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Forecasting product sales using text mining: a case study in new energy vehicle

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Abstract
This study aims to improve the prediction accuracy of product sales by developing an online review-driven combination forecasting model. The proposed model includes two parts: online reviews and the forecasting model. For online reviews, the sentiment value concerning different product attributes is defined from the sentiment score and the sentiment tendency based on prospect theory. Furthermore, the Mallat pyramid algorithm is used to mitigate the impact of reviews with nonstandard expressions, malicious reviews and spam on the sentiment value of online reviews. A combination forecasting model composed of a backpropagation neural network (BPNN), recurrent neural network (RNN) and long short-term memory (LSTM) neural network is constructed. Taking the sales of BYD-Tang as a case study, some statistical evaluation indicators and the Diebold-Mariano (DM) test indicate the superior performance of our proposed online review-driven combination forecasting model in prediction accuracy.

Keywords E-commerce · Sales forecasting · Online reviews · Combination forecasting

1 Introduction

In the current global environment of advocating energy conservation and emissions reduction, the development of the new energy vehicle (NEV) industry is in full swing. Some NEV enterprises, such as BYD (比亚迪), NIO (蔚来) and Tesla, have grown rapidly with China's policy support and capital investment. Under the fierce

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competition in China's NEV industry, the ability of an enterprise to meet market demand largely determines its competitive position in the industry. The accurate sales forecasting of NEVs can help NEV enterprises formulate production plans, make effective management decisions, reduce the losses caused by blind production, increase enterprise profits and improve enterprise competitiveness.

In recent years, with the rapid development of China's digital economy, according to the China Internet Network Information Center (CNNIC),[1] as of December 2021, the number of Chinese netizens reached 10.32 billion, an increase of 4.296 million compared with the number in December 2020, and the internet penetration rate reached 73.0%. It has become a norm for consumers to express their opinions on specific products on e-commerce websites and social media platforms [1], such as Taobao (https://www.taobao.com), Jingdong (https://www.jd.com) and Autohome (https://www.autohome.com.cn). Existing car sales forecasting models mainly use historical sales data and lack in-depth mining of user reviews in professional car forums. As the public's view of products will affect the sales of products, in-depth analysis of online reviews plays an important role in forecasting the future sales of products [2, 3]. A NEV is a new product and a high-involvement good, and public opinion will affect its sales. Therefore, in-depth analysis of online reviews plays an essential role in forecasting the future sales of NEVs.

Along with data, the forecasting model employed can also have a substantial impact on the accuracy of forecasts. Many current product sales forecasting models rely solely on a single forecasting method, but the efficacy of any individual method is constrained, and further improvements to prediction accuracy are challenging. To address this limitation, we introduce a novel online review-driven combination forecasting model that integrates the strengths of backpropagation neural network (BPNN), recurrent neural network (RNN), and long short-term memory (LSTM) neural network. This model enables a more systematic and comprehensive approach to product sales forecasting. The information of various individual forecasting results is used to a large extent, which improves the forecasting accuracy and stability [4].

The general steps of the proposed model for NEV sales forecasting are as follows. First, a dictionary-based sentiment analysis method is developed, and a lexical analysis module supported by BaiduAI is used to convert the online reviews concerning various product attributes into sentiment values, which are composed of sentiment scores and sentiment tendencies. Subsequently, we use the Mallat pyramidal algorithm to denoise the sentiment values, which are inevitably disturbed by nonstandard expressions and malicious reviews and spam. Finally, taking historical sentiment values and sales volume as the input data, an online review-driven combination forecasting model is presented to forecast NEV sales.

The main contributions of this paper are listed as follows:

[1] Statistical report on internet development in China. Available online at http://www.cnnic.net.cn hlwfzyj/hlwxzbg/hlwtjbg/202202/t20220225_71727.htm.

(1) Sentiment values of online reviews concerning different product attributes in each period are defined with a novel sentiment measure method and prospect theory, which can fully mine the information in online reviews
(2) The denoising algorithm is applied to sentiment values by taking into account the impact of nonstandard expression reviews, malicious reviews and spam on the quantification of online reviews, which can better reflect consumers' emotional attitudes
(3) An online review-driven combination forecasting model is proposed by integrating online reviews, denoising algorithm and combining forecasts, which is not only an innovation in the application field of combining forecasts, but also a meaningful attempt to improve the prediction accuracy. It is used to forecast NEV sales, and the computational results indicate that our proposed model can improve forecasting accuracy.

The rest of this paper is organized as follows. Section 2 reviews the literature on forecasting sales using online reviews, forecasting models of NEVs and combination forecasting models. Section 3 describes the online review-driven combination forecasting model construction process in detail. In Sect. 4, we take the monthly sales data forecast of BYD-Tang as an example to conduct experiments and compare the proposed method with nine benchmark models to verify its superiority. Furthermore, the model robustness test is provided. Finally, Sect. 5 summarizes the conclusions of this paper and outlines its future prospects.

2 Literature review

The related research indicates that 67% of consumers' daily consumption decisions are made from word-of mouth (WOM) recommendations. Online reviews, as a form of WOM recommendations, can express consumers' experiences of using products and profoundly influence consumers' purchasing behaviour. Many researchers have used sentiment analysis techniques to quantify online reviews to better forecast sales. In addition, the use of a combination forecasting model improves the forecasting accuracy substantially.

2.1 Forecasting sales using online reviews

Dellarocas et al. [5] significantly improved the accuracy of a linear model for movie box office forecasting by incorporating online reviews into a traditional diffusion model. Based on the TF-IDF algorithm, Chern et al. [6] analysed the attributes of online reviews, the characteristics of reviewers and the impact of online reviews; clarified how the electronic WOM effect affects product sales, and quantified this effect, which was used to construct a forecasting model for cosmetic sales. Using the bag-of-words method improved by the random projections approach, an attributes-based regression model was presented by Schneider and Gupta [7], and it was employed to forecast the sales of tablet computers. Fan et al. [8] used a naive

Bayes algorithm to extract sentimental indices from online reviews and incorporated them into the Bass/Norton model to improve the prediction accuracy of car sales. Zhang et al. [9]. calculated WOM effects using data from online reviews (e.g., ratings, browsing times and approvals) and forecasted car sales in combination with macroeconomic indicators. Shi et al. [10] used the total numbers of likes, links, and stories in online reviews on Facebook to calculate the sentiment scores and forecasted real estate sales. Pan and Zhou [11] used a convolutional neural network (CNN) to extract features from ecommerce data, including user reviews, to forecast sales. Hu et al. [12] proposed a tourism demand forecasting method by integrating tourist-generated online reviews corresponding to hotels, tourist attractions and shopping markets. Yakubu and Kwong [13] presented a forecasting method to forecast the future importance of product attributes based on online reviews provided by consumers and Google Trends.

The forecasting methods proposed in the above literature can enhance the forecasting performance based on online reviews. However, existing online review mining methods for the sales forecasting have two limitations such as insufficient information extraction and inadequate quantification of information. First, when mining the text, most of them did not consider the habits in the Chinese language sufficiently [5–9]. Second, in text quantization, the impact of consumer psychology on the quantitative results is not considered [4–6, 8–12]. Specifically, online consumers pay more attention to negative online reviews, which may play an overwhelming crucial role in their shopping decision process [9]. This phenomenon seems to be consistent with the prospect theory proposed by Kahneman and Tversky [14]. Prospect theory mainly reveals a truth that people are more sensitive to losses than gains. Hence, online reviews can be better and more comprehensively quantified by considering consumer psychology based on prospect theory. Compared to existing methods for mining online reviews, incorporating the habits of the Chinese language in the process can effectively extract information contained in the online reviews. Meanwhile, if the prospect theory is incorporated into forecasting model, it will help to capture the phenomenon that negative comments heavily influence expectations.

2.2 Forecasting using denoising algorithm

Denoising algorithms are frequently used in forecasting to remove data collection noise and reveal the true trends and patterns within the data. For wind speed data, Li et al. [15] applied the maximum overlap discrete wavelet transform (MODWT) to denoise it, and the proposed MODWT-RF-IGWO-LSTM model has high prediction accuracy. Bao et al. [16] used empirical mode decomposition (EMD) to denoise the data set of short-term electricity price, and it improve the prediction accuracy of the forecasting model by integrating CNN and LSTM. The forecasting model proposed by Egriboz and Aktas [17] also has high prediction accuracy by using the discrete wavelet transform (DWT) pre-processing method to denoise the price index data crawled from the web. Jaseena and Kovoor [18] used empirical wavelet transform (EWT) to denoise the wind speed data and further improved the prediction accuracy of deep bidirectional LSTM networks.

In summary, the denoising algorithm utilized in the aforementioned literature aims to reduce the noise of the predicted object by minimizing the noise generated during the data collection process. These attempts have indeed effectively improved the prediction accuracy. However, few of them focus on the problem of denoising quantified online reviews [15–18]. Additionally, it is also very necessary to reduce the noise of prediction indicators, which is not limited to the collected time series data set.

2.3 Forecasting models for NEV sales

Based on adaptive data processing and an optimized nonlinear grey Bernoulli model, Ding et al. [19] proposed a composite forecasting model to forecast NEV sales. According to the buffer operator and grey model, He et al. [20] presented an optimized grey buffer operator by using accumulation and translation transformations for forecasting the production and sales of NEVs. Liu et al. [21] designed a multifactor forecasting model by integrating a discrete wavelet transform and bidirectional LSTM. It is used to forecast NEV sales to determine the market penetration of NEVs. Li et al. [22] developed a forecasting method based on the Gompertz model to forecast electric vehicle ownership in China. In the context of environmental problems and energy security, Du et al. [23] constructed a forecasting method based on an extended logistic model for predicting the market demand of NEVs. Benefiting from the advantages of the grey model in small sample prediction, Ding and Li [24] proposed a new self-adaptive optimized grey model to forecast NEV sales. Based on the quarterly fluctuation features of NEV sales in China, Pei and Li [25] designed a data grouping approach based on a nonlinear grey Bernoulli model to forecast NEV sales.

The above research can be divided into two types, the grey econometric model and its improved forms. Some contributions have been made to NEV sales forecasting based on historical NEV sales. In addition, to show the validity of their approach in the existing literature, benchmark method is introduced, in which some benchmark models are constructed and used to compare with their proposed NEV sales forecasting model based on historical data. The results show that the benchmark method can be used to verify the advantages of the NEV sales forecasting model based on historical data. Moreover, the existing NEV sales forecasting models mainly use historical sales data and lack in-depth mining of user comment data (i.e., online reviews) from professional automobile forums [19–25].

2.4 Combination forecasting model

Given N forecasts of the same event, the forecast combination includes an estimate of the so-called combination weights assigned to each forecast such that the accuracy of the combination forecast is generally better than the accuracy of the individual forecasts [4]. A series of traditional statistical strategies are often used to estimate the combination weights include (1) minimizing the in-sample forecasting error variance of forecast candidates [26, 27], (2) estimating via OLS regression [28], (3) using Bayesian probability theory [29, 30], and (4) using a regime switching approach and time varying weights [31]. In addition, Kolassa [32] proposed Akaike weights based on Akaike's information criterion, and these weights have been used successfully to combine statistical models. More recently, the technology of cross-validation and aggregation have been used to generate and average multiple forecasts [33, 34]. Kourentzes et al. [35] proposed a model and criterion-independent approach to construct forecast pools.

Drawing upon the specific needs of their respective fields, numerous researchers have achieved noteworthy outcomes by applying the theoretical approach of combination forecasting. For more accurate forecasting, by combining three logistic regression models and three neural network models, Rodrigues and Stevenson [36] proposed a probability combination forecasting method. By using the particle swarm optimization algorithm, Zhu and Wei [37] used an autoregressive integrated moving average (ARIMA) model and the least squares support vector machine (LSSVM) to forecast the linear and nonlinear parts of carbon prices, respectively. Wang et al. [38] proposed a new combination model for electricity load forecasting based on the seasonal ARIMA (SARIMA) forecasting model, seasonal exponential smoothing model and weighted support vector machine model. Tan et al. [39] demonstrated that a combination forecasting model based on multitask learning and LSSVM can accurately forecast the electric, thermal, cooling, and gas loads of an integrated energy system on a campus. In response to the problem that traditional statistical models are not proficient in forecasting nonlinear time series and artificial intelligence models tend to fall into local optima, Li et al. [40] successfully established a combination forecasting model for multilevel wind speed forecasting by combining hybrid models based on decomposition methods with optimization algorithms using variable weight combination theory. Using LSTM as an ensemble tool, generalized autoregressive conditional heteroskedasticity (GARCH), ARIMA, support vector regression, a BPNN and LSTM were used to forecast the interval trend and residuals of carbon prices by Liu et al. [41]. Zhu et al. [42] proposed a hybrid forecasting approach that incorporated variational mode decomposition, mode reconstruction and an optimal combined forecasting model to forecast carbon prices. Based on linear regression, artificial neural networks and support vector machines, Wang et al. [43] established a combined forecasting model to forecast crude oil prices, and the optimal weighting vector was obtained by an artificial bee colony algorithm.

In summary, the existing research on the combination forecasting model mainly focuses on the weight settings and model combination. On the basis of abundant theory, the application of combined forecasting is quite mature and stable. The combined forecasting model fully integrates the advantages of various individual forecasting methods [35], which avoids the waste of actual information, reduces the impact of accidental factors on the forecasted results, and makes the forecasted results more accurate and stable.

3 The method

3.1 Overall framework

This paper presents an online review-driven combination forecasting model to forecast NEV sales using historical data and online reviews. The framework of this model is displayed in Fig. 1, and its modules are illustrated as follows:

(1) Quantification of online reviews: this module quantifies the text presented in online reviews by defining sentiment scores and sentiment tendencies according to word segmentation techniques, dictionary-based sentiment analysis methods, and the lexical analysis module of the Baidu AI open platform (hereinafter referred to as LABA). Then, sentiment values related to product attributes are defined by combining sentiment scores and sentiment tendencies using prospect theory.

(2) Sentiment value denoising: this module utilizes the Mallat pyramidal algorithm to denoise the sentiment values, effectively removing the impact of nonstandard expressions, malicious reviews, and spam.

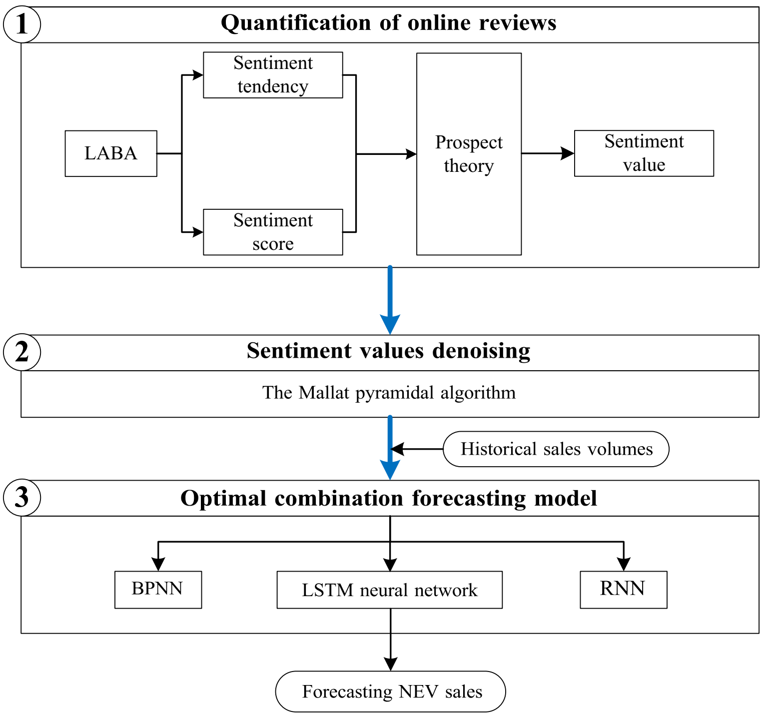

Fig. 1 Overall framework of the proposed model

(3) Combination forecasting model: this module designs an optimal combination forecasting model by integrating BPNN, RNN and LSTM according to weighted averaging to forecast NEV sales more accurately.

3.2 Quantification of online reviews

3.2.1 Sentiment measure method considering product attributes in each period

In Chinese, a typical adjective phrase consists of an adjective, possibly degree adverbs, and negation words that modify the adjective. These modifying words are usually positioned before the adjective. The adjective determines the polarity of the emotion, the adverb determines the intensity of the feeling, and the negation word reverses the polarity of the emotion. Several adjective phrases in an online review determine its sentiment score. The details of how adjective phrases are constructed are provided as follows.

(1) Segmenting Chinese sentences and tagging parts of speech. In contrast to English, Chinese sentences do not incorporate spaces for the separation of characters or words. Therefore, Chinese word segmentation must be carried out first. In this paper, we use LABA (https://ai.baidu.com/tech/nlp_basic/lexical) for segmenting sentences and tagging parts of speech. The review, "这辆车的动力系统非常不错!" ("This car has a great powertrain!") is used as an example. By using LABA, this sentence is split into "这" ("This"), "辆" ("a"), "车" ("car"), "的" ("of"), "动力" ("power"), "系统" ("system"), "非常" ("very"), "不错" ("great"), and "!" ("!"). The Chinese word segmentation results are arranged in the order of appearance in the sentence. Additionally, the part of speech of each word can be obtained using LABA.

(2) Constructing adjective phrases. A sentence can be split into a string of words using LABA. Then, we keep only the adjectives, degree adverbs and negation words. By considering the adjective as a division point, some adjective phrases can be obtained. Please see Fig. 2.

To obtain the sentiment scores of online reviews, the sentiment polarity and weight coefficient of an adjective are defined based on two types of dictionaries, including a sentiment dictionary and an auxiliary dictionary. The detailed steps are given as follows.

(3) Defining the sentiment polarity. Based on *HowNet*, the dictionary of positive (negative) sentiment words is constructed and denoted by $D^{+}(D^{-})$, which contains positive (negative) sentimental words and positive (negative) evaluation

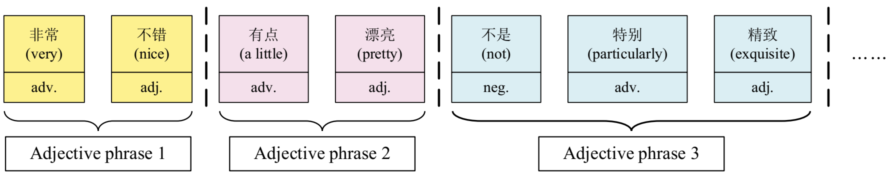

Fig. 2 The process of constructing adjective phrases

Table 1 Degree adverb dictionary and corresponding degree scores [44]

Dictionaries	Categories	Examples	Degree scores
D_1	Extreme/most	完全(completely), 至极(extremely)	$\phi_1 = 2.0$
D_2	Over	超级(super), 何止(beyond)	$\phi_2 = 1.8$
D_3	Very	非常(very), 特别(specially)	$\phi_3 = 1.5$
D_4	More	那么(so), 越来越(more)	$\phi_4 = 1.2$
D_5	A bit	稍微(slightly), 有点(a bit)	$\phi_5 = 0.5$
D_6	Insufficiently	轻度(mild), 微(insufficiently)	$\phi_6 = 0.2$

Table 2 The process of calculating the weight coefficient of an adjective phrase

Categories	θ
$\boxed{adj.}$	1
$\boxed{degree\quad adv.}\ \boxed{adj.}$	ϕ_f
$\underbrace{\boxed{neg.},\boxed{neg.},\cdots,\boxed{neg.}}_{N_{neg}}\ \boxed{adj.}$	$(-1)^{N_{neg}}$
$\underbrace{\boxed{neg.},\boxed{neg.},\ldots,\boxed{neg.}}_{N_{neg}-Na}\ \boxed{degree\quad adv.}$ $\underbrace{\boxed{neg.},\boxed{neg.},\ldots,\boxed{neg.}}_{Na}\ \boxed{adj.}$	$\theta = \begin{cases} (-1)^{N_{neg}}\phi_f, & if\ (-1)^{Na} = -1 \\ \frac{1}{(-1)^{N_{neg}+1}\phi_f}, & if\ (-1)^{Na} = 1 \end{cases}$

words. The numbers of elements in D^+ and D^- are 4566 and 4127, respectively. Subsequently, the sentiment polarity of each adjective is defined. For adjectives that do not belong to D^+ and D^-, LABA is used to analyse the probability of positive sentiment of the adjective. If the probability of positive sentiment is more significant than 0.5, i.e., $P_{pos} > 0.5$, it is regarded as a positive sentiment word. Then, the formula for calculating the sentiment polarity of an adjective is defined as follows:

$$\alpha = \begin{cases} 1, W \cap D^+ \neq \emptyset \quad or \quad P_{pos} > 0.5 \\ -1, other \end{cases}, \tag{1}$$

where α denotes the sentimental polarity of adjective W.

(4) Defining the weight coefficient. The weight coefficient expressed as θ of an adjective phrase is calculated by considering the location and number of degree adverb words and negation words before and after it. Hereinafter, the degree adverbs are determined based on Table 1 provided in [44]. According to Chinese expression habits, there are four different values for θ, as shown in Table 2.

If there are neither degree adverbs nor negation words, the weight coefficient of the phrase is $\theta = 1$.

If there is only a degree adverb before the adjective, the weight coefficient of the phrase is $\theta = \phi_f$, where $\phi_f (f = 1, 2, \ldots, 6)$ refers to the degree score of the degree adverb.

If there are only negation words before the adjective, the weight coefficient of the phrase is $\theta = (-1)^{N_{neg}}$, where N_{neg} denotes the number of negation words in the phrase.

If there are both a degree adverb that belongs to D_f and negation words before the adjective, the weight coefficient of the phrase is

$$\theta = \begin{cases} (-1)^{N_{neg}} \phi_f, \; if\, (-1)^{Na} = -1 \\ \frac{1}{(-1)^{N_{neg}+1} \phi_f}, \; if\, (-1)^{Na} = 1 \end{cases}, \tag{2}$$

where Na denotes the number of negation words after the degree adverb.

(5) Computing the sentiment scores of online reviews. By integrating the sentiment polarity and weight coefficient of an adjective phrase, the sentiment score of an adjective phrase is defined by $S = \alpha\theta$. Based on this, the sentiment score of the qth adjective phrase within the kth online review concerning attribute i in period t is defined by the following equation.

$$S_q^{tik} = \alpha_q^{tik} \theta_q^{tik}. \tag{3}$$

Then, for the kth online review concerning attribute i in period t, the sentiment score expressed by r'_{tik} is defined as follows.

$$r'_{\mathrm{tik}} = \sum_{q=1}^{Q^{\mathrm{tik}}} S_q^{\mathrm{tik}}, \tag{4}$$

in which Q^{tik} represents the number of adjective phrases of the kth online review concerning attribute i in period t. If $r'_{tik} > 0$, then the kth online review concerning attribute i in period t is a positive review. If $r'_{tik} < 0$, then the kth online review concerning attribute i in period t is a negative review. If $r'_{tik} = 0$, then the kth online review concerning attribute i in period t is a neutral review.

3.2.2 Defining the sentiment value based on prospect theory and sentiment measure

When customers evaluate products by perusing online reviews, they exhibit a greater degree of sensitivity towards negative reviews compared to positive ones of similar magnitude [9]. This consumer behaviour conforms to prospect theory. It is essential to modify the sentiment score by taking prospect theory into account. Therefore, the sentiment score of product attribute i in priority t is defined as follows.

$$SS_{t,i} = \frac{1}{K}\sum_{k=1}^{K}\{[\max(r'_{tik},\ 0)]^a - \beta|\min(r'_{tik},\ 0)|^b\}, \tag{5}$$

where $a \in (0, 1)$ and $b \in (0, 1)$ express the sensitivity of consumers to gains and losses, respectively. $\beta \geq 1$ reflects that consumers are more sensitive to losses compared to gains, and K indicates the number of online reviews about product attribute i in period t. Based on prospect theory assumption that most people are more sensitive to losses than to gains [50], $[\max(r'_{tik}, 0)]^a$ is used to minimize the impact of positive emotions in online reviews, and $-\beta|\min(r'_{tik},\ 0)|^b$ is used to amplify the impact of negative emotions in online reviews.

The sentiment score can quantify the subjective feelings from local to all online reviews using lexical analysis techniques. To better reflect the overall subjective feelings in an online review, we use LABA to measure the sentiment tendency of the online review. Let r''_{tik} be the probability that the kth online review concerning attribute i in period t conveys positive emotion. If $r''_{tik} > 0.5$, then the kth online review concerning attribute i in period t expresses positive emotion. If $r''_{tik} < 0.5$, then the kth online review concerning attribute i in period t expresses negative emotion. If $r''_{tik} = 0.5$, then the kth online review concerning attribute i in period t expresses neutral emotion. Then, the sentiment tendency is defined as follows.

$$ST_{t,i} = \frac{1}{K}\sum_{k=1}^{K}\{[\max(r''_{tik},\ 0.5)]^a - \beta|\min(r''_{tik},\ 0.5)|^b\}, \tag{6}$$

in which $a,\ b \in [0,\ 1]$, $\beta \geq 1$, and R''_{ti} refers to the sentiment tendency concerning attribute i in period t. Similarly, $[\max(r''_{tik},\ 0.5)]^a$ is used to minimize the impact of positive emotions in online reviews, and $-\beta|\min(r''_{tik},\ 0.5)|^b$ is used to amplify the impact of negative emotions in online reviews.

Using Eq. (5) and (6), the sentiment score $SS_{t,i}$ and sentiment tendency $ST_{t,i}$ of product attribute i in period t are calculated. Then, the sentiment value denoted by $SV_{t,i} = \left[SS_{t,i},\ ST_{t,i}\right]^{\mathbf{T}}$ of product attribute i in period t is defined.

3.3 Processing sentiment values through the Mallat pyramidal algorithm

Since the language expression of some reviews is nonstandard and malicious reviews and review spam exist, the calculation result of sentiment values is inevitably disturbed [45]. Therefore, it is necessary to remove the noise of the sentiment values to better reflect the sentiment attitudes of consumers.

The Mallat pyramidal algorithm used in this paper is an efficient wavelet decomposition and reconstruction algorithm that decomposes signals and noise at different scales. Let SS_i represents the time series of sentiment score concerning attribute i, where $SS_i = \{SS_{1,i}, SS_{2,i}, \ldots, SS_{T,i}\}$. Let ST_i represents the time series of sentiment tendency concerning attribute i, where $ST_i = \{ST_{1,i}, ST_{2,i}, \ldots, ST_{T,i}\}$.

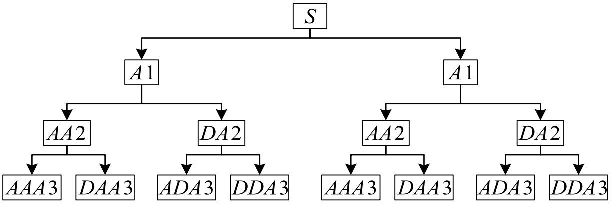

Fig. 3 The Mallat pyramidal decomposition

According to Mallat [46], the wavelet is decomposed by two filters, including a low-pass filter and a high-pass filter. After the discrete wavelet transform, the approximate expression and details of the time series $\omega_i\left(\omega_i \in \left\{SS_i,\ ST_i\right\}\right)$ are expressed as follows:

$$\begin{cases} \sigma_j^k \omega_i = \sum_{n \in Z} \pi(n-2j)\sigma_j^{k+1}\omega_i \\ d_j^k \omega_i = \sum_{n \in Z} \Phi(n-2j) d_j^{k+1}\omega_i \end{cases} \quad j = 1, 2, ..., J, \tag{7}$$

where n denotes the wavelength and $\pi(\cdot)$ and $\Phi(\cdot)$ represent the low-pass filter and high-pass filter, respectively. j is the decomposition scale, and σ_j^k and d_j^k refer to the discrete detail coefficient and discrete approximation coefficient at decomposition level k, i.e., the approximate signal and detail signal, respectively. When the filter length is M, the decomposition scale n and the low-pass filter coefficient π satisfy:

$$j(n) = (-1)^{-n}\pi(M-n). \tag{8}$$

A schematic diagram of the three-layer decomposition of signal S by Mallat is shown in Fig. 3.

After obtaining the decomposed wavelet coefficients of each layer, the soft threshold function *stf* is used to quantify each layer's threshold of wavelet coefficients. The soft threshold function can be expressed as:

$$stf(B,\ t) = \begin{cases} \text{sgn}(B)(B-t) & B \geq t \\ 0 & B < t \end{cases} \tag{9}$$

where η is the threshold of the soft threshold function and can be expressed as:

$$\eta = \vartheta\sqrt{2\lg M}. \tag{10}$$

The high-frequency coefficients quantified by the soft threshold function *stf* are reconstructed to obtain the sentiment value signal that eliminates the noise. The signal reconstruction can be expressed as:

$$a_{j-1}^k \omega_i = \sum_{n \in Z} \pi(n-2k) a_{j-1}^k \omega_i + \sum_{n \in Z} \Phi(n-2k) d_{j-1}^k \omega_i. \tag{11}$$

3.4 Construction of the combination forecasting model

The existing methods for sales forecasting can be broadly classified into two categories: traditional forecasting methods and artificial intelligence (AI) methods. Traditional forecasting methods encompass linear regression models, ARIMA, SARIMA, grey econometric models, and their improved versions [47]. AI methods, on the other hand, include BPNN, LSTM, and RNN, among others [48–50]. A large number of studies have demonstrated that AI methods exhibit superior performance compared to classical models due to their adaptability and ability [51]. Besides, Hence, BPNN, LSTM, and RNN are selected as being more effective than traditional forecasting methods.

3.4.1 Individual forecasting model

3.4.1.1 BPNN model A BPNN is a multilayered feed forward network trained by error backpropagation. The network topology consists of the input, hidden, and output layers. The basic idea of a BPNN is to use the gradient descent method to adjust the connection strength of the input layer node, the connection strength of the hidden layer node and the output layer node, and the threshold so that the error decreases along the gradient direction [52]. Finally, after repeated learning and training, the network parameters corresponding to the minimum error are obtained, namely, weights and thresholds. Hecht-Nielsen [53] proved that the three-layer BPNN can approximate any multivariable function. The number of prediction indicators, denoted as m, is also the number of neurons in the input layer, expressed as N_{in}. The number of neurons in the output layer is $N_{ou} = \varphi$, where n denotes the number of prediction targets. In addition, the number of neurons in the hidden layer is N_{hi}, which needs to be determined by the empirical formula $N_{hi} = \sqrt{m + \varphi} + c$, where $c \in [1, 10] \cap \mathbb{N}$ [44].

3.4.1.2 RNN model A RNN is a kind of neural network used to process sequence data, and it can effectively mine the temporal information and semantic information in data. One of the most superficial recurrent neural networks is called the Simple-RNN, which is the basis of the bidirectional RNN (Bi-RNN) and LSTM network. A single mention of an RNN generally refers to the Simple-RNN.

The structure of an RNN is shown in Fig. 4 and includes the input layer, output layer, and hidden layer. The input layer X is denoted by $\{x_0, x_1, \dots, x_t, x_{t+1}, \dots\}$, the output layer O is denoted by $\{o_0, o_1, \dots, o_t, o_{t+1}, \dots\}$, and the hidden layer H is

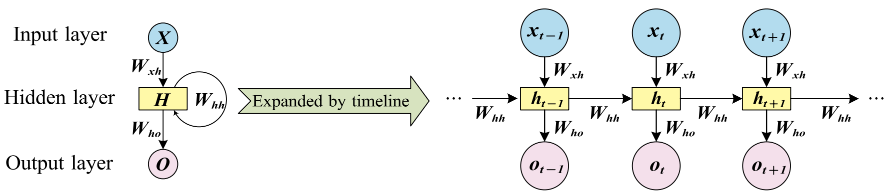

Fig. 4 The structure of RNN

denoted by $\{h_0, h_1, \ldots, h_t, h_{t+1}, \ldots\}$. W_{xh} represents the weight matrix from the input layer to the hidden layer, W_{ho} represents the weight matrix from the hidden layer to the output layer, and W_{hh} represents the weight matrix between the hidden layers. In period t, h_{t-1} and the current x_t are input and o_t is output and passed to period $t + 1$ [54]. Therefore, the RNN can transfer the state of the last moment to the next moment by using the connected hidden layer, which has a strong memory. Compared with the traditional fully connected neural network, an RNN can effectively reduce the prediction error in terms of time series prediction [55].

3.4.1.3 LSTM neural network model An LSTM neural network is a special RNN that can better deal with the long-term dependence of time series data. Its network structure contains a series of memory storage structures connected by loops to store a series of states generated in the process of the network loop. Each memory storage module contains one or more self-connected cells and three threshold unit systems of an input gate, an output gate, and a forgetting gate that control information flow. The memory storage structure of LSTM is shown in Fig. 5.

In period t, the input value of the memory storage unit is x_t, and the current value of the hidden layer is h_t. Therefore, the initial values I_t, f_t and o_t of the input gate, forgetting gate and output gate are distributed as follows [56]:

$$\begin{aligned} I_t &= \sigma\left(W_{xh}^{(i)} x_t + U_i h_{t-1} + b_i\right) \\ f_t &= \sigma\left(W_{xh}^{(f)} x_t + U_f h_{t-1} + b_f\right) \\ o_t &= \sigma\left(W_{xh}^{(o)} x_t + U_o h_{t-1} + V_o C_t + b_o\right) \end{aligned} \tag{12}$$

where σ is the sigmoid activation function, the range is [0, 1] the information flow weight is set to a value between 0 and 1, in which 0 means that the information is completely deleted and 1 means that all information is retained. W_{xh} represents the weight matrix from the input layer to the hidden layer, U represents the cyclic weight, and b denotes the bias. Furthermore, I, f, and o represent the input gate,

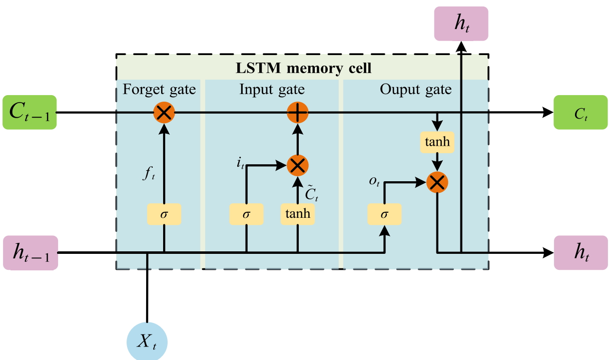

Fig. 5 The structure of LSTM memory cell

forgetting gate, output gate, respectively, and C_t is the candidate value of the memory storage unit.

An LSTM neural network contains the external cycle between hidden layer units involved in the RNN and the internal cycle of cells, and it effectively avoids the problem of gradient disappearance of RNNs and has better performance in time series data prediction [57].

3.4.2 Combination forecasting model based on online reviews

The combined forecasting model combines the advantages of the individual forecasting models and can effectively improve the prediction accuracy. Utilizing the sentiment values, the Mallat pyramid algorithm and the individual forecasting models, the combination forecasting model based on online reviews is proposed.

The combination method can be expressed as:

$$\hat{u}_t = \sum_{i=1}^{l} w_i u_{it}, \quad t = 1, 2, \ldots, T, \tag{13}$$

where $W = \left(w_1, w_2, \ldots, w_l\right)^{\mathbf{T}}$ represents the weight vector satisfying $\sum_{i=1}^{l} w_i = 1$ and $w_i \geq 0, i = 1, 2, \ldots, l$; u_{it} represents the predicted value of the ith individual prediction method in period t; and $\hat{u}_t$ represents the combined prediction value in period t.

In the process of combination, the setting of the weight is crucial and directly affects the combination effect. The weighted average (WA) method has been proven to be an effective method to improve forecasting accuracy. By minimizing the combined forecasting error under constraints, WA assigns different weights to different individual prediction methods and can be expressed as [42]:

$$\begin{gathered}
\min J = \sum_{t=1}^{T} e_t^2 = \sum_{i=1}^{l} \sum_{j=1}^{l} w_i w_j \left(\sum_{t=1}^{T} e_{it} e_{jt} \right) \\
s.t. \begin{cases} \sum\limits_{i=1}^{l} w_i = 1 \\ w_i \geq 0, \quad i = 1, 2, ..., l \end{cases}
\end{gathered} \tag{14}$$

where e_{it} represents the error of the ith individual prediction method in period t and can be written as $e_{it} = u_t - u_{it}$. e_t represents the error of the combined forecasting in period t and can be written as:

$$e_t = u_t - \hat{u}_t = u_t - \sum_{i=1}^{l} w_i u_{it} = \sum_{i=1}^{l} w_i \left(u_t - u_{it}\right) = \sum_{i=1}^{l} w_i e_{it}. \tag{15}$$

Let E be the combined forecasting error information matrix, which is written as:

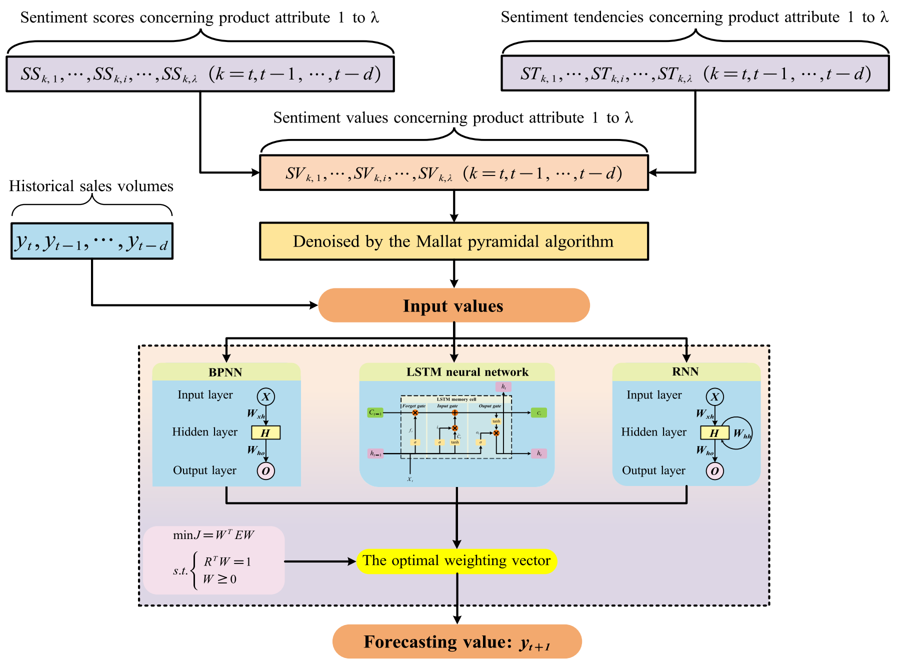

Fig. 6 Structure of the online review-driven combination forecasting model

$$E = \left(E_{ij}\right)_{l \times l} = \begin{pmatrix} e_1^T e_1 & e_1^T e_2 & \dots & e_1^T e_l \\ e_2^T e_1 & e_2^T e_2 & \dots & e_2^T e_l \\ \vdots & \vdots & \dots & \vdots \\ e_l^T e_1 & e_l^T e_2 & \dots & e_l^T e_l \end{pmatrix} \tag{16}$$

Let $R = (1, 1, \cdots, 1)^T_{1 \times l}$; then, Eq. (14) can be written in matrix form:

$$\begin{aligned} &\min J = W^T EW \\ &s.t. \begin{cases} R^T W = 1, \\ W \geq 0. \end{cases} \end{aligned} \tag{17}$$

By solving the above model, the optimal weighting vector can be obtained.

The structure of the online review-driven combination forecasting model is shown in Fig. 6.

4 Empirical study

4.1 The experimental design

The prediction accuracy of the online review-driven combination forecasting model proposed in this paper can be measured by three statistical evaluation indicators, including the mean absolute error (MAE), root mean square error (RMSE) and mean absolute percentage error (MAPE), which are presented as follows.

$$\mathrm{MAE} = \frac{1}{T}\sum_{t=1}^{T} |u_t - \hat{u}_t|, \tag{18}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T} \left(u_t - \hat{u}_t\right)^2}, \tag{19}$$

$$\mathrm{MAPE} = \frac{1}{T}\sum_{t=1}^{T} \left|\frac{u_t - \hat{u}_t}{u_t}\right|. \tag{20}$$

where T represents the number of samples, u_t represents the actual value in period t, and $\hat{u}_t$ represents the predicted value in period t. The closer the values of these evaluation indices are to 0, the higher the accuracy of model forecasting is.

The following nine benchmark models are established for comparison: M1: BPNN without sentiment values (BPNN); M2: RNN without sentiment values (RNN); M3: LSTM without sentiment values (LSTM); M4: BPNN with sentiment values (BPNN-SV); M5: RNN with sentiment values (RNN-SV); M6: LSTM with sentiment values (LSTM-SV); M7: BPNN with denoised sentiment values (BPNN-DSV); M8: RNN with denoised sentiment values (RNN-DSV); and M9: LSTM with denoised sentiment values (LSTM-DSV). The purpose of establishing the M1-M3 models is to prove the effect of sentiment values on forecasting sales. The purpose of establishing the M4-M6 models is to prove the benefit of denoising the sentiment values. The purpose of establishing the M7-M9 models is to prove the superiority of the online review-driven combination forecasting model over the individual forecasting model. Moreover, to show the superiority of the three individual forecasting methods selected in this paper, three methods of AIRMA, GARCH, GM(1, 1) and SVM, which are widely used in sales forecasting, are selected in this paper. Specifically, the following four benchmark models are also established for comparison: M10: SVM without sentiment values; M11: SVM with sentiment values; M12: SVM with denoised sentiment values; M13: GARCH; M14: ARIMA and M15: GM(1, 1). In addition, the online review-driven combination forecasting model is denoted by M16.

While the statistical loss function can serve as a benchmark for comparing the forecasting accuracy of various models, it is not capable of determining whether the forecasting performance of different models is statistically significant. Therefore, the Diebold-Mariano (DM) test is employed to achieve this goal. The null hypothesis of the DM test is that there is no significant difference in the forecasting performance between target model A and benchmark model B under the condition of a given significance level, and it can be expressed as:

$$H_0 : E\left[F\left(e_t^A\right)\right] = E\left[F\left(e_t^B\right)\right], \tag{21}$$

where e_t^A and e_t^B are the forecasting errors of models A and B and the loss function F is set to the mean square error. The DM statistic is defined as follows:

$$S_{DM} = \frac{\overline{g}}{\sqrt{\left(\hat{V}_{\overline{g}}/T\right)}}, \tag{22}$$

where

$$\overline{g} = \frac{1}{T}\sum_{t=1}^{T} g_t, g_t = \left(u_t - \hat{u}_{At}\right)^2 - \left(u_t - \hat{u}_{Bt}\right)^2, \tag{23}$$

and

$$\hat{V}_g = \gamma_0 + 2\sum_{t=1}^{\infty} \gamma_t, \left(\gamma_t = \mathrm{cov}\left(g_{t+1}, g_t\right)\right), \tag{24}$$

where γ_0 denotes the variance of g_t, and $\hat{u}_{At}$ and $\hat{u}_{Bt}$ represent the forecasting values of model A and model B in period t, respectively. T refers to the number of observations in the test set.

4.2 Data sources and clawing

In this paper, the primary sources of data include monthly sales volumes of BYD-Tang as well as online reviews related to BYD-Tang and its associated information.

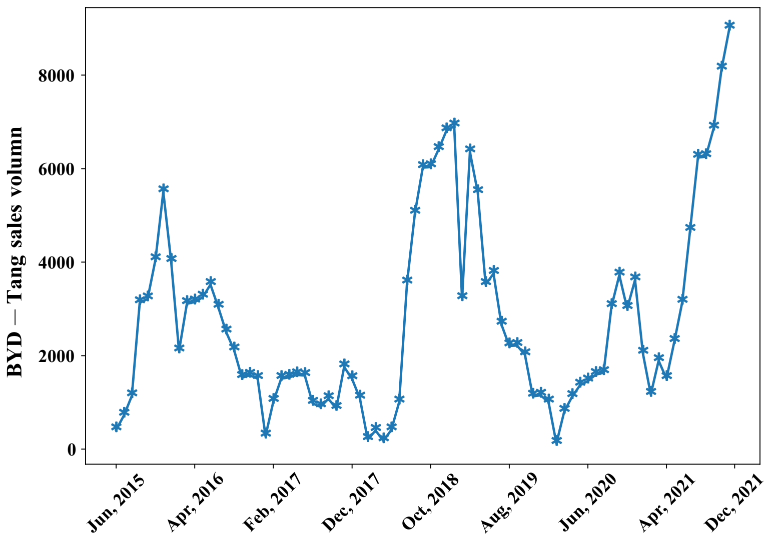

Fig. 7 Monthly sales volumes of BYD-Tang

Fig. 8 An example of online review page from the AutoHome website

Monthly sales volumes of BYD-Tang from June 2015 to December 2021 are obtained from the Chezhuzhijia website (https://xl.16888.com/s/126549-1.html), as shown in Fig. 7.

The online reviews concerning BYD-Tang are obtained from the *Autohome* website (https://k.autohome.com.cn/3430/#pvareaid=3454440) using web crawler technology. *Autohome* is a leading automotive internet platform in China; it has a large user base and a very active automotive forum. Therefore, online reviews concerning BYD-Tang are collected through this website. Figure 8 shows an example of an online review page from the *Autohome* website. Using Python 3.8, the *requests*, *lxml* and *re* libraries are utilized to obtain the online reviews of BYD-Tang related to eight product attributes, which include appearance, interior, space, power, controllability, power consumption, comfort, and cost performance. The data collection results are saved in a CSV file, as shown in Fig. 9.

4.3 Model implementation

4.3.1 Building sample set

According to the analysis results of Zhang et al. [44], we set $a = 1.0$, $b = 0.8$, and $\beta = 2.0$. Next, Python 3.8 is used to process the collected online reviews, and then the sentiment values of each attribute in each period are calculated. There were no online reviews on BYD-Tang in February 2017, so the average sentiment values of the two months before and after are used to replace the sentiment values of February 2017.

Based on the historical sale volumes and historical sentiment values, we build a sample set for forecast model training, including the feature set X and the label set Y. The feature set and label set contained in the kth are as follows:

	B	C	D	E	F	G	H	I	J	K
1	购买车型	购买时间	空间(Space)	动力(Power)	操控(Controllability)	能耗(Power consumption)	舒适性(Comfort)	外观(Appearance)	内饰(Interior)	性价比(Cost performance)
2	唐新能源 2021 款 DM 2.0T 四驱高性	44105	第排和第排空间非常宽裕，第三排座成人压力，座小孩子还是可以。储物空间方	动力非常满意，4.3秒零百速像起飞感觉，在上只要你想超车，从	方向精准，刹车灵敏，很安全感，弯时车辆侧倾制很好，尤其方向助力能在中屏幕调节，可调节方向助力运动模式，和标准模式	纯电能耗很满意，混动模式根据电量情况测试，高速况油耗7到8个油，市区混动8到9个油。电池预加热：唐DM可以手机遥控前打空调，夏季	座椅很舒适，新车没异味，配备负离子新风系统效果很明显，打后车内PM2.5很快就能清除	整车外观霸气，颜值很高，车灯设计是画龙点睛之笔，车漆工艺档次挺高	内饰很豪华，朋友们座进入直呼他们宝马奥迪内饰档次都高	性价很高车，尤其还是新能源车，从购车始就节省预算，用车程更是深切体会到行驶费用真很低。送5
3	唐新能源 2021 款 DM 2.0T 四驱高性能版尊	44409	前排乘坐空间没说完够，储物空间只两个杯座，板放进点水杯，扶手箱空间很常规，驾驶位险还	动力非常强劲，EV运动模式满电加速就已经很猛，再？一台2.0发动！第初段中	方向虚位比较，指向一般，油基本踩多多，很掌握！刹车便，刚上手需要去适应！防止点头舒适刹车这个功能体验一般还需要完善！驾驶辅助配置对于我说基本没	我对动力要求稍高，只要堵车管他电没电都HEV运动模式！油耗8个多，电没管他，一个星期充一两次，以后腻估计会佛系点，就EV！车库电桩，也方便！要想省油就	悬挂适中，轮胎255扁平高一点，这也没选顶配其中一个原因之一！舒适能证！颠！空调调节没物理按键，中控	尾部和侧面爱，前脸老龙颜看腻！比较圆润，气势上稍微弱一丢丢！侧面线条完美，一个这么车一点显臃肿！	内饰就棕色一个颜色，没其他颜色可选，稍显油腻！过类似奔驰S方向，还忍！感觉其他没啥亮	30到买到各种我想要，虽然现在电动混动车横行，点几秒30万也再神话，但对于我说买到自己想要！强劲动力，强驱带把
5	唐新能源 2021 款 DM-i 112KM 尊荣型	44409	空间这方面真的满意，四米八左右的车，轴距做到了两米八还要，空间绝对意想不到的亮点，	动力这方面只能说还比较满意，中大型的一个越野车，提速可以做到九秒内，已经	操控这一方面不算太满意，毕竟一辆适合家用的车，省油，另外这个车因为车尺寸比较大的原因，肯定会有一定的盲区，所以配备了并线辅助功能，大大减少了因为	能耗这方面就值得夸赞一下了，两吨的车重，陆地小坦克，油耗仅仅四个，而且送的还有充电桩，二十度左右的电量就可以充满，还能够支持快速充电，因为我入手	舒适确实做的比较，座椅通风加热，腰部支撑，腿部支撑都给安排了，空调还可以分区控制，对老人，	外观无可挑剔，车腰线给人一种强烈的力量感，车灯带迎宾功能，比市面大数车型都彰显出科技感，珍珠车	内饰属于一个双拼的，车机系统流畅无卡顿，可以识别种方言。原厂配备了氛围灯，夜晚效果杠	唐这个价位我感觉价比还蛮的，我比较成功的一次购车，维修成本相比于传统的燃油车要低不少。售后服务也到位
6	唐新能源 2021 款 DM-i 112KM 尊荣型	44470	间充足，前排调到很宽的位置，二排也会很宽松，毕竟将近4米9的车长，七座用的时候最后排可以收起来，这样	动力表现还挺好的，轻踩门动力说来就来，新能源车在动力这块都表现还挺好的，起步速都	方向盘操控很轻松，平时踩刹车踩，脚就可以离开，即使在坡也会后溜这点对女朋友很友好。之前在网看见总挂被吐槽，因为我平时开市区道路多，暂时没什么发现。刚买车时销售让我下载比	这个车的耗确实很的，这么的个车，百里耗只6个左，真的太，出乎我的意料，般这么个车耗都九个，平时在市区还可以用电。真的很省。	车子的乘舒适还比较可以的，也很柔软，包裹很强，而且真皮的，会像些车会显得内饰很廉价。隔音做得也错，基本听到什么	整车外观气，前脸龙脸造型出众机具辨识度，车身线条流畅看起很运动感，车漆工艺看起来很高档，贯穿式后尾灯也很亮点，	内饰可圈可点，没觉得很惊艳，可以接受的样子，中间屏非常酷，功能非常多，家里小孩很喜欢在面看动画	其实车子值值得，还要看自己喜喜欢，千金难买心头好，自己也看很多车子做对比，最后综合下来定的唐dmi，因为它价格合理的，间外观

Fig. 9 An example of crawled online reviews

$$X_k = \begin{bmatrix} SV_{k,1} & SV_{k,2} & \dots & SV_{k,\lambda} & y_k \\ SV_{k+1,1} & SV_{k+1,2} & \dots & SV_{k+1,\lambda} & y_{k+1} \\ \vdots & \vdots & \dots & \vdots & \vdots \\ SV_{k+d-1,1} & SV_{k+d-1,2} & \dots & SV_{k+d-1,\lambda} & y_{k+d-1} \end{bmatrix}$$
$$Y = y_{k+d} \tag{25}$$

where d, which is set as 1, represents the number of lags in the historical data; λ, which is equal to 8, denotes the number of attributes of BYD-Tang; y_k refers to the sales in period k; and $k = 1, 2, \dots, T - d$, where $T = 79$. The sample set contains $T - d$ samples.

4.3.2 Model training

The samples are divided into a training set and a testing set with the ratio of 3:1. Therefore, the first 59 samples are taken as the training set, and the remaining samples are taken as the testing set. For the training of neural networks, some hyperparameter settings have a great impact on the training results. To improve the prediction accuracy, Keras 2.7.0 is used to construct the network, and a

Table 3 Tuning parameters in the three neural networks part of the proposed model

Models	Hyper-parameters		
BPNN	Learning rate	0.0001	
	The active function	Relu	
	The number of neurons	Hidden layer 1	6
		Hidden layer 1	7
	Batch size	5	
	Iterations	50	
	Loss function	MSE	
	The optimizer	Adam	
RNN	Learning rate	0.0001	
	The active function	Relu	
	The number of neurons	RNN layer	17
		Hidden layer	8
	Batch size	5	
	Iterations	160	
	Loss function	MSE	
	The Optimizer	Adam	
LSTM	Learning rate	0.0001	
	The active function	Relu	
	The number of neurons	LSTM layer	17
		Hidden layer	8
	Batch size	10	
	Iterations	180	
	Loss function	MSE	
	The Optimizer	Adam	

random grid search is used to select hyperparameters [58]. The optimal parameters are selected, as shown in Table 3.

4.4 Forecasting performance comparisons

The online review-driven combination forecasting model proposed in this paper and the nine benchmark models are used to forecast the sale volume of BYD-Tang. Figure 10 shows the forecasted and observed sales volume of the proposed and benchmark models. Intuitively, we find that these forecasting models can capture the trend of sales well.

To verify whether online review data, denoising and combination forecasting help improve prediction accuracy, we quantitatively compare the performance of these models in terms of MAE, RMSE and MAPE. The computational results of the three statistical evaluation indicators are given in Table 4.

According to Table 4, that the following information is known:

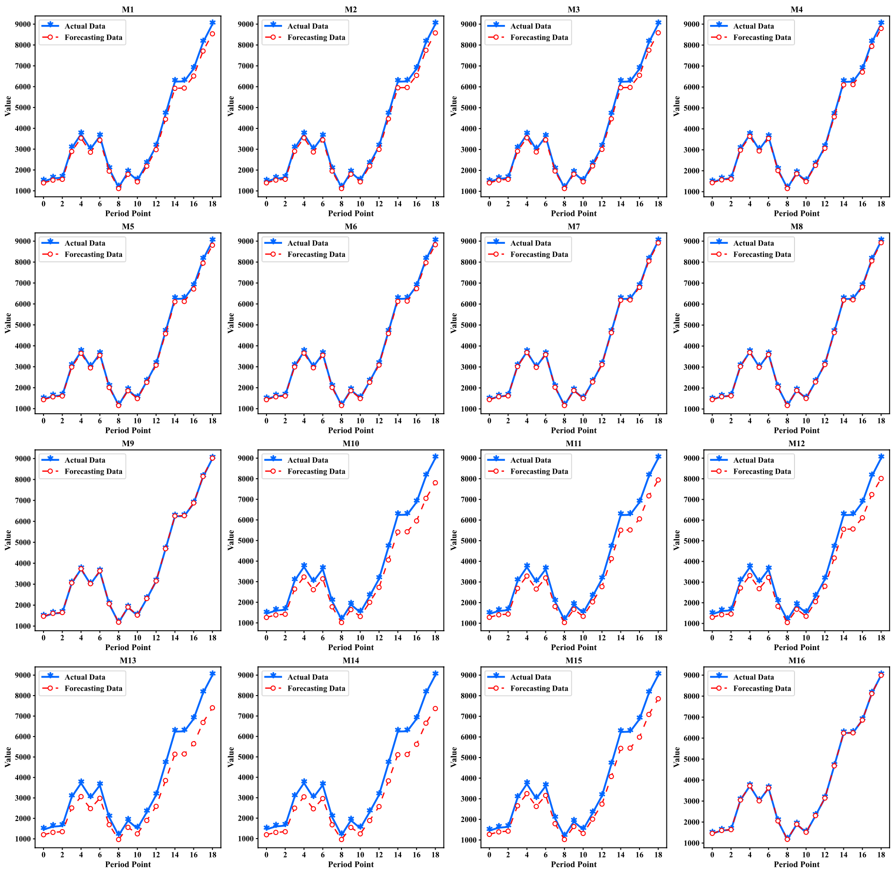

Fig. 10 Comparisons of the forecast versus actual data for different models

Table 4 The prediction accuracy of different models in testing set

Notations	Models	MAE	RMSE	MAPE (%)
M1	BPNN without sentiment values	192.3979	227.6572	5.1131
M2	RNN without sentiment values	174.7609	206.7510	4.6458
M3	LSTM without sentiment values	162.1786	197.6184	4.1157
M4	BPNN with sentiment values	80.5861	97.9703	2.0520
M5	RNN with sentiment values	77.8011	94.0850	1.9981
M6	LSTM with sentiment values	68.7048	82.5018	1.7846
M7	BPNN with denoised sentiment values	33.0792	40.0888	0.8469
M8	RNN with denoised sentiment values	26.6846	34.0426	0.6289
M9	LSTM with denoised sentiment values	15.3197	15.4873	0.5483
M10	SVM without sentiment values	496.0335	587.3892	13.1668
M11	SVM with sentiment values	438.7333	519.3736	11.6516
M12	SVM with denoised sentiment values	408.7180	483.7304	10.8582
M13	GARCH	661.7224	783.6599	17.5625
M14	ARIMA	682.9985	806.1409	18.2238
M15	GM(1,1)	476.5952	563.7478	12.6727
M16	Online review-driven combination forecasting model	4.7119	5.0893	0.2045

(1) Models M4–M6 are superior to M1–M3 in all MAE, RMSE, and MAPE metrics, as shown in Table 4. For model M4, MAE, RMSE, and MAPE are 80.5861, 97.9703, and 2.0520%, respectively, while for model M1, the values are 192.3979, 227.6572, and 5.1131%, respectively, which are all higher than those of M4. For model M5, MAE, RMSE, and MAPE are 77.8011, 94.0850, and 1.9981%, respectively, while for model M2, the values are 174.7609, 206.7510, and 4.6458%, respectively, which are all higher than those of M5. For model M6, MAE, RMSE, and MAPE are 68.7048, 82.5018, and 1.7846%, respectively, while for model M3, the values are 162.1786, 197.6184, and 4.1157%, respectively, which are all higher than those of M6. These results indicate that the single prediction model can improve the prediction accuracy after considering the sentiment value

(2) Models M7–M9 are superior to M4–M6 in all MAE, RMSE, and MAPE values, as shown in Table 4. For model M7, MAE, RMSE, and MAPE are 33.0792, 40.0888, and 0.8469%, respectively, which are all lower than those of M4. For model M8, MAE, RMSE, and MAPE are 26.6846, 34.0426, and 0.6289%, respectively, which are all lower than those of M5. For model M9, MAE, RMSE, and MAPE are 15.3197, 15.4873, and 0.5483%, respectively, which are all lower than those of M6. The above analysis shows that the prediction accuracy of single prediction model can be improved obviously after considering sentiment value and sentiment value denoising

(3) The online review-driven combination forecasting model (M10) proposed by this paper is superior to models M7–M9 in all MAE, RMSE, and MAPE values, as shown in Table 4. For model M10, MAE, RMSE, and MAPE are 4.7119, 5.0893,

and 0.2045%, respectively, which are all lower than those of the M7–M9 models. This shows that the combination of M7–M9 models considering sentiment value and sentiment value denoising can effectively improve the prediction accuracy

(4) Models M1–M3 are superior to M10–M15 in all MAE, RMSE, and MAPE values, as shown in Table 4, which demonstrates that three individual forecasting models used in this paper have better accuracy performance than SVM, GARCH, ARIMA, and GM(1, 1). It is worth noting that with the additon of the sentiment values and denoising algorithm, the forecasting performance of SVM gradually becomes better, as shown in the forecasting results of M10, M11, and M12.

From the values of MAE, RMSE and MAPE, our proposed model is superior to the benchmark model. Additionally, the DM test has been conducted to provide statistical evidence of the superiority of our proposed model. The testing results of the DM test are given in Table 5. In addition, as shown in Table 5, according to the DM test results, M4, M5, and M6 can be statistically verified to be significantly better than M1, M2 and M3 at a 1% significance level, respectively. This demonstrates that the sentiment values calculated from online reviews can lead to better forecasting results. M7, M8, and M9 can be statistically verified to be significantly better than M4, M5 and M6 at a 1% significance level, respectively. This demonstrates that denoising the sentiment values is valuable. The online review-driven combination forecasting model can be statistically verified to be significantly better than M7, M8 and M9 at a 5% significance level. This demonstrates the superiority of the optimal combination forecasting model.

4.5 Robustness test

4.5.1 Robustness test with sample splitting strategy

We adopted different sample splitting strategies to verify the robustness. The corresponding results are shown in Table 6, which demonstrates that the proposed model has good robustness when the sample splitting strategy is changed.

Table 6 indicates that in comparison to the benchmark models, the online review-driven combination forecasting model proposed in this paper exhibits higher accuracy and strong robustness.

4.5.2 Robustness test with other NEVs datasets

Two datasets of NEVs, including NIO-ES6 from May 2019 to October 2022 and Tesla-Model Y from February 2021 to October 2022, are selected to test the robustness and effectiveness of our proposed online review-driven combination forecasting model. The statistical evaluation indicators mentioned in subSect. 4.1 are used to compare the forecasting performance of online review-driven combination forecasting model and benchmark models. The corresponding results are provided by Tables 7, 8.

Table 5 The results of the DM test

	M1	M2	M3	M4	M5	M6	M7	M8
M1		3.602 (0.002**)	4.493 (0.000**)	3.659 (0.002**)	3.645 (0.002**)	3.628 (0.002**)	3.616 (0.002**)	3.621 (0.002**)
M2			9.940 (0.000**)	3.675 (0.002**)	3.657 (0.002**)	3.635 (0.002**)	3.619 (0.002**)	3.625 (0.002**)
M3				3.383 (0.003**)	3.373 (0.003**)	3.368 (0.003**)	3.387 (0.003**)	3.396 (0.003**)
M4					2.999 (0.008**)	3.215 (0.005**)	3.402 (0.003**)	3.443 (0.003**)
M5						3.297 (0.004**)	3.449 (0.003**)	3.491 (0.003**)
M6							3.512 (0.002**)	3.567 (0.002**)
M7								4.354 (0.000**)
M8								
M9								
M10								
M11								
M12								
M13								
M14								
M15								
M16								

	M9	M10	M11	M12	M13	M14	M15	M16
M1	3.596 (0.002**)	3.601 (0.002**)	3.604 (0.002**)	3.606 (0.002**)	3.601 (0.002**)	3.632 (0.002**)	3.612 (0.002**)	3.607 (0.002**)
M2	3.595 (0.002**)	3.601 (0.002**)	3.604 (0.002**)	3.606 (0.002**)	3.601 (0.002**)	3.632 (0.002**)	3.612 (0.002**)	3.608 (0.002**)
M3	3.372 (0.003**)	3.631 (0.002**)	3.644 (0.002**)	3.654 (0.002**)	3.617 (0.002**)	3.647 (0.002**)	3.645 (0.002**)	3.386 (0.003**)
M4	3.338 (0.004**)	3.608 (0.002**)	3.613 (0.002**)	3.616 (0.002**)	3.605 (0.002**)	3.634 (0.002**)	3.619 (0.002**)	3.395 (0.003**)
M5	3.370 (0.003**)	3.606 (0.002**)	3.611 (0.002**)	3.614 (0.002**)	3.604 (0.002**)	3.633 (0.002**)	3.617 (0.002**)	3.433 (0.003**)
M6	3.393 (0.003**)	3.604 (0.002**)	3.608 (0.002**)	3.611 (0.002**)	3.603 (0.002**)	3.632 (0.002**)	3.615 (0.002**)	3.475 (0.003**)
M7	3.005 (0.008**)	3.603 (0.002**)	3.606 (0.002**)	3.608 (0.002**)	3.602 (0.002**)	3.631 (0.002**)	3.613 (0.002**)	3.361 (0.003**)
M8	2.605 (0.018*)	3.604 (0.002**)	3.607 (0.002**)	3.610 (0.002**)	3.602 (0.002**)	3.632 (0.002**)	3.614 (0.002**)	3.079 (0.006**)

Table 5 (continued)

	M9	M10	M11	M12	M13	M14	M15	M16
M9		3.600 (0.002**)	3.602 (0.002**)	3.604 (0.002**)	3.600 (0.002**)	3.630 (0.002**)	3.610 (0.002**)	12.059 (0.000**)
M10			3.592 (0.002**)	3.592 (0.002**)	3.601 (0.002**)	3.663 (0.002**)	3.492 (0.003**)	3.602 (0.002**)
M11				3.590 (0.002**)	3.599 (0.002**)	3.649 (0.002**)	3.652 (0.002**)	3.604 (0.002**)
M12					3.598 (0.002**)	3.644 (0.002**)	3.625 (0.002**)	3.607 (0.002**)
M13						4.213 (0.001**)	3.590 (0.002**)	3.601 (0.002**)
M14							3.649 (0.002**)	3.630 (0.002**)
M15								3.612 (0.002**)
M16								

** Denotes the 1% significant level; *means the 5% significant level

Table 6 The robustness test of sample splitting strategy

Notations	MAE	RMSE	MAPE (%)
The number of samples in the training set: 10			
M1	513.7305	648.4716	18.6747
M2	476.8240	604.0364	17.1009
M3	493.6630	625.0870	17.7395
M4	429.0217	544.7528	15.2589
M5	420.0032	532.9726	14.9658
M6	417.0305	529.4266	14.8386
M7	394.2347	499.4177	14.1469
M8	397.8834	505.4849	14.1141
M9	390.6895	494.9106	14.0139
M10	594.6391	753.4192	21.3099
M11	513.7305	648.4716	18.6747
M12	498.0073	631.3016	17.8168
M13	1028.5820	1300.4280	37.1633
M14	860.6876	1089.0650	31.0037
M15	465.3639	590.0502	16.6399
M16	388.9789	493.9755	13.8258
The number of samples in the training set: 20			
M1	397.3936	508.6641	13.8054
M2	401.1495	515.9972	13.6930
M3	400.8754	516.6816	13.5645
M4	386.9224	494.9286	13.4716
M5	370.5864	474.4927	12.8551
M6	371.2614	476.1350	12.8118
M7	367.7304	470.2387	12.8060
M8	365.6542	467.3922	12.7684
M9	372.4179	479.5352	12.6595
M10	526.3774	673.1316	18.36026
M11	595.8343	760.9281	20.87771
M12	516.6268	661.7105	17.90454
M13	485.2805	622.2236	16.75074
M14	456.4675	584.9125	15.78706
M15	607.6903	777.5999	21.13722
M16	346.0465	441.6890	12.1433
The number of samples in the training set: 30			
M1	441.7322	551.3694	13.7680
M2	384.5384	480.6951	11.8953
M3	388.5158	486.7862	11.8917
M4	382.4772	477.6590	11.8716
M5	380.9448	475.6595	11.8452
M6	366.0964	455.0007	11.6633
M7	373.4965	466.2143	11.6278
M8	372.2903	465.0251	11.5682

Table 6 (continued)

Notations	MAE	RMSE	MAPE (%)
M9	369.6995	461.9690	11.4643
M10	497.0549	621.2648	15.3864
M11	491.0044	612.4277	15.3400
M12	499.9546	626.6557	15.2785
M13	524.5275	655.8143	16.2223
M14	522.8059	654.2638	16.0994
M15	483.4758	604.1014	15.0012
M16	351.6824	438.9341	10.9587
The number of samples in the training set: 40			
M1	336.9404	409.0895	9.2863
M2	326.4000	394.7074	9.1523
M3	320.0232	386.2027	9.0442
M4	322.2834	390.3880	8.9751
M5	357.9258	433.1539	9.9975
M6	309.8905	373.8385	8.7662
M7	287.2143	347.8556	7.9984
M8	279.6354	338.8977	7.7725
M9	265.7929	321.5310	7.4397
M10	483.8026	582.9386	13.7619
M11	472.2626	567.3115	13.5892
M12	477.2424	575.4025	13.5382
M13	590.426	709.7265	16.9490
M14	598.2337	721.5885	16.9369
M15	601.2634	724.9258	17.0588
M16	242.0785	292.1050	6.8418
The number of samples in the training set: 50			
M1	284.6232	366.0126	9.2806
M2	224.6883	285.6075	7.6236
M3	207.3610	263.7953	7.0189
M4	202.0829	257.0437	6.8421
M5	224.6883	285.6075	7.6236
M6	170.4491	215.6582	5.8652
M7	87.7875	115.0108	2.8742
M8	65.9967	87.3885	2.1811
M9	90.1283	118.1381	2.9660
M10	329.9815	420.4307	11.1090
M11	331.5775	423.2834	11.0788
M12	322.131	411.9826	10.7117
M13	542.25	689.3241	18.3927
M14	532.2951	676.8105	18.0490
M15	526.5258	671.1311	17.7000
M16	47.3751	61.0974	1.5452

Table 7 The prediction accuracy of different models in testing set of NIO-ES6

Notations	MAE	RMSE	MAPE (%)
M1	206.4183	228.9795	13.4820
M2	206.2981	228.8670	13.4661
M3	206.3627	228.9549	13.4633
M4	198.0750	219.7507	12.9269
M5	198.1677	219.8719	12.9258
M6	198.0886	219.7749	12.9242
M7	195.8089	217.1910	12.7966
M8	195.9480	217.3723	12.7953
M9	196.4158	217.9797	12.7917
M10	230.2262	255.3873	15.0379
M11	230.1172	255.2613	15.0327
M12	230.5706	255.8426	15.0321
M13	245.7478	272.5907	16.0574
M14	245.8924	272.7942	16.0501
M15	262.8383	291.5063	17.1902
M16	179.3146	198.9724	11.6889

Table 8 The prediction accuracy of different models in testing set of Tesla-Model Y

Notations	MAE	RMSE	MAPE (%)
M1	1706.3896	1771.5607	17.0157
M2	1704.3820	1769.4849	16.9955
M3	1589.4203	1650.1333	15.8491
M4	1525.5464	1583.8327	15.2120
M5	1524.4873	1582.7083	15.2018
M6	1490.1610	1547.0920	14.8592
M7	1430.4486	1485.1038	14.2637
M8	1429.8000	1484.4123	14.2575
M9	1366.7642	1418.9778	13.6288
M10	1493.4574	1550.5017	14.8923
M11	1468.8699	1524.9959	14.6468
M12	1374.3691	1426.8781	13.7046
M13	1712.2380	1777.6431	17.0738
M14	1707.8340	1773.0670	17.0300
M15	1909.4238	1982.3407	19.0404
M16	1222.5598	1269.2664	12.1908

(1) Models M4–M6 are superior to M1–M3 in all MAE, RMSE, and MAPE metrics. In addition, Models M7–M9 are superior to M4–M6 in all MAE, RMSE, and MAPE metrics. The results show that the prediction accuracy of BPNN, RNN, LSTM, and SVM is gradually improved with the addition of sentiment value and denoising algorithm.

(2) M16 are superior to M1–M15 in all MAE, RMSE, and MAPE metrics, which demonstrates that the accuracy of the online review-driven combination forecasting model proposed in this paper is better than that of individual forecasting model.
(3) Models M1–M3 are superior to M10–M15 in all MAE, RMSE, and MAPE metrics, which show that the individual forecasting method used in this paper: BPNN, RNN and LSTM are superior to SVM, ARIMA, GARCH, and GM(1, 1) in prediction accuracy.

5 Conclusion

In this paper, we propose an online review-driven combination forecasting model to forecast NEV sales. First, to quantify online reviews, the sentiment value concerning various product attributes composed of the sentiment score and the sentiment tendency is defined using prospect theory, which can depict the psychology of consumer behaviour. Second, the Mallat pyramidal algorithm is used to denoise the sentiment values to mitigate the impact of reviews with nonstandard expressions, malicious reviews and spam. Finally, an online review-driven combination forecasting model is developed by combining a BPNN, an RNN and an LSTM neural network. To verify the effectiveness and feasibility of the proposed model, we select the BYD-Tang NEV as an example to conduct experiments. The corresponding statistical evaluation indicators and the DM test show that the proposed forecasting model is better than the benchmark models. Furthermore, the robustness test shows that the proposed model is stable. It is worth pointing out that the effective combination of online reviews and forecasting models significantly enhances the accuracy of prediction.

Our research has certain implications for managers and consumers. Firstly, managers can gain valuable insights into product attributes through online review mining, and incorporate the emotional evaluation of consumers regarding key attributes into future product optimization and improvement. Additionally, they can use the sales forecasting results to effectively manage product inventory. Secondly, consumers can use online reviews to evaluate the advantages and disadvantages of products, and make purchase decisions based on product sales.

A limitation of the proposed model is its inability to handle unstructured online review information, such as hotel review information and mobile review information, which often lacks fixed topical features. The model is currently only suitable for structured online review data. In addition, for an unstructured comment framework, other textual features, including topical features or low-level vectors, should be considered by using text analysis algorithms [55].

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Declarations

Conflict of interest The authors declared that they have no conflicts of interest to this work. We declare that we do not have any commercial or associative interest that represents a conflict of interest in connection with the work submitted.

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