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ORIGINAL RESEARCH

# A hybrid ARIMA-LSTM model optimized by BP in the forecast of outpatient visits

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**Abstract**
Effective hospital outpatient forecasting is an important prerequisite for modern hospitals to implement intelligent management of medical resources. As outpatient visits flow may be complex and diverse volatility, we propose a hybrid Autoregressive Integrated Moving Average (ARIMA)-Long Short Term Memory (LSTM) model, which hybridizes the ARIMA model and LSTM model to obtain the linear tendency and nonlinear tendency correspondingly. Instead of the traditional methods that artificially assume the linear components and nonlinear components should be linearly added, we propose employing backpropagation neural networks (BP) to imitate the real relationship between them. The proposed hybrid model is applied to real data analysis and experimental analysis to justify its performance against single ARIMA model, single LSTM model and the hybrid ARIMA-LSTM model based on the traditional method. Compared with competitors, the proposed hybrid model produced the lowest RMSE, MAE and MAPE. It achieves more accurate and stable prediction. Therefore, the proposed model can be a promising alternative in outpatient visit predictive problems.

**Keywords** Hybrid forecasting model · Neural networks · ARIMA · LSTM · BP · Outpatient visits

## 1 Introduction

As the aging population increases, medical services in China are facing a shortage of health resources and a disproportional distribution of medical investment (Kadri et al. 2014; Luo et al. 2017). With the rapid development of the Internet of Medical Things, hospital medical work has become increasingly meticulous, intelligent and efficient. Thus, how to make reasonable health resource management decisions has received more attention. In addition, accurately forecasting the healthcare demand and resource availability becomes more important and critical (Kadri et al. 2014; Liu 2009). Outpatient departments (ODs) which are windows of hospital service, experiences increasing pressure year by year (Luo et al. 2017). Effective hospital outpatient forecasting is an important prerequisite for modern hospitals to manage medical resources intelligently. Accurate outpatient visit prediction aids in planning and decision-making for future arrangements and is the foundation for better utilization of resources and improving the levels of service (Zhou et al. 2016).

Based on the forecasting results, outpatient departments can make a better schedule for doctors and nurses and can also make a better distribution plan for drugs and materials (Kadri et al. 2014). Reliable prediction of outpatients' periodic changes contributes to scientifically allocating the medical supply, such as medical equipment, surgical equipment and hospital beds. Overall, the outpatient visit prediction system can act as a decision support system for policy makers and improve the service of outpatient departments to increase patient satisfaction. The ways that the outpatient visit prediction system benefits a hospital include an improvement in the outpatient throughput arrangement, a more effective operational plan, more comfortable service, more effective staff management. Therefore, it has motivated numerous researchers to build mathematical models to realize accurate forecasting

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(Sundaram et al. 2017; Yu et al. 2017; Zhao et al. 2017; Zhou et al. 2016).

The ARIMA model was first proposed by Box and Jenkins (1976), and Hillmer and Tiao (1982a, b), and can capture the linear components in time series with less computation burden. Li et al. (2014) adopted an "ARIMA model to predict monthly outpatient visits in a grade 3 hospital in China". Sun et al. (2009) and Kadri et al. (2014) applied ARIMA models to forecast daily numbers of patients at hospital EDs, which indicated that the model was simple, easy to master and very practical for predicting ED workloads. In the literature, many extensions of this model have been proposed, such as the seasonal ARIMA (SARIMA) and multiplicative seasonal ARIMA (MSARIMA) models (Kalpakis et al. 2000). However, in the real world, the volatility in time series is complex and diverse. Thus, a single linear model may not be sufficient to select all the characteristics and may lead to poor prediction. A hybrid model is a combination of different models and can synthesize the characteristics of the individual models. For example, a hybrid model consisting of a linear model and a nonlinear model will theoretically have both linear and nonlinear fitting capabilities. Using a hybrid model to solve complex time series forecasting problems will inevitably be more accurate than using a single model. Since 2003, inspired by Zhang (2003), many statisticians have focused on the usage of machine learning techniques that perform well in nonlinear tasks as a complement to traditional linear models, such as artificial neural networks (ANNs) and support vector machines (SVMs) (Zhang et al. 2018b; Wang et al. 2017). An increasing number of hybrid or mixture models have been provided, and the literature on this aspect has expanded dramatically (Kumar and Thenmozhi, 2014; Luo et al. 2017; Zhang 2003). Flores et al. (2010) proposed a hybrid model composed of an ARIMA model and artificial neural networks (ANNs) for time series forecasting. Kumar et al. (2014) compared the ARIMA-SVM, ARIMA-random, and ARIMA-ANN hybrid models. However, the construction of the above popular hybrid models inspired by Zhang (2003) are mostly based on the idea that complex time series data are composed of linear components and nonlinear components, and the two parts are simply linearly added. Therefore, when dealing with complex prediction problems, the time series can be decomposed into two parts. According to the respective characteristics of the different parts obtained after decomposition, different models are used. The final result is the superposition of the forecasting values of individual models. However, if the linear components and the nonlinear components in the time series are not simply linearly added, the traditional blending methods will reduce the prediction accuracy, and the prediction accuracy may even be lower than that of the individual models.

This paper proposes a hybrid ARIMA-LSTM model, where the LSTM model is one of the most suitable neural network models for time series data. Instead of presuming that the linear components and the nonlinear components are simply linearly added, we propose back-propagation (BP) neural network to train and imitate the real relationship between them. Here, we propose a hybrid ARIMA-LSTM model optimized by BP, among which the ARIMA model obtains the linear components and the LSTM model obtains the nonlinear components (Qian et al. 2019). The most obvious advantage of LSTM networks is their ability to precisely retain and remember information in long sequences or time series (Salman et al. 2018), which overcomes the problem of vanishing gradients during "backward propagation over time" (Siami-Namini et al. 2018; Zhang et al. 2018a). However, few researchers have combined LSTM with an ARIMA model to exploit their respective advantages. Here, instead of any assumption, we use the BP neural network model to train the real relationship between the ARIMA and LSTM models. To prevent overfitting, choosing the BP neural network with a simple internal structure is a necessary choice (Huang et al. 2009).

To assess the proposed method, we applied it to the forecasting analysis of outpatient visits in the respiratory department of the First Hospital of Shanxi Medical University in China. In the experimental analysis, we further tested it with another two datasets of the outpatient visits of the digestive department and cardiology department of the Shanxi Provincial People's Hospital. Through real data analysis and experimental analysis, the proposed model outperformed the single ARIMA model, the single LSTM model and the ARIMA-LSTM hybrid model based on the traditional method proposed by Zhang (2003). The purposed model was proven to be an accurate and practical predictive model.

## 2 Materials and methods

### 2.1 ARIMA model section

An ARIMA model consists of three sections: autoregressive (AR), integration (I), and moving average (MA) (Zhang et al. 2018c). The parameters of the corresponding parts are p, d, and q, which represent the autoregressive order, the difference order and the moving average order, respectively (Kalpakis et al. 2000). The ARIMA model assumes that the future value of the variable is a linear function of several past observations and random errors (Siami-Namini et al. 2018).

The equation of the ARMA model is as follows:

$$\begin{aligned} x_t =& \delta + \emptyset_1 x_{t-1} + \emptyset_2 x_{t-2} + \cdots + \emptyset_p x_{t-p} + \mu_t \\ &+ \theta_1 \mu_{t-1} + \theta_2 \mu_{t-2} + \cdots + \theta_q \mu_{t-q} \end{aligned} \tag{1}$$

where $x_t$ represents the value at current time; $\varnothing_1, \varnothing_2, \ldots\ldots, \varnothing_p$ are autoregressive coefficient of AR model;$\theta_1, \theta_2, \ldots\ldots, \theta_p$ are moving average coefficient of MA model; $\mu_t$ is the residual sequence; δ is the constant term.

$$\varnothing(\mathrm{L})x_t = \theta(L)\mu_t \tag{2}$$

where L is the lag operator. For unstable sequences, the difference operator $\nabla^d$ is needed. The following formula is considered:

$$\varphi(\mathrm{L}) = \nabla^d = (1 - L)^d \tag{3}$$

Thus the formula of the ARIMA (p, d, q) model can be described as follows:

$$\varnothing(\mathrm{L})\varphi(\mathrm{L})x_t = \theta(L)\mu_t \tag{4}$$

Seasonal autoregressive integrated moving average (SARIMA) model is used when the time series displays a seasonal variation. There are six parts in an SARIMA model: autoregressive (AR), seasonal autoregressive (SAR), integration (I), seasonal integration (SI), moving average (MA) and seasonal moving average (SMA), where p, d, q, P, D, and Q are the corresponding parameters. The general SARIMA model can be written as SARIMA (p, d, q) (P, D, Q) $_{[m]}$, where m is the seasonal differencing order. For weekly time series, m = 24; for monthly time series, m = 12.

Although, for the time series forecasting problems, the ARIMA model is perhaps one of the most widely used models. However, to assume the linear functional form of the model in advance is its major limitation, which presumes there are only linear inner correlations between the time series. As a result, the nonlinear characteristics cannot be captured. The approximation of only linear models in complex problems cannot always be fit.

### 2.2 LSTM model section

The advantage of LSTM models is their extraordinary ability to retain and remember information in long sequences or time series. Before understanding the LSTM network, recurrent neural networks (RNNs), which are specifically designed to handle sequence dependency, should first be introduced. An RNN that is a sequential model is outstanding for time series prediction. The inner structure of an RNN is shown in Fig. 1. It takes a vector of time series as input values x = $x_1, x_2, x_3 \ldots\ldots x_t$ and then outputs a vector computed by its neural network structures in its model's cells (denoted by "A" in Fig. 1). The vector spanning a period is sequentially passed through cell A. At each time step, the cell outputs a computed value, which is also a part of the inputs of the next time step. The process is then repeated until the last time step. Cell A in Fig. 1 can be replaced with various forms of cells.

In this paper, we set cell A to a standard LSTM cell. In deep learning, LSTM is a widely used RNN because of its excellent performance. The hidden layer module of LSTM is also called the memory module. It is composed of three computing components that are called input gates, forget gates and output gates, which control reading, storing and writing respectively (Gers and Eck 2010; Janardhanan and Barrett 2017). The three gates are similar to valves, and their opening and closing affect the transmission of neuronal information. They determine how much information is involved in the calculation of the current neuron and how much is passed to the next neuron (Gers and Eck 2010). An illustration of the inner structure of the LSTM is provided in Fig. 2. (1) The σ function, denoted by "σ" in Fig. 2, is a logistic and special function of LSTM model. It is used as an activation function that enables the nonlinear capabilities of the LSTM model. The input gates and the candidate gates work together to render the new cell $C_t$, which will be passed along to the next stage as the renewed cell. The input gates use a sigmoid function ($i_t$) as the activation function, and the input candidate gates use a hyperbolic tangent function ($m_t$) as the activation function. The tanh function, which is denoted by "tanh" in Fig. 2, is also a special function of LSTM. (2) The forget gates outputs a forget vector, whose values will be between 0 and 1. The function $f_t$ serves as a forgetter multiplied by the cell values from the former time

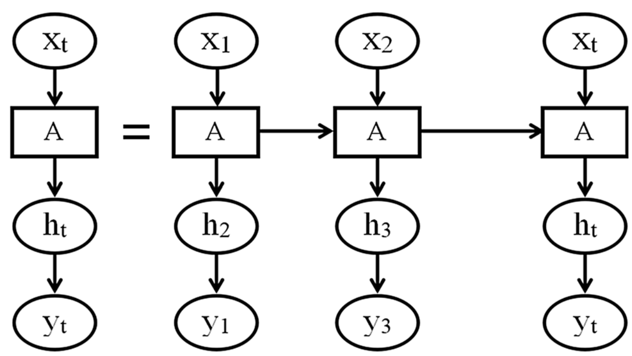



**Fig. 1** Structure of a recurrent neural network

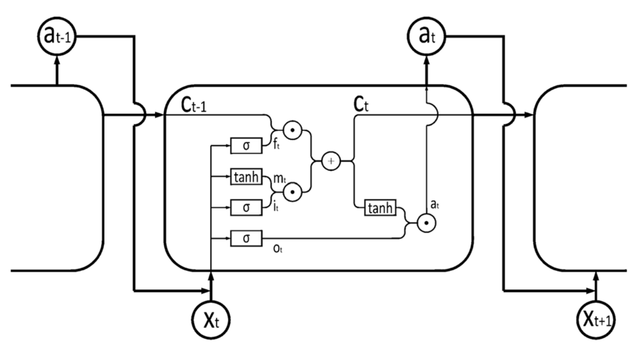



**Fig. 2** Internal structure of an LSTM neural network

step to drop the values that are not needed. (3) The output gates determine which values can be retained. As a result, the $o_t$ and the tanh-applied values are incorporated into the output $a_t$. The final cell is a hybrid of the last forgot-gate-applied cell and the new "tanh"-applied cell. The cell $C_t$ and output $a_t$ will be the input of the next stage. The next loop will be repeated.

### 2.3 ARIMA-LSTM hybrid model optimized by BP

This paper proposes a hybrid ARIMA-LSTM model optimized by BP for outpatient visit forecasting. The ARIMA and LSTM models are proposed to train the linear and nonlinear components accordingly. The proposed model can be processed in the following steps.

In the first step, an ARIMA model is introduced to model the linear components. Then, the residuals of ARIMA model may not contain linear tendency. However, it is assumed that the sequence residuals may contain some nonlinear tendency that cannot be detected by the linear ARIMA model. In the second step, the residuals of the ARIMA model are regarded as the input of the LSTM model, and the LSTM model is utilized to train the nonlinear tendency by modelling the residual series. At the last step, differing from most methods that artificially assume the relationships between the linear components and nonlinear components are linearly added, we use the BP model to learn and imitate the real relationships between them. The flow chart of the hybrid model is shown in Fig. 3.

Before exploring the theory of the proposed model, we introduce a way by Zhang (2003) to combine the LSTM and ARIMA models. They presume that the linear and nonlinear forecasting values can be summed to obtain an aggregated output, which is the final forecasting result, as follows:

$$y_t = M_t + N_t \tag{5}$$

where $y_t$ is the raw values. $M_t$ and $N_t$ are the linear and nonlinear components, respectively. The residuals are obtained from the linear modelling process of the ARIMA model:

$$r_t = y_t - \widehat{M}_t \tag{6}$$

where the residuals $r_t$ are the input of the LSTM model here.$\widehat{M}_t$ and $\widehat{r}_t$ are the predicted values of $M_t$ and $r_t$ estimated by the ARIMA model and LSTM model, respectively. Thus, the hybrid ARIMA-LSTM model based on the traditional method can be defined by the following formula:

$$\widehat{y}_t = \widehat{M}_t + \widehat{r}_t \tag{7}$$

However, the relationship between them may not be linear and can be any form. Here, we use the BP neural network model to train the real relationship.

$$\widehat{y}_t = f\left(\widehat{M}_t, \widehat{r}_t\right) \tag{8}$$

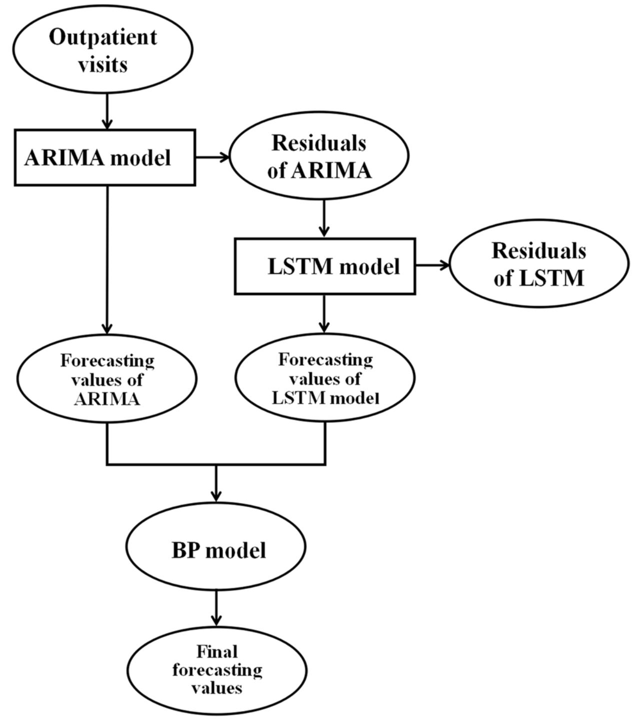



**Fig. 3** The construction of the proposed hybrid ARIMA-LSTM model

where $\widehat{y}_t$ is the forecasting value of the proposed model at time t.$\widehat{M}_t$ and $\widehat{r}_t$ are the forecasting results of the single ARIMA and LSTM models, respectively. We do not prematurely assume their linear relationship, so we regard it as an unknown functional relationship. The $f$ function here is unknown and can be any form. During the training progress, the forecasting values of the ARIMA model and the forecasting values of the LSTM model are regarded as the inputs of the BP model, and the final predictions of the BP network are the raw values.

BP models are one of the most commonly used neural networks and use a gradient descent method to minimize the total error (Xing et al. 2018). This classic neural network consists of an input layer section, an output layer section, and one or more hidden layers between them (Liu 2009). Each layer has several nodes (neurons), and each node accepts information from other nodes through connection weights and then outputs information. The BP algorithm consists of two processes: forward propagation and backpropagation. In forward propagation, the inputs are passed from the input layer to the output layer via the hidden layer. If the outputs do not capture the desired error, the algorithm goes to backpropagation. To minimize the total error, the training process of the BP network is a continual readjustment between the initial weight and threshold. The inner structure of the BP neural network is shown in Fig. 4.

## 3 Results

Here, we performed an outpatient visit prediction analysis of the respiratory department of the First Hospital of Shanxi Medical University. The number of outpatient visits in the respiratory department may explode in winter and is greatly affected by seasonal factors. Upper respiratory tract infections are directly related to sudden decreases in temperature and large temperature differences between the morning and evening (Wang et al. 2019). These diseases put considerable pressure on hospital management. At the same time, the media have reported that strengthening the medical power of the respiratory departments and emergency departments in winter is needed (Hadavandi et al. 2012). Therefore, it is of great significance for hospitals to monitor, compare and study the changes in outpatient visits to respiratory departments for sound management. A plot of the raw numbers of outpatient visits (from June 1, 2014 to February 17, 2019) in the respiratory department is shown in Fig. 5. The dataset in Fig. 5 was divided into two sub-datasets: a training dataset (from June 1, 2014, to September 9, 2018) and a testing dataset (from September 9, 2018, to February 17, 2019). The training dataset is used to train model, and testing dataset is proposed to test model accuracy.

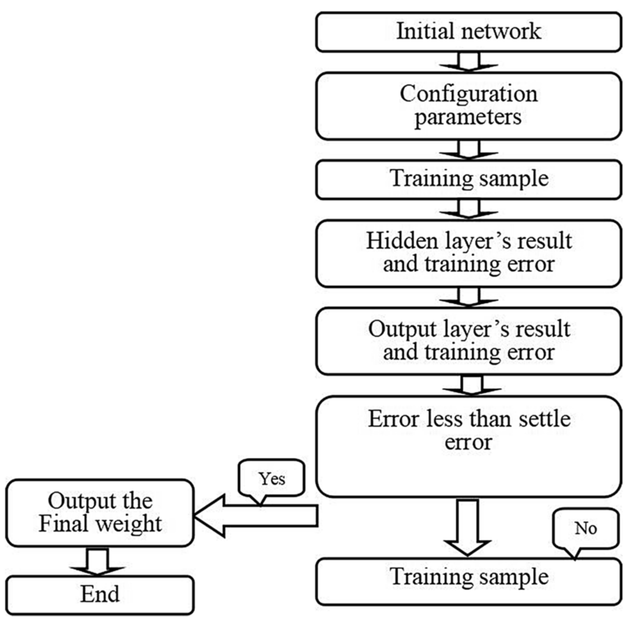


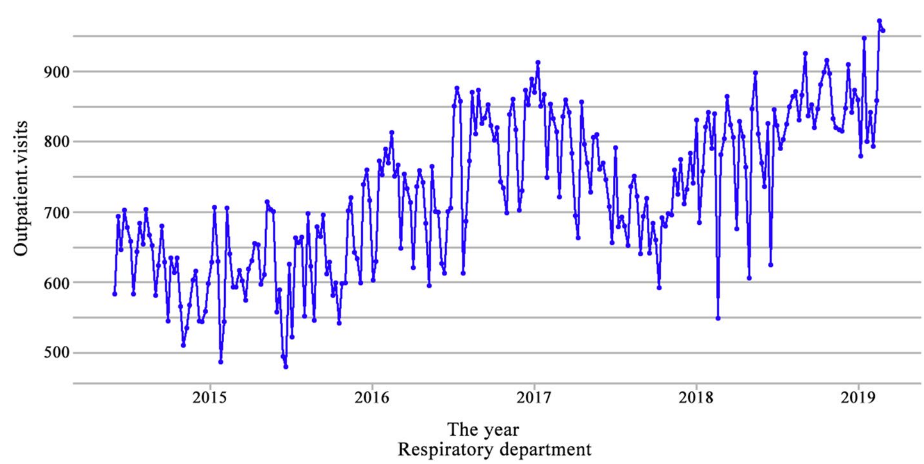

**Fig. 4** The inner structure of the BP neural network

### 3.1 ARIMA modelling

Five steps are involved in modelling and forecasting for the ARIMA model: model identification, establishing a stable time series, parameter estimation, model diagnosis, and forecasting. As a nonstable trend and seasonal trend are observed in the time series of outpatient visits of the respiratory department, the SARIMA model is proposed. After one non-seasonal difference step, the time series became stable.

In Fig. 6, the possible parameters (p, P) were estimated by the plots of the autocorrelation function (ACF), and the possible parameters (q, Q) were estimated by the plots of partial autocorrelation function (PACF). Then, we obtained a few possible models with different coefficient combinations. To determine the optimal model among all possible models, we selected the Akaike information criterion (AIC) and the Bayesian information criterion (BIC) as the judgement criteria. Finally, the SARIMA (3, 1, 1) (0, 0, 1) $_{[48]}$ model with the lowest AIC and BIC was chosen as the optimal model. As the dataset consists of weekly outpatient visits, we set the period to 48 here. If we were to test the monthly outpatient visits, the period would be set to 12. After applying the white noise test to the proposed model, we obtained $p > 0.05$, which means that the model was reasonable.

**Fig. 5** The number of outpatient visits to the respiratory department (from June 1, 2014, to February 17, 2019)



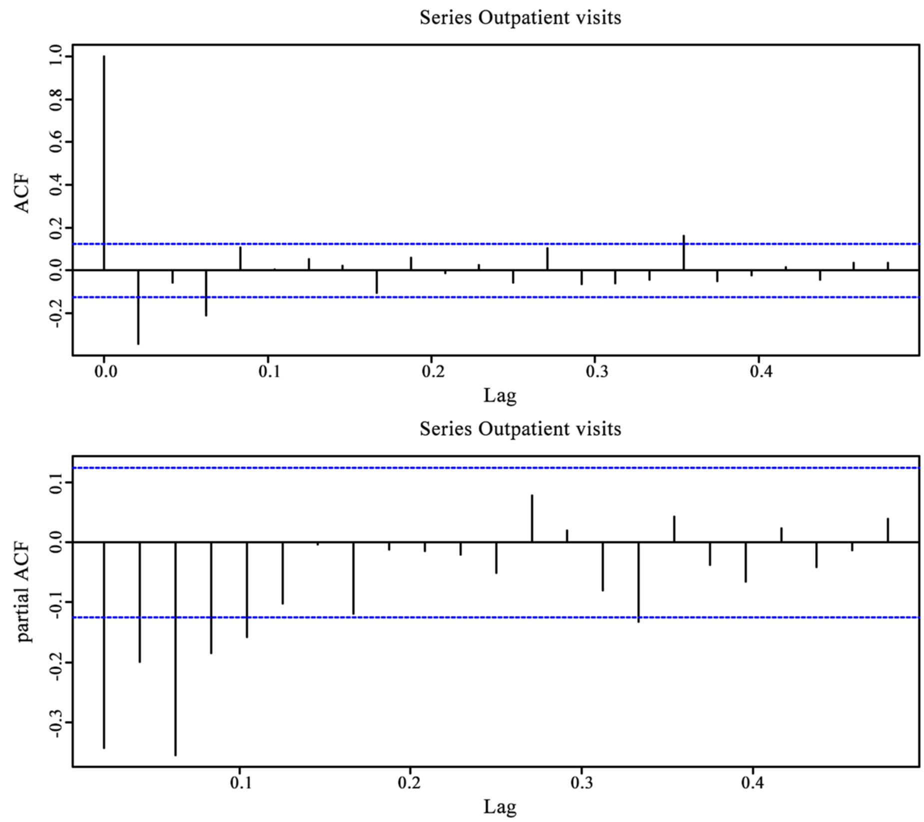



**Fig. 6** The ACF and PACF plots of the outpatient visits in respiratory department after one non-seasonal differencing

## 3.2 LSTM network modelling

In this part, the time series should be normalized and transformed into a range between 0 and 1. The output functions can be most sensitive if the data are between 0 and 1, which will improve the efficiency of training. LSTM networks with different numbers of epochs and neurons in the hidden layer are applied to adjust the hyperparameters. Through multiple attempts, we obtained the optimal LSTM model, which coincidentally was the default model in the "Keras" library of the R language pack. The loss function was the mean squared error, the optimizer was the Adam algorithm, and the number of training epochs was set to 300. See the "Keras" package for more details.

## 3.3 ARIMA-LSTM hybrid model optimized by BP modelling

$\widehat{M}_t$ is the predicted value of the ARIMA model and $r_t$ is the forecasting value of LSTM model. At the training step, the $y_t$ is the raw value of outpatient visits, while at the forecasting step, the $y_t$ is the final forecasting value. In BP neural network, $\widehat{M}_t$ and $r_t$ should also be normalized and transformed into a range between 0 and 1. In the optimal BP model, there was only two hidden layer consist of five neurons.

To compare the performance of the three models, we apply the single ARIMA model, single LSTM model and the ARIMA-LSTM model optimized by BP to forecast the outpatient visits in the respiratory department correspondingly. Figure 7 shows the comparison of the raw values and the forecasting values of three different models for 24 weeks (the testing dataset). In the ARIMA model, "p" preceding data points are required to predict the upcoming one. When move on to predict the next one, just the predicted value of the current data points are taken forward to predict next data point. In the single LSTM model, we set the "timestep" as 48. For example, we set the raw data points of 48 weeks in the preceding year as the input vector, and then output the forecasting data point of the first week in the upcoming year. In the ARIMA-LSTM model optimized by BP, we also set the "timestep" of the residuals of ARIMA model as 48, and then we apply the LSTM model to select the nonlinear tendency in the residuals. At last, we put the BP model to learn the real relationship between the forecasting values of ARIMA model and forecasting values of LSTM model. As shown in Fig. 7, the prediction accuracy of the three models decreases with extension of the forecasting period. However, the forecasting trend from the proposed method is closest to the trend in the

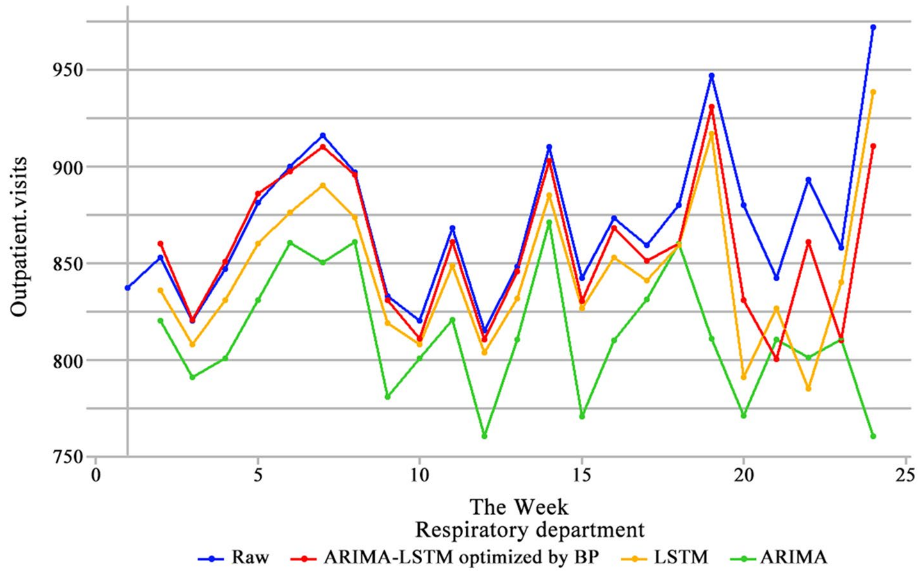



**Fig. 7** The comparison of the raw values, single ARIMA model, single LSTM model and the ARIMA-LSTM model optimized by BP for the respiratory department over 24 weeks (from September 9, 2018, to February 17, 2019)

**Table 1** Performance comparison of the evaluation statistics in respiratory department for the three models during the 24 weeks (from September 9, 2018, to February 17, 2019)

| | Single ARIMA model | Single LSTM model | ARIMA-LSTM optimized by BP |
|---|---|---|---|
| RMSE | 62.00 | 55.13 | 33.17 |
| MAE | 40.81 | 38.10 | 20.00 |
| MAPE (%) | 23.56 | 20.95 | 14.13 |

original data. Through the analysis of the above dataset, we also compare the performance of three models by error estimation functions: the mean absolute error (MAE), root mean square error (RMSE) and mean absolute percentage error (MAPE) (Khazaee et al. 2019). As Table 1 shows, the hybrid model achieves superior performance.

## 4 Experimental analysis

In the experimental analysis, we chose the datasets from the People's Hospital of Shanxi Province to validate the proposed model. These datasets consist of the outpatient visits to the digestive department and cardiology department. The datasets were also divided into two sub-datasets: the training dataset (from June 1, 2014, to September 9, 2018) and the testing dataset (from September 9, 2018, to February 17, 2019). The outpatient visits (from June 1, 2014, to February 17, 2019) to the digestive department and cardiology department are shown in Fig. 8.

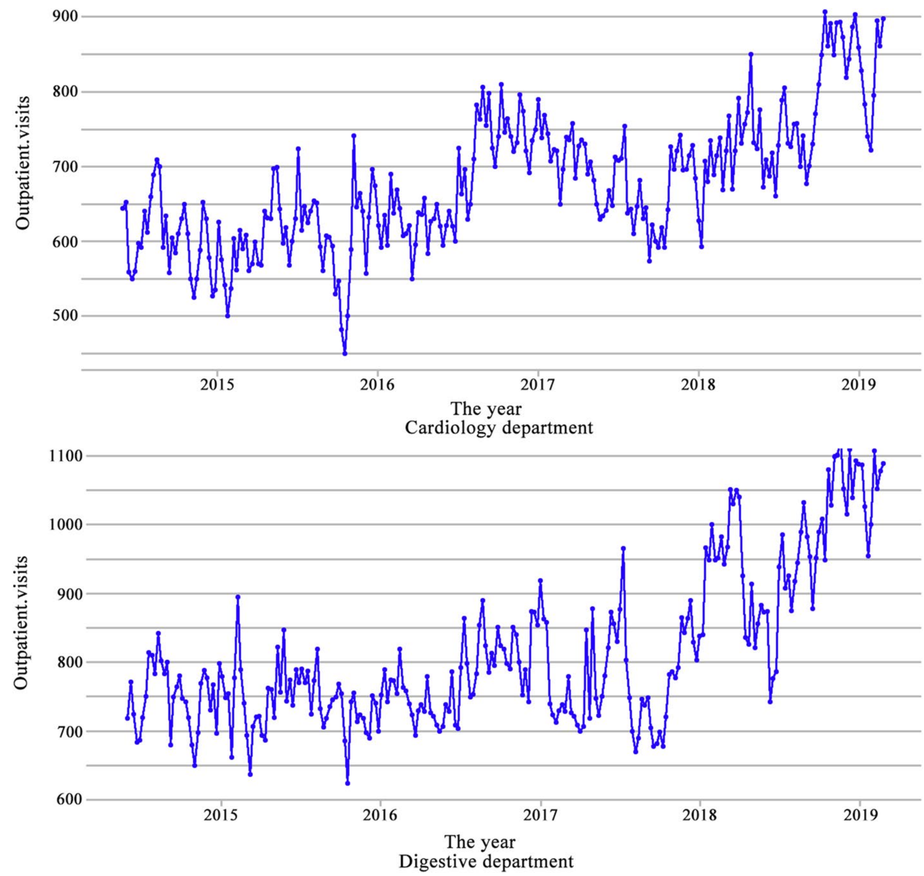
In this section, we compared the performance of the ARIMA-LSTM hybrid model based on the traditional method proposed by Zhang (2003) and the ARIMA-LSTM hybrid model optimized by BP. The predictions of the 24 weeks (testing dataset) were computed by two hybrid models based on two methods. The performance contrasts of two different hybrid models and raw values for the digestive department and cardiology department during the 24 weeks (from September 9, 2018 to February 17, 2019) are presented in Fig. 9.

The comparison of two models (the ARIMA-LSTM hybrid model based on the traditional methods proposed by Zhang (2003) and the ARIMA-LSTM hybrid model optimized by BP) for the cardiology department and digestive department in terms of the three error criteria is shown in Table 2. Whether the analysis for the cardiology department or digestive department, the proposed model produced the lowest RMSE, MAE and MAPE, indicating that it was more accurate than the other model and achieved stable prediction.

## 5 Discussion

This paper presented a hybrid ARIMA-LSTM model optimized by BP for outpatient visit forecasting. The analysis of the real-world data from the respiratory department of the First Hospital of Shanxi Medical University shows that the hybrid model displays higher accuracy than the single ARIMA or LSTM models. In the experimental analysis, it has been shown that the proposed hybrid model outperforms the competing methods by achieving the lowest RMSE,

**Fig. 8** The outpatient visits from June 1, 2014, to February 17, 2019 to the cardiology and digestive departments




MAE and MAPE. Therefore, the proposed model can be a suitable tool for outpatient visit forecasting problems.

This hybrid model helps policy makers know in advance the changes in outpatient volume in the coming weeks or months. The predicted outpatient volume can be compared with the volume in the same period in the previous year to determine the allocation of medical resources to increase revenue and decrease costs. If there is a significant drop in the number outpatient visits in a department, we should adjust the staff configuration, equipment configuration and medicine storage, which will save medical costs to avoid unnecessary waste. If there is a significant increase in the number of outpatient visits, we need to add more doctors, nurses and medical supplies, such as medical equipment, surgical equipment and hospital beds, to prevent overcrowding caused by insufficient preparation and to prevent providing unsatisfactory medical services to patients.

The proposed model has the following advantages:

1. Although the single ARIMA and single LSTM model can forecast outpatient visits, there are considerable advantages to combine these two complementary methods together. The linear ARIMA model and the nonlinear LSTM model are used jointly to capture different components of time series. For the complex prediction problem, the combination of the two models can be a valid way to increase the forecasting performance.
2. Most methods artificially assume that the relationship between linear trends and nonlinear trends are linear. This is one view. In this paper, we used a BP neural network to learn and imitate the real relationship between the ARIMA and LSTM models.

However, there are still shortcomings and downsides of our model, especially in practical applications. Considering only the perspective of statistics, this model is suitable for time series data with relatively simple influence factors. For more complicated situations, further adjustments are needed. In the real world, the number of outpatient visits in large general hospitals are affected by numerous uncertain factors, such as randomness, periodicity and trends (Dechanont et al. 2018; Mitiku et al. 2018). They are also affected by the weather, traffic, service environment, hospital business activities, Medical

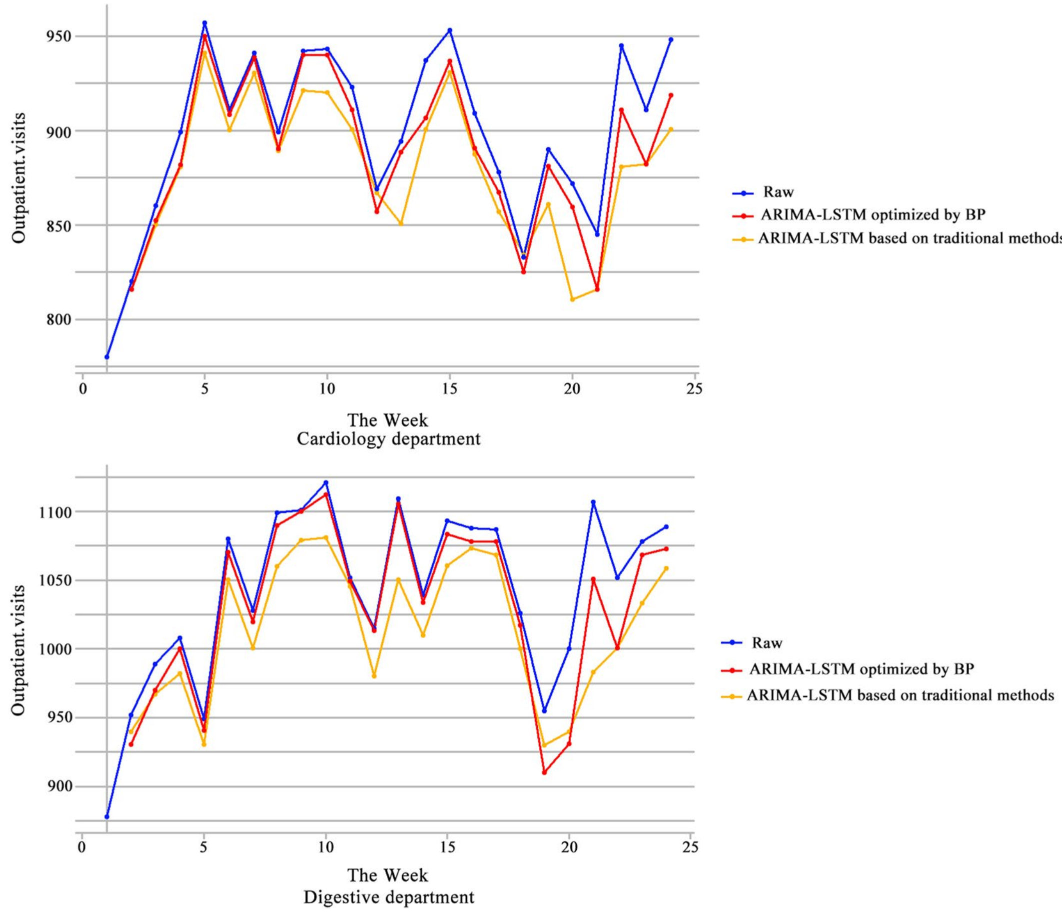



**Fig. 9** The comparison of the fitting and forecasting performances of the two methods for the cardiology department and digestive department over 24 weeks (from September 9, 2018, to February 17, 2019)

**Table 2** The comparison of the evaluation statistics of the two categories for the cardiology department and digestive department during the 24 weeks (from September 9, 2018, to February 17, 2019)

| | ARIMA-LSTM based on traditional methods | | | ARIMA-LSTM optimized by BP | | |
|---|---|---|---|---|---|---|
| | RMSE | MAE | MAPE (%) | RMSE | MAE | MAPE (%) |
| Cardiology | 50.71 | 28.11 | 18.27 | 41.25 | 21.71 | 10.82 |
| Digestive | 48.68 | 32.49 | 19.68 | 30.79 | 25.68 | 12.33 |

& Health policy and so on. To introduce the covariates into the hybrid model is our main task in the next stage.

## 6 Conclusion

This paper proposed a hybrid model for the forecasting of time series and a strategy to integrate linear and nonlinear trends. Building a more targeted forecasting model according to the specificity of actual datasets will be our focus in future studies. Furthermore, the proposed model is by no means limited to applications in outpatient visit prediction and can easily be adapted to other research. Our hybrid model not only make use of the linear trend of the time series, but also utilize its nonlinear trend to improve the prediction accuracy. It can be applied to the general time series forecasting problems, such as sales forecasting, weather forecasting, infectious disease prediction and stock trend forecasting.

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**Data availability** The outpatient visit data used to support the findings of this study are available from the corresponding author upon request.

## Compliance with ethical standards

**Conflict of interest** The authors declare no conflicts of interest.

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