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RETRACTED: Application of VMD–SSA–BiLSTM algorithm to smart grid financial market time series forecasting and sustainable innovation management

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RETRACTED

Introduction: This paper proposes a deep learning algorithm based on the VMD-SSA-BiLSTM model for time series forecasting in the smart grid financial market. The algorithm aims to extract useful information from power grid signals to improve the timing prediction accuracy and meet the needs of sustainable innovation management.

Methods: The proposed algorithm employs the variational mode decomposition (VMD) method to decompose and reduce the dimensionality of historical data, followed by singular spectrum analysis (SSA) to perform singular spectrum analysis on each intrinsic mode function component. The resulting singular value spectrum matrices serve as input to a bidirectional long short-term memory (BiLSTM) neural network, which learns the feature representation and prediction model of the smart grid financial market through forward propagation and backpropagation.

Results: The experimental results demonstrate that the proposed algorithm effectively predicts the smart grid financial market's time series, achieving high prediction accuracy and stability. The approach can contribute to sustainable innovation management and the development of the smart grid.

Discussion: The VMD-SSA-BiLSTM algorithm's efficiency in extracting useful information from power grid signals and avoiding overfitting can improve the accuracy of timing predictions in the smart grid financial market. The algorithm's broad application prospects can promote sustainable innovation management and contribute to the development of the smart grid.

KEYWORDS

VMD, SSA, BiLSTM, smart grid, financial market, time series prediction, sustainable innovation management frontiers

1 Introduction

Time series forecasting and sustainable innovation management of the smart grid financial market are comprehensive subjects involving energy, finance, and sustainable development. Its main purpose is to use artificial intelligence and data analysis technology to predict the timing changes of the smart grid financial market and to promote the sustainable development of the smart grid through sustainable innovation management. In recent years, the rapid development of deep learning technology has provided a more convenient and efficient application solution for timing forecasting and sustainable innovation management of smart grid financial markets (Frisch, 2019). As a deep learning algorithm, the VMD–SSA–BiLSTM model has the advantages of adaptability, high precision, and high stability and has achieved good results in time series data analysis and forecasting.

In recent studies, many scholars have also focused on the forecasting problem of smart grid financial markets and proposed some new forecasting models. For example, some scholars proposed a forecasting model based on multi-scale chaotic Fourier transform and long short-term memory (LSTM), which can forecast the electricity market at multiple time scales. Still, the model does not consider the intrinsic structure and characteristics of the time series. In addition, some scholars proposed a forecasting model based on deep learning and particle swarm optimization, which can forecast the electricity market at different time scales. However, the model does not consider problems such as nonlinearity and non-stationarity of the time series. There still needs to be more in-depth research and exploration on applying the VMD–-SSA–BiLSTM model in smart grid financial time series forecasting and sustainable innovation management. Therefore, this paper proposes a smart grid financial order algorithm based on the VMD–SSA–BiLSTM model. Modulo accuracy: Our model can also deal with the relationship between multiple variables involved in the financial order of the smart grid to predict the interaction between various indicators better, and it can use the decomposition and feature extraction of time series data to improve the interpretability of the model to better understand the changing rules of the data and the forecast results. According to the work of Górski (2018), the most important factor is that the model can process time series data in real time and make predictions quickly so that it can support the time series of the real-time smart grid financial market prediction and sustainable development of smart grid through sustainable innovation management.

The methods commonly used for the time series prediction of the smart grid financial market mainly include time series models, regression models, integrated models, and deep learning models.

Time series model: A time series model is a statistical model used to process time series data, which can be used to predict values or trends over a while in the future. Time series data are arranged chronologically, such as stock prices, temperature changes, website traffic, and intelligent hospital scheduling. Commonly used time series models include the autoregressive integrated moving average (ARIMA) model, exponential smoothing model, and vector autoregressive (VAR) model. The advantages of time series models are that they can analyze and model historical data and predict future trends and changes. In the case of sufficient time series data in the smart grid financial market, the prediction accuracy of the time series model is relatively high. The time series model can also be applied to various types of data, such as continuous, discrete, and seasonal, and can deal well with different data types in the smart grid financial market time series. However, its disadvantages are also obvious; if more data are needed, it may affect the accuracy and predictive ability of the model. In addition, the smart grid financial time series involves multiple data dimensions, and the time series model cannot handle it.

Regression model: A regression model is a statistical model used to establish the relationship between an independent and dependent variable. It can predict the value of the dependent variable by modeling the linear relationship between the independent and dependent variables. The regression model has the following advantages in the application of smart grid financial time series forecasting and sustainable innovation management: the regression model can explain the influence of the independent variable on the dependent variable by modeling the linear relationship between the independent variable and the dependent variable, and it can help managers better understand the data; the regression model can filter out independent variables that have a significant impact on the dependent variable through feature selection methods, thereby improving the predictive ability of the model. However, its shortcomings are also obvious (Gerke et al., 2020). If the regression model is too complex or has too many independent variables, it may lead to overfitting, making the model perform well on training data but not new data.

Integrated model: The integrated model is a method of integrating multiple basic models. By combining multiple models, the predictive ability and stability of the model can be improved. The advantages and disadvantages of the integrated model in the application of smart grid financial timing forecast and sustainable innovation management are also obvious. The integrated model can reduce the possibility of over-fitting and improve the model's generalization ability by combining multiple basic models. At the same time, the integrated model can also deal with complex data types and complex relationships between variables in smart grid financial time series and improve the model's predictive ability. However, since the ensemble model must combine and adjust multiple basic models, its computational complexity is high, requiring large computing resources and time. In addition, the integrated model must select multiple basic models and combine and adjust them. The prediction accuracy may be affected if the selected basic models are appropriate or properly combined.

Deep learning algorithm: The deep learning model is a machine learning model based on a neural network, which can learn and represent the characteristics of data through the multi-layer neural network to realize tasks such as classification, prediction, and data generation. Common deep learning algorithms include deep recurrent neural networks (RNNs), generative confrontation networks (GANs), and LSTM networks, which learn from a large amount of data by automatically extracting data. The advantage of this model is that the deep learning algorithm model can cope with large-scale data in the smart grid financial time series and can use a large amount of data to train the model through distributed learning and other technologies to improve the model's predictive ability and be able to learn non-linear relationships between data (Wu et al., 2021). At the same time, the deep learning algorithm can automatically learn features so that the algorithm can automatically discover the laws and patterns in the data. However, the disadvantage is that its training time is longer and its interpretability is poor, so it is not easy to be convincing.

Based on the advantages and disadvantages of the aforementioned models, this paper proposes a VMD–SSA–BiLSTM prediction model. First, the smart grid financial time series prediction and sustainable innovation management-related prediction indicators are input into the variational mode decomposition (VMD) model for signal decomposition, and multiple intrinsic mode functions (EMD) are obtained. Then, each EMD sequence is input into the singular spectrum analysis (SSA) model for subsequence decomposition to get multiple subsequences. Then, each subsequence is input into the bidirectional long short-term memory (BiLSTM) model for sequence modeling and prediction to obtain the prediction result of each subsequence, and finally, the prediction results of each subsequence are combined to obtain the full prediction result. The contribution points of this paper are as follows:

- Compared with time series models, it can handle nonlinear relationships that time series cannot handle, and its scope of application is wider than that of time series models
- Compared with ensemble models, the model has stronger learning ability and higher reliability and interpretability
- Compared with the deep learning models like RNN, GAN, and CNN, the BiLSTM model is not only simple in structure but also can process data more quickly, and the VMD and SSA models are added to further improve the prediction accuracy

In the remainder of this paper, we present recent related work in Section 2. Section 3 introduces the proposed method: overview, the VMD model, the SSA model, and the BiLSTM model. The fourth part introduces the experimental part, including experimental details and group experiment comparison. The fifth part is the summary.

2 Related work

2.1 ARIMA model

The ARIMA model is a classic time series analysis and forecasting model that can predict future values or trends. The ARIMA model is based on the autoregressive (AR) and moving average (MA) characteristics of the time series to build a model and considers the difference (I) of the time series so that it can deal with the problem of non-stationary time series (Benzidia et al., 2021). The general steps of the ARIMA model include visualization and preliminary analysis of the time series to determine whether difference and smoothing are required. For the stabilized time series, through the analysis of autocorrelation and partial autocorrelation functions, we determine the parameters of the ARIMA model and evaluate and optimize the model type. The model is then tested and predicted, and the accuracy and reliability of the predictions are evaluated.

The advantage of the ARIMA model is that it can deal with the problem of non-stationary time series very well, has relatively high explanatory power, and can explain the prediction results more intuitively. It is widely used in finance, economy, meteorology, and transportation. However, it also has some disadvantages (Shokouhifar, 2021). For example, when it predicts long-term and complex time series, it may require a higher model order and more historical data, thereby increasing calculation and time costs.

2.2 Support vector machine model

The support vector machine (SVM) model is a common supervised learning model mainly used for classification and regression problems (Mohsin et al., 2021). The core idea of the SVM model is to separate samples of different categories by constructing an optimal hyperplane and maximizing the interval between different categories as much as possible.

In the SVM model, for linearly separable cases, hard margin maximization (hard margin SVM) can be used to construct a hyperplane; for linearly inseparable cases, soft margin maximization (soft margin SVM) can be used to introduce a certain degree of error tolerance, thus constructing a hyperplane. In addition, the SVM model can also map the data in the low-dimensional space to the high-dimensional space through the kernel function, thereby improving the classification ability of the model.

The advantage of the SVM model is that it can effectively deal with high-dimensional data and nonlinear problems and has good generalization ability for small sample data. In addition, the SVM model can also use kernel functions to process complex data structures, such as text classification and image recognition. SVM models are widely used in machine learning and data mining, such as image classification, text classification, bioinformatics, and financial forecasting.

2.3 RNN model

The RNN is a common type of neural network model mainly used to process sequence data, such as speech signals, natural language, and time series (Jia et al., 2022). Unlike traditional feedforward neural networks, RNNs have feedback connections that process current inputs by memorizing previous information.

The core of the RNN model is the recurrent unit (RU), which can calculate the current output and new state by receiving the current input and the previous state. Common cyclic units include basic RNN units, LSTM units, and gated recurrent units (GRUs).

RNN models can be used for sequence modeling and prediction, such as language models, machine translation, speech recognition, and time series prediction. In sequence modeling, according to the work of Mohammed et al. (2021), the RNN model can improve the predictive ability of the model by learning long-term dependencies in the sequence. In time series prediction, the RNN model can predict by learning features such as periodicity and trends in the sequence. The advantage of the RNN model is that it can process sequence data of any length, has the ability of memory and recursion, and can improve the model's predictive ability by learning long-term dependencies in the sequence.

3 Methodology

3.1 Overview of our network

The VMD–SSA–BiLSTM model proposed in this paper is applied to the smart grid financial timing forecast and sustainable innovation management, which can effectively process the smart grid financial market timing data, improve the smart grid management and service level, and simultaneously realize the smart grid—sustainable development.

First, the price, transaction volume, market trend, and other important indicators of the power grid financial market are input into the model, then we enter the data preprocessing stage, and operations such as cleaning, normalization, and feature extraction are performed on these data to facilitate subsequent model training and prediction. Then, our model uses VMD and SSA algorithms to decompose the time series data to obtain the original data's main components and trend information. This step aims to transform the raw data into small pieces of data that are easy to process for subsequent modeling. Then, BiLSTM (bidirectional long short-term memory network) is used to model the time series data. Historical data are used for training to optimize the model's parameters and loss function. After model training, the model can predict the future situation and make sustainable innovation management decisions. The algorithm can select the optimal scheduling scheme according to the forecast results and real-time resource conditions to maximize the utilization efficiency of the smart grid financial market time series data. At the same time, during the operation process, the algorithm can update and adjust the data in real time to adapt to the ever-changing smart grid financial market environment and resource conditions.

The VMD–SSA–BiLSTM model consists of three parts: the VMD module, SSA module, and BiLSTM module. Through their advantages, the three parts complete the forecast application of the smart grid financial market timing forecast and sustainable innovation management. The overall structure of the model is shown in Figure 1.

This is the algorithm flow chart of the model. First, the data of different smart grid financial time series are input (Algorithm 1), the data at the data input layer are preprocessed and normalized, and then, the dataset is put into VMD for feature extraction. The feature sequence is then output, and then, the feature data are entered into the SSA module for feature learning. Finally, the optimal parameters of the model are obtained through BiLSTM, the accuracy of prediction is improved, and the prediction result is output.

```
Require: Datasets: MyGridGB, Elia, Eurostat, and EIA.
Ensure: VMD–SSA–BiLSTM model trained for time series prediction
1:  Feature extraction:
2:  // Extract features from the dataset, such as historical power consumption.
3:  Data preprocessing:
4:  // Handle missing values, outliers.
5:  Data normalization:
6:  // Scale feature values to a specific range, e.g., [0, 1].
7:  Transfer learning (optional):
8:  // Fine-tune pre-trained model or use pre-trained embeddings.
9:  Apply VMD on the time series data.
10: // Decompose the original time series into a set of band-limited IMFs.
11: Apply SSA on VMD results.
12: // Further decompose the IMFs to obtain the main components, reducing noise and improving signal quality.
13: Use BiLSTM for time series prediction.
14: // Input the processed time series data to the BiLSTM model to capture both forward and backward dependencies.
15: Calculate loss using mean squared error (MSE) loss function.
16: // Minimize the difference between predicted values and ground truth.
17: Update model parameters using optimization algorithms (e.g., Adam and SGD).
18: // Adjust the model weights to minimize the loss.
19: Repeat steps 9–12 until convergence or a predefined number of epochs.
20: return Trained VMD–SSA–BiLSTM model.
```

Algorithm 1. VMD–SSA–BiLSTM training process.

3.2 VMD model

VMD is a signal decomposition technique that can decompose a signal into multiple local modes (Kumar et al., 2022). The basic idea of the VMD model is to decompose the signal into a series of local modes with different frequencies and amplitudes, through which the characteristics of the signal can be analyzed. As a model commonly used in signal analysis and processing, the VMD model has the following advantages: it can deal with non-stationary and nonlinear signals, such as non-stationary vibration signals and nonlinear biological signals, because it does not depend on the stationarity and linearity; it can decompose the signal into a set of local mode functions, and each local mode function can preserve the local characteristics of the signal; it is reversible and scalable, which means that the signal can be reconstructed using the VMD model structure and can increase or decrease the details of the decomposition by adding or deleting components; and it can be based on local signal processing, so the computational complexity is relatively low, and it can be efficiently processed on large-scale data, so we choose it as the part of the model that is applied.

The VMD model mainly implements the decomposition process through an iterative optimization algorithm. VMD decomposes the original signal into multiple frequency bands of band-pass filters, then performs Hilbert transform on each frequency band to obtain a complex envelope, then determines the local mode of each frequency band through a series of iterative optimization steps, and finally, obtains the decomposition of the signal result. Therefore, in the time series forecasting and sustainable innovation management of the smart grid financial market, managers can collect and organize various data, such as important indicators such as prices, transaction

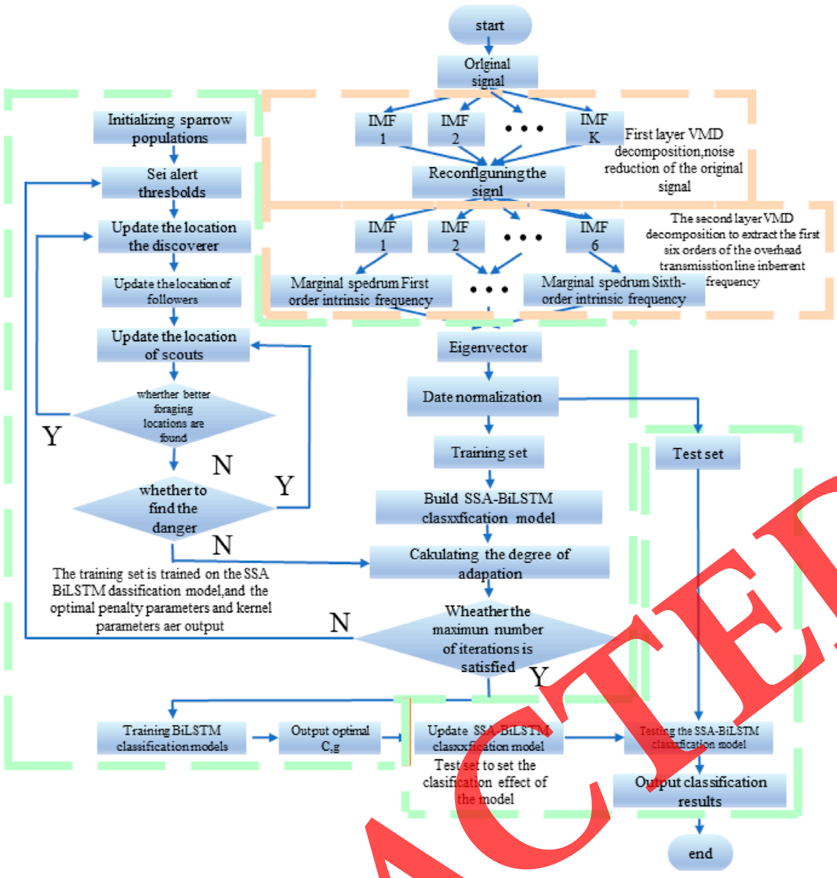

FIGURE 1
VMD–SSA–BiLSTM structural unit.

volumes, and market trends in the grid financial market, and input them into the VMD model for decomposition. Machine learning algorithms are used to predict price fluctuations, market trends, and other information in the smart grid financial market, helping managers better allocate resources and formulate management plans to achieve sustainable innovation management. The expression of VMD for component signal construction is

$$\begin{cases} \min_{(\{u_k\},\{\omega_k\})} \left\{ \sum_k \left| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) {}^* u_k(t) \right] e^{-j\omega_k t} \right|_2^2 \right\} \\ \text{s.t.} \sum_k u_k(t) = f(t). \end{cases} \tag{1}$$

In **Formula (1)**, $\{u_k\}$ is the set of modal functions after decomposition; $\{\omega_k\}$ is the set of center frequencies of each modal function; $\delta(t)$ is the Dicras function; * is the convolution calculation signal; j is the imaginary unit; and f(t)is the original signal.

Table 1 shows the meaning of the parameters in the aforementioned VMD formulas.

TABLE 1 Meaning of each parameter in **Formula 1**.

Parameter	Meaning
$\{u_k\}$	The set of modal functions after decomposition
$\{\omega_k\}$	The set of center frequencies of each modal function
$\delta(t)$	Dicras function
*	The convolution calculation signal
j	The imaginary unit
f(t)	The original signal

3.3 SSA model

The SSA model is based on time series decomposition, which can be used to analyze and predict time series data (Vali et al., 2022). It decomposes time series into multiple components, including trend, cycle, and noise, and then reconstructs and forecasts them. As a model commonly used in signal analysis and processing, SSA has the following advantages: the SSA model does not require prior knowledge; that is, it does not need to know the frequency and period of the signal, which makes the SSA model suitable for various types of signal analysis and processing tasks. SSA has a strong self-adaptive ability and can automatically adapt to the local characteristics and changes of the signal, so the SSA model has high adaptability and flexibility when dealing with different types of

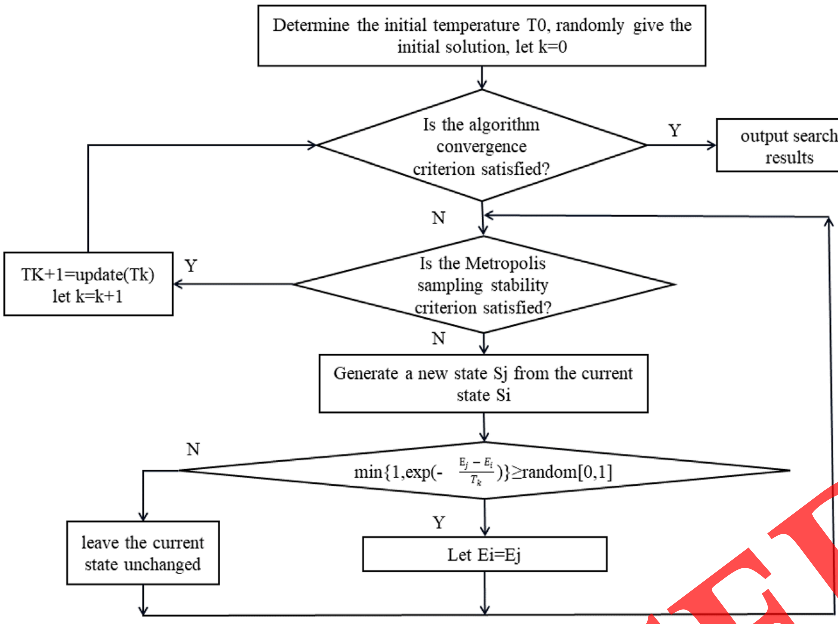

FIGURE 2
SSA structural unit.

signals. The decomposition results of the SSA model are very good. The interpretability of the SSA model can decompose the signal into a group of components with physical meaning, such as trend, seasonality, and noise, making the results more intuitive and easy to understand. The most important factor is that the SSA model can handle multivariate signals; that is, it can handle relationships between multiple variables at the same time. This makes the SSA model highly applicable and flexible when dealing with multi-dimensional signal data, so SSA can also be well applied to our research.

In the time series forecasting and sustainable innovation management of the smart grid financial market, the SSA model can be used to analyze the time series data of the smart grid financial market, extract the trend, cycle, and noise components, and use these components to predict the time series of the future smart grid financial market data to help managers better analyze and predict smart grid financial market time series data. The diagram is shown in Figure 2.This algorithm imitates the foraging process of sparrows, which divides the sparrow population into two parts: finders and joiners, according to the sequence of the process. Assuming a population of n sparrows, it can be expressed as

$$\boldsymbol{X}=\begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,m} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,m} \\ \vdots & \vdots & & \vdots \\ x_{n,1} & x_{n,2} & \cdots & x_{n,m} \end{bmatrix}. \tag{2}$$

In Formula (2), X represents the sparrow population matrix; $x_{n,m}$ represents the sparrow population; and m and n represent the dimensions of the variables to be optimized.

The finder is a type of sparrow with better fitness, responsible for obtaining food location information first during the search process, and the location update is expressed as

$$x_{i,j}^{t+1}=\begin{cases} x_{i,j}^{t}\cdot\exp\left(-\dfrac{j}{\alpha\cdot I_{\text{iter,max}}}\right), & R_2<S_{\text{ST}} \\ x_{j,i}+Q\cdot L, & R_2\geqslant S_{\text{ST}}. \end{cases} \tag{3}$$

In Formula (3), t is the current iteration number; i = 1, 2, 3, .., m; $I_{\text{iter,max}}$ is the maximum number of iterations; $x_{i,j}^{t}$ is the position information of the jth sparrow in the I dimension; α is the range (0.1] A random number; R_2 is the warning value, and the value is [0.1]; S_{ST} is the safety value, and the value is [0.5,1]; Q is the random machine number; and L is a 1× m-dimensional matrix with each element being 1.

When $R_2<S_{\text{ST}}$, it means there are no predators in this area, and the discoverer can safely expand the search range.

When $R_2\geqslant S_{\text{ST}}$, it means that a predator has appeared in this area, and the discoverer will issue an alarm at this time, and the rest of the sparrows will be led to fly to other sites to find food.

$$X_{i,j}^{t+1}=\begin{cases} \mathrm{Q}\cdot\exp\left(\dfrac{x_{\text{worst}}^{t}-x_{i,j}^{t}}{i^2}\right) & i>n/2 \\ X_p^{t+1}+\left|X_{i,j}^{t}-X_p^{t+1}\right|\boldsymbol{A}^{+}\boldsymbol{L} & \text{otherwise}. \end{cases} \tag{4}$$

In Formula (4), $A^{+}=A^{T}(AA^{T})^{-1}$; A is a 1× d matrix with 1× d elements randomly assigned to 1 and −1, $X_p$is the best follower position; x_{worst} is the global worst position.

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TABLE 2 Summary of parameters in the SSA formula.

Parameter	Meaning
X	Sparrow population matrix
$x_{n,m}$	The set of center frequencies of each modal function
m	Dimensions of the variables to be optimized
n	Dimensions of the variables to be optimized
t	Current iteration number
$I_{\text{iter,max}}$	Maximum number of iterations
$x_{i,j}^{t}$	Position information of the jth sparrow in the I dimension
α	The range [0.1] A random number
R_2	Warning value
S_{ST}	Safety value
Q	Random machine number
L	A 1× m-dimensional matrix with each element being 1
A	A 1× d matrix with 1× d elements randomly assigned to 1 and -1
X_p	The best follower position
x_{worst}	The global worst position
X_g^t	The global optimal position
β	Normal distribution
K	Direction of movement of the sparrow
f_j	Fitness value of the current individual sparrow
f_g	The globally optimal fitness value
f_b	The global worst fitness value
ε	Count

When the sparrow population is facing danger, it will follow anti-predation behavior, and its mathematical expression is

$$x_{i,j}^{t+1} = \begin{cases} X_g^t + \beta \cdot \left| X_{j,i}^{t+1} - X_g^t \right|, & f_j \neq f_g \\ x_{i,g}^t + K \cdot \left(\dfrac{\left| X_{j,i}^{t+1} - X_{\text{worst}} \right|}{\left(f_j - f_b \right) + \varepsilon} \right), & f_j = f_g. \end{cases} \tag{5}$$

In **Formula (5)**, X_g^t is the global optimal position; β and K are the step size control parameters, and β obeys the normal distribution with the mean value of 0 and the variance of 1; K represents the direction of movement of the sparrow, and the value is one of [−1, 1] random number; f_j is the fitness value of the current individual sparrow; $f_g$and f_b are the global best and worst fitness values, respectively; and ε is a constant to avoid zero-point errors. When $f_j \neq f_g$, it means that the vigilantes are at the edge of the group, representing the global optimal position X_g^t and its surrounding safety.

When $f_j = f_g$, it indicates that the vigilant is within the population, which means there are predators in the sparrow group. In order to reduce the risk of sparrows being caught, at this time, $R_2 \geqslant S_{\text{ST}}$, and then, returning to **Formula (4)**, the discoverer leads the population to other safe places for foraging. Up to **Formula (5)** is a cyclic process of the algorithm, updated according to the aforementioned steps, and the fitness value of the population will continue to increase. After several iterations, the optimal parameters can be obtained.

Table 2 shows the meaning of the parameters in the aforementioned SSA formulas.

3.4 BiLSTM model

The BiLSTM model is a deep learning model often used for modeling and predicting sequence data (Abdul et al., 2021). It combines forward and backward LSTM models to learn long-term dependencies and timing features in time series. As a model commonly used in sequence data processing, the BiLSTM model has the following advantages: the BiLSTM model is based on the LSTM unit and can have long- and short-term memory, which can effectively process long-sequence data and long-term model dependencies. Therefore, the BiLSTM model is in the sequence. It has high flexibility and applicability in data processing; BiLSTM can process and model sequence data from both forward and backward directions simultaneously so that the model can capture the global information and context of sequence data and improve the model's performance. The BiLSTM model is based on a neural network structure, which can be easily applied to various sequence data processing tasks, such as text classification, speech recognition, and machine translation. At the same time, it can be expanded and optimized by improving the model structure, loss function, and training strategy to improve model performance and adaptability; the key point is that the BiLSTM model has strong robustness, even in the presence of noise and missing data. Still, it can effectively model and process sequence data, which is well suited for our research.

By decomposing data by the previous VMD and SSA models, the BILSTM model can learn the decomposed feature data and long-term dependencies and use these features and relationships to predict the time series data of the smart grid financial market and optimize sustainable innovation management. Its structure diagram is shown in Figure 3.

The forward and reverse hidden layer states are spliced and input to the fully connected layer. The splicing formula is as follows:

$$\boldsymbol{h} = \{ \boldsymbol{h}_{\text{R},t}, \boldsymbol{h}_{\text{L},t} \}. \tag{6}$$

In **Formula (6)**, $h_{\text{R},t}$ is the hidden layer state of the time series input in the reverse direction at time t; $h_{\text{L},t}$ is the hidden layer state of the time series input in the forward direction at time t.

The BiLSTM in Figure 3 is composed of input X_t at time t, cell state C_t, temporary cell state $\tilde{\boldsymbol{C}}_t$, hidden layer state h_t, forgetting gate f_t, input gate i_t, and output gate o_t. The special structure of the gate has the function of regulating the flow of information. Therefore, the information of the earlier time step can also be carried to the cells of the later time step, which overcomes the influence of short-term memory. The forgetting gate f_t, input gate i_t, and output gate o_t are as follows:

$$\boldsymbol{f}_t = \sigma\left(\boldsymbol{W}_f \left[\boldsymbol{h}_{t-1}, \boldsymbol{X}_t \right] + \boldsymbol{b}_f \right), \tag{7}$$

$$\boldsymbol{i}_t = \sigma\left(\boldsymbol{W}_i \left[\boldsymbol{h}_{t-1}, \boldsymbol{X}_t \right] + \boldsymbol{b}_i \right), \tag{8}$$

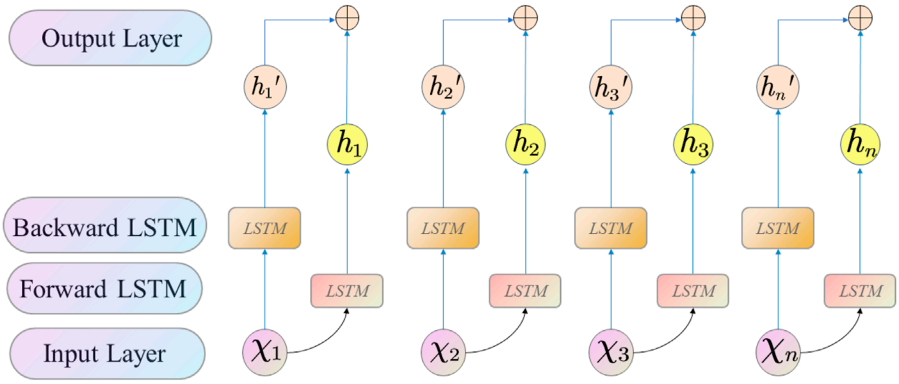

FIGURE 3
BiLSTM structural unit.

$$\boldsymbol{o}_t = \sigma\left(\boldsymbol{W}_{\boldsymbol{o}}\left[\boldsymbol{h}_{t-1}, \boldsymbol{X}_t\right] + \boldsymbol{b}_{\boldsymbol{o}}\right). \tag{9}$$

In **Formulas (7)–(9)**, W_f, W_i, and W_o are the weight matrix of the forgetting gate f_t, input gate i_t, and output gate o_t, respectively; b_f, b_i, and b_o are bias items; and σ is the sigmoid activation function.

$$\sigma(x) = \frac{1}{1 + \mathrm{e}^{-x}}. \tag{10}$$

The cell state is used to store the timing information of the memory data, and its formula is as follows:

$$\tilde{\boldsymbol{C}}_t = \tanh\left(\boldsymbol{W}_{\boldsymbol{C}}\left[\boldsymbol{h}_{t-1}, \boldsymbol{X}_t\right] + \boldsymbol{b}_{\boldsymbol{C}}\right), \tag{11}$$

$$\boldsymbol{C}_t = \boldsymbol{f}_t \boldsymbol{C}_{t-1} + \boldsymbol{i}_t \tilde{\boldsymbol{C}}_t. \tag{12}$$

In **Formula (11), (12)**, W_c is the weight matrix of the cell state; b_c is the bias item; and tanh is the activation function.

$$\tanh(x) = \frac{\mathrm{e}^{2x} - 1}{\mathrm{e}^{2x} + 1}. \tag{13}$$

The final output is determined by the output gate and cell state with the following formula:

$$\boldsymbol{h}_t = \boldsymbol{o}_t \tanh \boldsymbol{C}_t. \tag{14}$$

4 Experiment

4.1 Datasets

In this article, the data we use come from the MyGridGB, Elia, Eurostat, and EIA databases as the original data.

MyGridGB: MyGridGB is an online platform developed by National Grid, which is used to monitor and manage the operation status and electricity market conditions of the United Kingdom power system. The platform's main purpose is to provide real-time and historical electricity system data and information to help all parties make decisions and plan in the United Kingdom electricity market (Yang et al., 2022).

TABLE 3 Selected dataset data.

Quota	MyGridGB	Elia	Eurostat	EIA
Price	2,787	2,689	2,634	2,524
Supply and demand	1,795	2,137	1,479	553
Trading volume	915	1,581	1,549	1,273
CO_2 emission reduction	854	1,810	1,493	731
Energy use factor	854	881	1,493	731

The MyGridGB platform includes multiple functional modules, including real-time data monitoring, historical data query, power market analysis, power grid planning, and other functions. It brings great convenience for users to view the real-time operation of the power system and query past power load, power generation, market price, and other data through the platform (Lee et al., 2021). At the same time, the power market analysis and power grid planning functions of the MyGridGB platform can help analyze power market trends and predict future market development, including market price forecasting, power demand forecasting, market participant analysis, transmission line planning, power load forecasting, and power market participants. Users can plan the future development of the power system and optimize the operation of the power system through the platform.

The data sources of the MyGridGB platform include the British National Grid Corporation and the British electricity market operator, and the data are updated frequently, usually every minute. The data and information of the platform play an important role in the monitoring and management of the United Kingdom electricity market and can help the United Kingdom government, electricity market participants, and academic researchers make more accurate and timely decisions.

Elia: Elia is a Belgian electricity transmission system operator that manages Belgium's high-voltage electricity transmission grid and connections to other countries' electricity grids. Elia's main

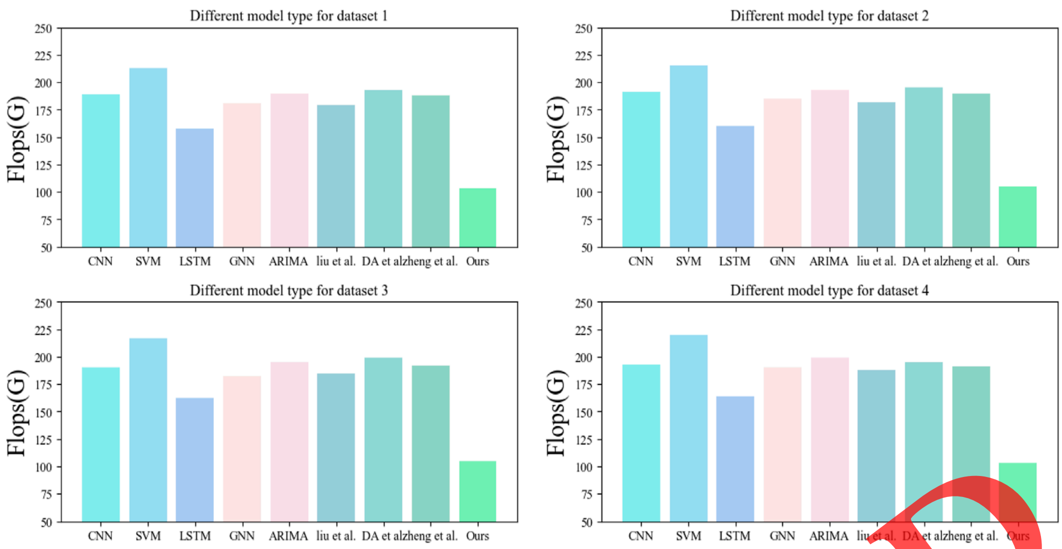

FIGURE 4
FLOPS comparison experiment results chart required for each model operation (dataset 1 is the MyGridGB dataset, dataset 2 is the Elia dataset, dataset 3 is the Eurostat dataset, and dataset 4 is the EIA dataset).

FIGURE 5
Comparison of the experimental results of the parameters required for each model operation.

mission is to ensure the stability, safety, and reliability of the Belgian electricity system and promote the electricity transition and the spread of renewable energy. At the same time, Elia is also connected with the power systems of other countries to promote the interconnection of energy markets (Al-Hamdan et al., 2020). In terms of research and development and renewable energy, Elia actively promotes the development and application of renewable energy, provides access and integration services for renewable energy, and promotes the transformation and intelligence of the power system to improve the efficiency and reliability of the power system to promote the development of sustainable energy.

Elia plays an important role in the Belgian power system. It provides key energy support for Belgium's economic and social stability and plays an important role in promoting the integration of the European power market and the development of renewable energy.

Eurostat: The Eurostat database is an official statistical database provided by the European Union Statistics on Income and Living Conditions, which mainly collects and provides statistical

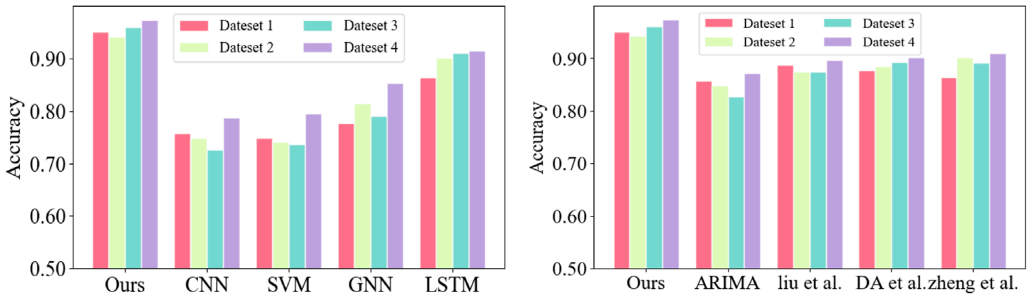

FIGURE 6
Experimental results of each model's operational accuracy (dataset 1 is the MyGridGB dataset, dataset 2 is the Elia dataset, dataset 3 is the Eurostat dataset, and dataset 4 is the EIA dataset).

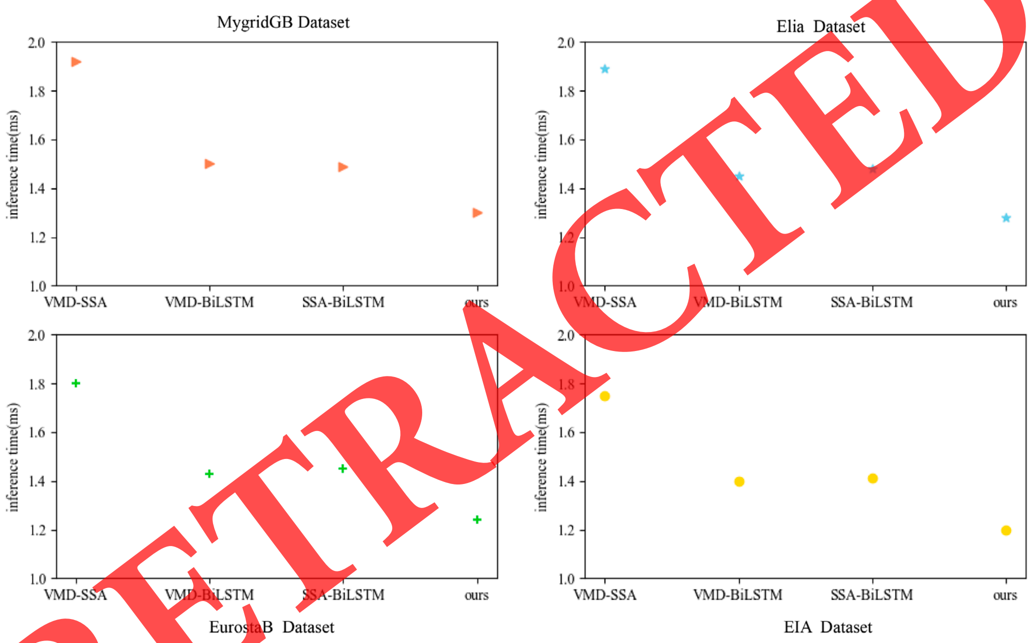

FIGURE 7
Inference time ablation experiment result graph (based on the MyGridGB dataset, Elia dataset, Eurostat dataset, and EIA dataset).

data and indicators of EU member states (Setiawan, 2021). The database is one of the most important official statistical databases in the European Union, containing many socio-economic and environmental statistics covering multiple fields within Europe, including economy, population and society, and environment.

The Eurostat database provides various data query and analysis tools, and users can choose different data categories and dimensions for query and analysis according to their own needs (Visvanathan et al., 2022). The data in the Eurostat database can be accessed and used in various ways, such as data download, API interface, and online data query. The data of the Eurostat database are widely used in policy formulation, academic research, business decision making, and other fields in the EU and play an important role in understanding the economic and social conditions of the EU, as well as cross-country comparative analysis.

EIA: The U.S. Energy Information Administration (EIA) is an independent agency of the U.S. government that collects, analyzes, and publishes data and information about U.S. and global energy. The EIA's data and analysis cover many aspects, including energy production, consumption, price, and environmental impact. It is one of the world's most important energy data sources.

The main tasks of the EIA include collecting, collating, and analyzing energy-related data through various channels, including indicators such as energy production, consumption, price, import, and export, as well as energy-related environmental, economic, and social indicators; collecting and analyzing data and information released to the public and policymakers, including various reports, databases, charts, dynamic dashboards, and energy policy advice and technical support to the

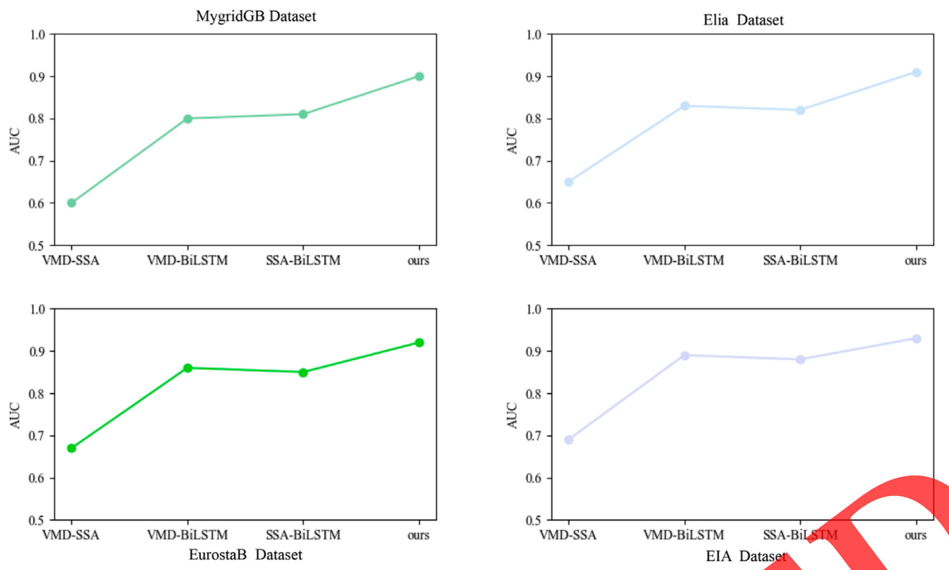

FIGURE 8
AUC ablation experiment result graph (based on the MyGridGB dataset, Elia dataset, Eurostat dataset, and EIA dataset).

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government and industry to help policymakers make energy decisions.

The EIA's data and analysis play an important role in the U.S. government, businesses, academic research, and the public, helping them understand energy markets and environmental conditions, predict future energy demand and supply, and formulate energy policies and management strategies (Rajendran et al., 2021). EIA data and information are also widely used in global energy market analysis and research.

Here, we use these four databases as raw data, and our database is shown in Table 3.

We use the first 90% of the data in the selected database as the training set and the last 10% of the data as the test set. Giving the model more training data can make our model prediction results more accurate and the prediction results more convincing.

4.2 Experimental setup and details

To verify that our model can be applied to smart grid financial market timing forecasting and sustainable innovation management with good response, we designed several experiments to validate our model. Here, we have selected eight models to compare with our model, and our experiments revolve around the metrics FLOPs, parameters, accuracy, AUC, and mAP. However, our model is the least affected and has the best performance. We also designed two sets of ablation experiments to find out which part of our model plays the most important role, and we found that BiLSTM has the most influence on our fused model. The comparative conclusions of several sets of experiments have demonstrated that our model can be well applied to the field of smart grid financial market time series forecasting and sustainable innovation management and can help decision makers effectively handle smart grid financial market time series data to achieve sustainable development through sustainable innovation management. Here are some of our experimental steps:

Step 1: Data pre-processing

- Determining the dataset: The historical dataset of the smart grid financial market is selected to ensure the quality and applicability of the data; here, we select the MyGridGB dataset, Elia dataset, Eurostat dataset, and EIA dataset
- Data cleaning: We perform missing value processing, outlier processing, and noise processing on the data to ensure data completeness and accuracy
- Feature extraction: We decompose and downscale the data using the VMD method and perform singular spectrum analysis on each component using the SSA method to get the corresponding singular value spectrum matrix to extract useful information from the data
- Normalization: We normalize the data to ensure comparability and consistency among different data

Step 2: Model design

- Determining the model structure: A deep learning algorithm based on VMD–SSA–BiLSTM is used to learn the feature representation and prediction model of the smart grid financial market using the BiLSTM network
- Hyperparameter adjustment: We adjust the hyperparameters of the model, such as learning rate, batch size, and optimizer, according to the experimental requirements and data features to improve the training effect of the model

Step 3: Experimental design

- Dataset selection: We select the MyGridGB dataset, Elia dataset, Eurostat dataset, and EIA dataset for experiments to ensure the generalization ability and applicability of the model
- Experimental metrics selection: We select FLOPs, parameters, accuracy, mAP, and AUC metrics to evaluate the performance and generalization ability of the model
- Experimental item steps and process design: We design the practical steps and process, including data pre-processing, model training, and model evaluation, to ensure the credibility and reproducibility of the experimental results

Step 4: Model training and evaluation

- Model training: We use cross validation, adaptive learning rate, and other techniques to improve the model's training
- Model evaluation: We evaluate the performance and generalization ability of the model using metrics such as FLOPs, parameters, accuracy, mAP, and AUC

Step 5: Model interpretability analysis

- Feature importance analysis: We analyze the degree of influence of different features in the model on the prediction results to assess the interpretability of the model and its ability to guide decisions
- Visualization analysis: We visualize the prediction results and feature the importance of the model using visualization techniques to improve the interpretability and visualization ability of the model
- Case study: We conduct case studies on different experimental datasets to explore the effectiveness of model interpretability and guidance ability in different scenarios

Step 6: Experimental result analysis

- Model performance analysis: We analyze and compare the experimental results of the model on different datasets to evaluate the performance and generalization ability of the model
- Model interpretability analysis: We analyze and evaluate the interpretability and guiding ability of the model to determine the effectiveness and feasibility of the model in practical applications

Step 7: Conclusion

- We summarize the experimental results and evaluate the validity and feasibility of the model
- We explore the insights and application prospects of the experimental results and provide new ideas and methods for smart grid financial market forecasting and sustainable innovation management
- We propose the direction and focus of future research to promote the sustainable development and innovation of smart grid and financial markets

TABLE 4 Ablation experiment comparison experiment data result graph.

Model	Inference time (ms)	AUC
VMD–SSA	1.75	0.6
VMD–BiLSTM	1.4	0.8
SSA–BiLSTM	1.41	0.81
Ours	1.18	0.9

4.3 Experimental results and analysis

In Figure 4, we compare our selected models in terms of FLOPS; through the experimental results, we can find that the performance of each model varies from one dataset to another, but the magnitude of the impact is small, and the rest of the models have higher FLOPS compared to ours. Smaller FLOPS means that our model is less computationally complex; i.e., the model needs to perform fewer floating-point operations with the same computing resources.

In the set of experiments in Figure 5, we compared the number of parameters required for the operation of each model. The necessary parameters for each model differ depending on the dataset, and the impact is significant. It can be seen that CNN and LSTM perform poorly, but in contrast to our model, the required number of parameters is the least, and the dataset received does not change much, so our model is better than other models in terms of parameter size, and fewer parameters mean that our model is more lightweight. The model requires fewer computing resources for training and inference to run faster.

In Figure 6, we compare the accuracy of each model. The performance of the CNN and SVM is relatively poor and is greatly affected by the dataset, but our model has the best performance in the face of different datasets. In terms of stability and the highest accuracy, higher accuracy means that the model has a more vital ability to classify or predict test data and has higher reliability and strength, which also means that our model has a wider application field.

We designed ablation experiments for inference time and AUC to find the essential part of our model. Figure 7 shows each model's inference time comparison test, and Figure 8 shows the AUC comparison test of each model. Table 4 shows the results of ablation experiment comparison experiment data. In these two sets of experiments, we compared VMD–SSA, SSA–BiLSTM, VMD–BiLSTM, and our model for better search. It is not difficult to see from the following two sets of experiments that between the model with BiLSTM and the inference without the BiLSTM model, time and AUC experimental results are quite different, so we can be sure that the BiLSTM module plays the most significant role in our model. With the BiLSTM module, our model solves the problem of gradient disappearance and dramatically improves the performance.

In Figure 9, we compare each model's AUC and mAP performance in different datasets. The CNN and SVM have abysmal performance in other datasets, and the rest of the models are affected to a certain extent. However, our model is very stable and excellent in the face of different datasets, with higher AUC and

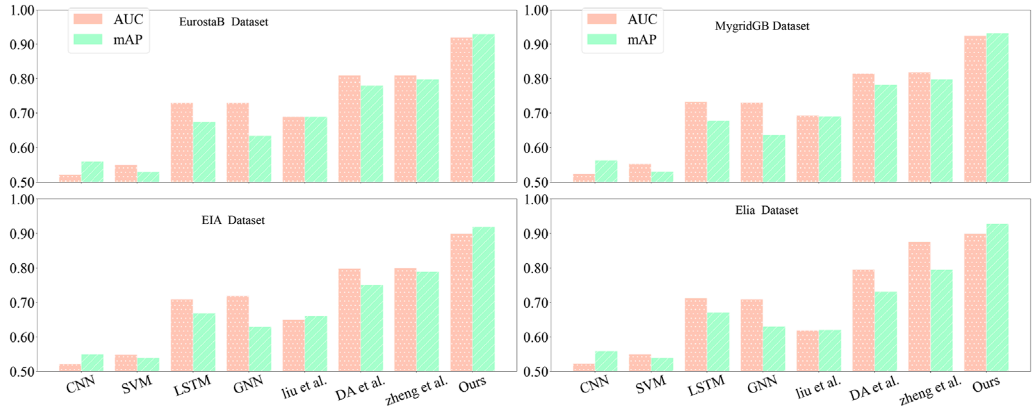

FIGURE 9
Comparison chart of AUC and mAP experimental results of each model (based on the MyGridGB dataset, Elia dataset, Eurostat dataset, and EIA dataset).

TABLE 5 **Summary chart of experimental results.**

Model	Accuracy	FLOPS	Parameters (M)	AUC	mAP
CNN, Elbagoury et al. (2023)	0.787	189	26.34	0.524	0.564
SVM, Chandra and Bedi. (2021)	0.795	213	14.79	0.553	0.531
LSTM, Panagiotou and Dounis. (2022)	0.915	158	35.49	0.734	0.679
GNN, Tong et al. (2022)	0.854	181	14.93	0.731	0.637
ARIMA, Deng et al. (2020)	0.871	190	21.68	0.783	0.693
Liu and Pu. (2022)	0.897	179	17.53	0.694	0.691
Da Costa et al. (2018)	0.901	193	16.64	0.815	0.783
Zheng and Zheng. (2021)	0.909	188	17.87	0.89	0.799
Ours	0.973	103	13.18	0.925	0.933

mAP. A higher AUC means that the model can better distinguish between positive and negative samples. Vigorous, higher mAP implies that the model performs better on target detection tasks; therefore, our model can be better applied in the field of smart grid financial market time series forecasting and sustainable innovation management.

This is the general data table of our experiments. In Table 5, we select several important metrics and the best data values for each group of models to visualize the results of our experiments.

5 Conclusion

This study uses a VMD–SSA–BiLSTM model for smart grid financial market time series prediction and sustainable innovation management applications. The model combines three different techniques, including VMD, SSA, and BiLSTM, to effectively handle time series data in smart grid financial markets. The experimental results show that the VMD–SSA–BiLSTM model for smart grid financial market time series prediction and sustainable innovation management application can significantly improve the dispatching efficiency and accuracy. Compared with traditional dispatching methods, the model can better predict the smart grid financial market time series data with better interpretability and visualization, which can help decision makers and managers better understand the forecast results and trends. In addition, the adoption of the VMD–SSA–BiLSTM model has good scalability and applicability, which can be applied to different power markets and power systems to provide strong support for the development and popularization of sustainable energy, and the model can perform online real-time forecasting, which provides a more reliable and efficient solution for smart grid financial market timing forecasting and sustainable innovation management.

6 Discussion and limitations

Although our VMD–SSA–BiLSTM model achieves good results in sequential data processing, it still has some shortcomings; as the VMD–SSA–BiLSTM model combines three different techniques, it is more complex and requires more computational resources and training time. It requires the original data to be decomposed, reconstructed, and transformed several times, including VMD decomposition, SSA decomposition, and time series transformation. These processes require a lot of data pre-processing work, which may affect the training efficiency and practical application effect of the model. Meanwhile, the applicability of the method to other types of financial data, such as futures and foreign exchange, needs further research and validation. In addition, our study did not consider the relationship between different markets, so in future research, we can explore how to combine data from different markets for forecasting.

The study of smart grid financial market time series prediction and sustainable innovation management has significance, mainly in the following aspects: First, the study can promote the development of the smart grid. With the rapid development of renewable energy and the progress of smart grid technology, sustainable innovation is the inevitable trend of future grid development. The smart grid financial market timing prediction and sustainable innovation management is an important part of smart grid construction and operation, which has an important role in promoting the development and application of smart grid. Second, it can improve the efficiency and competitiveness of the power industry. The research of smart grid financial market timing prediction and sustainable innovation management can help the power industry to predict the market demand and supply better, optimize the load and operation of the power system, and improve the efficiency and competitiveness of the power industry. Third, it can promote sustainable development. Sustainable development has become a global consensus and goal. Research on smart grid financial market timing forecasting and sustainable innovation management can help realize renewable energy access and optimization and promote sustainable development and energy utilization. Fourth, this area has important reference value for financial markets and investors. Research on smart grid financial market timing forecasting and sustainable innovation management can provide important reference value and decision basis for financial markets and investors, helping them to predict market trends and risks more accurately and optimize investment portfolios and decisions.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material; further inquiries can be directed to the corresponding author.

Author contributions

CY and GW contributed to the conception and design of the study. JL organized the database. CY performed the statistical analysis. CY wrote the first draft of the manuscript. CY and GW wrote sections of the manuscript. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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