DBN-GRU Fusion and Decomposition-Optimisation-Reconstruction Algorithm in Advertising Traffic Prediction

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***Abstract*—As the premise and foundation of advertisement traffic selling and distribution, effective IPTV advertisement traffic prediction not only reduces the operation cost, but also improves the intelligent level of new media advertisement traffic management. In order to further improve the accuracy of new media advertisement traffic prediction, this paper proposes a new media advertisement traffic prediction method based on the hybrid prediction framework of decomposition-optimisation-integration, which is a hybrid model of gated recurrent unit neural network and deep confidence network improved by capsule swarm optimisation algorithm. Firstly, according to the principle of system construction, paper analyses the influencing factors and construct a complete new media advertisement traffic prediction index system; secondly, paper improves the optimisation process of the parameters of the deep confidence network and the gated recurrent unit network by using the quilt group optimisation algorithm, and put forward a new media advertisement traffic prediction method based on the decomposition-optimisation-integration framework; Finally, the proposed method is analysed using new media advertisement traffic data. The results show that the proposed method improves the accuracy of the prediction model and solves the problem of large prediction error in new media advertisement traffic prediction methods.**

***Keywords*—New media advertising traffic prediction; kernel principal component analysis; variational modal decomposition; quilt group algorithm; deep learning; decomposition-optimisation-reconstruction algorithm**

I. INTRODUCTION

With the development of Internet technology, network-based IPTV (Internet Protocol Television) [1] enters people's vision and life, ware using the programme resources provided by the broadcasting network, and adopting the broadband communication network with higher data transmission rate, wider coverage, and better operation condition as the basic network facilities [2].The introduction of IPTV makes people enjoy the personalised, interactive and customisable audiovisual services [3]. IPTV service adopts the model of cooperation between broadcasters and telecommunication, the user data is not peer-to-peer sharing, and the user behaviour data cannot be accurately managed, which leads to the increase in the cost of bidding and targeting advertisement, the decrease in the efficiency, and the lack of obvious effect [4]. Effective IPTV advertisement traffic prediction, as the premise and foundation of advertisement traffic selling and distribution, not only reduces the operation cost, but also improves the intelligent level of new media advertisement traffic management [5]. Currently, new media advertising traffic prediction using time series prediction model [6], from the time series smoothness, linearity or not, the prediction method is divided into Autoregressive integrated moving average model (ARIMA) [7], BP neural network model [8], support vector machine [9], fuzzy theory [10], Elman recurrent neural network [11] and other methods. The study in [12] used ARIMA model to construct the energy demand forecasting problem in Turkey, and analysed the mapping relationship between energy influencing factors and energy demand; study in [13] analysed the multivariate data structure characteristics, combined with neural networks, and carried out the forecasting analysis of power energy consumption; literature [14] constructed the risk function based on the empirical error and the canonical term, and used SVM algorithm to construct the stock price index for the prediction; study in [15] combines K-means clustering algorithm and fuzzy neural network to construct the market sales trend prediction model; study in [16] uses Elman neural network and SVM algorithm to construct the cat catch quantity prediction model. In response to the analysis of the above literature, the existing new media advertising traffic prediction method indicator system selection lacks objectivity and the prediction accuracy is not high [17-19]. The factors affecting advertisement traffic prediction include not only statistical variables, but also time series data. In order to improve the accuracy of advertising traffic prediction, this paper adopts different prediction models for different variables. The single prediction model and simple combination prediction model can no longer adapt to the significant volatility and nonlinearity of advertising traffic data, and the prediction accuracy requirements are increasing, the hybrid prediction model based on Decomposition-optimization-ensemble (DOE) [20] is applied to the new media advertising traffic prediction problem. The study in [21] combines EMD, LSTM and SVR to solve the prediction problem; study in [22] uses complementary integration of empirical modal decomposition, singular spectrum analysis, and ELM to construct a time series prediction model. Deep learning, as a prediction method based on intelligent algorithms, has been widely used in all kinds of prediction problems, and the prediction effect is relatively excellent. With the advertisement traffic fluctuation showing randomness and non-stationarity, the advertisement traffic prediction faces the influence of complex and variable factors, and a single deep learning model can no longer meet the requirements of advertisement traffic prediction.

In order to further improve the new media advertisement traffic prediction accuracy, this paper adopts the hybrid prediction framework of decomposition-optimisation-integration.

- Analyse the influencing factors of the new media advertisement traffic prediction model and construct the input vector of new media advertisement traffic prediction;
- Decompose the original new media advertisement traffic data using the variational modal decomposition algorithm to obtain more detailed information features of the new media advertisement traffic sequence;
- Improve the GRU and DBN network by combining with the quilt swarm algorithm, and at the same time, put forward a new media advertisement traffic prediction method based on the quilt optimization algorithm improving the DBN-GRU hybrid model for new media advertisement traffic prediction;
- The new media advertisement traffic data verifies that this paper's method has higher prediction accuracy.

II. Analysis of the Problem of Predicting Advertising Traffic in New Media

In order to construct an objective, scientific and reasonable system of influencing factors for new media advertising traffic prediction, this section analyses the influencing factors and constructs a completely new media advertising traffic prediction index system according to the principle of system construction.

Scientific, objective and comprehensive new media advertising traffic prediction influencing factors system construction index selection should be in line with the following principles [23]: 1) independent and comprehensive; 2) operable; 3) temporal; 4) comparable. Influence factors can be compared not only in the time dimension, but also vertically over a number of cycles. The principles of impact factor selection are shown in Fig. 1.

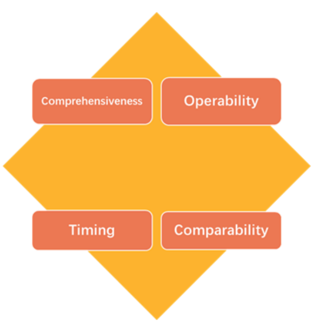


Fig. 1. Schematic diagram of the principle analysis.

According to the principled analysis of the selection of influencing variables for new media advertisement traffic prediction, the factors affecting the prediction should include the following dependent variables [24]: 1) daily click peak X1; 2) daily click peak X2; 3) platform code X3, the value of X3 is 1 means that the platform code is Inmobi, 2 means Zplay, 3 means Baidu, and 4 means Iflytek; 4) bidding reserve price X4; 5) Full insertion screen advert X5, the value of X5 is 0 for No and 1 for Yes; 6) Ad placement location information X6; 7) Ad provider X7; 8) Peak click time X8, Table I.

TABLE I. Influencing Variables of New Media Advertisement Flow

No.	Descriptions	Variables
1	The highest peak of daily clicks	X1
2	The lowest peak of daily clicks	X2
3	The platform code	X3
4	The reserve price of the auction	X4
5	Full interstitial ads	X5
6	The location information of the ad	X6
7	The value of the advertising provider	X7
8	The peak time of the click	X8

The new media advertisement traffic prediction impact variable system takes the key elements such as daily click peak X1, daily click minimum peak X2, platform code X3, bidding reserve price X4, full insertion screen advertisement X5, advertisement placement location information X6, advertisement provider X7, click peak time X8 as indicators, which fully embodies the whole elements of new media advertisement traffic prediction, and builds a scientific, objective, comprehensive and reasonable new media advertising traffic prediction impact vector system.

III. Related Technologies

A. KPCA

In order to extract the indicators with high contribution of the influence variables of new media advertisement traffic prediction, this paper adopts the Kernel Principal Component Analysis (KPCA) [25] method for feature extraction and dimensionality reduction of the influence variables. The principle of KPCA is shown in Fig. 2.

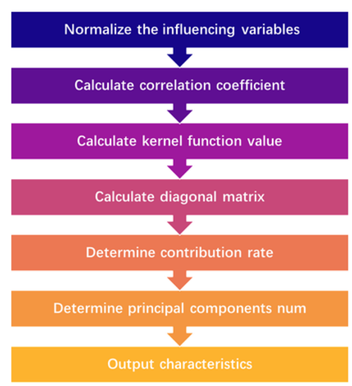


Fig. 2. The principle of kernel principal component analysis.

B. VMD

In order to better find the regularity of the time series of new media advertising traffic, this paper adopts the variational modal decomposition method to preprocess the predicted time series.

The main process of Variational mode decomposition (VMD) [26] is as follows:

1) Decompose $f(t)$ into k modal components with centre frequency and finite bandwidth, so that each mode satisfies the relevant conditions;

2) Obtain the optimal solution by obtaining the extreme points, update each modal component u_k with centre frequency ω_k;

3) Update λ with the value; 4) Judge whether the iteration stop condition is satisfied. satisfy the iteration stop condition. Repeat steps 2)-4) until the following iteration conditions are satisfied:

$$\frac{\sum_k \left\| \hat{u}_k^{n+1} - \hat{u}_k^n \right\|_2^2}{\left\| \hat{u}_k^n \right\|_2^2} < \varepsilon \tag{1}$$

In Eq. (1), $\varepsilon > 0$ is the determination accuracy.

C. Encapsulated Swarm Algorithm

Tunicate Swarm Algorithm (TSA) [27] is an intelligent swarm algorithm proposed to simulate the foraging behaviour of marine tunicate swarms, whose foraging process includes jet propulsion and swarm behaviour. The jet propulsion behaviour avoids conflicts between searching individuals and moves towards the optimal individual by means of the individual's own gravity, seawater current dynamics, and the interaction force between groups. The group determines the location of its companions through neural sensing of the current changes around itself and the light source of its companions, and gathers towards the food location to achieve group foraging (see Fig. 3).

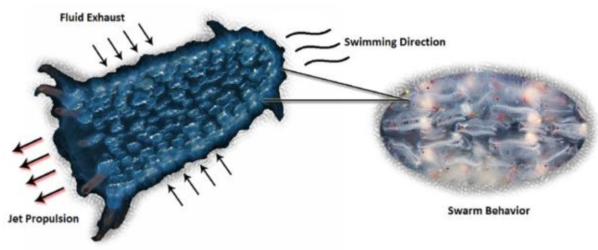


Fig. 3. Foraging behaviour of the periphyton

1) Jet propulsion: The quilt of the quilt swarm algorithm needs to avoid conflicts between individuals during jet propulsion. To avoid conflicts, new individuals are represented as follows:

$$A = \frac{G}{M} \tag{2}$$

In Eq. (2), G denotes the individual pendant force of the vesicle and M denotes the interaction force between the vesicle individuals, the calculation formula is as follows:

$$M = P_{\min} + c \cdot \left(P_{\max} - P_{\min} \right) \tag{3}$$

In Eq. (3), $P_{\max}$, $P_{\min}$ refers to the maximum and minimum values of the initial interaction velocity of individuals, respectively, which are usually set to $P_{\max} = 4, P_{\min} = 1$, and c is a random number.

After avoiding conflicts, the individual completes the search direction calculation using the distance between the optimal position and the current individual:

$$PD_i^t = \left| x_{best}^t - rand \cdot x_i^t \right| \tag{4}$$

In Eq. (4), x_{best}^t denotes the optimal individual, x_i^t denotes the current individual position, and $rand$ denotes a uniformly distributed random number.

Combining the distance between the optimal position and the current individual as well as the conflict avoidance strategy, the optimal individual drive-in formula for each vesicle individual term is as follows Eq. (5):

$$x_i^t = \begin{cases} x_{best}^t + A \cdot PD_i^t & rand \geq 0.5 \\ x_{best}^t - A \cdot PD_i^t & rand < 0.5 \end{cases} \tag{5}$$

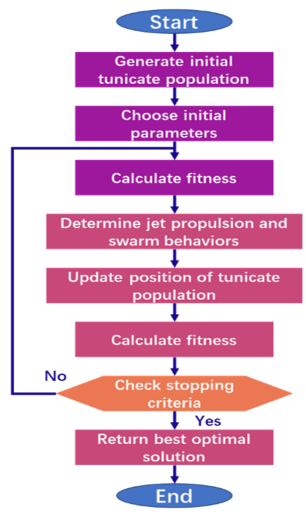


Fig. 4. Flowchart of TSA algorithm.

2) Group behaviour: The model for calculating the group behaviour of the quilt group is as follows:

$$x_i^{t+1} = \frac{x_i^t + x_i^{t-1}}{2 + c} \tag{6}$$

In Eq. (6), x_i^{t-1} denotes the updated position of the previous generation of vesicles relative to the most available individual, and c denotes a random value between 0 and 1.

3) TSA algorithm process and steps: According to the principle of TSA algorithm, the flowchart is shown in Fig. 4. During each iteration of the TSA algorithm, the location information of the encapsulated group is continuously evaluated and selected by the evaluation and selection strategy to obtain the final optimal solution.

This paper analyses the iterative optimization process of the TSA algorithm (see Fig. 5). From Fig. 5, the number of iterations increases and the population gradually converges to a centralised position.

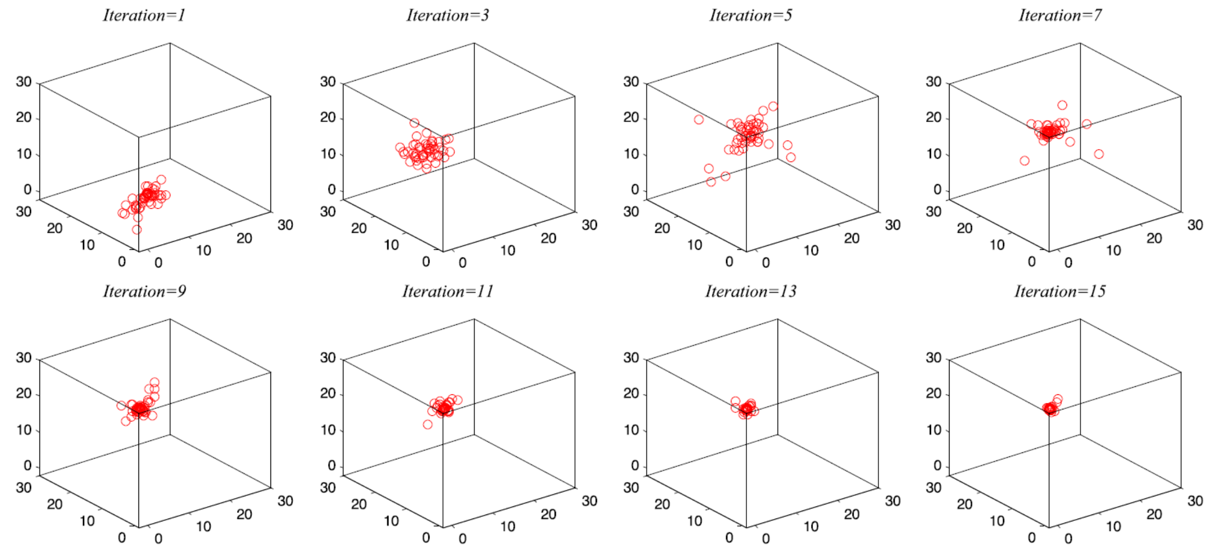


Fig. 5. Iterative optimisation process of the TSA algorithm.

D. Deep Confidence Networks

In order to analyse the mapping relationship between the influence variables of new media advertisement traffic prediction and the predicted value of traffic, this paper adopts deep confidence network as the prediction model construction algorithm, which solves the problem of constructing the model of influence variables and predicted value of traffic.

Deep Belief Networks (DBN) [28] consists of multiple layers of Restricted Boltzmann Machines (RBM), and the specific structure is shown in Fig. 6. The input layers v and h^1 constitute the first layer of Restricted Boltzmann Machines, and the input data is mapped through the activation function h_1, which is input to the second layer of Restricted Boltzmann Machines, and passes to reach the output layer in turn.

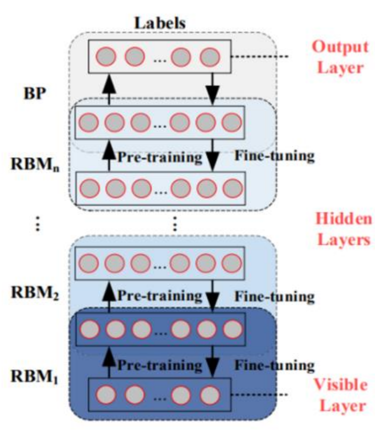


Fig. 6. Structure of deep confidence network.

1) Assuming that $\theta=(\omega,a,b)$ is a DBN network parameter, the energy function of RBM is expressed as:

$$E(v,h|\theta)=-\sum_{i=1}^{n}a_iv_i-\sum_{j=1}^{m}b_jh_j-\sum_{i=1}^{n}\sum_{j=1}^{m}v_i\omega_{ij}h_j \tag{7}$$

In Eq. (7) (v,h) is the state value, ω is the connection weight, and a and b are the biases.

2) Solve for θ^* by solving for the maximum value of the log-likelihood function:

$$\theta^*=\arg_\theta\max L(\theta)=\arg_\theta\max\sum_{k=1}^{K}\ln p\left(v^k|\theta\right) \tag{8}$$

In Eq. (8) K is the number of training samples.

3) Calculate the joint probability distribution function, Eq. (8) and Eq. (9):

$$p(v,h|\theta)=\frac{e^{-E(v,h|\theta)}}{Z(\theta)} \tag{9}$$

$$Z(\theta)=\sum_v\sum_h e^{-E(v,h|\theta)} \tag{10}$$

4) Calculate the activation probability of hidden layer nodes to determine the visible layer state, Eq. (11):

$$p(h_j=1|v,\theta)=sigmoid\left(b_j+\sum_{i=1}^{n}v_i\omega_{ij}\right) \tag{11}$$

5) Calculate the activation probability of the visual layer node as Eq. (12)

$$p(v_i=1|h,\theta)=sigmoid\left(a_i+\sum_{i=1}^{n}h_j\omega_{ij}\right) \tag{12}$$

(6) Update the RBM parameter θ, Eq. (13) to Eq. (15):

$$\Delta\omega_{ij}=\frac{\partial\log p(v)}{\partial\omega_{ij}}=\varepsilon\left(\left\langle v_ih_j\right\rangle_{data}-\left\langle v_ih_j\right\rangle_{predict}\right) \tag{13}$$

$$\Delta a_i = \frac{\partial \log p(v)}{\partial a_i} = \varepsilon\left(\langle v_i\rangle_{data} - \langle v_i\rangle_{predict}\right) \quad (14)$$

$$\Delta b_j = \frac{\partial \log p(v)}{\partial b_j} = \varepsilon\left(\langle h_j\rangle_{data} - \langle h_j\rangle_{predict}\right) \quad (15)$$

where ε denotes the learning rate, $\langle \square \rangle_{data}$ is the expectation of training after input data, and $\langle \square \rangle_{predict}$ is the expectation of the model itself.

E. Neural Network of Gated Recurrent Units

Compared with LSTM and RNN, GRU has a simple structure with fewer parameters and uses update gates and reset gates to control the network [29], and the structure is shown schematically in Fig. 7.

$$r_t = \sigma(W_{hr}h_{t-1} + W_{xr}x_t + b_r) \quad (16)$$

$$\tilde{h}_t = \tanh(W_{r\tilde{h}} \square (r_t * h_{t-1}) + W_{x\tilde{h}}x_t + b_{\tilde{h}}) \quad (17)$$

In Eq. (16) and Eq. (17), r_t is the reset gate which determines the amount of historical memory of h_{t-1}. $\tilde{h}_t$ is the latest information of the node at the current moment. h_{t-1}, h_t is the hidden layer information of the cell state at the moment of $t-1$ and t respectively, $W_{r\tilde{h}}$, $W_{x\tilde{h}}$, W_{xr}, W_{hr} are the weights, b_r, $b_{\tilde{h}}$ are the biases.

$$z_t = \sigma(W_{hz}h_{t-1} + W_{xz}x_t + b_z) \quad (18)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t \quad (19)$$

In Eq. (18) and Eq. (19), W_{hz}, W_{xz} are weights and b_z is bias. z_t is the forgetting gate.

$$y_t = \sigma(W_{yt}h_t) \quad (20)$$

In Eq. (20), W_{yt} denotes the weights between the current hidden layer output h_t and the final output layer.

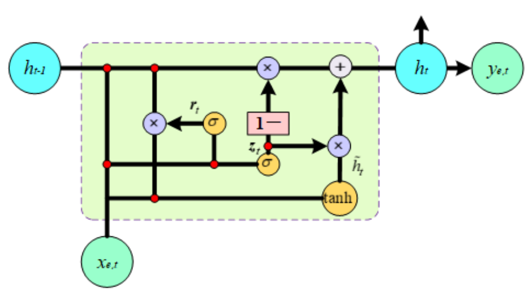


Fig. 7. GRU network.

F. Evaluation Indicators

This paper uses three evaluation indexes testing models such as Mean Absolute Error (MAE), Root Mean Square Five Error (RMSE), and Mean Absolute Percentage Error (MAPE), which are calculated by the following formulas:

$$RMSE = \sqrt{\left(\sum_{i=1}^{M}(\hat{y}_i - y_i)^2\right)\Big/M} \quad (21)$$

$$MAE = \frac{1}{M}\sum_{i=1}^{M}|\hat{y}_i - y_i| \quad (22)$$

$$MAPE = \frac{1}{M}\sum_{i=1}^{M}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \quad (23)$$

In Eq. (21) – Eq. (23), $\hat{y}_i$ denotes the predicted value based on the proposed algorithm, y_i denotes the true value and M is the number of test samples.

IV. A Methodological Process of New Media Advertisement Traffic Prediction based on TSA-DBN-GRU Algorithm Under Decomposition-Optimisation-Reconfiguration Framework

A. DBN-GRU Prediction Model Based on TSA Algorithm

The combined DBN-GRU prediction model based on the TSA algorithm uses the TSA algorithm to optimise the DBN and GRU bias and weight values, and adopts the RMSE as the fitness function. The specific steps are as follows:

- Step 1: The Z-Score method was used to pre-process the raw data and divide the data set;
- Step 2: The TSA algorithm encodes the initial parameters of the DBN-GRU and calculates the value of the fitness function;
- Step 3: Using jet advancement and group behaviour, the DBN-GRU bias and weight value information is updated with the global optimal bias and weight values;
- Step 4: If the number of iterations satisfies the maximum number of iterations, output the bias and weight values and perform step (5), otherwise continue with step (3);
- Step 5: Decoding to obtain DBN-GRU bias and weight value training parameters;
- Step 6: Training to construct the TSA-DBN-GRU prediction model and analysing the prediction model using the test set.

B. Steps of the New Media Advertisement Traffic Prediction Process based on the Decomposition-Optimisation-Reconfiguration Framework

Combining VMD and KPCA, the TSA-DBN-GRU prediction method proposed in this paper is applied to the new media advertisement traffic prediction problem, and the flow chart is shown in Fig. 8, with the main steps:

- Step 1: Decompose the original new media advertisement flow time series by using Variable Modal Decomposition (VMD) to obtain $n+1$ components $\{VMF_1, \cdots, VMF_i, \cdots, VMF_k, Res_{vmd}\}$; use KPCA to perform principal component analysis and dimensionality reduction on the influencing variables of new media advertisement flow to obtain the transformed set of main influencing variables of new media advertisement flow;
- Step 2: For the eigenmode component VMF, GRU constructs the prediction model; for the main influencing variable of new media advertisement flow, DBN constructs the prediction model. In order to improve the accuracy of the prediction model, the TSA algorithm is used to optimise the bias and weight values of DBN-GRU, and select the optimal parameter values of bias and weight values;
- Step 3: Input each component and the influence factor data after dimensionality reduction into the component prediction model, and the output is superimposed and reconstructed to obtain the final prediction results.
- Step 4: Analyse the predictive model performance results.

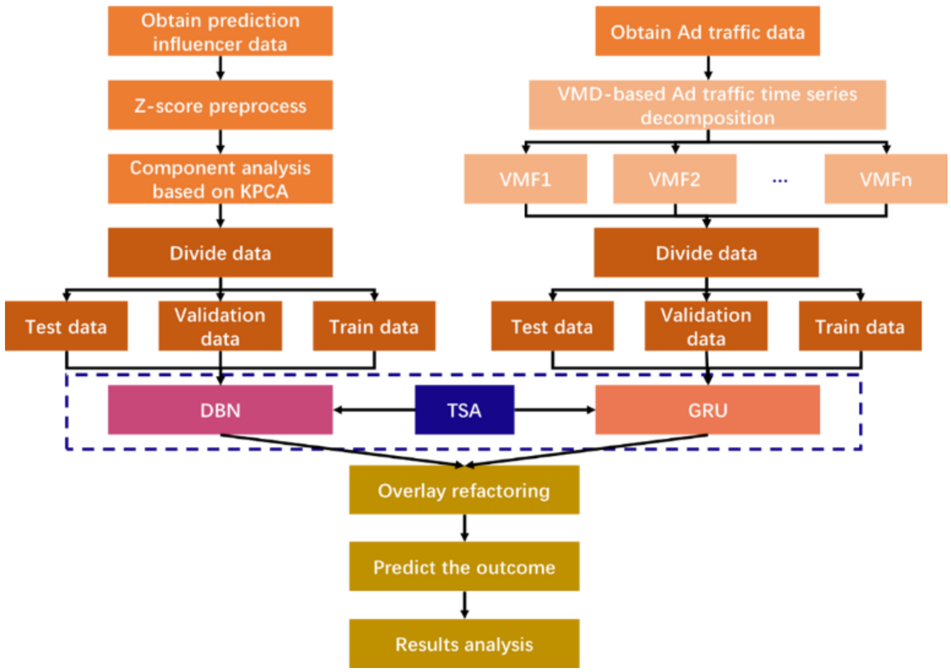


Fig. 8. New media advertisement traffic prediction.

V. Experiments and Analysis of Results

A. Algorithm Setup

The parameters of the new media advertising traffic prediction comparison algorithm are set in Table II.

B. Data Description

The data used in this paper comes from real data from a new media company's IPTV business. The data describes the number of viewing clicks of viewers 24 hours a day for almost three months. 70% of the data is selected as training set, 10% validation set and 20% as test set.

TABLE II. Parameter Settings of New Media Advertising Traffic Prediction Methods

Serial number	Arithmetic	Parameterisation
1	DBN-GRU	The number of DBN hidden nodes is 100, the number of GRU hidden nodes is 50, the activation function is the Relu function, and Adam's optimisation adjusts the weights
2	TSA-DBN-GRU	The number of DBN hidden nodes is 100, the number of GRU hidden nodes is 50, the activation function is Relu function and the number of TSA populations is 100
3	vmd-tsa-dbn-gru	The number of DBN hidden nodes is 100, the number of GRU hidden nodes is 50, the activation function is Relu function, the number of TSA populations is 100, and the VMD parameter settings refer to literature [30].
4	kpca-tsa-dbn-gru	The number of DBN hidden nodes is 100, the number of GRU hidden nodes is 50, the activation function is the Relu function, the number of TSA populations is 100, and the KPCA uses the Gaussian kernel function as the kernel function
5	vmd-kpca-tsa-dbn-gru	The number of DBN hidden layer nodes, the number of GRU hidden layer nodes, and the GRU network activation function is the Relu function

C. Correlation Analysis

In order to analyse the redundancy of the feature vectors of the new media advertising traffic prediction impact, this section uses Person correlation analysis method to analyse the feature vectors and advertising traffic. In Fig. 9, the new media advertising traffic is correlated with other variables, and all of them show positive correlation.

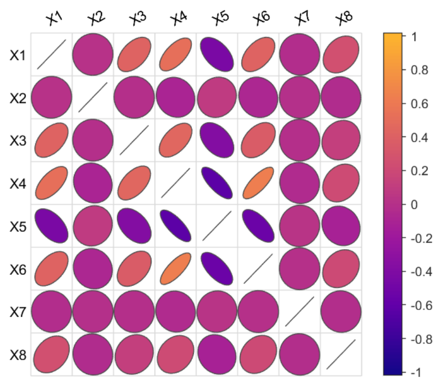
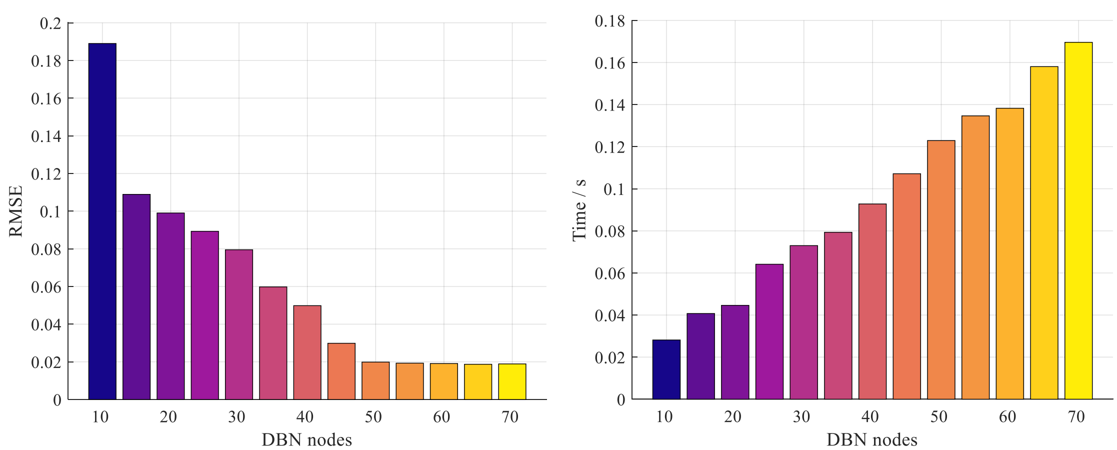


Fig. 9. Correlation analysis of factors influencing new media advertisement traffic prediction.

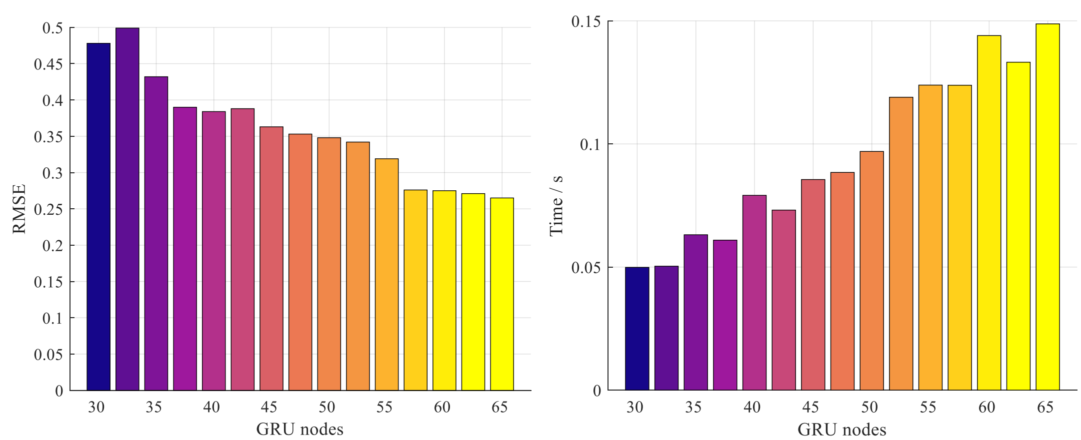
D. Parametric Analysis

In order to determine the optimal parameters, this paper analyses the results of choosing the parameters with higher prediction accuracy and less time-consuming by analysing different DBN hidden layer node number, GRU hidden layer node number, and population number conditions as shown in Fig. 10, 11, and 12. From Fig. 10, with the increase of the number of DBN hidden layer nodes, the prediction accuracy of the VMD-KPCA-TSA-DBN-GRU model increases, the time consumed increases, and the prediction accuracy tends to be stable when the number of DBN hidden layer nodes is 50; from Fig. 11, with the increase of the number of GRU hidden layer nodes, the prediction error of the VMD-KPCA-TSA-DBN-GRU model decreases, and the time consumed increases, and the prediction accuracy tends to be stable when the number of GRU hidden layer nodes is 60; from Fig. 12, the model prediction error decreases and the time-consuming time increases with the increase of the population. In summary, the VMD-KPCA-TSA-DBN-GRU model has a DBN hidden layer node number of 50, a GRU hidden layer node number of 60 and a population size of 80.



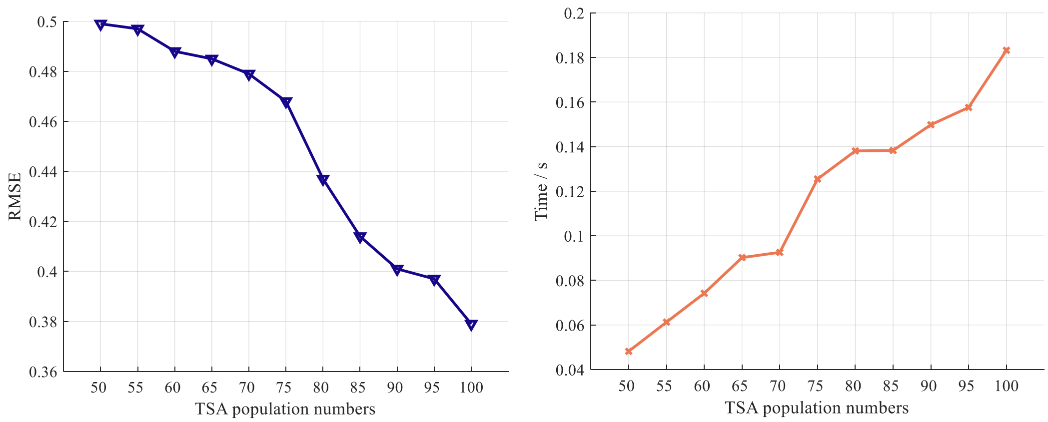
(a) Forecasting accuracy (b) Forecasting time

Fig. 10. Analysis of the impact of different number of DBN hidden layer nodes on prediction performance.



(a) Forecasting accuracy (b) Forecasting time

Fig. 11. Analysis of the impact of different number of GRU hidden layer nodes on the prediction performance.



(a) Forecasting accuracy (b) Forecasting time

Fig. 12. Analysis of the impact of different TSA population sizes on prediction performance.

E. Performance Analysis

1) Flow breakdown analysis: The result of decomposing the original new media advertisement traffic sequence using VMD decomposition algorithm is shown in Fig. 13. From Fig. 13, the detailed features of the new media advertisement traffic sequence data are better decomposed by using the VMD decomposition algorithm for decomposition.

2) Performance comparison: In order to verify the effectiveness and superiority of the new media advertising traffic prediction method based on the VMD-KPCA-TSA-DBN-GRU algorithm, VMD-KPCA-TSA-DBN-GRU is compared with four other models, and the prediction results of each model are shown in Fig. 14 and 15. The prediction results of different algorithms with relative error results are given in Fig. 14 and 15, respectively. The new media advertising traffic prediction based on the VMD-KPCA-TSA-DBN-GRU algorithm has the smallest error and the highest prediction accuracy, and the rest of the algorithms ranked as KPCA-TSA-DBN-GRU, VMD-TSA-DBN-GRU, TSA-DBN-GRU, and DBN-GRU, respectively.

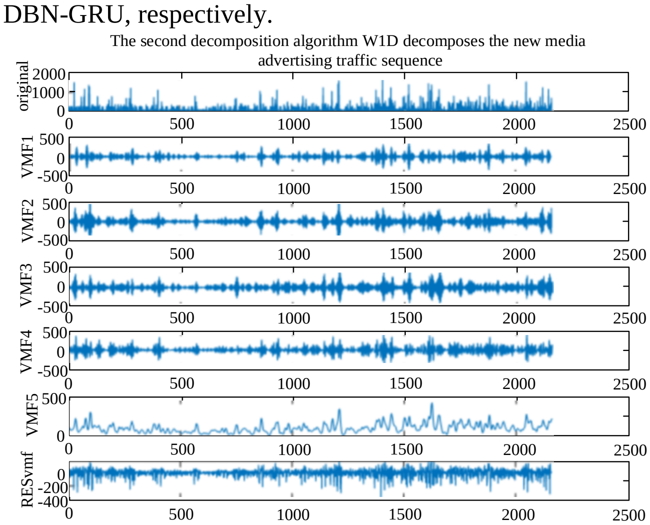


Fig. 13. Decomposition analysis of new media advertising traffic sequence.

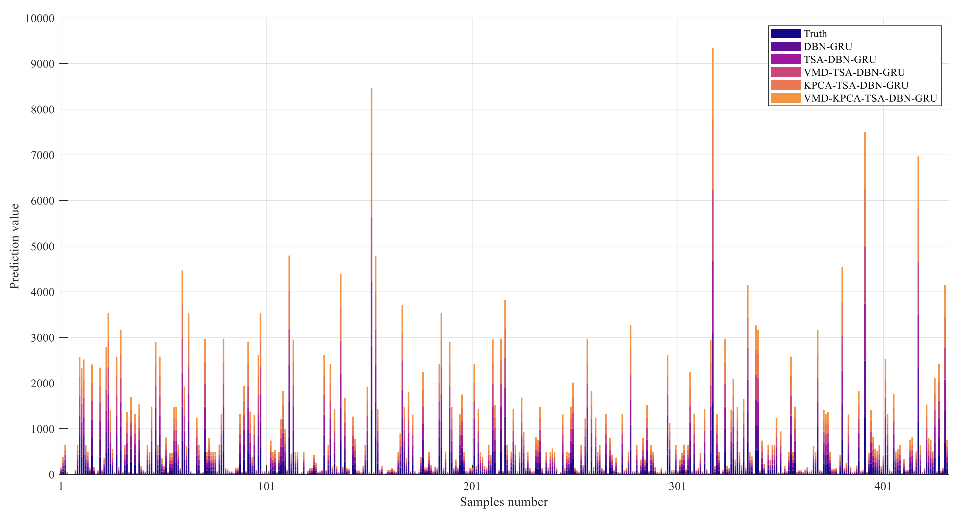


Fig. 14. Prediction results of different algorithms.

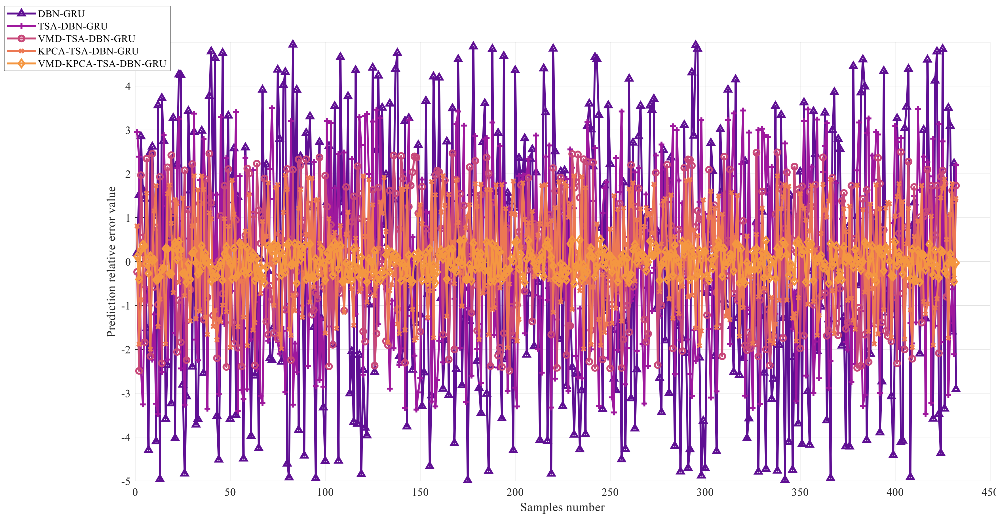


Fig. 15. Relative error results of different algorithms for prediction.

VI. Conclusion

In order to further improve the accuracy of new media advertisement traffic prediction, this paper proposes a new media advertisement traffic prediction method based on the optimisation of improved DBN-GRU network by the saccade swarm algorithm using the hybrid prediction framework of decomposition-optimisation-integration. The method analyses the new media advertisement traffic prediction problem, constructs a system of influence feature vectors, and adopts the nuclear principal component analysis method to analyse the principal components of the influence feature vectors; decomposes the original new media advertisement traffic time series using the variational modal decomposition method; and constructs a new media advertisement traffic prediction method by using the optimization of DBN-GRU network with the use of the quilt swarm algorithm. The specific conclusions are as follows:

- Kernel Principal Component Analysis (KPCA)-based methods were used to analyse the principal components of the eigenvectors of advertising traffic influence, and by comparing the prediction models that did not use KPCA, it was verified that KPCA analysis could improve the efficiency of the prediction models;
- The time series of new media advertisement flow is decomposed based on the VMD decomposition method, and by comparing the prediction model without the decomposition algorithm, it is verified that the VMD decomposition algorithm is able to improve the accuracy of the prediction model;
- The prediction accuracy of VMD-KPCA-TSA-DBN-GRU network prediction model is better than other models;
- The robustness of the prediction model proposed in this paper does not perform well, and further improving the VMD-KPCA-TSA-DBN-GRU prediction stability is the next research focus.

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