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Analysis and Prediction of Epidemic Prevention and Control by Police Stations Based on Time Series

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Abstract. It has been over two years since the outburst of the COVID-19 pandemic. Currently, China has entered into a normalization stage and police stations are still in the endeavor of improving their epidemic prevention and control measures. However, grassroots police stations are still backward in epidemic prevention and control, and lack of response measures for each period of the epidemic. This paper uses time series models to predict the epidemic trend and analyze the measures undertaken by the police stations. In the process of data pretreatment, this paper focuses on the data processing of the epidemic control period. Then the epidemic trend is predicted based on five different time series models and two different time intervals. The results indicate that the tertiary exponential smoothing prediction model with day as the interval is the best and accurate prediction method. According to the prediction model, it can be determined the current stage of the epidemic development by time points, so as to give targeted reference for the police stations. The basic idea in using various time series models is to predict the accumulated number of confirmed cases based on the existing data not only to help, guide and refine the existing epidemic measures but also offer suggestions for epidemic prevention and control by police stations in response to each period of the epidemic. Based on the findings exhaustive recommendations are proposed for real-time and targeted epidemic prevention and control by police administration.

Keywords: epidemic prevention and control, police station, floating population, time series model

1 Introduction

In the first four months of the COVID-19 outbreak, hundreds of thousands of people died, millions were infected, tens of millions lost their jobs, and hundreds of millions were forced to quarantine at home [1-2]. In this case, police stations in the front line had to play a crucial role in combating the spread. The effectiveness of the epidemic prevention and control measures taken by the police stations is directly related to the citizens' safety under their jurisdiction. Only when the frontline workers do a stupendous job, the risks can be minimized and the epidemic can be contained before the virus spread uncontrollably. Based on the last two years of data, we investigated that although all the government departments jointly shouldered the responsibility, many loopholes and deficiencies still exist in the epidemic prevention and control measures by the police stations. The management of floating population and cooperation with other non-public security units are the key issues that grassroots police stations need to focus in epidemic prevention and control. Application of the models to predict the number of confirmed cases can make the epidemic prevention and control measures of public security real-time and targeted. In this study, time series models are used to predict the epidemic trend and to provide scientific recommendations for effective epidemic prevention and control in each time point. The main contribution of this work are as follows:

- This paper uses time series models to predict the epidemic trend.
- Whether the time period when the epidemic is largely under control should be taken into account in time series model for prediction is discussed.
- Five different time series models are compared for prediction of confirmed cases.
- The interval of accumulated number of confirmed cases is predicted with day and month.

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- Time series models are applied to predict the epidemic trend and to determine the current stage of the epidemic development by time points.
- The epidemic prevention and control measures undertaken by the police stations can be adjusted according to the predicated time period.

This study is divided into four sections. An extensive literature review of the studies on epidemic prevention and control measures in China and abroad is presented in Section 2. In Section 3, five different time series models are used to predict the future trend of the epidemic to understand which method gives more reliable and accurate predictions and Section 4 summarizes the results.

2 Literature Review

As early as 1998, Heath pointed out that public crisis managers should actively use modern information technology to collect, analyze and study the information about public crises in order to respond efficiently and accurately to any public disasters [3]. In 2000, Bardes and Oldendick studied the public opinion system built by the US government using information technology and tools and found that the system has significantly improved the efficiency of public crisis management [4]. In view of the practical applications, Google successfully predicted in 2009 the outbreak of influenza in winter in the United States by using a keyword search based on the big data, and the predicted time was more than a week earlier than that proclaimed by the Centers for Disease Control and Prevention (CDC). In 2011, Polgreen used Google log keywords to model the spread of dengue fever in Bolivia, Brazil, India, and Indonesia, and the model predictions correlated well with the actual surveillance data [5]. In 2015, James *et al.* used the m-Health strategy for relief assistance, needs assessment, and disease surveillance based on the big data analysis of population movement signals to significantly improve the efficiency of Ebola control in West Africa [6].

In 2004, China launched the first nationwide advanced technology “Infectious Diseases and Public Health Emergencies Reporting System”, to coordinate a nationwide response to infectious disease outbreaks by extending its coverage to all the primary health units across the country. Subsequently, various improved systems have been reported. In 2017, Feng et al. studied and designed an infectious disease surveillance system to monitor and analyze big data, that can give early warning signals, identify the disease, trace the source of infection, and predict its development trends [7]. In 2020, Zhou et al. studied the purpose, participants, main contents, spatial and temporal presentation, and construction strategy of big data profile of public health emergencies by applying the theory of user profile to public health emergencies [8]. Mei *et al.* discussed the role of big data in supporting the continuous improvement of clinical diagnosis and treatment and proposed that big data can contribute to epidemic prevention and control. They also analyzed the problems in the application of big data in the prevention and control of major epidemics, such as low data accuracy, data fragmentation, and insufficient data disclosure and privacy protection [9]. Samah and Taresh mentioned various emergency management key factors in colleges and universities during the COVID-19 epidemic [10]. Kong et al. studied emergency management measures and countermeasures in the community, street, and other levels [11]. Liu et al. investigated the psychological impact of community police officers under epidemic prevention, control and countermeasures [12]. These studies are based on different application scenarios, which combine different application functions and scenario requirements while predicting epidemic trends.

Although studies on the prevention and control of the COVID-19 epidemic have been conducted from a variety of perspectives, but have following limitations:

- Most are from the public health and epidemiological perspectives, while the epidemic prevention and control measures taken by the basic units especially, police stations have rarely been discussed.
- Lack of specific guidance and suggestions for public security in each period through epidemic prediction.

In this research, we determine the current stage of the epidemic development by the time series models, and the epidemic prevention and control measures undertaken by the police stations can be adjusted according to the current time period. In addition, this paper makes comparative analysis of whether to add the control period data, five different time series models and two types of intervals of confirmed cases. In this study, the epidemic prevention and control measures of police stations are analyzed by time series models to predict the epidemic trend, which can help police administration to plan epidemic prevention and control work in advance and provide some references for further development.

3 Prediction of Epidemic Trend Using Time Series Prediction Models

As the epidemic spreads, police stations cannot always take preempted epidemic prevention and control measures since such measures are always one step behind the virus hence, the effectiveness of the prevention and control measures is always compromised. Therefore, this chapter uses time-series models to predict the accumulated number of confirmed cases to ascertain the recent epidemic trend, with an aim to prevent and control one step ahead of the virus. In order to test the accuracy and scope of the application of the time series models, the prediction is divided into two parts namely, daily and monthly basis.

3.1 Data Source

The required data on the accumulated number of confirmed cases were collated daily from the official website of Henan Province, China from January 2020 to March 2022.

3.2 Principles of Time Series Models

In this study, the time series prediction models are computed by using five methods, which are primary movement average method, secondary movement average method, primary exponential smoothing method, secondary exponential smoothing method, and tertiary exponential smoothing method. The prediction method and predicable range of the five time series prediction models vary.

Primary Movement Average Method. The following formula is used for primary movement average:

$$M_t = \frac{Y_t + Y_{t-1} + \ldots + Y_{t-N+1}}{N}. \quad \textbf{(1)}$$

Where, M_t is the primary movement average of the t th period, t is the number of periods, N is the amount of data in each time period, and Y is the moving average item [13]. The advantage of the primary movement average method is that the calculation is small, and the moving average can reflect the trend and change of time series.

Secondary Movement Average Method. The secondary movement average method is the second moving average of the primary movement average. First, the primary movement average $M_t^{(1)}$ is calculated by Eq (1), and then the secondary movement average is calculated by using:

$$M_t^{(2)} = \frac{M_{\mathrm{t}}^{(1)} + M_{\mathrm{t-1}}^{(1)} + \ldots + M_{\mathrm{t-N+1}}^{(1)}}{N}. \quad \textbf{(2)}$$

The secondary movement average formula is:

$$F_{\mathrm{t}+T} = a_t + b_t T. \quad \textbf{(3)}$$

Where, T is the number of periods, a_t is the intercept, that is, the base level of the t th period, and b_t is the slope, that is, the amount of change per unit time of the t th period. Herein, $a_t = 2M_t^{(1)} - M_t^{(2)}$ and $b_t = \frac{2}{n-1}(M_t^{(1)} - M_t^{(2)})$. The secondary movement average method can be used not only for short-term forecast, but also for a short period of time, which is more applicable than the primary movement average.

Primary Exponential Smoothing Method. When the time series has no obvious trend change, the primary exponential smoothing method can be used for prediction. The initial value is calculated using:

$$S_0^{(1)} = \frac{y_1 + y_2}{2}. \tag{4}$$

The primary exponential smoothing formula is:

$$S_{\mathrm{t}}^{(1)} = ay_t + (1-a)S_{t-1}^{(1)}. \tag{5}$$

Where, a is the weight (0 < a < 1) and y_t is the primary exponential smoothing of the t th period [14-15].

Secondary Exponential Smoothing Method. When the linear trend of time series appears, there will be obvious lag deviation when using the primary exponential smoothing method to predict, and the secondary exponential smoothing method can be used on the basis of the primary exponential smoothing method. The primary exponential smoothing can be calculated by Eq (5) and the initial value of secondary exponential smoothing is calculated by primary exponential smoothing by using:

$$S_0^{(2)} = \frac{S_1^{(1)} + S_2^{(1)}}{2}. \tag{6}$$

The secondary exponential smoothing formula is:

$$S_{\mathrm{t}}^{(2)} = aS_t^{(1)} + (1-a)S_{t-1}^{(2)}. \tag{7}$$

Where, $a_t = 2S_{\mathrm{t}}^{(1)} - S_t^{(2)}$, $b_t = \frac{a}{1-a}(S_t^{(1)} - S_t^{(2)})$ and $F_{\mathrm{t}+T} = a_t + b_t T$. **(8)**

Tertiary Exponential Smoothing Method. If the time series has a tendency of conic curve and it is believed that the future will change according to this trend, the tertiary exponential smoothing method should be used for prediction [16]. After using the above two methods, the initial value of the tertiary exponential smoothing is calculated as:

$$S_0^{(3)} = \frac{S_1^{(2)} + S_2^{(2)}}{2}. \tag{9}$$

The tertiary exponential smoothing formula is:

$$S_{\mathrm{t}}^{(3)} = aS_t^{(2)} + (1-a)S_{t-1}^{(1)}. \tag{10}$$

Where,

$$\begin{aligned}
a_t &= 3S_{\mathrm{t}}^{(1)} - 3S_t^{(2)} + S_{\mathrm{t}}^{(3)}, \\
b_t &= \frac{a}{2(1-a)^2}((6\text{-}5a)\ S_t^{(1)} - 2(5-4a)S_t^{(2)} + (4-3a)S_t^{(3)}), \\
c_t &= \frac{a^2}{(1-a)^2}(S_t^{(1)} - 2S_t^{(2)} + S_t^{(3)}), \\
F_{\mathrm{t}+T} &= a_t + b_t T + \mathrm{c}_t T^2.
\end{aligned} \tag{11}$$

Calculation of Error Rate. The error rate is the percentage of the difference between the actual data and the predicted data calculated by the time series model. The error rate is kept around 1%, because when the error rate is small, the prediction results are accurate and are useful for reference and use [17].

3.3 Data Pre-Processing Based on COVID-19 Development Characteristics

Since the calculated values from the time series prediction model are subject to the cyclical and stochastic fluctuations, the initial pre-processing of the values is required in the forecasting process. In the analysis of the data for prediction, we found that the accumulated number of official confirmed cases in Henan Province remained constant over a 15 months period meaning there were no new cases registered and the spread was under control.

In order to analyze whether this 15 months period data will make an impact on the calculation of the prediction results, the model was computed in two ways. One is to add the 15 months period data in the calculation, and the other is to exclude it from the calculation and compare the mean squared error (MSE).

The MSE is calculated by:

$$MSE = \frac{1}{N}\sum_{t=1}^{N} e_t^{\,2} = \frac{1}{N}\sum_{t=1}^{N} (Y_t - F_t)^2 . \quad (12)$$

As the value of MSE increases, the error as well as the prediction error also increases [18].

The results of the original MSC and the current MSE obtained by primary movement average method and the secondary exponential smoothing method in the comparative experiments are depicted below:

Table 1. Original MSE of primary movement average method

MSE	MSE	MSE
N=2	N=4	N=6
65277.16	61713.38043	67590.84524

Table 2. Current MSE of primary movement average method

MSE	MSE	MSE
N=2	N=4	N=6
182582.44	350937.68	606409.12

Table 3. Original MSE of secondary exponential smoothing method

MSE (a=0.3)	MSE (a=0.7)
40333597.75	64731141.63
23355251.7	106180717.6
45989218.61	177534506.3
81837501.99	300913221.8
1957814225	2308798327
40333597.75	64731141.63

Table 4. Current MSE of secondary exponential smoothing method

MSE (a=0.3)	MSE (a=0.7)
92129020.2	163322284.5
130468764.4	318517077.5
184904245.5	616638210.5
205977400.85	947211851.39
254525857.08	1392858207.02
92129020.2	163322284.5

It is noticed from the Table 1 to Table 4 that the MSE values, when the data were included, increased by a factor of 10 or even 20, which are significantly larger than the MSE computed values after the exclusion of the data. This demonstrates that the errors of the prediction results increase and the results are of less reference value after the data are removed. Therefore, when a time series model is used for the prediction, the time period when the epidemic is largely under control should also be taken into account in prediction of the data instead of being removed.

3.4 Predictions with Day as the Interval

Primary Movement Average Method. According to Fig. 1, the prediction by the primary movement average method with day as an interval and N = 2, the predicted data and actual data exhibit similar and almost match each other. Whereas, the error rate of the accumulated number of confirmed cases fluctuates between 0% and 1%, with the maximum error rate not exceeding 1.5%, and is within the ideal range.

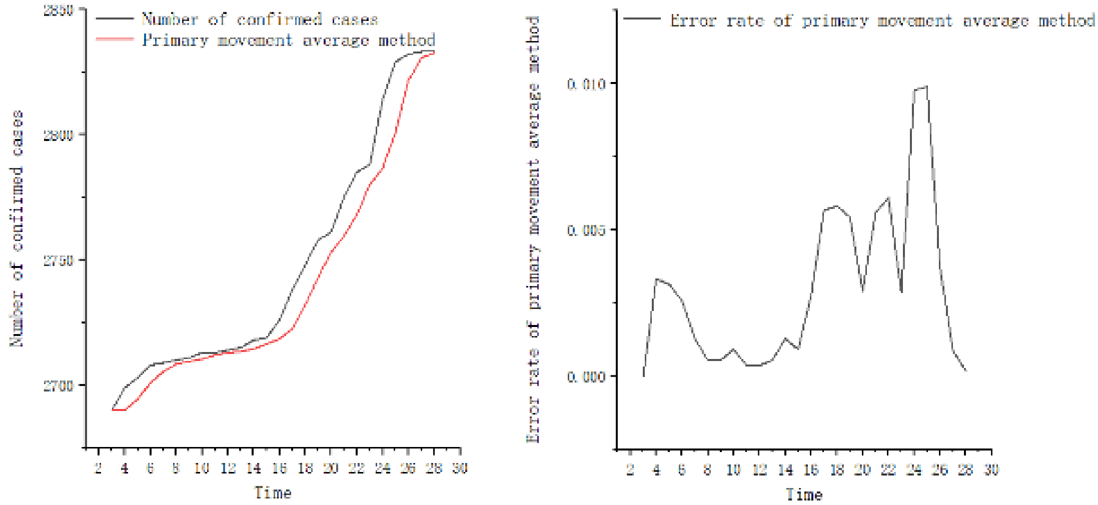

Fig. 1. Accumulated number of confirmed cases obtained by primary movement average method (time unit = day)

Secondary Movement Average Method. Similarly in Fig. 2, the prediction by the secondary movement average method with day as an interval and T = 1, the actual and predicted data almost match each other. However, the consistency of the actual data and the predicted data obtained by the secondary movement average method is significantly inferior to that by the primary movement average method. Meanwhile, the error rate fluctuated from -2% to 2%, indicating that the range is significantly larger than the results obtained by the primary movement average method. Therefore, in the predictions with day as an interval, the accuracy of the results obtained by the primary movement average method is higher than that by the secondary movement average method.

Primary Exponential Smoothing Method. As observed from Fig. 3, the prediction by the primary exponential smoothing method with day as an interval and a = 0.7, the consistency between the actual and predicted data is relatively high, but the trend remains the same. Meanwhile, the error rate of the accumulated number of confirmed cases also fluctuates between 0% and 1.5%, indicating an ideal prediction result.

Secondary Exponential Smoothing Method. As seen from Fig. 4, the prediction by the secondary exponential smoothing method with day as an interval, the consistency of the actual and predicted data is relatively high when a = 0.3 (compared to that when a = 0.7). However, for a =0.3, the error rate fluctuates between 0% and 1%; for a =0.7, the error rate fluctuates between -0.5% and 2%, indicating a significant fluctuation range. Therefore, for predictions by the secondary exponential smoothing method with day as the interval, in consideration of data characteristics, it is more reasonable to keep the value of ‘a’ between 0 to 0.5, which can ensure the accuracy between 0% and 1% and yield more accurate prediction results.

Tertiary Exponential Smoothing Method. As shown in Fig. 5, predictions by the tertiary exponential smoothing method with day as an interval, the values of the actual data and predicted data of the accumulated number of confirmed cases when a = 0.3 are higher than that in the case of a = 0.7, while the error rates in both cases fluctuate between -1% and 1%, showing a less difference.

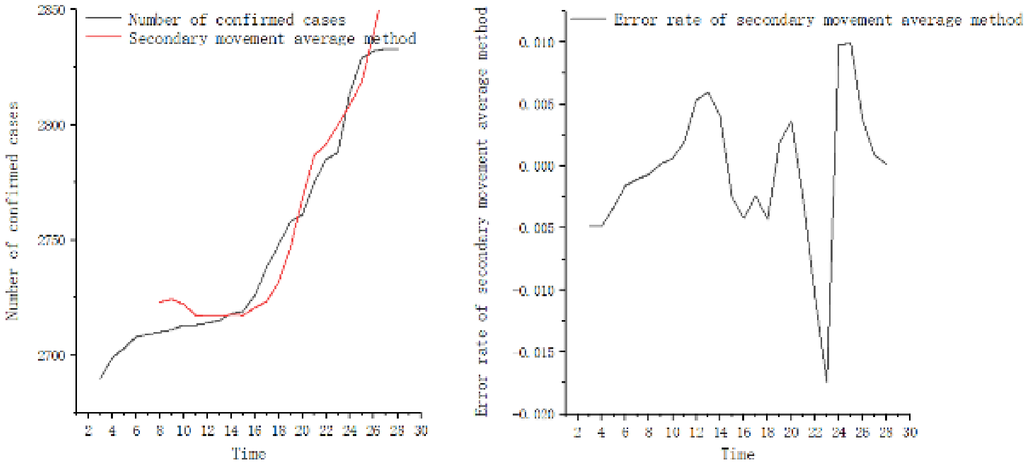

Fig. 2. Accumulated number of confirmed cases obtained by secondary movement average method (time unit = day)

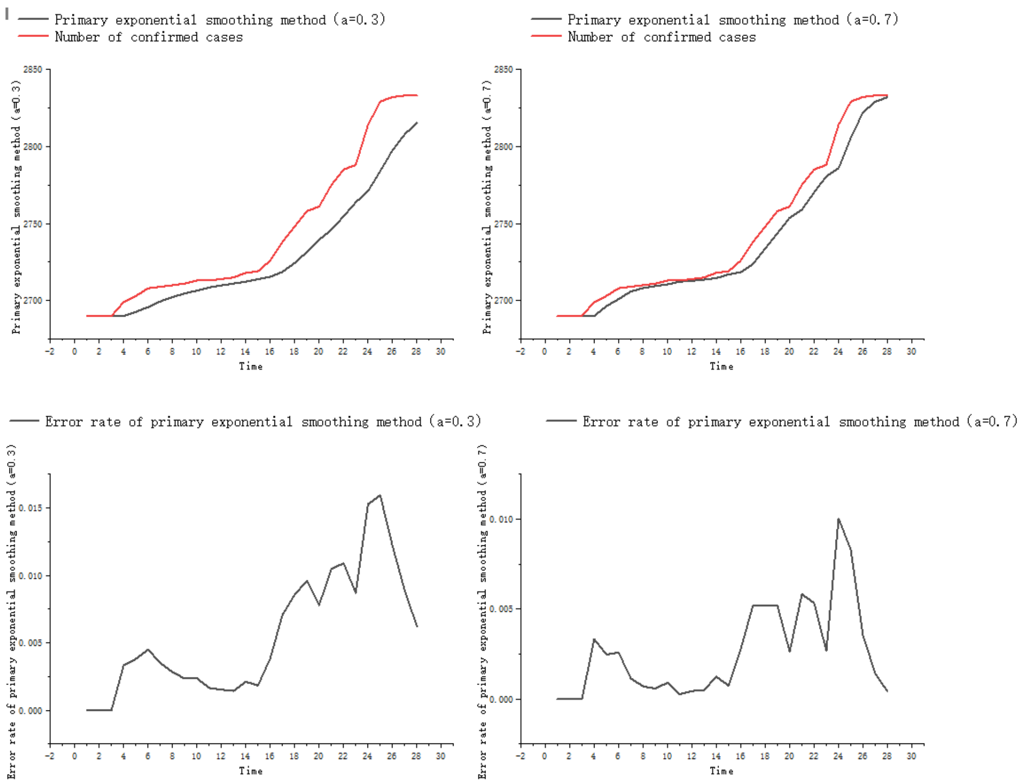

Fig. 3. Accumulated number of confirmed cases obtained by primary exponential smoothing method (time unit = day)

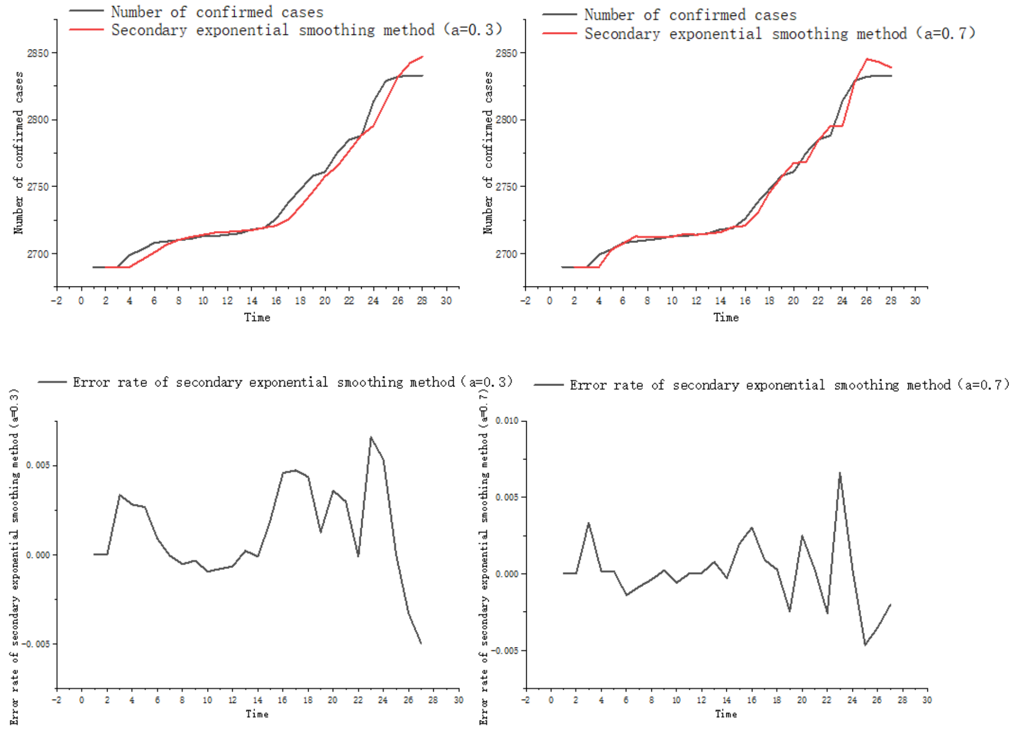

Fig. 4. Accumulated number of confirmed cases obtained by secondary exponential smoothing method (time unit = Day)

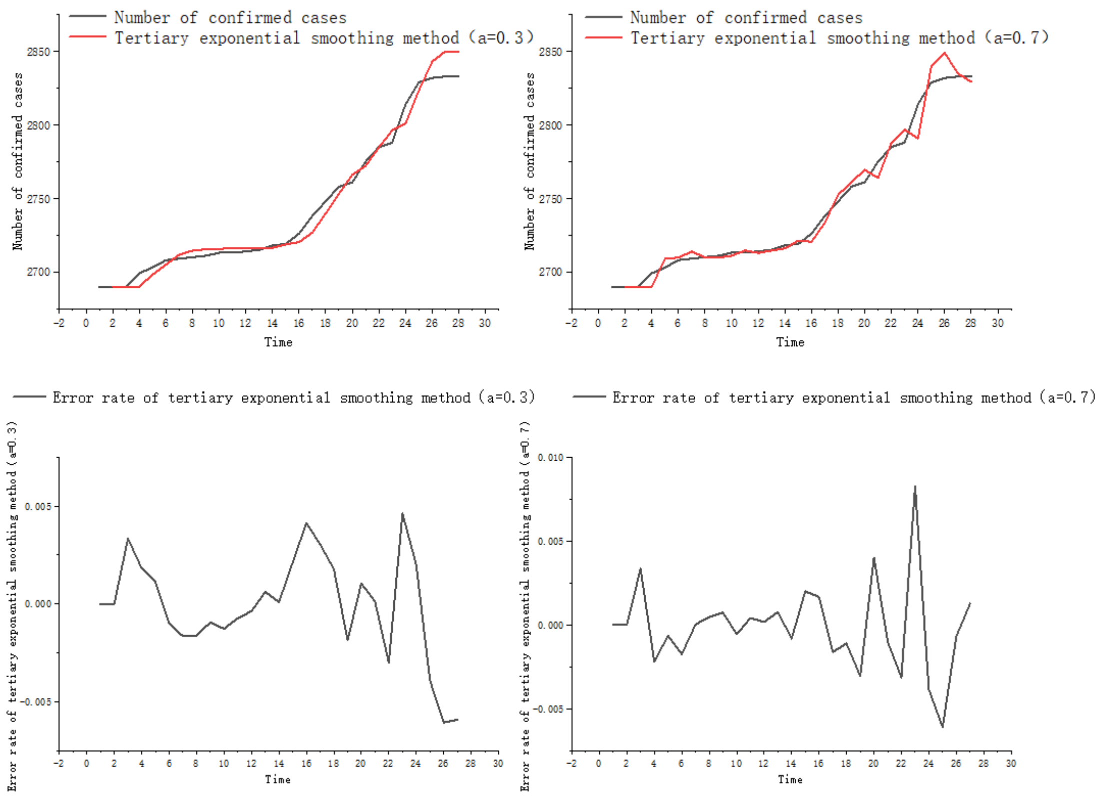

Fig. 5. Accumulated number of confirmed cases obtained by tertiary exponential smoothing method (time unit = day)

3.5 Predictions with Month as the Interval

Primary Movement Average Method. Fig. 6 reveals that the predicted data of the accumulated number of confirmed cases are close to the actual data when N = 2, when the predictions are done by the primary movement average method. However, the fluctuation of the data starts increasing in the latter part along with the error rate, with the overall error fluctuation between 0% and 25% and do not meet the requirements of an ideal model prediction results.

Secondary Movement Average Method. As seen from Fig. 7, the predictions by the secondary movement average method when T = 1, the predicted data of the accumulated number of confirmed cases are close to the actual data. However, it is observed that, even in the part where the predicted data are close to the actual data, the fluctuation trend of the predicted data and actual data differ significantly. Therefore, in predictions with month as an interval, the stability of the prediction results by the secondary movement average method was lower than that of the prediction results by the primary movement average method. It can be observed that the movement average methods are more sensitive to time hence are not suitable for predictions with month as an interval.

Primary Exponential Smoothing Method. As seen from Fig. 8, in the primary exponential smoothing method when a = 0.7, the predicted data of the accumulated number of confirmed cases are close to the actual data, and the trend of the data in the subsequent fluctuating part is also consistent. However, the error rate is still not about 1%, and does not meet the prediction requirements. Therefore, the prediction results by the primary exponential smoothing method with month as the interval is also unsatisfactory.

Secondary Exponential Smoothing Method. According to Fig. 9, the predictions by the secondary exponential smoothing method with month as an interval and T = 1, both the predicted data and the actual data are almost close to each other, and the trend of the data in the subsequent fluctuating part is also consistent. The fluctuating range of the error rate in the case of a = 0.3 is lower than that in the case when a = 0.7. Therefore, the predictions by the secondary exponential smoothing method with month as the interval are more reasonable when "a" varies from 0 to 0.5, which ensures more accurate prediction results.

Tertiary Exponential Smoothing Method. Fig. 10 reveals that the predictions by the tertiary exponential smoothing method with month as an interval and T = 1, both the predicted data and the actual data are close to each other, and the data trend is also consistent. The fluctuating range of the error rate when a = 0.3 is lower than that when a = 0.7. Therefore, in this prediction method, it is more reasonable set "a" between 0 and 0.5, to ensure more accurate prediction results.

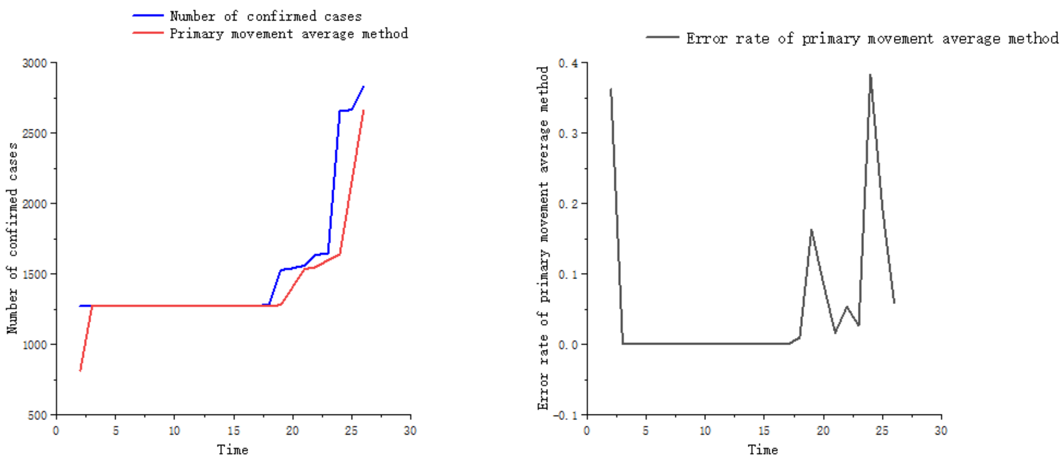

Fig. 6. Accumulated number of confirmed cases obtained by primary movement average method (time unit = month)

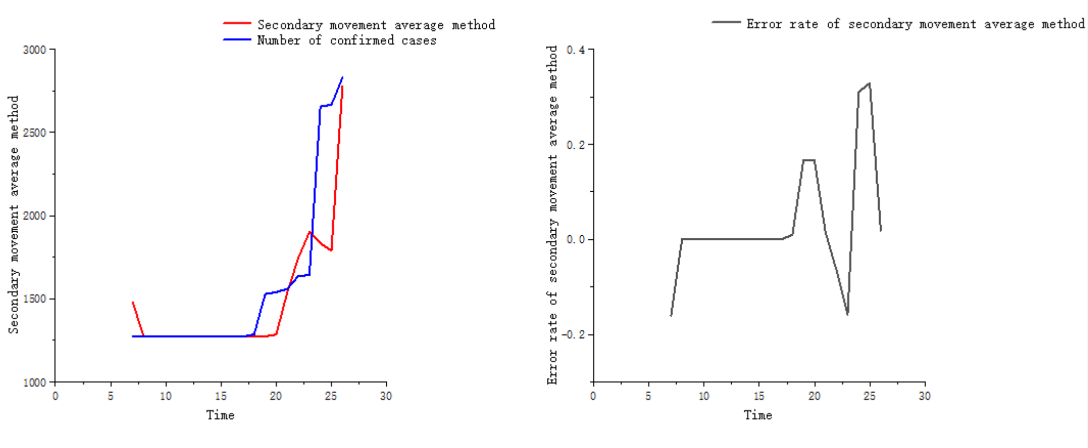

Fig. 7. Accumulated number of confirmed cases obtained by secondary movement average method (time unit = month)

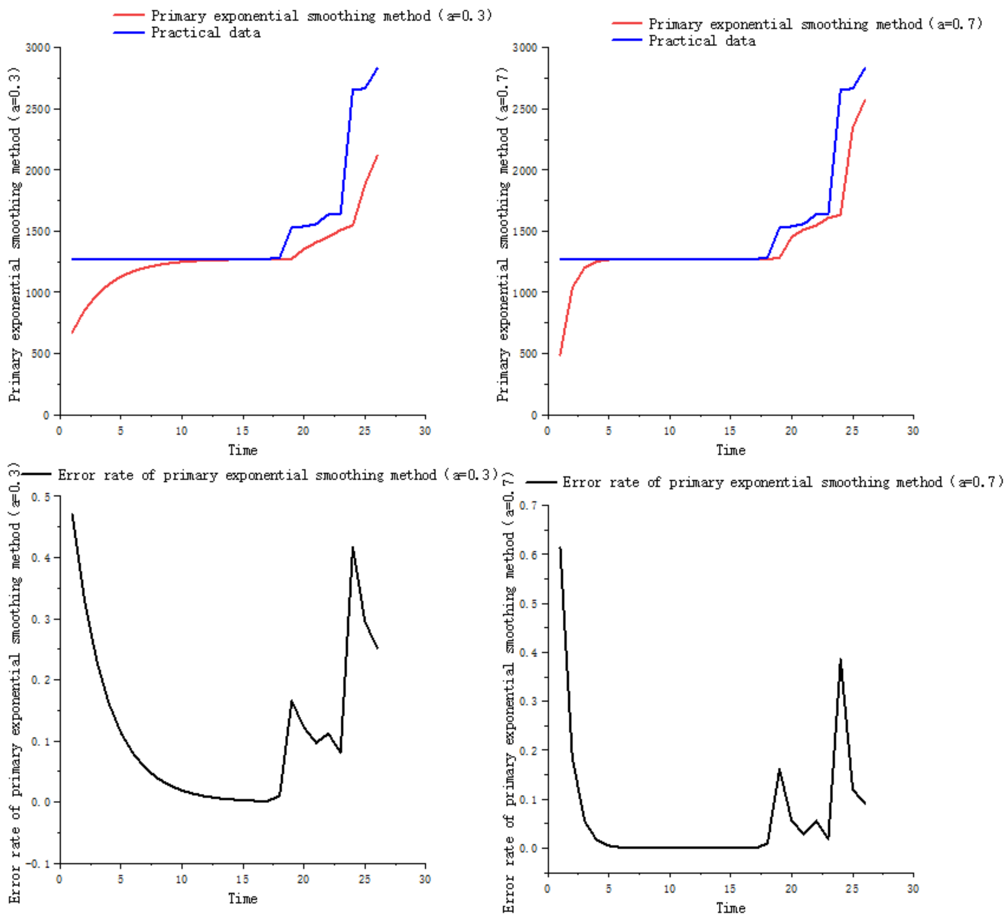

Fig. 8. Accumulated number of confirmed cases obtained by primary exponential smoothing method (time unit = month)

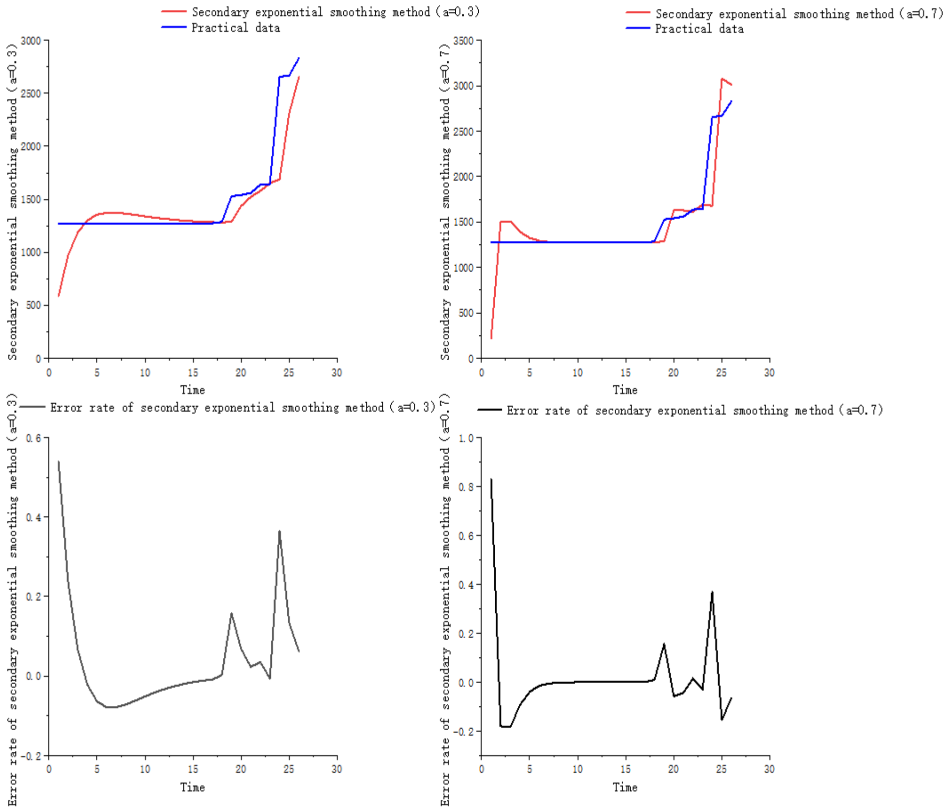

Fig. 9. Accumulated number of confirmed cases obtained by secondary exponential smoothing method (time unit = month)

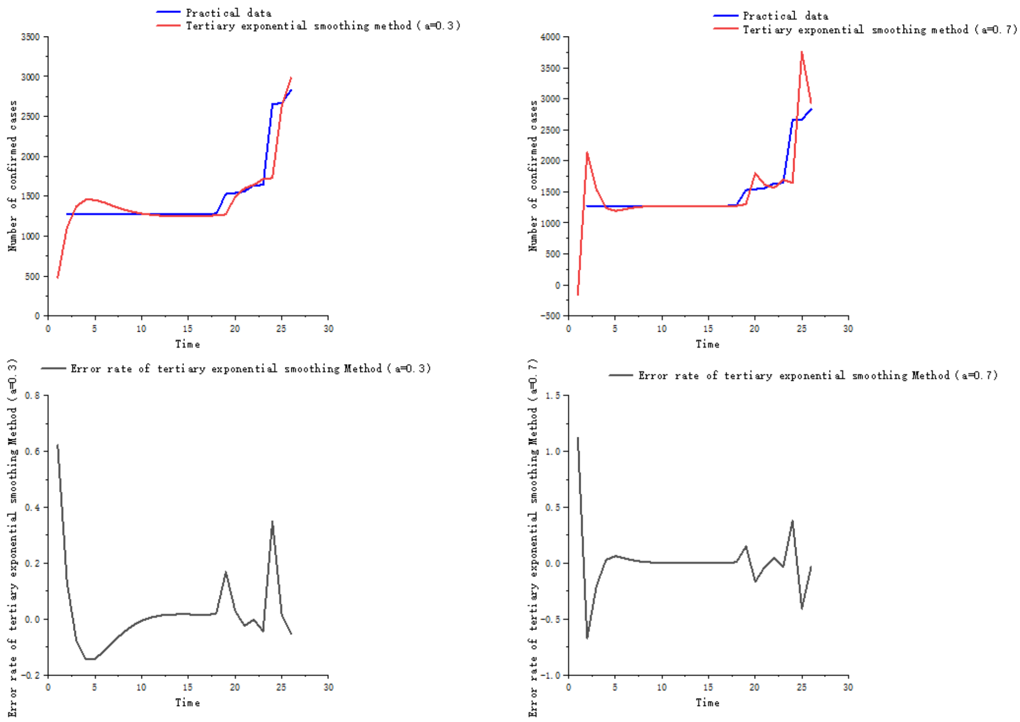

Fig. 10. Accumulated number of confirmed cases obtained by tertiary exponential smoothing method (Time unit = month)

3.6 Summary of Model Prediction Results

Model Selection. Among the movement average methods, the secondary movement average method is an improved version of the primary movement average method. The average of the results obtained by the primary movement average method always lags behind the change in the observed data whereas, the secondary movement average method corrects this lagging bias. Hence, this method can be used for predictions in both the short term and near term thus, ensuring wider applications than the primary movement average method.

For the exponential smoothing methods, the key to successful prediction lies in the value of the parameter "a". From the preceding figures, we can see that when the value of the parameter "a" is different, the consistency and the fluctuating range of the error rate of the predicted data and the actual data vary. Among the afore mentioned five model methods, the tertiary exponential smoothing method is an improved version of the first four, where the prediction results generally are more accurate in practical prediction.

Interval Selection. Furthermore, in the case of monthly accumulated number of confirmed cases, although some of the actual data overlap with the predicted data in the case of a small number of periods, the difference between the predicted results and the actual results is large and the error rate is also high resulting in inaccurate predictions due to the large time span of the data collection.

If the accumulated number of confirmed cases is predicted with day as the interval, the data matches closely. In the case of a smaller number of periods, the consistency between the predicted results and the actual results is higher, and the error rate is small and limited to about 1% giving more accurate practical values. Hence, the prediction results can not only provide guidance for the adjustment of the subsequent epidemic control measures but also of the reference value.

However, in case of monthly data interval the model predicts the results, where the predicted values and the actual values differ widely and the error is also high. Thus, when the data is constantly updated with short time span (daily), the predictions are more accurate.

3.7 Epidemic Trend Graphs Obtained from Model Prediction Results

The purpose of using a time series model is to predict the accumulated number of confirmed cases over a certain period of time so as to determine how long it takes before the cases stop increasing, and finally comes to halt. When there are no new cases reported for the two consecutive days, the outbreak is considered to be under control and is expected to end at this point.

Fig. 11 depicts the epidemic trend of the accumulated number of confirmed cases in Henan Province from January 22, 2020, to April 2, 2022. According to the epidemic trend, epidemic prevention and control measures can be adjusted. This graph can be obtained by using a time series model to predict the number of confirmed cases in order to take adequate epidemic prevention and control measures.

Time 1 was the time when the first confirmed case was registered in the province; Time 2 was the phase when the accumulated number of confirmed cases in the province remain unchanged; Time 3 was the period when a new round of outbreak again began after the outbreak was under control; Time 4 was the spell when the number of new cases suddenly increased significantly while, Time 5 was the span when the number of new cases changed steadily.

All the five time phases are critical points in the epidemic spread to keep the cases under control through prompt and effective epidemic prevention and control measures. Time 1 to Time 2 was the initial outbreak stage when first patient was reported in the province; Time 2 to Time 3 was the stage when the outbreak was well under control and stabilized; During phase 3 when a confirmed patients started reporting again and a new round of outbreak started; In stage 4 when the number of confirmed cases increased rapidly and exceptions occurred, the targeted investigation was required; While in last stage the exceptions were resolved and the outbreak stabilized.

3.8 Adjustment of Epidemic Prevention and Control Measures Based on Time Series Model Prediction Results

A time series model is used to predict the epidemic trend and to determine the current stage of the epidemic development, as shown in Fig. 11, so that the epidemic prevention and control measures can be adjusted according to the current time period.

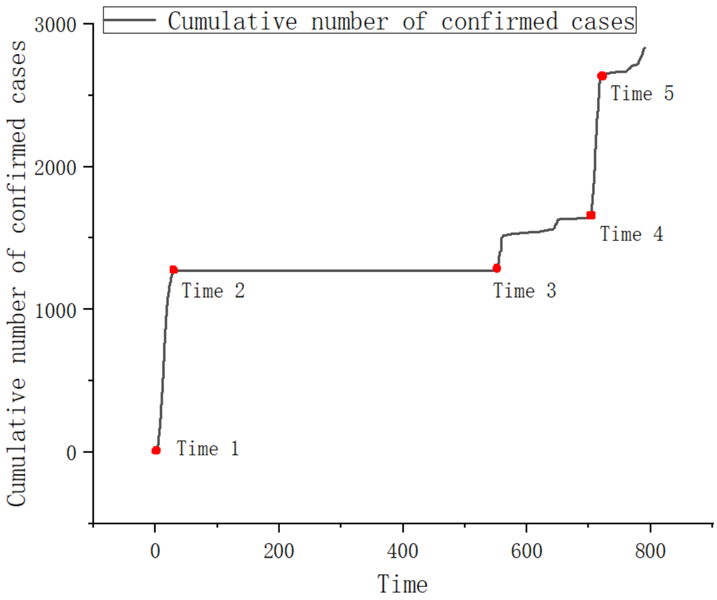

Fig. 11. Epidemic trend graph

Limit the Spread Range in the Initial Outbreak Stage. The first two stages showcase the rapid spread when the outbreak begun. Time 1 is when the first confirmed case appears. If the number of confirmed cases in the province increases too quickly, an immediate response is needed to find the sources of the spread and immediately isolate the surrounding area to prevent the widespread of the virus. During this stage, the stringent epidemic prevention and control measures need to be taken, mainly through cooperation from medical institutions. In addition, the screening of relevant people and locations have to be administered and large-scale nucleic acid testing be conducted to eliminate the potential risks.

Control the Movement of People in the Stabilization and Control Stage. In the phase 2 to 3, when the epidemic is largely under the control and no new confirmed cases are reported that is, when the number of new cases is zero for two consecutive days, the epidemic is considered to be stabilized. At this point, the focus should be on cooperation from the concerned transport departments, so as to control movement of people and to focus on the detection of the floating population coming from other provinces or regions to ensure stability during the initial outbreak. Meanwhile, police stations should work in association with the medical professionals at all levels to focus on patients with fever, dry cough, weakness, sore throat, vomiting, diarrhea, and other typical symptoms. Once the suspected patients with fever are diagnosed, they should conduct nucleic acid testing and isolate for observation. At the same time, health service stations, health clinics, and private clinics should be prohibited to admit the patients with fever and direct them to the public hospital or special isolation centers.

Identify Prevention and Control Loopholes when the Outbreak Resumes. Time 3 is when a new round of outbreak starts and the number of confirmed cases increases again but at a slower rate than at Time 1, suggesting that the outbreak is partially prevented and controlled in a timely manner. At this point, the relevant service personnel need to strictly control the public movements in congested, high-traffic, fast-personnel-movement places such as airports, railway stations, medical institutions, agricultural markets, rallies, fairs and exhibitions so as to minimize the spread of the epidemic.

Exceptions Occurred When the Number of Confirmed Cases Increases Rapidly. In stage 4, when the number of new confirmed cases dramatically increases, suggests that some infected people must have been missed or careless or asymptomatic and instrumental in the widespread transmission of infection or that the isolation measures may have some drawbacks. Further, severer lapses in the epidemic prevention and control, specifically, key personnel and isolation areas might not be strictly controlled or have lifted the lockdown too soon. In this case, the police officers should carry out the preliminary screening of the personnel at the isolation site with adequate and dedicated prevention and control personnel. In addition, training in infection control and personal hygiene needs to be arranged for management, medical staff, service personnel, besides regular administration of nucleic acid testing and mass awareness programs on media.

Normalization of Outbreak. The slowdown of the increase in the number of new cases in stage 5 indicates that the exceptions that occurred in Time 4 have been resolved and slowly the registration of new cases has come to an end. Although, the situation is normalizing, still adequate precautions have to be exercised like slowly lifting the lockdowns in the most affected key areas and stepwise closure of isolation sites.

4 Conclusions

This study uses time series models to predict the epidemic trend in the near future, so that the epidemic trend can be ascertained well in advance and the spread of the virus can be identified to take preventive measures before the number of confirmed cases grows at a faster rate. Five time series models are tested and compared to understand the best and reliable prediction model. The results indicate that the tertiary exponential smoothing prediction model is the best and accurate prediction method. Based on the findings exhaustive recommendations are proposed for real-time and targeted epidemic prevention and control by police administration. Although the time series prediction models have wider applications but only time factor is considered as an influencing factor, ignoring the other relevant factors. Considering that the results generated are often affected by the interactions between many factors, the models are not perfect and need to be improved. In addition, due to the limited time interval of data collection, the analysis conclusion is one-sided, with strong pertinence and weak universality. The accumulated number of confirmed cases is not only influenced by time, the total number of a city, personnel flow, air temperature, air humidity may affect the evolution of the epidemic. In the future, we will apply more data mining models, and the factors affecting the model to further improve the prevention and control measures of police stations.

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