. Use the LSTM network to predict each component and get the predicted value of each component for the next day. The hidden layer of LSTM is 3 and the number of neurons in each layer are 128, 64, and 64 respectively;
4. Sum the predicted values of $N + 1$ components to obtain the predicted value of the >2 MeV electron fluxes 1 day ahead.

The EMD-LSTM model is a rolling prediction model. The time step of the combined forecasting model is 5 steps and it means that the daily flux of the >2 MeV electron fluxes 1 day ahead is predicted by the historical data of the previous 5 days.

4. Results and Analysis

4.1. The Evaluation of Forecasting >2 MeV Electron Fluxes

In this work, we use three indicators; Root Mean Square Error (RMSE), Correlation Coefficient (R), and the Prediction Efficiency (PE), to evaluate the performance of the >2 MeV electron fluxes forecasting. In the
experiments, we compare the performance indicators between the EMD-LSTM model and the other classical models. They are defined as follows:

\[
RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (f_i - F_i)^2}
\]

(9)

\[
R = \frac{\sum_{i=1}^{n} (f_i - \bar{F})}{\sqrt{\sum_{i=1}^{n} (f_i - \bar{F})^2} \sqrt{\sum_{i=1}^{n} (F_i - \bar{F})^2}}
\]

(10)

\[
PE = 1 - \frac{\sum_{i=1}^{n} (F_i - F_i)^2}{\sum_{i=1}^{n} (F_i - \bar{F})^2}
\]

(11)

where, \(f_i\) is the forecasting value, \(F_i\) is the observation value, \(\bar{F}\) is the mean of the forecasting value, \(\bar{F}\) is the mean value of the observation, and \(n\) is the number of samples. Each of these indicators evaluates the model from a different perspective. The RMSE and R are used to evaluate the level of fitting between the prediction value and the observation. The PE evaluates the accuracy of the prediction of the \(>2\) MeV electron fluxes. As such, the smaller RMSE, the larger R and PE, the better the prediction performance.

### 4.2. The Prediction Results of the EMD-LSTM Model

In this work, the data series of the \(>2\) MeV electron fluxes from 2001 to 2008 (the maximum-minimum period of the solar cycle 23) is used by the training set, and the electron fluxes from 2009 to 2011 (the ascending phase of the next solar cycle 24) are set as the test set. We use the 30 parameters (consists of six input parameters/day \(\times 5\) days) selected as the inputs into the EMD-LSTM model. Figure 6 shows the prediction results of the EMD-LSTM model from January 2009 to December 2010 (The green line represents the prediction values of the EMD-LSTM model and the black line represents the observed values of the \(>2\) MeV electron fluxes). The forecasting values of the EMD-LSTM model are close to the observed values of the \(>2\) MeV electron fluxes, and the results are also supported by Table 2. It is worth noting that when the amount of log10 (electron fluxes) is even

![Figure 6. The comparison of the Empirical Mode Decomposition algorithm-Long Short Term Memory neural network (EMD-LSTM) prediction values with the observations from January 2009 to December 2010.](image-url)

| Year | Model  | PE  | RMSE | R    |
|------|--------|-----|------|------|
| 2010 | LSTM   | 0.89| 0.37 | 0.94 |
|      | EMD-KLM| 0.88| 0.35 | 0.93 |
|      | EMD-LSTM| 0.93| 0.30 | 0.97 |
| 2011 | LSTM   | 0.75| 0.39 | 0.88 |
|      | EMD-KLM| 0.77| 0.41 | 0.89 |
|      | EMD-LSTM| 0.82| 0.35 | 0.92 |
up to 8–9, the prediction values of the EMD-LSTM model are still close to the observations in some cases, especially for events with observations more than 8 in 2010. There are two main reasons. First, when the amount of log10 (electron fluxes) is measured at 8 or 9, this is often caused by the sudden acceleration of relativistic electrons which is often related to the Pc5 wave (Lam, 2017; Mathie & Mann, 2000). Consequently, the Pc5 is set as one of the input parameters, and the prediction results are ideal. Second, the LSTM network could capture the historical information of data series to process nonlinear problems, and the EMD algorithm could reduce the influence of nonstationary data series (Qian et al., 2020). Therefore, even if the high-energy electron fluxes change suddenly, the EMD-LSTM model can also fit the >2 MeV electron fluxes well.

Compared with the data sequences of the >2 MeV electron fluxes in 2010, the >2 MeV electron flux data series changed more dramatically in 2009, so the levels of nonstationary and non-linearity are significantly enhanced. The inclusion of EMD in the EMD-LSTM model allows for the effective processing of nonstationary data, while the LSTM network improves the ability of the model to deal with nonlinear problems. Compared with the standard RNN that can only remember information in a short period, the LSTM network can remember data information within a long time and captures useful information from the training set to predict the >2 MeV electron fluxes 1 day ahead. The LSTM network can record the characteristics of the changes of the >2 MeV electron fluxes during the historical high-energy electron storms and retain useful information. Therefore, the LSTM network can deal with a sudden change of the relativistic electron flux events. Figure 6 shows that the EMD-LSTM model can also fit actual observation of the >2 MeV electron fluxes reaching peak values during the high-energy electron flux storm. In the actual operation, the sudden enhancement of the high-energy electron fluxes should be paid more attention to the forecast, to minimize the loss by protection measures taken to the satellite equipment.

Table 2 shows the comparison of the EMD-LSTM model with the LSTM model and the EMD-KLM model (Qian et al., 2020) based on the same datasets (time intervals 2001–2011). The results in Table 2 indicate that the effectiveness of the EMD-LSTM model is greatly improved compared with the other two models, based on the performance indicators of PE, RMSE and R.

Table 3 shows the PE of the EMD-LSTM model comparison with the previous classical models. It indicates that the PEs of the EMD-LSTM model is higher than that of those models in 2003–2006. In particular, the improvement of PE in 2003–2004 is the most obvious. Fourteen high-energy electron flux storm events occurred in 2003–2004, more than double times in 2005–2006. Therefore, the variation of the >2 MeV electron fluxes in 2003–2004 is more drastic, and the level of nonstationary and non-linearity of the data series is significantly enhanced. So, the PEs of all prediction models in 2003–2004 is lower than that in 2005–2006. The EMD-LSTM model can deal with the nonstationary and nonlinear problems of data series well by the improvement of the mathematical method. In addition, most models such as NICT, Low-energy, RDF, LSTM-FRK model (Li et al., 2001; Turner & Li, 2008; Wei et al., 2018) in Table 3, used solar wind as input parameters, but the EMD-LSTM model uses Pc5 and related geomagnetic indices to forecast the >2 MeV electron fluxes. Based on the experimental results, it is found that geomagnetic pulsation parameters can also achieve a better forecasting effect. The prediction results of the EMD-LSTM model verify the feasibility of geomagnetic pulsation parameters as a predictor of high-energy electron fluxes.

Table 3: The Comparison of Prediction Efficiency (PE) Between the Empirical Mode Decomposition Algorithm-Long Short Term Memory Neural Network (EMD-LSTM) and the Previous Classical Models in the Period of 2003–2006

| Model/Year | 2003–2004 | 2005–2006 |
|------------|------------|------------|
| NICT (PE)  | 0.72       | 0.79       |
| Low-energy (PE) | 0.66       | 0.74       |
| RDF (PE)  | 0.64       | 0.75       |
| LSTM-FRK (PE) | 0.74       | 0.81       |
| EMD-LSTM (PE) | 0.78       | 0.83       |
of the EMD-LSTM model are close to the observation of the >2 MeV electron fluxes. Particularly, the prediction values coincide with the observed values at the extreme points and are few times offset.

There are two reasons for highly effective prediction. First, the EMD algorithm greatly reduces the nonstationary problem caused by the drastic changes of the high-electron fluxes (Qian et al., 2020). Second, the LSTM network can remember the variation characteristics of the high-energy electron storm events in the training set and extract the relevant information (Wei et al., 2018). Therefore, when the high-energy electrons suddenly drop, the EMD-LSTM network can accurately predict the subsequent values of the >2 MeV electron fluxes, based on the analysis of the information of the training set samples. This is very important in practical forecasting, to accurately predict the start time of high-energy electron storms and provide immediate protection for satellite equipment.

5. Conclusion

In this paper, we combine the EMD algorithm and the LSTM network to construct the EMD-LSTM model to predict the >2 MeV electron fluxes at GEO. The EMD-LSTM model can deal with the nonstationary and nonlinear data series, and the effectiveness of the model is improved compared with other classical models.

The prediction results of the EMD-LSTM model are excellent during the high-energy electron fluxes storm. Particularly, the extreme points of the >2 MeV electron fluxes data series are accurately predicted and are few times offset.

Pc5 wave and related geomagnetic indices are used to predict the >2 MeV electron fluxes. Those data acquisition of parameters are stable and lower cost.

Data Availability Statement

The high-energy electron fluxes observations originate from the GOES satellite on the website of NOAA (https://satdat.ngdc.noaa.gov/sem/goes/data/). Geomagnetic indices come from the World Geomagnetic Data Center of the Memanbetsu station in Japan (http://wdc.kugi.kyoto-u.ac.jp/wdc/Sec3.html). The daily Pc5 power datasets
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