Received 14 June 2024, accepted 13 August 2024, date of publication 15 August 2024, date of current version 27 August 2024.
Digital Object Identifier 10.1109/ACCESS.2024.3444282

RESEARCH ARTICLE

Advancing Logistics Management: E3L-Net for Predictive Demand Analytics

YAO LU
College of Business, Yangzhou University, Yangzhou, Jiangsu 225000, China
e-mail: enshua5466@163.com

This work was supported in part by Jiangsu Province Industry-University-Research Guiding Plan Project-Gaoyou Cross-Border E-Commerce Intelligent Logistics System Platform Technical Service under Grant FZ20221270, and in part by the Research on School Teaching Reform under Grant yzucx2021-3A.

ABSTRACT The essence of smart logistics lies in leveraging information resources and intellectual assets to efficiently and precisely match the multidimensional demands and supplies within the logistics system. Unlike supply, demand is more dynamic, making the accurate capture and prediction of demand variations across different levels and time dimensions the core and key to developing smart logistics systems. Temporary micro-level demand prediction not only enhances the timeliness, accuracy, and cost-effectiveness of micro-level supply but also reveals macro trends and extended patterns of logistics demand, providing decision support for logistics management at all levels. This study addresses the challenges in predicting temporary logistics demand, characterized by variability, high stochasticity, and abrupt changes. We propose an advanced E3L-Net model, combining ensemble empirical mode decomposition, local mean decomposition, long short term memory networks, and local error correction. The E2L-Net model, formed by integrating ensemble empirical mode decomposition and local mean decomposition, decomposes the original data to stabilize it and mitigate endpoint effects. LSTM is then used to predict these decomposed signals, leveraging its superior temporal modeling capabilities. The LEC model further refines these predictions by correcting local abrupt changes. Our experimental analysis, utilizing logistics demand data from a company, demonstrates that the proposed model significantly outperforms 11 other models, highlighting its effectiveness and generalization capability in handling temporary logistics demand predictions.

INDEX TERMS Advancing logistics management, smart logistics, deep learning, LSTM.

I. INTRODUCTION

The essence of smart logistics lies in leveraging information resources and intellectual assets to efficiently and precisely match the multidimensional demands and supplies within the logistics system [1]. Unlike supply, demand is more dynamic, making the accurate capture and prediction of demand's variations across different levels and time dimensions the core and key to developing smart logistics systems. Temporary micro-level demand prediction not only enhances the timeliness, accuracy, and cost-effectiveness of micro-level supply but also reveals the macro trends and extended patterns of logistics demand, providing decision support for logistics management at all levels [2].

The associate editor coordinating the review of this manuscript and approving it for publication was Libo Huang.

Research on logistics demand prediction has traditionally focused on macro and meso levels over extended periods, and there is already a substantial body of research in this area [3], [4], [5]. Because extended demand statistics are typically measured annually, their trends are relatively stable. However, temporary demand is influenced by numerous factors and complex mechanisms, resulting in variability, strong stochasticity, and sudden changes, making it challenging to ensure the accuracy of estimations using existing methods [6].

Given that temporary logistics demand represents variable time-series data, the use of deep learning techniques, specifically Long Short Term Memory (LSTM) networks, which excel in temporal modeling with their extended memory capability, is considered [7]. This ability addresses issues of gradient vanishing and explosion during long-sequence training. Additionally, the Empirical Mode Decomposition (EMD) technique is advantageous for processing variable data by decomposing signals to stabilize them [8]. However, EMD has limitations such as mode mixing and endpoint effects. To address these, reference [9] proposed the Ensemble Empirical Mode Decomposition (EEMD) method to tackle mode mixing. Therefore, we aim to combine LSTM with EEMD to estimate temporary logistics demand. Nevertheless, since EEMD only resolves the mode mixing in EMD and not the endpoint effects, we also incorporate Local Mean Decomposition (LMD) [10], which can address issues related to information extraction in the original signals and endpoint effects in EEMD. Furthermore, the local abrupt changes in temporary logistics demand increase the complexity of prediction, prompting this study to propose the use of Local Error Correction (LEC) [11] to address this challenge.

Compared to existing research, our main contributions are as follows:

1) More novel research subjects: Current studies mainly examine annual logistics demand, whereas our study focuses on 12-hour temporary logistics demand.

2) More challenging data characteristics: While current research typically involves stable, periodic demand data, our data exhibits variability and strong stochasticity, with existing machine learning and deep learning models struggling to capture underlying data features.

3) More comprehensive research methods: Unlike traditional statistical and machine learning approaches, our study begins with feature decomposition and extraction. We introduce the E2L-Net model to address the challenges of irregularity and instability in raw demand data, reducing prediction errors and delays. Additionally, we design the E3L-Net to tackle significant prediction errors at abrupt changes, further enhancing the model's predictive accuracy.

The structure of our paper is organized as follows: Section I is the introduction, Section II reviews the existing methods of logistics demand prediction, data decomposition, and local error correction. Section III presents materials and methods, Section IV is the experiment and analysis, and Section V concludes.

II. RELATED WORKS

A. CURRENT RESEARCH ON LOGISTICS DEMAND PREDICTION

Currently, logistics demand prediction methods can be primarily categorized into four types:

1) Mathematical statistical models: Representative methods include the Grey Model (GM) [12], Exponential Smoothing [13], Auto Regressive Integrated Moving Average Model (ARIMA) [14], and Multiple Linear Regression models [15]. These models are based on statistical principles and offer strong interpretability of the relationships between variables. However, their assumptions are relatively simple, and they do not perform well in predicting highly stochastic and irregular data.

2) Shallow machine learning models: Representative methods include BP Neural Networks [16], Radial Basis Function Neural Networks [17], and Support Vector Machines (SVM) and their variants [18], [19]. These models can effectively capture the irregular patterns in logistics demand, enhancing prediction accuracy. However, their feature learning capabilities are limited, and their generalization ability is constrained.

3) Deep learning models: A representative method is the LSTM network [7]. Due to their deeper structures and emphasis on feature learning, deep learning models can accurately describe the complex relationships between inputs and outputs. They generally outperform statistical models and SVMs in predicting time series data and are easier to implement. However, their prediction accuracy for highly stochastic and variable data still needs improvement.

4) Hybrid Models: These models combine two or more of the aforementioned methods, such as the combined GM(1,1) model and BP Neural Network model [20]. Hybrid models can leverage the strengths of each individual model, thereby improving prediction accuracy.

B. CURRENT RESEARCH ON DATA DECOMPOSITION

1) RESEARCH ON ENSEMBLE EMPIRICAL MODE DECOMPOSITION

Ensemble Empirical Mode Decomposition (EEMD) is a noise-assisted data analysis method proposed by [9] to address the mode mixing problem [21]. As an efficient data decomposition algorithm, the EEMD model is widely used in the related research. For instance, EEMD has been used for predicting financial time series by decomposing data to reduce the complexity of time series [22]. Another study utilized EEMD to decompose data into high, medium, and low-frequency components, constructing a frequency-mixing model for financial time series prediction [23]. Additionally, a method combining EEMD and inverse cloud models was proposed for extracting compound fault features in gearboxes [24].

2) RESEARCH ON LOCAL MEAN DECOMPOSITION

Local Mean Decomposition (LMD) is another data decomposition method known for its high adaptability. It can decompose any complex variable signal into several physically meaningful Product Function (PF) components [25], and then combine the instantaneous frequency and amplitude of these PF components to obtain the complete information distribution of the original signal [26]. When external factors influencing the time series remain relatively constant, the PF components obtained through LMD can effectively describe the temporal evolution of one or more influencing factors [27]. Therefore, LMD provides a solid foundation for extracting relevant information about internal data changes. For example, LMD has been used to address variability and irregularity in wind speed time series [28]. By combining LMD with Singular Value Decomposition (SVD), signal denoising effects were enhanced [29]. Another study

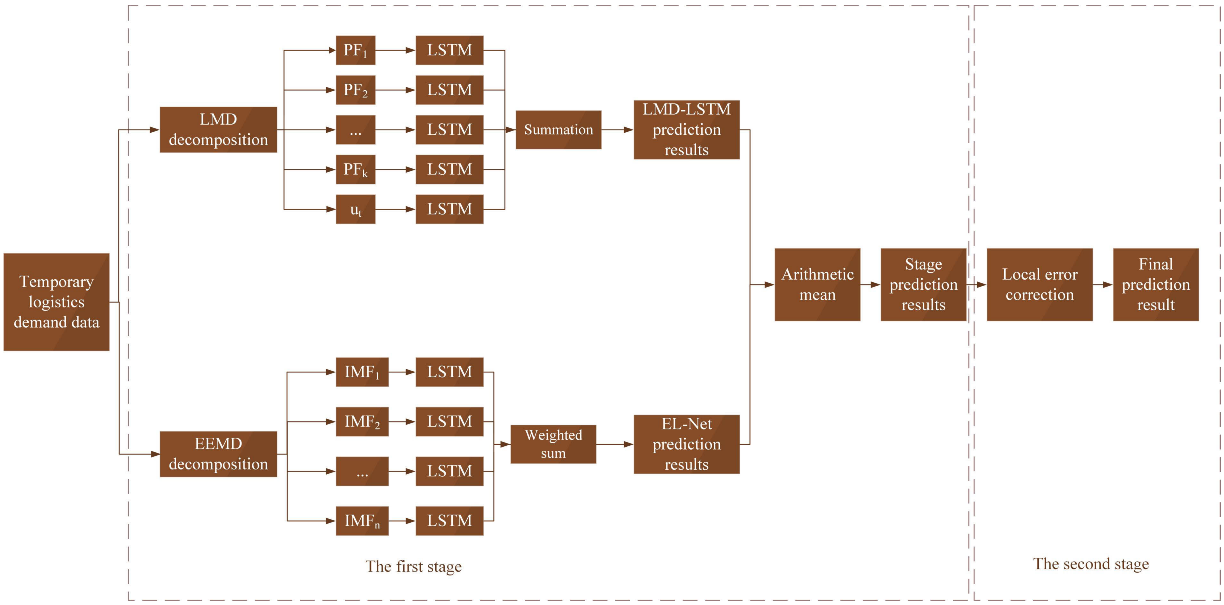


FIGURE 1. Our E3L-Net architecture.

proposed a new temporary wind speed prediction method based on LMD and Least Squares Support Vector Machine (LSSVM), demonstrating that LMD-decomposed data can effectively explain temporary wind speed fluctuations, periodicity, and trends [30].

C. CURRENT RESEARCH ON LOCAL ERROR CORRECTION

Prediction models generally reflect the overall relationship between input and output variables but often overlook the rich hidden information within the error values [31]. Therefore, some researchers have focused on error correction, constructing error prediction models to analyze and extract internal information from prediction error sequences and using the results to correct the initial predictions. Representative error prediction models include GM(1,1) [32], Linear Regression [33], and ARIMA [14]. For instance, a method based on local ramp error correction was proposed to improve the lag in wind speed prediction [34]. Another study used local dynamic approximation to locate simulation points and correct numerical prediction model errors [35].

In summary, while considerable analysis and research on logistics demand predicting have been conducted by extensive scholars, and these research outcomes are of significant reference value, limitations still exist. For example, most studies focus on regional logistics volume with annual statistical units, where data trends are relatively stable. There is a lack of research on temporary logistics demand characterized by variability, high stochasticity, and local mutations. Applying existing methods directly to temporary logistics demand predicting often results in low accuracy. In response, this paper proposes an E3L-Net model for temporary logistics demand predicting. By combining EEMD and LMD for signal decomposition, the model deeply explores data characteristics, reducing prediction errors caused by variability and high stochasticity in temporary logistics demand and mitigating issues like mode mixing and endpoint effects from EMD. Furthermore, the LSTM processes the signal decomposition results of EEMD and LMD in parallel, leveraging its extended memory advantages. Additionally, the LEC model is constructed to correct the LSTM prediction results, addressing local mutations in temporary logistics demand by extracting hidden information and variable traces from the error values.

III. THE PROPOSED METHOD

Our E3L-Net prediction model is divided into two stages: the E2L-Net model and the LEC model. The framework of the the proposed model is shown in Figure 1.

A. E2L-NET MODEL CONSTRUCTION

In this stage, the raw temporary logistics demand data is first decomposed using EEMD and LMD, leveraging their complementarity to reduce significant endpoint effects in EEMD and address over-smoothing issues in LMD that could impact predictive performance. The decomposed signals are then predicted using LSTM, which is known for its strong performance in time series prediction. The basic process of the E2L-Net prediction model in the first stage is divided into four steps:

1) Data decomposition. The raw temporary logistics demand data is decomposed using EEMD and LMD, resulting in n Intrinsic Mode Function (IMF) components and k PF components along with a residual component.

2) LSTM prediction. The LSTM prediction model is used to estimate the n IMF components and the k PF components and residual components separately.

3) Aggregation of prediction results. The predicted results of the n IMF components are weighted and summed, with weights based on the Pearson correlation coefficients of each IMF component, to obtain the EL-Net prediction results. The predicted results of the k PF components and the residual components are summed to obtain the LMD-LSTM prediction results.

4) Final prediction. The arithmetic mean of the two sets of prediction results obtained in step 3 is taken as the final prediction value of the first stage.

1) EEMD DECOMPOSITION OF TEMPORARY LOGISTICS DEMAND DATA

Given the variable and highly stochastic characteristics of temporary logistics demand data, the proposed model first performs EEMD decomposition on it.

Assume $X = x(1), x(2), \ldots, x(t)$ is the preprocessed temporary logistics demand series, where $x(t)$ is the temporary logistics demand at time t. The main steps of EEMD decomposition for this data are as follows:

1) Add m types of Gaussian white noise to the logistics demand data to obtain noisy pseudo-signals.

$$y_j(t) = x(t) + g_j(t), \quad j = 1, 2, \ldots, m \tag{1}$$

where $y_j(t)$ represents the j-th noisy pseudo-signal at time t, and $g_j(t)$ represents the j-th Gaussian white noise at time t. Typically, m is set to 1000.

2) Perform EMD decomposition on the noisy pseudo-signals to obtain n IMF components and a residual component.

$$y_j(t) = \sum_{i=1}^{n} imf_{ij}(t) + r_j(t), \quad j = 1, 2, \ldots, m \tag{2}$$

where $imf_{ij}(t)$ is the i-th IMF component obtained from EMD decomposition of $y_j(t)$, and $r_j(t)$ is the residual component from EMD decomposition of $y_j(t)$.

3) Average the IMF components obtained from the EMD decomposition of the m noisy pseudo-signals to get n IMF components.

$$IMF_i(t) = \frac{\sum_{j=1}^{n} imf_{ij}(t)}{m}, \quad i = 1, 2, \ldots, n \tag{3}$$

where $IMF_i(t)$ represents the i-th IMF component of the temporary logistics demand at time t obtained from EEMD decomposition. These n IMF components will be used in the next stage of LSTM prediction.

2) LMD DECOMPOSITION OF TEMPORARY LOGISTICS DEMAND DATA

Since the EMD method used in the EEMD decomposition process has significant endpoint effects, the proposed model also performs LMD decomposition on the original temporary logistics demand series.

LMD extracts pure frequency modulation signals and envelope signals iteratively from the temporary logistics demand series X. Multiplying these signals produces PF components, which are then separated from the original series X to obtain the residual signal. This process is repeated until the final residual signal is a constant or monotonic, providing the time-frequency distribution of the original signal.

The LMD decomposition of the logistics demand $x(t)$ at time t results in k PF components and a residual component $u(t)$, such that the original logistics demand $x(t)$ can be reconstructed from these components.

$$x(t) = \sum_{i=1}^{k} PF_i(t) + u(t) \tag{4}$$

The k PF components $PF_i(t), i = 1, 2, \ldots, k$ and the residual component $u(t)$ will be used in the next stage of LSTM prediction.

3) LSTM PREDICTION OF EEMD AND LMD DECOMPOSED SIGNALS

Given the temporal dependencies in temporary logistics demand data, the proposed model employs LSTM to predict the signals decomposed by EEMD and LMD.

During data decomposition, EEMD decomposes the temporary logistics demand data into n IMF components and one residual component. Multiple experiments showed that this residual component does not significantly improve prediction accuracy and is therefore disregarded. For time t, let $IMF(t) = \{IMF_1(t), IMF_2(t), \ldots, IMF_n(t)\}$. LMD decomposes the data into k PF components and a residual $u(t)$, represented as $PF(t) = \{PF_1(t), PF_2(t), \ldots, PF_k(t), u(t)\}$. These signals essentially reflect the features of the temporary logistics demand data X over the time series $T = 1,2,\ldots, t$. For ease of description in subsequent LSTM calculations, the IMF and PF signals are denoted as $F(t) = \{F_1, F_2, \ldots, F_n, \ldots, F_{n+k}, F_{n+k+1}\}$.

For each signal F_i at time t, the feature value is denoted as f_i^t. Considering the influence of the logistics demand feature values from the previous q time periods on the feature value at time t, the dataset of logistics demand feature values for the previous q time periods $\{f_i^{t-q}, \ldots, f_i^{t-2}, f_i^{t-1}\}$ is used as the input Z_i^t to LSTM at time t. The output of LSTM at time $t-1$ is h_i^{t-1}, and the cell state at time $t-1$ is C_i^{t-1}. Both are also used as inputs to LSTM.

The output and cell state at time t are denoted as h_i^t and C_i^t respectively. The weight matrices of the input gate, output gate, forget gate, and cell state at time t are denoted as W_e, W_o, W_f, and W_c respectively, while b_e, b_o, b_f, and b_c are the corresponding bias vectors. F_i^t, I_i^t, O_i^t, and $\hat{C}_i^t$ represent the forget gate output, input gate output, output gate output, and candidate cell state at time t. The entire LSTM unit calculation process is as follows:

$$Forget\ gate: F_i^t = \sigma(W_f f_i^t + W_f h_i^{t-1} + b_f) \tag{5}$$

$$Input\ gate: I_i^t = \sigma(W_e f_i^t + W_e h_i^{t-1} + b_e) \tag{6}$$

$$Output\ gate: O_i^t = \sigma(W_o f_i^t + W_o h_i^{t-1} + b_o) \tag{7}$$

$$Candidate\ cell\ state : \hat{C}_i^t = \tanh(W_c f_i^t + W_c h_i^{t-1} + b_c) \tag{8}$$

$$Cell\ state : C_i^t = F_i^t C_i^t + I_i^t \tanh(\hat{C}_i^t) \tag{9}$$

$$Cell\ output : h_i^t = O_i^t \tanh(C_i^t) \tag{10}$$

In these equations, σ represents the sigmoid activation function. Throughout this process, the features extracted from the decomposed temporary logistics demand data are further refined by three interacting gates: forget gate, input gate, and output gate. The output gate ultimately uses a sigmoid layer to filter the cell state, and the filtered state is multiplied by O_i^t after passing through a tanh layer to produce the temporary logistics demand output h_i^t.

B. CONSTRUCTION OF THE E3L-NET TEMPORARY PREDICTION MODEL

When logistics demand shows sudden increases or decreases within a short period, resulting in local abrupt changes, the prediction results can exhibit significant errors at these points, as indicated by the solid circle in Figure 2. Additionally, due to the high stochasticity of temporary logistics demand, predicted values can become negative, causing prediction errors, as indicated by the dashed circle in Figure 2.

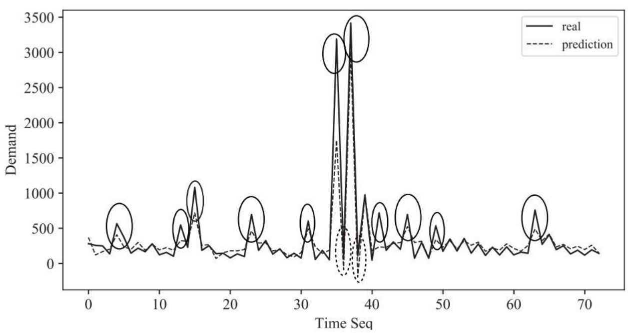


FIGURE 2. Local sudden change of temporary logistics demand.

To reduce prediction errors caused by abrupt changes and negative values, and to improve prediction accuracy, this paper proposes a LEC method. This method predicts the error value sequence of temporary logistics demand and corrects the first stage prediction values accordingly. The framework of the LEC model is shown in Figure 3.

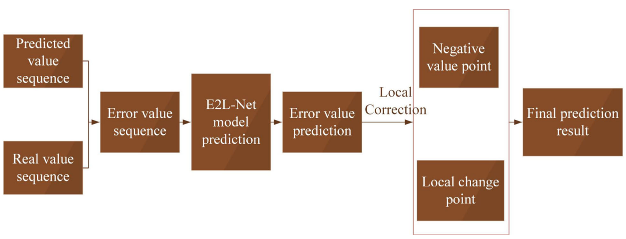


FIGURE 3. LEC architecture.

The basic process of the second stage LEC model consists of four steps:

1) Calculate the difference between the predicted value sequence obtained from the first stage and the actual value sequence to get the error value sequence.

2) Use the E2L-Net model to predict the error value sequence to obtain the error predictions.

3) Identify the abrupt change points and negative value points in temporary logistics demand.

4) Perform local error correction on the abrupt change points and negative value points in the first stage predictions according to the correction rules, resulting in the final prediction values.

1) DEFINITION OF LOCAL ABRUPT CHANGES IN TEMPORARY LOGISTICS DEMAND

Based on the actual changes in logistics demand, the trend can be categorized into four types: steadily increasing, steadily decreasing, suddenly increasing, and suddenly decreasing. The first two can be considered non-local abrupt changes, where the time series inertia does not cause significant errors between the predicted and actual values of logistics demand. The latter two can be considered local abrupt changes, where the actual value of logistics demand significantly differs between two consecutive time points. To accurately describe this, let t and $t-1$ be two consecutive time points, and the absolute value of the difference in temporary logistics demand be γ, defined as:

$$\gamma = |x(t) - x(t-1)| \tag{11}$$

where $x(t)$ represents the actual logistics demand at time t, and $x(t-1)$ represents the actual logistics demand at time $t-1$.

When $\gamma \geq \alpha$, this state is defined as a local abrupt change, and the temporary logistics demand point at time t is termed a local abrupt change point. The threshold α varies with different data series and can be determined through parameter optimization.

C. CORRECTION OF LOCAL ABRUPT CHANGE ERRORS IN TEMPORARY LOGISTICS DEMAND PREDICTION

If the logistics demand point at time t is identified as a local abrupt change point or a negative value point, the correction is performed as follows:

$$x\_correct(t) = pred(t) + eer(t) \tag{12}$$

where $x\_correct(t)$ represents the corrected logistics demand prediction at time t, $pred(t)$ represents the first stage logistics demand prediction at time t, and $err(t)$ represents the error prediction at time t, obtained from the E2L-Net model's prediction of the error value sequence.

IV. EXPERIMENT

A. DATASET

To validate the effectiveness of the proposed E3L-Net, we used the logistics demand order data from a company between July 1, 2023, and December 31, 2023 comprising a total of 100,000 entries.

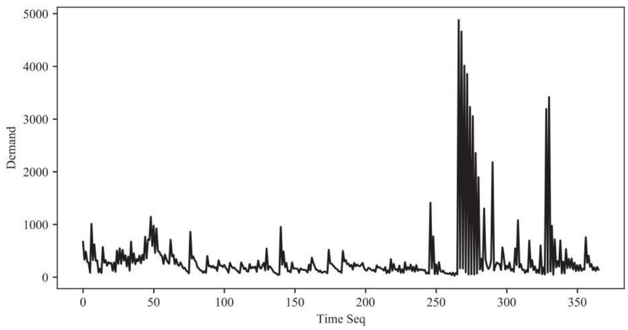


FIGURE 4. Data distribution.

Considering the discreteness and sparsity of the raw data, we chose a 12-hour interval for statistical analysis. For example, the logistics demand from 00:00 to 12:00 on July 1, 2023, is aggregated as the first data point, and the demand from 12:00 to 24:00 on July 2, 2023, is aggregated as the second data point, and so on. This results in 366 entries of temporary logistics data, with the data distribution shown in Figure 4.

As depicted in Figure 4, the temporary logistics demand data exhibit characteristics of variability, high stochasticity, local abrupt changes, and irregularity.

To enhance accuracy and accelerate convergence, we applied min-max normalization to the raw data, mapping the values to the range [0, 1] using the following transformation function:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{13}$$

B. EVALUATION METRICS

To determine the prediction accuracy, we selected the commonly used metrics: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Adjusted Coefficient of Determination (R^2).

1) ROOT MEAN SQUARED ERROR (RMSE)

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{14}$$

In which:

y_i : The actual observed value.

$\hat{y}_i$: The predicted value.

n: The total number of observations.

RMSE measures the square root of the average squared differences between the predicted values and the actual values. It provides a measure of the magnitude of prediction errors, where larger errors are penalized more due to the squaring operation.

2) MEAN ABSOLUTE ERROR (MAE)

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{15}$$

MAE calculates the average of the absolute differences between the predicted values and the actual values. It provides a straightforward measure of prediction accuracy, reflecting the average magnitude of errors without considering their direction.

3) MEAN ABSOLUTE PERCENTAGE ERROR (MAPE)

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}|\frac{y_i - \hat{y}_i}{y_i}| \tag{16}$$

MAPE expresses the prediction error as a percentage of the actual values. It measures the average absolute percentage error between the predicted values and the actual values, making it useful for comparing prediction accuracy across different datasets and scales.

4) ADJUSTED COEFFICIENT OF DETERMINATION (R^2)

$$\begin{aligned} Adjusted\ R^2 &= 1 - (\frac{(1-R^2)(n-1)}{n-k-1}) \\ Where\ R^2 &= 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \end{aligned} \tag{17}$$

Explanation:

$\bar{y}$: The mean of the actual observed values.

k: The number of predictors in the model.

The adjusted R^2 adjusts the coefficient of determination for the number of predictors in the model. It accounts for the complexity of the model and provides a more accurate measure of the goodness of fit, especially when comparing models with different numbers of predictors.

C. EXPERIMENT SETTINGS

Based on existing research, we used the first two sets of logistics demand data to predict the third set, forming a two-dimensional input and one-dimensional output prediction model. Additionally, to improve the prediction accuracy, we optimized the number of hidden units q in the LSTM model and the abrupt change threshold α in the LEC model.

1) SELECTION OF THE NUMBER OF HIDDEN UNITS q

Since the number of hidden units q affects prediction accuracy, we performed parameter optimization for the hidden units. Given the two-dimensional input data for LSTM and based on related research, we experimented with q values of 4, 8, 16, 32, and 64 hidden units. Other parameters were set as follows: 3000 training iterations, initial learning rate of 0.002, and 20% of the data as the test set. The evaluation metrics for different q values are shown in Table 1.

As shown, when $q = 4$, the four evaluation metrics are optimal, indicating the best prediction performance. Therefore, we selected 4 hidden units for the LSTM's hidden layer.

2) SELECTION OF THE ABRUPT CHANGE THRESHOLD α

According to the definition of abrupt changes in temporary logistics demand prediction errors, the choice of α in the

TABLE 1. The results for different values of *q*.

q value	RMSE	MAE	MAPE	R^2
4	213.57651	112.47531	54.30778	0.84875
8	246.36023	131.35877	55.74628	0.79430
16	230.98683	126.68528	72.41933	0.82258
32	265.72375	129.78927	55.03826	0.76321
64	246.28349	131.94131	56.24635	0.78609

LEC model is crucial for prediction accuracy. Generally, a smaller α value broadens the range of error correction, improving the final correction effect. However, if α is too small, insignificant errors might lead to increased corrected prediction errors, reducing model performance. Therefore, we tested α values of 0, 50, 100, 200, 300, 400, and 500, with the evaluation metrics shown in Table 2.

TABLE 2. The results for different values of α.

α value	RMSE	MAE	MAPE	R^2
0	124.17662	83.48765	45.34599	0.94726
50	115.85166	78.87960	43.70024	0.95357
100	116.02847	80.82616	46.62076	0.95342
200	117.48034	84.51057	49.67801	0.95277
300	116.23329	82.31371	48.58403	0.95345
400	123.63375	86.08532	51.61664	0.94751
500	123.25911	88.31186	52.21511	0.94836

As indicated, the choice of α significantly affects prediction accuracy. When $\alpha = 50$, the model achieves the highest prediction accuracy, with R^2 reaching 0.95357. Conversely, when $\alpha = 0$, the prediction performance is the worst, indicating over-correction issues. Therefore, the abrupt change threshold α is set to 50.

D. EXPERIMENTAL RESULTS ANALYSIS

1) ANALYSIS OF MODEL PREDICTION PERFORMANCE

1) EEMD Decomposition. The collected temporary logistics demand data were decomposed using EEMD, resulting in 7 IMF components and 1 residual component, as shown on the Figure 5.

(2) LMD Decomposition. The temporary logistics demand data were decomposed using LMD, producing 6 PF components and 1 residual component, as shown on the Figure 6. The solid lines represent PF components, and the dashed lines represent the corresponding envelopes.

(3) LSTM Prediction. The components obtained from the EEMD and LMD decompositions were input into the LSTM for prediction. The first stage prediction results are shown in Figure 7.

The model's prediction performance indicators are as follows: RMSE is 213.57651, MAE is 112.47531, MAPE is 54.30778%, and R^2 is 0.84875. As seen in Figure 7, the

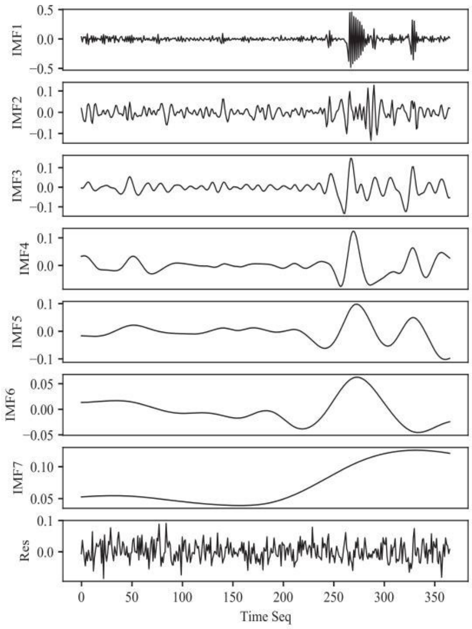


FIGURE 5. EEMD decomposition results.

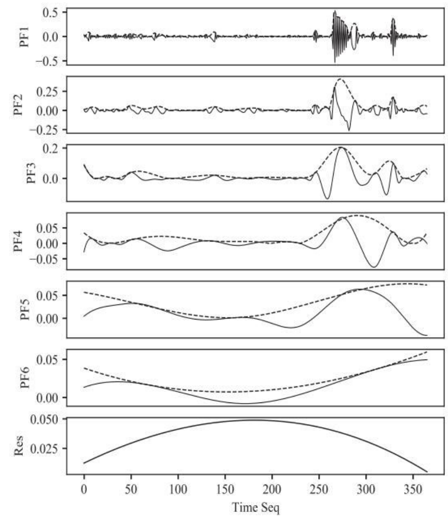


FIGURE 6. LMD decomposition results.

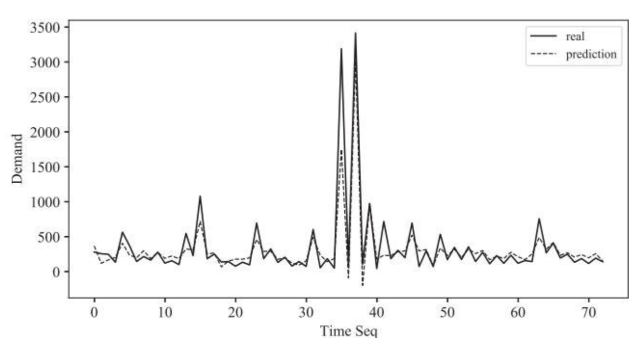


FIGURE 7. E2L-Net prediction results.

overall trend of the actual values aligns well with the predicted values, but the prediction performance at peaks and

TABLE 3. The comparison results.

Method	RMSE	MAE	MAPE	R^2
ARIMA	633.96627	329.23129	103.74294	-0.38120
SVR	487.56258	267.28190	96.58527	0.18656
FNN	463.26966	213.57313	63.83137	0.27176
ConvNet	437.83574	210.31332	79.44510	0.34138
LSTM	436.94834	184.90101	57.74701	0.35130
DNB-LSTM	527.11747	250.51219	111.75201	0.04824
LMD-LSTM	244.62032	203.96364	127.78303	0.80167
EMD-LSTM	410.62603	279.43123	112.67406	0.42060
EL-Net	396.81166	228.26317	82.86694	0.46920
EMD-LMD-LSTM	214.39278	116.61517	48.37697	0.84121
E2L-Net	213.57651	112.47531	54.30778	0.84875
E3L-Net	115.85166	78.87960	43.70024	0.95357

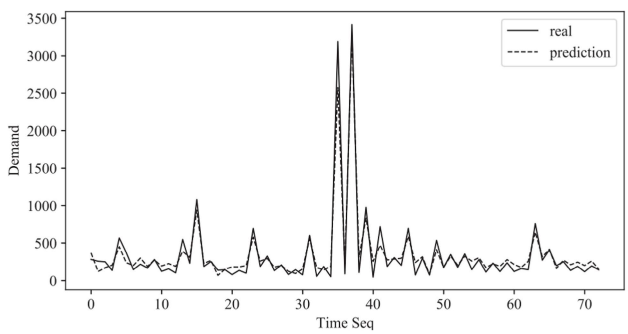


FIGURE 8. LEC correction results.

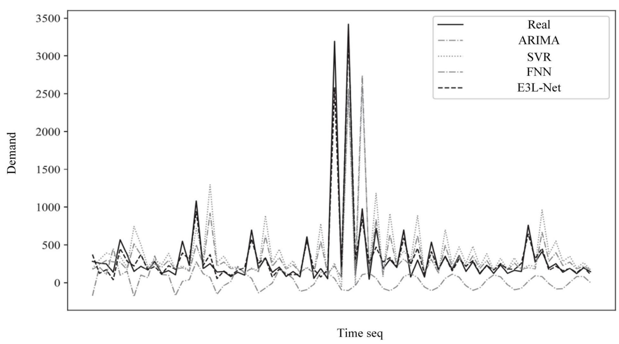


FIGURE 9. Comparison results of Group-a.

abrupt changes is poor. Therefore, the second stage local error correction is performed.

(4) LEC Correction. The prediction results after the second stage local error correction are shown in Figure 8.

The prediction performance indicators are: RMSE is 115.85166, MAE is 78.87960, MAPE is 43.70024%, and R^2 is 0.95357. It can be seen that local error correction has achieved excellent results compared to the first stage, with R^2 improving by about 10% and other indicators also significantly improving. This demonstrates the superiority of the proposed E3L-Net model in temporary logistics demand prediction.

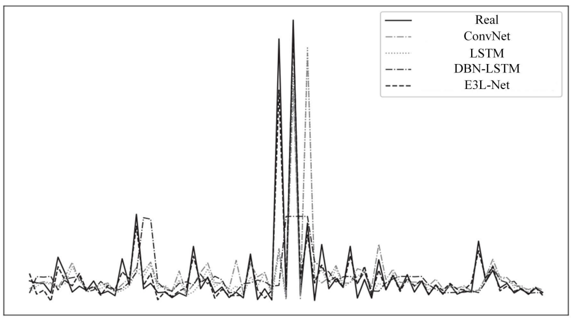


FIGURE 10. Comparison results of Group-b.

TABLE 4. The results for different values of α for air conditioning products.

α value	RMSE	MAE	MAPE	R^2
0	39.16279	26.18277	197.43892	0.83613
10	39.00286	25.73907	198.34213	0.83760
20	37.07999	25.13543	214.56614	0.85413
30	37.81627	25.88050	212.28422	0.84830
40	37.60833	25.76789	210.94216	0.84915
50	37.70311	25.83709	208.21201	0.84869
100	38.12861	25.59819	204.73176	0.84439

2) MODEL COMPARISON

To further demonstrate the effectiveness of the proposed model, we compared it with 11 other logistics demand prediction models, including:

(1) Mathematical Statistical Model: ARIMA.

(2) Shallow Machine Learning Models: Support Vector Regression (SVR) and Feedforward Neural Network (FNN).

(3) Single Deep Learning Models: Convolutional Neural Networks (ConvNet) and LSTM.

TABLE 5. The comparison results for air conditioning products.

Method	RMSE	MAE	MAPE	R^2
ARIMA	104.70752	53.72325	262.24036	-0.15089
SVR	93.56768	68.79787	541.69011	0.05311
FNN	94.33412	54.11821	375.92172	0.06740
ConvNet	103.64976	59.16004	429.26181	-0.17541
LSTM	90.29509	51.97654	370.65450	0.11385
DNB-LSTM	102.29104	61.84243	503.75385	-0.11576
LMD-LSTM	52.76719	36.54861	412.41545	0.69581
EMD-LSTM	85.85222	47.42904	202.13317	0.20819
EL-Net	75.47272	47.99143	233.51332	0.38906
EMD-LMD-LSTM	55.05402	31.48363	209.36132	0.67032
E2L-Net	51.62593	29.74833	188.81092	0.72092
E3L-Net	37.96429	26.34617	214.33266	0.85541

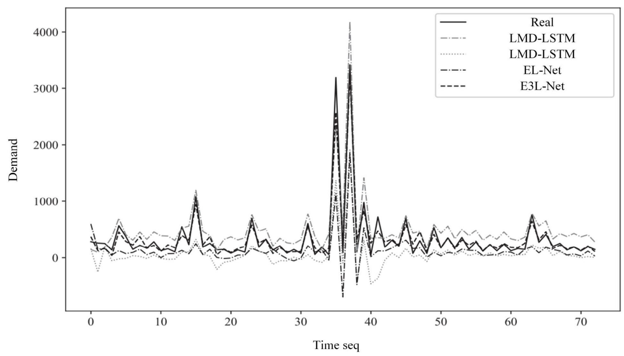


FIGURE 11. Comparison results of Group-c.

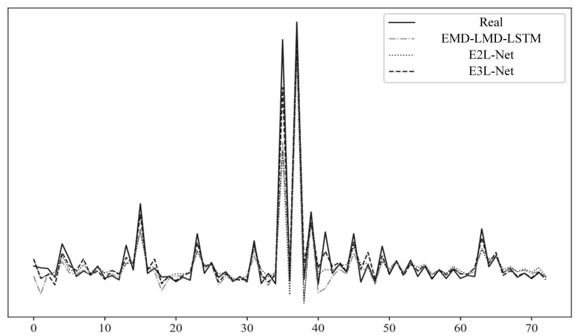


FIGURE 12. Comparison results of Group-d.

(4) Hybrid Prediction Models: Deep Belief Network (DBN)-LSTM, EMD-LSTM, EEMD-LSTM (EL-Net), LMD-LSTM, EMD-LMD-LSTM, and EEMD-LMD-LSTM (E2L-Net).

The comparison results are shown in Figures 9-12. Given the large number of comparative algorithms, we grouped them into four sets for better visualization of the prediction results:

Group-a: ARIMA, SVR, FNN.

Group-b: ConvNet, LSTM, DBN-LSTM.

Group-c: EMD-LSTM, EL-Net, LMD-LSTM.

Group-d: EMD-LMD-LSTM, E2L-Net.

Each group is represented in a subplot, and each subplot includes the proposed E3L-Net and the original temporary logistics demand data for comparison.

To accurately assess prediction accuracy, we compared the RMSE, MAE, MAPE, and R^2 of all models as shown in (14)-(17), as shown in Table 3.

From Figures 9-12 and Table 3, it is evident that the proposed E3L-Net model significantly outperforms the other 11 models in terms of RMSE, MAE, MAPE, and R^2, with R^2 reaching 0.95357. This indicates the advantage of the proposed model in temporary logistics demand prediction. Models using data decomposition, such as LMD-LSTM, EMD-LSTM, EL-Net, EMD-LMD-LSTM, and E3L-Net, perform significantly better than those without data decomposition, highlighting the importance of data decomposition for highly variable and stochastic temporary logistics demand. Furthermore, EL-Net and LMD-LSTM outperform EMD-LSTM, demonstrating that EEMD and LMD effectively address the mode mixing and endpoint effect problems of EMD. The E2L-Net model outperforms EL-Net and LMD-LSTM, showing that the combination of EEMD and LMD effectively leverages the advantages of both individual decomposition models. The E3L-Net model outperforms E2L-Net, verifying the effectiveness of LEC for local error correction.

E. GENERALIZATION ABILITY OF THE PREDICTION MODEL

The generalization ability of a model reflects its adaptability to different data. In addition to validating the model's effectiveness using the data from Section IV-A, we collected 361 entries of logistics demand data for air conditioner products from a company to further verify the effectiveness of the proposed prediction model and demonstrate its generalization ability. The data were also aggregated at 12-hour intervals, and the distribution is shown in Figure 13. The abrupt change threshold α was optimized, with results shown in Table 4.

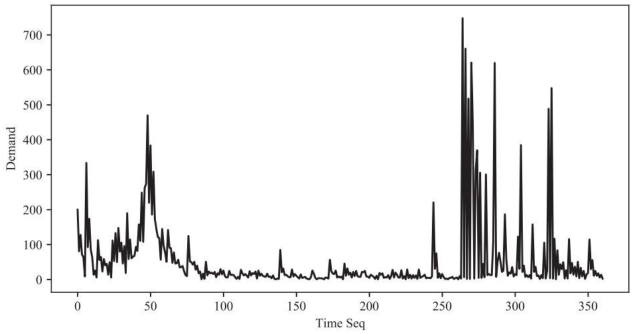


FIGURE 13. Data distribution for air conditioning products.

From Table 4, it can be seen that the prediction performance is optimal when α is 20. Other model parameters were set as previously described.

The prediction results of different models are shown in Table 5.

From Table 5, it can be seen that for temporary logistics demand data for air conditioner products, the proposed E3L-Net model significantly outperforms the 11 comparative models, further verifying the effectiveness of the proposed model in temporary logistics demand prediction.

V. CONCLUSION

This paper presents a comprehensive approach to address the challenges associated with temporary logistics demand prediction by introducing the E3L-Net model, which integrates EEMD, LMD, LSTM, and LEC techniques. Our experimental results demonstrate the model's superiority over traditional statistical methods, shallow machine learning models, single deep learning models, and hybrid models, in terms of RMSE, MAE, MAPE, and R^2. The generalization tests with different datasets, such as air conditioner logistics demand data, further verified the model's adaptability and robustness, confirming its potential application across various logistics scenarios. The E3L-Net model's ability to handle highly variable and stochastic data makes it a valuable tool for advancing smart logistics systems, providing accurate and reliable demand predictions for better logistics management and decision support.

REFERENCES

[1] Y. Ding, M. Jin, S. Li, and D. Feng, "Smart logistics based on the Internet of Things technology: An overview," *Int. J. Logistics Res. Appl.*, vol. 24, no. 4, pp. 323–345, Jul. 2021.

[2] N. Wang, S. Jia, and Q. Liu, "A user-based relocation model for one-way electric carsharing system based on micro demand prediction and multi-objective optimization," *J. Cleaner Prod.*, vol. 296, May 2021, Art. no. 126485.

[3] A. Alqatawna, B. Abu-Salih, N. Obeid, and M. Almiani, "Incorporating time-series forecasting techniques to predict logistics companies' staffing needs and order volume," *Computation*, vol. 11, no. 7, p. 141, Jul. 2023.

[4] J. M. Rožanec, B. Fortuna, and D. Mladenić, "Reframing demand forecasting: A two-fold approach for lumpy and intermittent demand," *Sustainability*, vol. 14, no. 15, p. 9295, Jul. 2022.

[5] R. Tian, B. Wang, and C. Wang, "MAGRU: Multi-layer attention with GRU for logistics warehousing demand prediction," *KSII Trans. Internet Inf. Syst.*, vol. 18, no. 3, pp. 1–23, 2024.

[6] C. Chen, X. Xu, B. Zou, H. Peng, and Z. Li, "Optimal decision of multi-objective and multiperiod anticipatory shipping under uncertain demand: A data-driven framework," *Comput. Ind. Eng.*, vol. 159, Sep. 2021, Art. no. 107445.

[7] Y. Li and Z. Wei, "Regional logistics demand prediction: A long short-term memory network method," *Sustainability*, vol. 14, no. 20, p. 13478, Oct. 2022.

[8] X. Jiang, L. Zhang, and X. (Michael) Chen, "Short-term forecasting of high-speed rail demand: A hybrid approach combining ensemble empirical mode decomposition and gray support vector machine with real-world applications in China," *Transp. Res. C, Emerg. Technol.*, vol. 44, pp. 110–127, Jul. 2014.

[9] J. Gu and Y. Peng, "An improved complementary ensemble empirical mode decomposition method and its application in rolling bearing fault diagnosis," *Digit. Signal Process.*, vol. 113, Jun. 2021, Art. no. 103050.

[10] Z. Wang, H. Chen, J. Zhu, and Z. Ding, "Daily $PM_{2.5}$ and PM_{10} forecasting using linear and nonlinear modeling framework based on robust local mean decomposition and moving window ensemble strategy," *Appl. Soft Comput.*, vol. 114, Jan. 2022, Art. no. 108110.

[11] D. A. Eckhardt and P. Steenkiste, "A trace-based evaluation of adaptive error correction for a wireless local area network," *Mobile Netw. Appl.*, vol. 4, pp. 273–287, Dec. 1999.

[12] X. Luo, H. Duan, and K. Xu, "A novel grey model based on traditional Richards model and its application in COVID-19," *Chaos, Solitons Fractals*, vol. 142, Jan. 2021, Art. no. 110480.

[13] E. S. Gardner, "Exponential smoothing: The state of the art," *J. Forecasting*, vol. 4, no. 1, pp. 1–28, Jan. 1985.

[14] S. Pasari and A. Shah, "Time series auto-regressive integrated moving average model for renewable energy forecasting," in *Proc. 3rd Indo-German Conf. Sustainability Eng. Enhancing Future Skills Entrepreneurship*. Cham, Switzerland: Springer, 2020, pp. 71–77.

[15] S. Etemadi and M. Khashei, "Etemadi multiple linear regression," *Measurement*, vol. 186, Dec. 2021, Art. no. 110080.

[16] J. X. Han, M. Y. Ma, and K. Wang, "Product modeling design based on genetic algorithm and BP neural network," *Neural Comput. Appl.*, vol. 33, pp. 4111–4117, May 2021.

[17] S. Panda and G. Panda, "On the development and performance evaluation of improved radial basis function neural networks," *IEEE Trans. Syst. Man, Cybern. Syst.*, vol. 52, no. 6, pp. 3873–3884, Jun. 2022.

[18] S. Suthaharan and S. Suthaharan, "Support vector machine," in *Machine Learning Models and Algorithms for Big Data Classification: Thinking With Examples for Effective Learning*, 2016, pp. 207–235.

[19] D. A isner and D. M. Schnyer, "Support vector machine," in *Machine Learning*. New York, NY, USA: Academic, 2020, pp. 101–121.

[20] Q. Guo, B. Guo, and Y. Wang, "A combined prediction model composed of the GM (1,1) model and the BP neural network for major road traffic accidents in China," *Math. Problems Eng.*, vol. 2022, no. 1, 2022, Art. no. 8392759.

[21] G. Xu, Z. Yang, and S. Wang, "Study on mode mixing problem of empirical mode decomposition," in *Proc. Joint Int. Inf. Technol., Mech. Electron. Eng.*, 2016, pp. 389–394.

[22] A. Erdiş, M. A. Bakir, and M. I. Jaiteh, "A method for detection of mode-mixing problem," *J. Appl. Statist.*, vol. 48, nos. 13–15, pp. 2847–2863, Nov. 2021.

[23] H. Ke, Z. Zuominyang, L. Qiumei, and L. Yin, "Predicting Chinese commodity futures price: An EEMD-Hurst-LSTM hybrid approach," *IEEE Access*, vol. 11, pp. 14841–14858, 2023.

[24] S. Zhang, J. Zhou, and W. Wang, "State of the art on vibration signal processing towards data-driven gear fault diagnosis," *IET Collaborative Intell. Manuf.*, vol. 4, no. 4, pp. 249–266, 2022.

[25] Y. Xu, K. Zhang, C. Ma, S. Li, and H. Zhang, "Optimized LMD method and its applications in rolling bearing fault diagnosis," *Meas. Sci. Technol.*, vol. 30, no. 12, Dec. 2019, Art. no. 125017.

[26] S. M. Shareef and M. V. Rao, "Estimation and interpreting instantaneous frequency of signals in non-stationary measurement sensor systems: An overview," *Meas., Sensors*, vol. 27, Jun. 2023, Art. no. 100758.

[27] W. Luo, J. Dou, Y. Fu, X. Wang, Y. He, H. Ma, R. Wang, and K. Xing, ''A novel hybrid LMD–ETS–TCN approach for predicting landslide displacement based on GPS time series analysis,'' *Remote Sens.*, vol. 15, no. 1, p. 229, Dec. 2022.

[28] B. Yan, P. W. Chan, Q. Li, Y. He, and Z. Shu, ''Dynamic analysis of meteorological time series in Hong Kong: A nonlinear perspective,'' *Int. J. Climatol.*, vol. 41, no. 10, pp. 4920–4932, Aug. 2021.

[29] X. Cheng, J. Mao, J. Li, H. Zhao, C. Zhou, X. Gong, and Z. Rao, ''An EEMD-SVD-LWT algorithm for denoising a LiDAR signal,'' *Measurement*, vol. 168, Jan. 2021, Art. no. 108405.

[30] Q. Zhu, J. Chen, D. Shi, L. Zhu, X. Bai, X. Duan, and Y. Liu, ''Learning temporal and spatial correlations jointly: A unified framework for wind speed prediction,'' *IEEE Trans. Sustain. Energy*, vol. 11, no. 1, pp. 509–523, Jan. 2020.

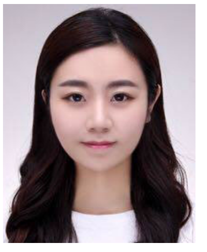
[31] W. Zhou, Z. Yan, and L. Zhang, ''A comparative study of 11 non-linear regression models highlighting autoencoder, DBN, and SVR, enhanced by SHAP importance analysis in soybean branching prediction,'' *Sci. Rep.*, vol. 14, no. 1, p. 5905, Mar. 2024.

[32] B. Zeng, X. Ma, and J. Shi, ''Modeling method of the grey GM(1,1) model with interval grey action quantity and its application,'' *Complexity*, vol. 2020, no. 1, 2020, Art. no. 6514236.

[33] D. C. Montgomery, E. A. Peck, and G. G. Vining, *Introduction to Linear Regression Analysis*. Hoboken, NJ, USA: Wiley, 2021.

[34] M. Lochmann, H. Kalesse-Los, and M. Schäfer, ''Analysing wind power ramp events and improving very short-term wind power predictions by including wind speed observations,'' *Wind Energy*, vol. 26, no. 6, pp. 573–588, 2023.

[35] V. Babovic, S. A. Sannasiraj, and E. S. Chan, ''Error correction of a predictive ocean wave model using local model approximation,'' *J. Mar. Syst.*, vol. 53, nos. 1–4, pp. 1–17, Jan. 2005.



YAO LU was born in Yangzhou, Jiangsu, China, in 1990. She received the Ph.D. degree from Woosong University, Republic of Korea. She is currently with the Department of Economics, School of Business, Yangzhou University. Her research interests include statistics and cross-border e-commerce.