

Forecasting of ROTI index in polar regions using BWO-VMD-LSTM hybrid model

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Key Points:

- We present a hybrid forecasting model combining BWO, VMD, and LSTM methods for adjusting ROTI index data.
- The proposed model achieves high prediction accuracy during both geomagnetically quiet periods and substorm periods.
- Integrating optimization and decomposition techniques substantially improves the forecasting performance of the baseline LSTM network.

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Abstract: The Rate of TEC Index (ROTI), a crucial indicator of fluctuations in the ionospheric Total Electron Content (TEC), has long served as an effective proxy for characterizing ionospheric activity. However, ROTI sequences exhibit significant nonstationary and nonlinear characteristics, which intensify during substorms, making high-accuracy prediction challenging for traditional models. To address these complications, we propose a hybrid forecasting model, named BWO-VMD-LSTM, that integrates the Beluga Whale Optimization (BWO) algorithm, Variational Mode Decomposition (VMD), and Long Short-Term Memory (LSTM) networks. Our methodology first employs BWO to adaptively optimize the key parameters of VMD, achieving an optimal decomposition configuration. The optimized VMD then decomposes the original non-stationary ROTI sequence into several relatively stable Intrinsic Mode Functions (IMFs). Subsequently, an LSTM model is constructed to independently forecast each IMF. Finally, the predictions of all components are reconstructed to produce the final ROTI forecast. Experimental results demonstrate that our model outperforms baseline models under various geomagnetic conditions (including quiet, normal, and substorm periods), showing significant improvements in key metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE), thereby exhibiting superior prediction accuracy and stability. This study presents an effective and robust tool for high-precision ROTI forecasting, with promising potential for enhancing space weather monitoring and scintillation warning services.

Keywords: ROTI forecasting; polar ionosphere; Long Short-Term Memory; Beluga Whale Optimization; Variational Mode Decomposition

1. Introduction

As a critical component of Earth's upper atmosphere, the ionosphere is highly sensitive to space weather. Solar flares and coronal mass ejections (CMEs) can trigger sudden ionospheric disturbances

and large-scale ionospheric storms, which are marked by intense spatial and temporal fluctuations in electron density (e.g., Liu LB et al., 2011; Liu JJ et al., 2023). These density disturbances/structures often lead to ionospheric scintillation—a phenomenon that causes amplitude fading and phase fluctuations in trans-ionospheric radio signals, significantly degrading signal strength and reliability (Wang Y et al., 2025). Such effects disrupt satellite-based communication and navigation systems, posing serious challenges to modern, technology-reliant societies. Therefore, monitoring and forecasting ionospheric conditions is of great importance.

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The detection and interpretation of ionospheric plasma density structures remain challenging due to their generation and modulation by a wide range of factors, including space weather, as well as diurnal and seasonal variations in ionization (Zhao XK et al., 2021). The rapid advancement of Global Navigation Satellite Systems (GNSS), with their continuous, global-scale observations, has made GNSS vital tools for monitoring and researching ionospheric scintillation (Guo K et al., 2021). A key observable in this context is the Total Electron Content (TEC), which represents the total number of electrons integrated along the signal path between a satellite transmitter and a ground-based receiver. TEC values fluctuate in the presence of plasma density structures (Jin YQ et al., 2014, 2017). The Rate of TEC Index (ROTI), derived from carrier phase and pseudo range measurements of dual-frequency GNSS receivers, quantifies these fluctuations and serves as an effective proxy for ionospheric density variability (Pi X et al., 1997).

ROTI therefore effectively captures rapid variations in ionospheric total electron content, enabling detection of irregularities caused by auroral particle precipitation and plasma convection. This capability makes ROTI highly valuable for monitoring and forecasting ionospheric space weather. Leveraging the global GNSS network—comprising approximately 700 IGS stations—ROTI benefits from extensive spatial and temporal coverage as well as continuous observations (Jin YQ et al., 2023). These advantages support long-term global modeling and demonstrate high sensitivity to space weather events, such as enhanced ionospheric activity during magnetic storms and equatorward expanding polar disturbances. Thus, ROTI has become a standard metric widely adopted in daily ionospheric monitoring, forecasting, and scientific research (Pi X et al., 1997; Xu FL et al., 2020; Atabati et al., 2021; Abadi et al., 2025; Liu L et al., 2021; Jin YQ et al., 2023; Jia HY et al., 2024).

To forecast ionospheric behavior, various methods and models have been employed, including analytical, global climatological, and empirical or hybrid models based on in situ measurements (Priyadarshi, 2015). However, the ROTI index exhibits inherent nonlinearity and nonstationarity. This nonstationarity causes the data to exhibit trends, periodicity, or random walk characteristics and to change over time. Combined with significant noise, these factors pose challenges for traditional prediction techniques. In contrast, machine learning approaches have shown superior capability in capturing these complex temporal patterns, resulting in substantially improved forecasting accuracy. Jin YQ et al. (2023) developed a climatological model of ROTI in the Arctic region using the Empirical Orthogonal Function (EOF) method, effectively capturing its long-term statistical patterns. Xu FL et al. (2020) achieved accurate short-term predictions of ROTI at high-latitude stations by employing a Bidirectional Gated Recurrent Unit (BGRU) deep learning model. Atabati et al. (2021) integrated artificial neural networks with genetic algorithms to jointly predict S4 and ROTI, yielding promising results. Liu L et al. (2021) introduced an image-based ConvLSTM model capable of capturing the spatial evolution of ROTI during geomagnetic storms, demonstrating strong spatio-temporal modeling capabilities. Jia HY et al. (2024) established a statistical regression model linking ROTI to GNSS positioning errors, thereby enhancing its applicability in real-

world navigation systems.

However, the robustness of existing models remains insufficient. On one hand, the polar ionosphere is significantly influenced by the solar wind–magnetosphere coupling process (Jin YQ et al., 2014). During substorms, intense energy injections lead to rapid development of ionospheric irregularities. General models fail to accurately capture these irregularities due to their transient, highly nonlinear nature. Moreover, models specifically trained for disturbed periods often perform poorly during quiet periods, limiting their operational adaptability. Moreover, the sparse distribution of polar observation stations leads to inadequate spatial coverage, impairing the training completeness and validation accuracy of two-dimensional and three-dimensional models—particularly during extreme space weather events (e.g., Paul et al., 2024).

Therefore, given the limitations of the models mentioned above and the polar ROTI data's characteristics, this paper proposes a single-station polar ROTI prediction model that integrates parameter optimization, signal decomposition, prediction, and reconstruction via an optimization algorithm. The results demonstrate that the proposed model outperforms existing single- and combined-models in prediction accuracy, both during geomagnetic storms and during quiet periods.

2. Data and Model Description

2.1 Data Set

The data used in this study are derived from GNSS observations at the INVK station, located at geographic coordinates 68.31°N, 133.53°W (geomagnetic coordinates: 71.32°N, 80.02°W), covering the period from January to September 2023. This station was selected from 28 stations in the northern polar region, provided by the IGS Data Center of Wuhan University for the years 2015 to 2023. We found that the TEC observations of some stations are discontinuous, and the continuity of TEC is a necessary condition for calculating ROTI. Therefore, stations with an annual observation rate greater than 90% are within our consideration. During data processing, observations with elevation angles below 20 degrees were excluded. Our ROTI calculation method is same as previous studies (Xu FL, 2020; Wu JY et al., 2022). Cycle slip detection and pseudo range smoothing—using a 30-epoch smoothing window—were then applied to the remaining data. Based on the smoothed pseudo range, the ROTI index was computed at a 5-minute temporal resolution. The calculation formula of ROTI is:

$$\text{ROT} = \frac{\text{STEC}_i - \text{STEC}_{i-1}}{t_i - t_{i-1}}, \quad (1)$$

$$\text{ROTI} = \sqrt{\langle \text{ROT}^2 \rangle - \langle \text{ROT} \rangle^2}. \quad (2)$$

Among them, STEC is calculated by using the carrier phase smoothing pseudorange method (Jin R et al., 2012). The formula is as follows:

$$\text{STEC} = \frac{-f_1^2 f_2^2}{40.3(f_1^2 - f_2^2)} (P_{4,\text{sm}} - c\text{DCB}_j - c\text{DCB}^i) \quad (3)$$

where f_1 and f_2 are the carrier frequencies in the L1 and L2 bands, respectively; $P_{4,\text{sm}}$ are smoothed pseudo-range-combined obser-

variations that reduce the effects of noise and multipath; DCB_i and DCB_j are the hardware delay biases of the station and satellite, respectively.

When calculating the ROTI index using STEC, for a continuous observation arc from the same receiver, the DCBs of the satellite and the receiver remain constant. As a result, these biases can be directly eliminated through time differencing. Therefore, the influence of DCB can be disregarded in the computation of ROTI.

The INVK station collects observational data from multiple satellites, each with a distinct elevation angle. Since higher elevation angles provide more reliable measurements directly above the station, the ROTI values are weighted according to elevation angle and then averaged. This approach ensures an accurate representation of the level of ionospheric activity directly overhead at the INVK station. The weighting formula is:

$$ROTI = \frac{\sum_i^n \sin(Elv_i) \times ROTI_i}{\sum_i^n \sin(Elv_i)},$$

where Elv_i denotes the elevation angle of the i -th satellite.

We use the first 80% of the ROTI data for training and the remaining 20% for validation. In addition to ROTI, the input features include the $F_{10.7}$ solar radio flux index, the Z-component of the interplanetary magnetic field (B_z), geomagnetic activity indices (Dst , Kp , AE , and Ap), the polar cap index (PCN), and Universal Time (UT). All feature data are obtained from the CDAWeb database.

2.2 Model Method

2.2.1 Variational Mode Decomposition

Variational Mode Decomposition (VMD) is a method for signal processing proposed by Dragomiretskiy and Zosso (2014). It effectively addresses the issue of mode mixing inherent in empirical mode decomposition (EMD, Huang NE et al., 1998), reduces the nonstationarity of an unstable time series, and produces more stable subseries through decomposition. By formulating a constrained variational problem, VMD iteratively seeks the optimal solution to the model, thereby determining modes with distinct central frequencies and bandwidths. The VMD decomposition process is shown in Figure 1a). Its optimization objective is

$$\min_{\{u_k\}, \{\omega_k\}} \left\{ \sum_{k=1}^n \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) \cdot u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \right\}. \quad (4)$$

The constraints are

$$\sum_{k=1}^n u_k(t) = f(t). \quad (5)$$

By introducing a penalty factor (α) and the Lagrange multiplier ($\lambda(t)$), the augmented Lagrangian function is constructed as follows:

$$L(\{u_k\}, \{\omega_k\}, \lambda) = \alpha \sum_{k=1}^K \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) \cdot u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 + \left\| f(t) - \sum_{k=1}^K u_k(t) \right\|_2^2 + \left\langle \lambda(t), f(t) - \sum_{k=1}^K u_k(t) \right\rangle \quad (6)$$

Among them, α controls the modal bandwidth; K is the preset number of modes. Through iterative solution, using the Alternating Direction Method of Multipliers (ADMM), a series of Intrinsic Mode Functions (IMFs) is finally obtained.

The selection of the α and the K in the VMD decomposition has a significant impact on the decomposition performance (Yao XY et al., 2021; Zhang X et al., 2023). An excessively large α may lead to spurious modes, whereas an overly small α hinders the complete extraction of underlying time series characteristics. Similarly, if K is too small, mode mixing tends to occur; if K is too large, it may result in local information loss. To determine optimal parameter values, we propose a parameter optimization approach based on the Beluga Whale Optimization (BWO) algorithm (Zhong CT et al., 2022).

2.2.2 Beluga Whale Optimization

BWO is a nature-inspired metaheuristic algorithm that mimics the swimming, preying, and "whale fall" behaviors of beluga whales (Zhong CT et al., 2022). BWO's first stage (exploration phase) focuses on the algorithm's global search capability, analogous to the capabilities acquired during free movement of beluga whales in space (swimming). The algorithm's second stage (exploitation phase) is the algorithm's local fine-tuning search around current optimal solutions, analogous to gains achieved in cooperative hunting among whales. The third BWO stage (escaping local optima) introduces randomness into the algorithm, with probabilities suited to help the algorithm escape local optima and thus become more generalized, in analogy with what happens when a whale dies and its carcass sinks to the ocean bottom and nucleates a growing ecosystem of creatures that feed on the carcass. The BWO optimization process is shown in Figure 1b).

This approach effectively balances exploration and exploitation through a self-adaptive mechanism; it incorporates Levy flight to enhance convergence, and employs a unique "whale fall" phase to avoid local optima. These features make BWO a robust and efficient optimizer, demonstrating strong competitiveness against established algorithms such as Particle Swarm Optimization (PSO) and Grey Wolf Optimizer (GWO) in solving complex optimization problems.

2.2.3 Long Short-Term Memory

Long Short-Term Memory (LSTM) is a specialized variant of recurrent neural networks (RNNs), designed to effectively capture long-term dependencies in sequential data (Hochreiter and Schmidhuber, 1997; Gers et al., 1999; Greff et al., 2017). Unlike traditional RNNs, which are prone to vanishing or exploding gradients, LSTMs overcome these limitations through a gated structure comprising memory cells and three regulatory mechanisms: the forget gate, the input gate, and the output gate. The forget gate selectively discards irrelevant information from previous states; the input gate controls the integration of new information into

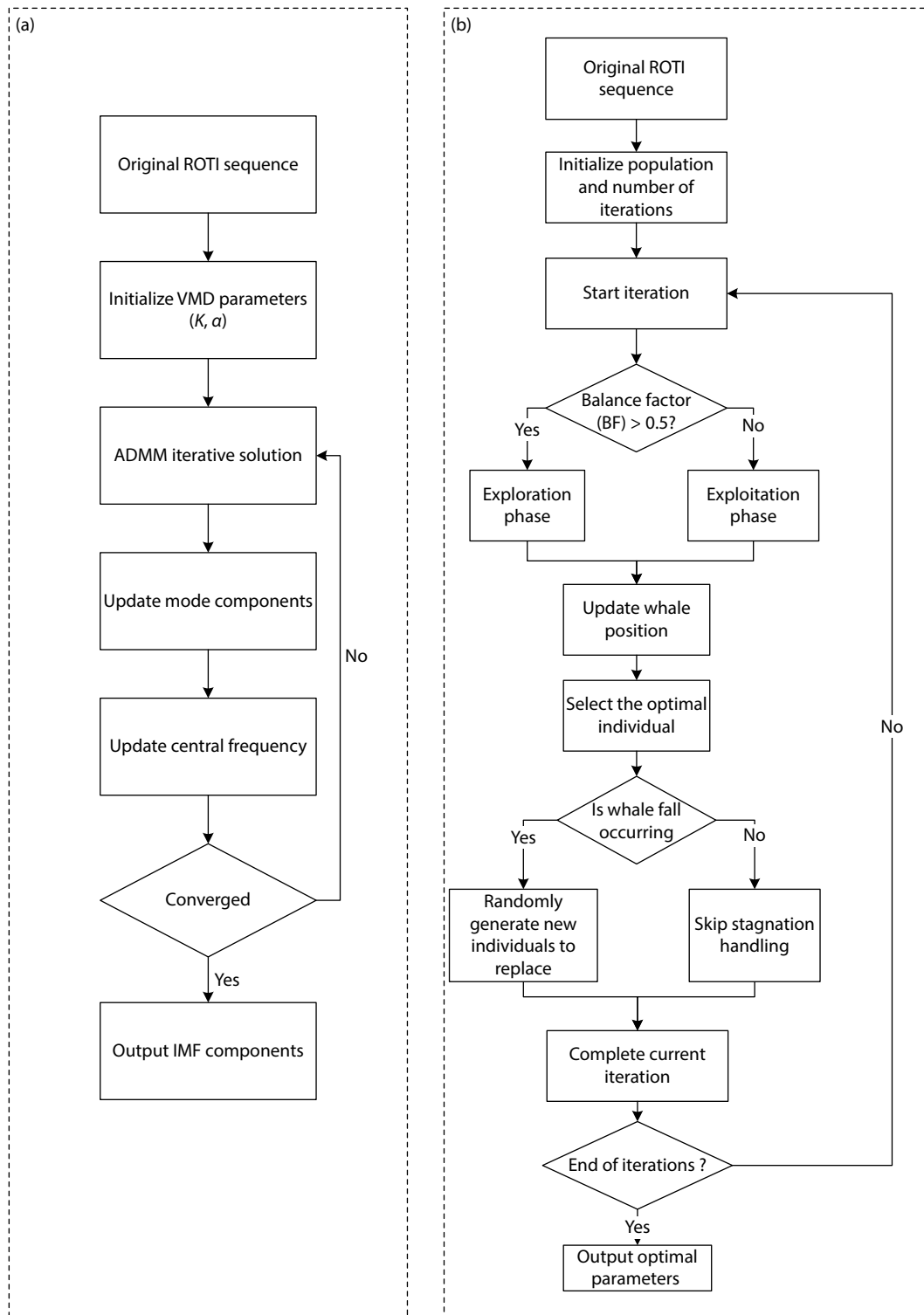


Figure 1. Process diagram. (a) VMD decomposition process. (b) BWO parameter optimization process.

the current memory; and the output gate governs the information flow to the next time step. This sophisticated gating mechanism enables LSTMs to model complex temporal relationships with exceptional effectiveness, making them particularly suitable for tasks requiring memory over extended sequences.

2.3 BWO-VMD-LSTM Model

The ROTI index exhibits nonlinear, non-stationary, and stochastic

characteristics. To address this, VMD is employed to decompose the original ROTI series into multiple relatively stable sub-sequences with distinct frequency components. An optimal parameter combination for VMD is selected using the BWO algorithm, with the minimum average envelope entropy serving as the fitness function. Once the optimal parameters are determined, the original ROTI sequence is decomposed using VMD under these settings. The resulting sub-sequences are then fed into an

LSTM model for training and testing. This hybrid approach has been shown to improve the predictive performance of LSTM models for time series forecasting (e.g., Yang SM et al., 2020).

By integrating the strengths of BWO-VMD for time-series decomposition and LSTM for long-sequence forecasting, we constructed a hybrid BWO-VMD-LSTM prediction model. In addition to the decomposed sub-sequences, input variables include all feature data described in Section 2.1. The final output is the predicted

ROTI index, reconstructed from the forecasted components.

The procedure is carried out as follows: First, the ROTI index from a single station is extracted to construct the original time series, and the BWO optimization algorithm is applied to determine the optimal parameter set for VMD. Second, using these optimized parameters, the ROTI time series is decomposed into several IMFs via VMD. Subsequently, the dataset is divided in an 80:20 ratio, with the initial 80% serving as the training set and the remaining

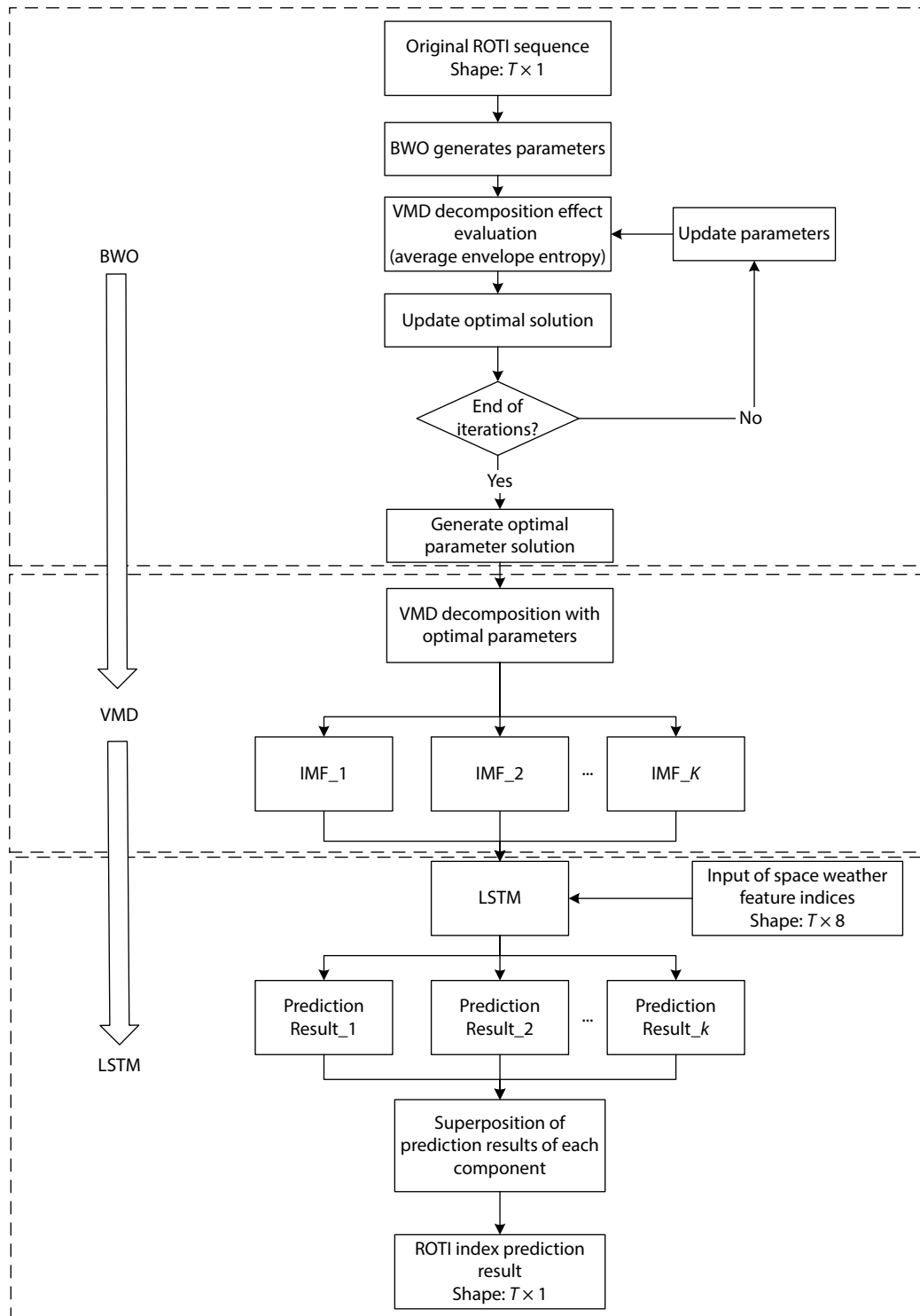


Figure 2. Overall workflow of the BWO-VMD-LSTM model.

20% reserved for testing. Each IMF component, along with spatial characteristic variables, is then fed into a LSTM neural network for model training and prediction. Finally, the predicted outputs of all components are reconstructed through superposition to obtain the complete forecasted ROTI values, and the prediction accuracy is evaluated using standard performance metrics. The overall workflow is illustrated in Figure 2.

2.4 Evaluation Metrics

We use mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE) and coefficient of determination (R^2) to quantify the prediction performance of the machine learning model:

$$MAE = \frac{1}{n} \sum_{i=1}^n |\hat{y}_i - y_i|, \quad (7)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)^2}, \quad (8)$$

$$MAPE = \frac{100\%}{n} \sum_{i=1}^n \left| \frac{\hat{y}_i - y_i}{y_i} \right|, \quad (9)$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (\hat{y}_i - \bar{y})^2}{\sum_{i=1}^n (\bar{y} - y_i)^2}, \quad (10)$$

where y_i represents the true value, $\bar{y}$ denotes the mean value, and $\hat{y}_i$ stands for the predicted value.

In addition to the aforementioned metrics, the True Skill Statistic (TSS) is employed to evaluate the model's overall performance. Referencing the results of Wu JY et al. (2022), a threshold of ROTI < 0.5 TECU·min⁻¹ is used to define the absence of significant ionospheric disturbance.

$$TSS = \frac{TP}{TP + FN} - \frac{FP}{FP + TN}, \quad (11)$$

where, TP, FN, FP, and TN represent true positive, false negative, false positive, and true negative, respectively.

3. Results

3.1 VMD Decomposition Based on BWO Optimization

Given the non-stationary nature of the ROTI sequence, VMD was employed to decompose the data. However, the performance of VMD critically depends on two key parameters—decomposition level (K) and the penalty factor (α). When these parameters are determined empirically, the selection process becomes not only cumbersome but also susceptible to suboptimal decomposition outcomes. To address these issues, we use the BWO algorithm to optimize the parameter configuration. The BWO algorithm was configured with a population size of 15 and a maximum of 20 iterations. The search ranges for K and α are set to [3, 8] and [100, 5000], respectively, with the remaining parameters fixed as follows (Zhang X et al., 2023): tau = 0 (noise tolerance), DC = 0 (no DC component), init = 1 (uniform initialization of center frequencies), and tol = 1e-7 (convergence tolerance). Envelope entropy

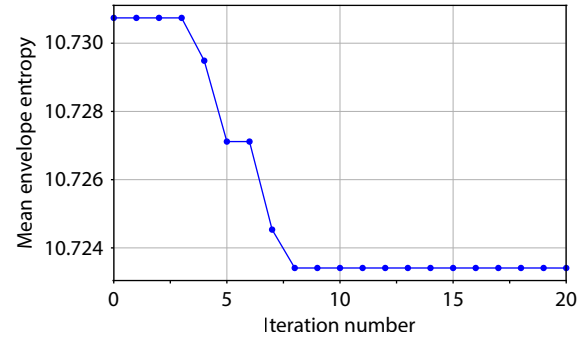


Figure 3. BWO optimization results.

effectively characterizes the noise level within each IMF component, with lower values indicating reduced noise and more prominent characteristic information. Therefore, we adopt the mean envelope entropy across all IMF components as the fitness function for the BWO algorithm. As shown in Figure 3, each point represents the optimal result from the start of the iteration to the current iteration. The fitness value converges to 10.7234 after multiple iterations, yielding the optimal parameter combination: $K = 5$ and $\alpha = 510$.

Subsequently, the optimal parameter combination is applied to decompose the original ROTI sequence using VMD. The decomposition results are presented in Figure 4, where the original ROTI sequence is effectively decomposed into five distinct components (IMF 1–IMF 5). Notably, the IMF 5 component exhibits a trend that closely aligns with the original sequence, indicating its dominance.

To evaluate the quality of the decomposition, the reconstructed sequence—obtained by summing IMFs 1–5—was compared with the original sequence. As illustrated in Figure 5, the reconstructed sequence closely matches the original, with a correlation coefficient of 0.9920, indicating minimal information loss during decomposition. The high correlation suggests that the combined components effectively preserve the majority of the original signal's information. Thus, the decomposition can be regarded as both practical and reliable.

3.2 Comparative Analysis: Forecasting Accuracy of BWO-VMD-LSTM vs. Other Models

The components obtained from BWO-VMD decomposition were split into training and test sets. To eliminate scale differences, all data were normalized. A two-layer LSTM network was constructed for modeling: the first layer contained 64 neurons, followed by a second layer with 32 neurons, both utilizing the tanh activation function. To mitigate overfitting, a 10% Dropout layer was applied after each LSTM layer. The Adam optimizer was used with a batch size of 32 and a learning rate of 0.001, and the Mean Squared Error (MSE) was used as the loss function. During training, 20% of the training set was allocated as a validation set for performance monitoring. The maximum number of epochs was set to 100, and both training and test losses were recorded at each iteration. We employed an early stopping method: if the validation loss did not improve for 10 consecutive epochs, training was halted and the best-performing weights were to be restored. To evaluate the

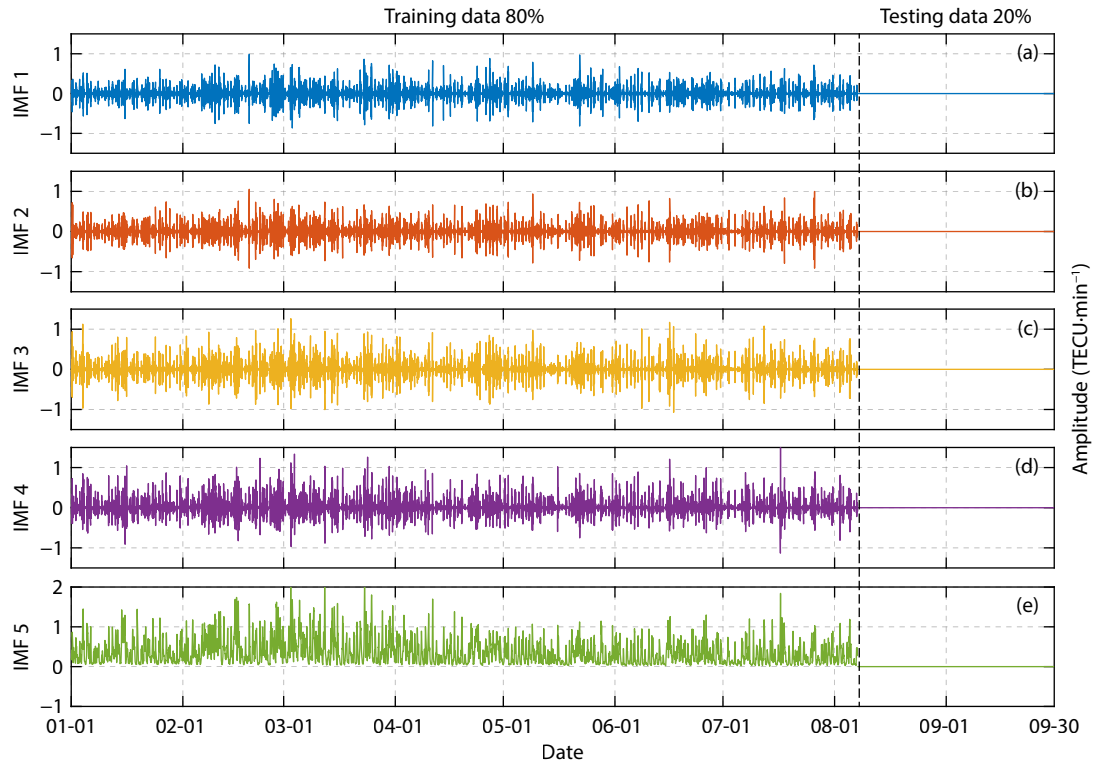


Figure 4. VMD decomposition results obtained using the optimal parameter combination determined by BWO optimization. The data after August 07 is our testing data.

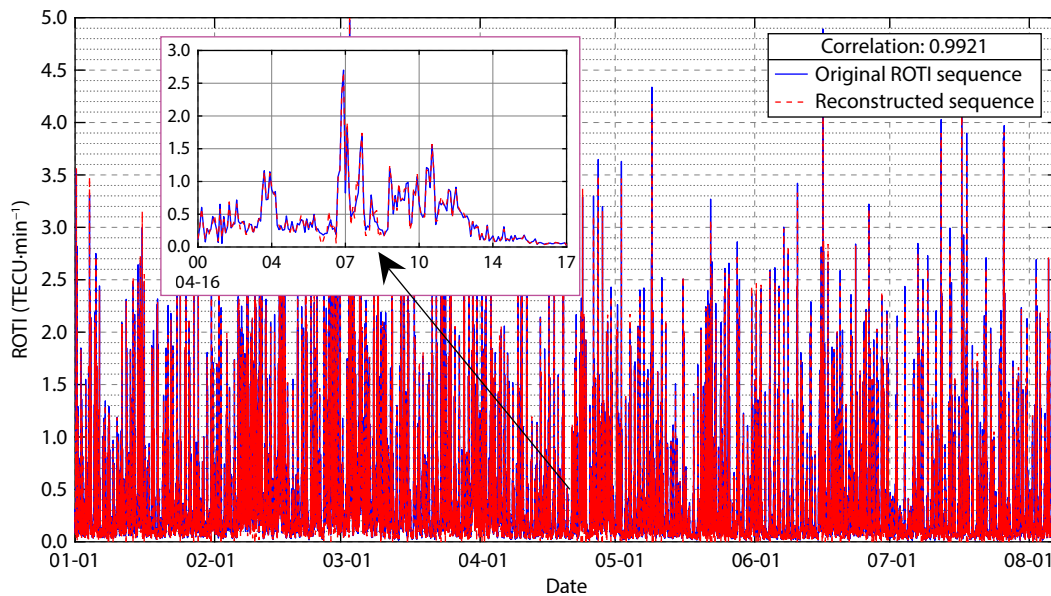


Figure 5. The original ROTI sequence and the reconstructed sequence. The inset shows a detailed view of the time interval between 00:00 and 17:00 UT on 16 April.

effectiveness of the proposed BWO-VMD-LSTM model, we conducted comparative experiments using VMD-LSTM, EMD-LSTM, and baseline LSTM models.

We evaluated all test set data points using a 1-hour observational ROTI sequence to predict the subsequent 5-minute ROTI; the results consistently demonstrated the stronger predictive capability of the BWO-VMD-LSTM model. Due to the high density of sample points, presenting all predictions would result in substan-

tial overlap, thereby impairing the clarity of model comparisons. Therefore, we present prediction results from 0:00 to 12:00 on August 9, 2023.

Figure 6 displays the predictions from the four models. All models successfully captured the occurrence characteristics of ionospheric scintillation and reflected the abrupt changes in ROTI. It should be noted, however, that all models also exhibited specific forecasting errors.

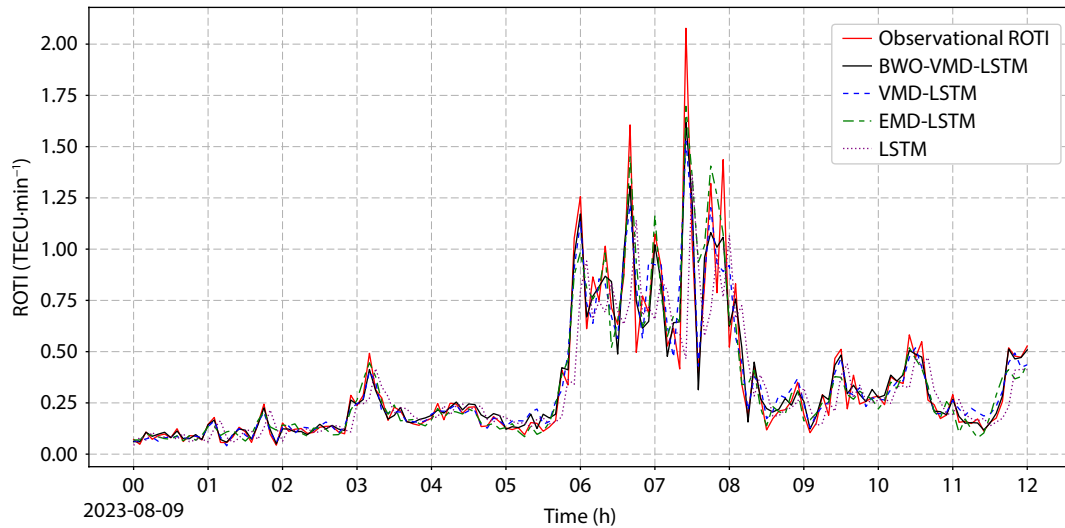


Figure 6. A comparison between the observational ROTI sequence and the predictions from four distinct models. The red line represents the observational data. The forecasts from the BWO-VMD-LSTM, VMD-LSTM, EMD-LSTM, and baseline LSTM models are depicted by black solid, blue dashed, green dash-dotted, and purple dotted lines, respectively. The predicted ROTIs were derived from a 1-hour observational ROTI sequence, which was input into each model.

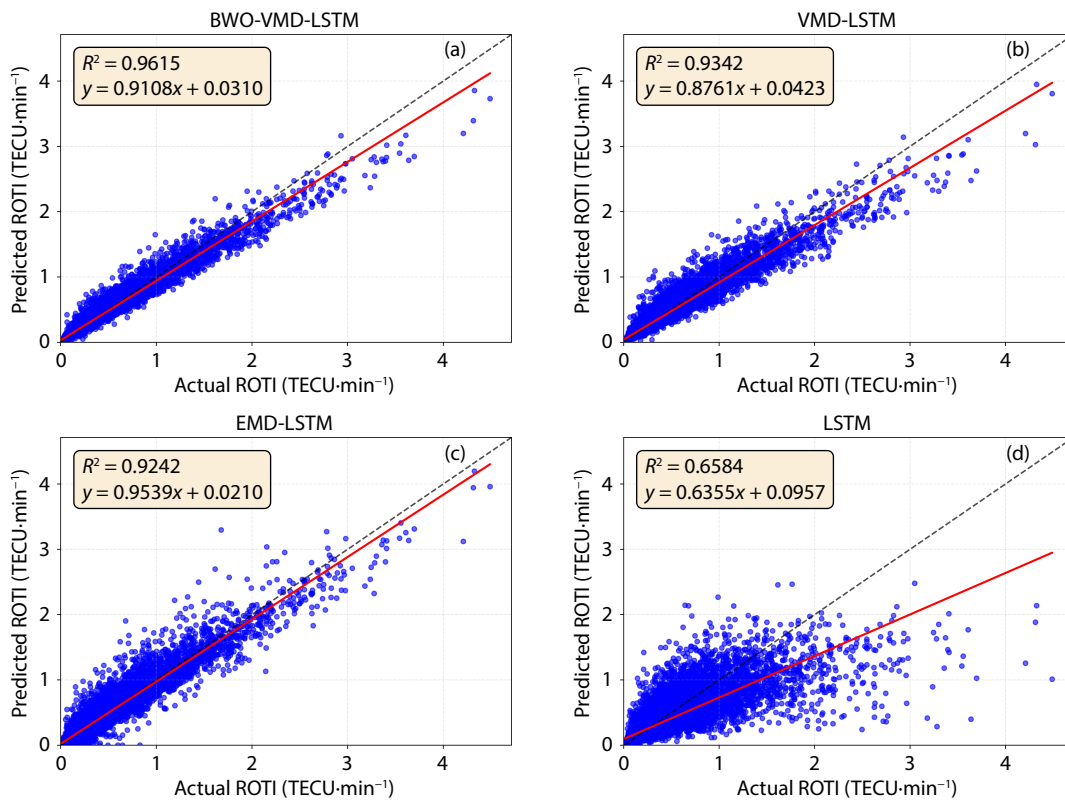


Figure 7. Scatter plots comparing the prediction performance of the four models.

Figure 7 presents a scatter plot illustrating the prediction performance of the four models. The black dashed diagonal line serves as a reference, indicating the naively ideal scenario in which the raw observations and model predictions are identical (i.e., the 1:1 line). The red line indicates the linear regression between predicted and actual values. The upper-left corner of each panel displays the coefficient of determination (R^2) and the corresponding linear fitting equation. It is evident that the BWO-VMD-LSTM

model achieves the highest predictive accuracy, with data points closely aligned along both the diagonal and the fitted line, and an R^2 value of 0.9615—the highest among all models. The VMD-LSTM model performs slightly better than the EMD-LSTM model, yielding R^2 values of 0.9342 and 0.9242, respectively. In contrast, the baseline LSTM model performs the worst, with an R^2 of only 0.6584.

Figure 8 presents the distributions of prediction error for four

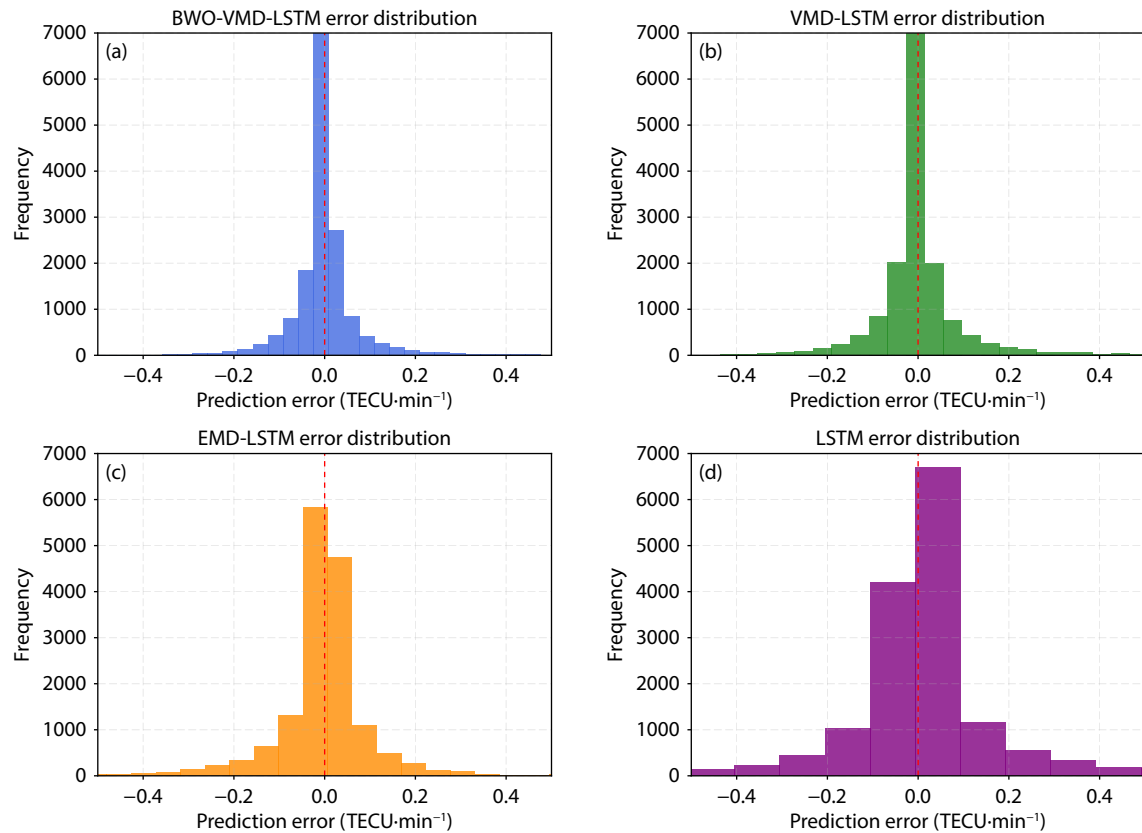


Figure 8. The prediction error distributions of four models.

models. As shown, both the BWO-VMD-LSTM and VMD-LSTM models exhibit prediction errors tightly clustered around zero with high frequencies, indicating excellent prediction stability. In contrast, the EMD-LSTM and LSTM models display more scattered error distributions, wider error ranges, and a higher frequency of significant deviations. This suggests that VMD decomposition is superior in extracting essential signal features and suppressing noise, effectively addressing the mode-mixing problem inherent in the EMD method. Incorporating the BWO optimization algorithm enables adaptive tuning of VMD's key parameters, aligning them more closely with real-world data characteristics and thereby significantly improving the model's overall predictive accuracy.

As evidenced by Figures 7 and 8, the BWO-VMD-LSTM model demonstrates superior performance. For a more concrete and comprehensive evaluation, we employed the five metrics detailed in Section 2.4—MAE, RMSE, MAPE, R^2 , and TSS—to conduct a systematic assessment. The results, summarized in Table 1, show that the decomposition–reconstruction strategy significantly improves the prediction accuracy for the original ROTI sequence. The EMD-LSTM, VMD-LSTM, and BWO-VMD-LSTM models all

substantially outperform the baseline LSTM model across all metrics.

Among them, the BWO-VMD-LSTM model achieves the best overall performance. It records the lowest errors, with values of 0.0435 TECU/min, 0.0810 TECU/min, and 13.7971% for MAE, RMSE, and MAPE, respectively. Concurrently, it achieves the highest scores for R^2 (0.9615) and TSS (0.9100). Specifically, compared to the baseline LSTM model, the BWO-VMD-LSTM model reduces MAE, RMSE, and MAPE by 63.41%, 66.43%, and 59.71%, respectively, while increasing R^2 and TSS by 46.04% and 30.56%. Notably, the BWO-VMD-LSTM model also surpasses both the VMD-LSTM and EMD-LSTM models on all evaluated metrics. This thoroughly validates the effectiveness of integrating BWO-optimized VMD parameters into the LSTM prediction framework, demonstrating the model's significant potential to improve the accuracy and reliability of ionospheric scintillation forecasts.

3.3 Model Prediction Performance Across Quiet and Substorm Periods

To evaluate the model's applicability during extreme space

Table 1. Model result evaluation value.

	MAE (TECU·min ⁻¹)	RMSE (TECU·min ⁻¹)	MAPE (%)	R^2	TSS
LSTM	0.1189	0.2413	34.2443	0.6584	0.6970
EMD-LSTM	0.0622	0.1137	20.5089	0.9242	0.8709
VMD-LSTM	0.0558	0.1059	17.3014	0.9342	0.8821
BWO-VMD-LSTM	0.0435	0.0810	13.7971	0.9615	0.9100

weather events, this study conducted a comparative analysis of its predictive performance during geomagnetically quiet periods and substorm periods. Magnetospheric substorms are transient disturbances in Earth's magnetic field typically lasting two to three hours, characterized by enhanced auroral electrojet currents (e.g., [Grocott et al., 2009, 2010](#)). Normally, the intensity of such substorms is quantified using the *AE* index (e.g., [Zong QG et al., 2021](#)). In this work, hourly-resolution *AE* index data are employed for classification: a threshold of 500 nT is used to distinguish substorm periods from quiet periods. Specifically, when the *AE* index exceeds 500 nT within an hour, that interval is classified as a substorm period; otherwise, it is categorized as a quiet period.

The prediction performance of each model during geomagnetically quiet and substorm periods is summarized in [Tables 2 and 3](#), respectively. The cross-period comparison reveals a marked increase in prediction errors during substorms compared to quiet periods. This degradation is attributed to the more dynamic, noisy nature of TEC fluctuations during substorms, which are characterized by sudden disturbances, in contrast to the relatively stable and calm conditions of quiet periods. It is clear that model accuracy is adversely affected by extreme space weather conditions.

Furthermore, an inter-model comparison within the same period demonstrates the consistent superiority of the BWO-VMD-LSTM model across all evaluation metrics in both substorm and quiet conditions. Progressive improvement is observed from the baseline LSTM to the BWO-VMD-LSTM model, evidenced by significant reductions in MAE, RMSE, and MAPE, alongside a substantial increase in R^2 . In particular, during the substorm period, the baseline LSTM model is mainly ineffective, with an R^2 of only 0.4425. In

contrast, the EMD-LSTM and VMD-LSTM models maintain R^2 values above 0.87, while the BWO-VMD-LSTM model achieves an R^2 of approximately 0.93. These results underscore the critical role of signal decomposition techniques and optimization algorithms in dramatically enhancing the predictive capability of the baseline LSTM model.

[Table 4](#) summarizes the confusion matrix data of each model in different periods. During non-magnetospheric substorm periods, the number of irregular phenomena is small, resulting in a low recall rate. Therefore, the TSS in [Table 1](#) is slightly higher than that in [Table 2](#); the number of samples during magnetospheric substorm periods is small, and even a small number of false alarms will increase the false alarm rate. Thus, the TSS in [Table 1](#) is better than that in [Table 3](#).

The BWO-VMD-LSTM model maintains high prediction accuracy during both geomagnetically quiet and disturbed periods, confirming its robustness and stability even under extreme space weather disturbances, and proving its utility for reliable ROTI index forecasting. To mitigate potential biases from relying on a single station's data, we conducted an identical training and testing procedure using data from the IQAL station. The corresponding results are compiled in Supplementary [Tables S1–S3](#) (not show in main text). Our analysis reveals that the results from the IQAL station closely align with those from the INVK station, confirming the consistency of our findings.

4. Conclusion

To overcome the limitations of traditional methods for predicting complex, nonstationary, and stochastic ROTI time series driven by

Table 2. Model result evaluation value during non-substorm periods.

	MAE (TECU·min ⁻¹)	RMSE (TECU·min ⁻¹)	MAPE (%)	R^2	TSS
LSTM	0.1032	0.2165	33.2732	0.6612	0.6661
EMD-LSTM	0.0543	0.1019	19.9791	0.9250	0.8622
VMD-LSTM	0.0485	0.0944	16.9039	0.9356	0.8747
BWO-VMD-LSTM	0.0379	0.0725	13.4093	0.9620	0.9035

Table 3. Model result evaluation value during substorm periods.

	MAE (TECU·min ⁻¹)	RMSE (TECU·min ⁻¹)	MAPE (%)	R^2	TSS
LSTM	0.2730	0.4122	43.7824	0.4425	0.5204
EMD-LSTM	0.1394	0.1949	25.7127	0.8754	0.7440
VMD-LSTM	0.1277	0.1844	21.2053	0.8884	0.7595
BWO-VMD-LSTM	0.0980	0.1393	17.6058	0.9363	0.8215

Table 4. Confusion matrix data values of various models in different periods.

	Non-substorm periods				Substorm periods				All			
	TN	FP	FN	TP	TN	FP	FN	TP	TN	FP	FN	TP
LSTM	11165	551	730	1815	352	204	101	795	11517	755	831	2610
EMD-LSTM	11340	376	269	2276	436	120	36	860	11776	496	305	3136
VMD-LSTM	11390	326	248	2297	444	112	35	861	11834	438	283	3158
BWO-VMD-LSTM	11446	270	187	2358	471	85	23	873	11917	355	210	3231

dynamic space weather, this paper presents a novel hybrid model combining BWO, VMD, and LSTM networks. The proposed framework is designed to enhance prediction accuracy by excavating deep features and complex patterns within the data. This is achieved by first employing BWO to adaptively tune the VMD parameters, using minimum average envelope entropy as the criterion to generate informative, well-separated IMFs with reduced mode aliasing. These components are then independently processed by LSTMs to capture their temporal dynamics. The final output is reconstructed from the collective LSTM-processed IMF predictions.

Validation with observational data from both the INVK and IQAL stations confirms that the BWO-VMD-LSTM model faithfully captures features and dependencies in the ROTI time series. It remains highly accurate and notably robust even under substorm conditions, as evidenced by its stable performance with minimal deviation. This capability is vital for delivering reliable ionospheric scintillation forecasts in operational scenarios.

Although the introduced BWO-VMD-LSTM model marks a step forward in ROTI index forecasting, a comprehensive exploration of its characteristics remains necessary. The current implementation, trained on 8 months of data to make 5-minute-ahead predictions from 1-hour inputs, may not be the most effective configuration. A systematic investigation is needed to determine optimal choices for training duration, input sequence length, and forecasting horizon. Besides, in this study, we accepted default parameter settings of the BWO algorithm. It is well recognized that optimization algorithms applied to a particular data set typically converge to a local optimum, which may not necessarily correspond to the global optimal solution. Therefore, a critical issue for the BWO-VMD-LSTM model in practical applications is how to effectively balance the computational cost of the BWO algorithm with the overall prediction efficiency of the model. A natural next step is a comprehensive evaluation of the model's capabilities and robustness across varying temporal scales and computational costs.

Data availability

The data supporting this study were sourced from the following repositories:

- ROTI Calculation: The pseudo range and phase observations for the INVK station were provided by the IGS Data Center of Wuhan University (<ftp://igs.gnsswhu.cn/pub/gps/data/daily/>).
- Space Weather Parameters: The solar radio flux ($F_{10.7}$) and geomagnetic activity indices (IMF B_z , Dst , K_p , A_p , AE , PCN, PCS) were acquired from NASA's OMNIWeb database (https://omni-web.gsfc.nasa.gov/html/ow_data.html).

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