ISBN: 978-981-18-5852-9
WCSE 2022 Spring Event: 2022 9th International Conference on Industrial Engineering and Applications
doi: 10.18178/wcse.2022.04.151

A Method for Predicting Atmospheric Temperature in Navigation Safety

Liwan Zhou[1], Mi Yan[2], Xin Luo[2] ,Shengwei Li[2],Lei Wang[2]

[1]Wuhan Huazhong Numerical Control co.,ltd

[2]Wuhan University of TechnologySchool of Automation

Abstract. The change of atmospheric temperature is closely related to the safety of ship sailing, so it is of great significance to make accurate prediction of atmospheric temperature. In this paper, the atmospheric temperature data of the first three months of 2016 are modeled and predicted using the autoregressive quadrature moving average model (ARIMA), using the high-precision atmospheric temperature data set of th ERA-5 reanalysis data set provided by the European Weather Forecast Center. The prediction results show that the mean absolute error of single-step prediction is about 0.4196, and the short-term prediction accuracy is high, which can be used as an effective method for atmospheric temperature prediction.

Keywords: Time series forecasting, Atmospheric temperature, ARIMA models

1. Introduction

For a long time, the change of atmospheric temperature has been closely related to human production and life. On the one hand, it affects the normal daily activities of human beings and can ensure the normal travel of human beings and the normal operation of society [1]. On the other hand, the change of atmospheric temperature also affects the development of agriculture, social industry, manufacturing industry and other industries [2]. Extreme high temperature, low temperature and other weather phenomena have a great impact on the production of all walks of life, especially in the process of shipping, so it is necessary to make a reasonable analysis and prediction of atmospheric temperature [3].

In the field of atmospheric temperature research, meteorologists were the first to predict the possible drastic temperature changes in the future through their own experience in meteorological prediction [4]. However, this method lacks scientific data interpretation and analysis, and has high requirements for researchers, so the prediction error is relatively large. Then, as researchers apply statistical knowledge to the field of atmospheric temperature research, they first collect historical data of atmospheric temperature to obtain the correlation between various meteorological factors, and establish more accurate prediction models with the help of available mathematical statistics and other principles [5].

In this paper, the Autoregressive Integrated Moving Average model (ARIMA) was used for modeling and forecasting atmospheric temperature data because of its cyclical and autocorrelation characteristics [6]. ARIMA is a method to predict future values based on historical values of time series, which does not rely on external variables and can overcome the problem of insufficient model accuracy caused by insufficient consideration of influencing factors to a certain extent , ARIMA model has high prediction accuracy and is suitable for short-term prediction of non-stationary time series, which is just suitable for short-term wind speed prediction in this paper. Moreover, this method has small data demand, complete modeling theory and strong operability[7]. The reason why this paper adopts ARIMA model to predict atmospheric temperature is that ARIMA prediction method is simpler than deep learning-based prediction method, with small data demand, complete modeling theory and strong practical operability. According to the final error comparison, the atmospheric temperature prediction based on ARIMA model has a strong practical value.

2. BASIC THEORY OF ARIMA MODEL

Time series refers to a discrete set of orderly observation records arranged in chronological order. Data contains objective records of the observed system at various time points. Time series analysis is a branch of probability theory and mathematical statistics. It analyzes random data series on the theoretical basis of probability statistics, and establishes mathematical models for them, that is, model ordering, parameter estimation, and further application in prediction, adaptive control, optimal filtering and many other aspects [8].

At present, time series prediction methods mainly include statistical learning methods, traditional machine learning methods and neural network methods. Traditional statistical learning methods, such as moving average method, autoregressive method, exponential smoothing method, are mostly to build statistical models in line with the hypothesis conditions. These methods assume that the time series is generated by a linear process, so they only need to establish the dependence between the data points of the time series according to the linear relationship, which belongs to model-driven prediction methods [9]..

2.1. ARIMA model

In 1970, Geopre E. P. Box, an American statistician, and Gwilym M. Jenkins, a British statistician, proposed a set of methods for time series analysis, prediction and control, which were called box-Jenkins modeling method, or B-J method for short[10]. Summing autoregressive moving average (ARIMA) model is one of the most important basic models. ARIMA model has high prediction accuracy and is suitable for short-term prediction of non-stationary time series [11].

Consider the non-stationary time series y_t, if it can be converted into stationary series by d-order difference:

$$w_t = \Delta^d y_t = (1-B)^d y_t \tag{1}$$

Where w_t is stationary sequence and B is delay operator, ARMA (p,q) model can be established:

$$\phi(B) w_t = \delta + \theta(B)\varepsilon_t \tag{2}$$

The ARMA(p,q) model after d-order difference is called ARIMA(p,d,q) model, and its general expression is:

$$\phi(B)\Delta^d y_t = \delta + \theta(B)\varepsilon_t \tag{3}$$

Where $\phi(B)$ is an auto regression operator, $\theta(B)$ is a moving average operator, p is the order of the auto regression model, q is the order of the moving average model, and ε_t is a white noise sequence.

The representation of the ARIMA model is as follows:

$$y_t^{'} = c + \phi_1 y_{t-1}^{'} + \phi_2 y_{t-2}^{'} + \cdots \phi_p y_{t-p}^{'} + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \cdots \theta_q\varepsilon_{t-q} + \varepsilon_t \tag{4}$$

In the above formula, $y_t^{'}$ is the difference sequence, c is the constant term, ε_t is the white noise sequence, and ε_t is assumed to be the random error term with mean equal to 0 and standard deviation equal to σ. We call this model ARIMA (p,d,q) model, in which parameter p represents the order of autoregression model, parameter d represents the order of model difference, and parameter q represents the order of moving average model.

2.2. Stationarity and stationarity test of time series

Time series modeling is established on the premise of large number theorem and central limit theorem, that is, to satisfy the same distribution of samples, that is, to satisfy the stationarity of time series. [10] If the statistical characteristics of a time series do not change over time, the following two conditions are met:

(1) For any time t, its mean is a constant.

(2) For any time t and s, the autocovariance function and autocorrelation coefficient depend only on the time interval t-s, and have nothing to do with the starting and ending points of t and s.

A time series can be said to be stationary. The properties of stationary time series do not change with observation time. Therefore, trending or seasonal time series are not stationary time series -- trends and seasonality make time series exhibit different properties at different time periods. In contrast, white noise sequences are stationary and should look the same regardless of the time of observation.

There are three main methods to test the stationarity of time series, which are trend graph test, correlation graph test and unit root test, among which the unit root test is the most widely used and the least subjective.

Therefore, this paper adopts the unit root test to judge the stationarity of time series. The basic principle of unit root test is as follows:

It is assumed that the detected time series meets the autoregressive model. For the model of the following form:

$$x_t = \phi_1 x_{t-1} + \varepsilon_t \tag{5}$$

Where ϕ_1<=1 and ε_t is a white noise term with an average expectation of 0. If ϕ_1=1, a time series is said to have a unit root. If ϕ_1>=1, the unit root exists and the model is nonstationary. Therefore, the stationarity of time series can be judged by examining the position of unit root of original time series.

Since most sequences in real life are non-stationary, the original hypothesis of unit root test is as follows:

H_0: The sequence x_t is nonstationary ⇔ $H_0: |\phi_1| \geqslant 1$

The corresponding alternative hypothesis is:

H_1: The sequence x_t is stationary ⇔ $H_1: |\phi_1| < 1$

The test statistics are:

$$\tau(\phi_1) = \frac{\hat{\phi}_1 - \phi_1}{S(\phi_1)} \tag{6}$$

DF test is unilateral test. When the significance level is α and τ_α is the α subsite of DF test, then

When $\tau \leqslant \tau_\alpha$, the null hypothesis is rejected and the sequence x_t is considered to be remarkably stationary.

When $\tau > \tau_a$, the null hypothesis is rejected and the sequence x_t is considered to be remarkably nonstationary.

3. MODEL IDENTIFICATION AND GRADING

Fig. 1 shows the process of time series prediction using ARIMA model. That is, stationarity test of time series should be carried out before time series prediction. If the original time series is not a stationary series, difference operation should be carried out on the original time series. Generally, the order of difference does not exceed 2. When the difference of sequence is a sequence of stationarity, also need to random inspection on the difference of sequence, because there is no connection between the pure random sequence and sequence in complete disorder of random fluctuations, can be thought of the random events does not contain any worth to extract useful information, we should stop the analysis。

When the original sequence becomes a stationary non-random sequence after difference operation, the parameters P and Q in ARIMA(P,D,Q) model can be calculated by graph test and minimum information criterion. When the parameters of the model are determined, it is necessary to test the residual of the fitting model. The residual in the time series model can be understood as the remaining value after the fitting model. For most (but not all) time series models, the residual is equal to the difference between the observed value and the corresponding fitted value.

$$e_t = y_t - \hat{y}_t \tag{7}$$

Residual is the difference between the actual value and the predicted value. If the residuals are correlated. - Information is left in the residuals, which are used to calculate the forecast. If the average of the residuals is not zero, the prediction is biased. When the fitted model passes the residual test, the original sequence can be used for prediction.

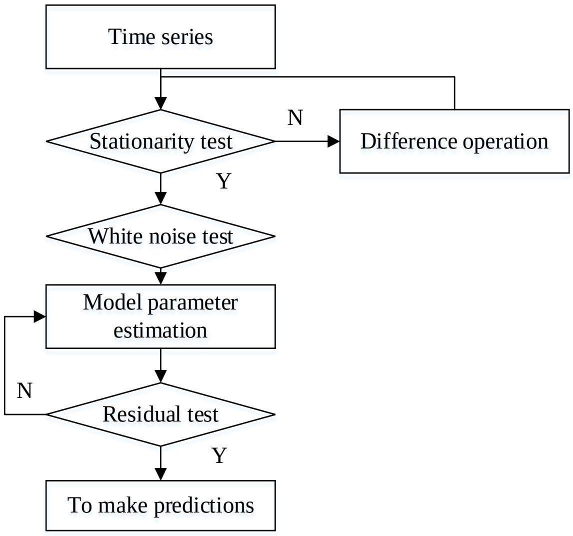

Fig.1: Flow chart of prediction

The forecast is based on data from the ERA5 reanalysis dataset of the European Centre for Medium-Range Numerical Forecasts (ECMWF). Reanalysis data is a complete set of reanalysis data obtained by quality control and assimilation of the observation data from various sources (ground, ship, radiosonde, atmosphere sphere, aircraft, satellite, etc.), which has a high similarity with the observation data.

According to the global grid temperature data provided by ECMWF with a spatial resolution of 0.25degree × 0.25degree and a temporal resolution of hourly. A grid of 113°00 '-113°25' E and 29°5 '-29°75' N was selected in space, and a total of 91 days of 2m surface temperature data per hour from January 1, 2016 to March 30, 2016 were selected in time. There are 2184 records in the original data, and the trend chart of the original sequence is shown in Fig. 2.

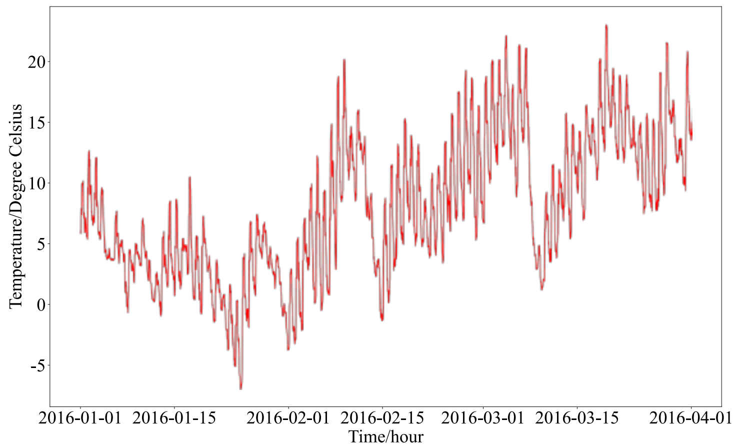

Fig. 2: Original sequence trend diagram

The original sequence, the original sequence after first-order difference and the original sequence after second-order difference are tested by unit root test, so as to test the stationarity of corresponding sequences. The test results are shown in Table 1.

Table 1: Unit root test results

Sequence types	**Test value**		**Confidence interval**		
	t-Statistic	***P-value.***	***1% Level***	***5% Level***	***10% Level***
original sequence	-2.7979	0.0585	-3.4333	-2.8628	-2.5674

First order difference sequence	-8.3868	2.4255×10^{-13}	-3.4333	-2.8628	-2.5674
Second order difference sequence	-21.8189	0	-3.4333	-2.8628	-2.5674

In the TABLE I, t-Statistic indicates T statistics, and P-value indicates the probability value corresponding to T statistics. The null hypothesis of ADF test is the existence of unit root. Where, Test Value 1% means the corresponding Value under t Value less than 1%, that is, the null hypothesis can be overturned when the confidence degree is 99%, that is, the original sequence is stable. 1% Level corresponds to strict rejection of the null hypothesis; 5% is rejection of the null hypothesis; As can be seen from Table 2-1, t-statistic of first-order difference -8.3868 is less than t-statistic of corresponding 99% confidence -3.4333. Therefore, first-order difference series can be considered as stationary series under 99% confidence, while the original sequence is non-stationary series, and the sequence after second-order difference is also stationary series.

Therefore, the difference order d can be selected as 1 or 2 in the prediction model, and the autocorrelation diagram of the first-order difference sequence and the second-order difference sequence can be drawn, as shown in Fig. 3.

By second order differential autocorrelation sequence diagram, the second order difference sequence in delay time the first-order autocorrelation coefficient soon becomes negative, this is a sign of excessive difference obvious, because of the difference operation is essentially a process of information extraction, processing, each time difference there will be the loss of information, above all, determine the time sequence of the differential order number is 1.

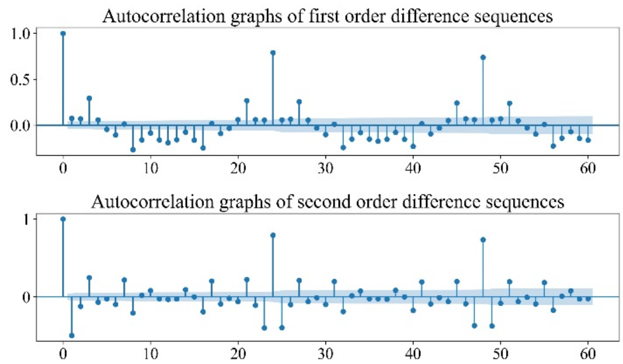

Fig. 3: Autocorrelation graphs of first and second order difference sequences

The trend diagram of the first-order difference series is shown in Fig. 4. It can be seen from the figure that the first-order difference series has no obvious upward or downward trend, and the observed values fluctuate up and down around their mean values, meeting the basic characteristics of stationary series.

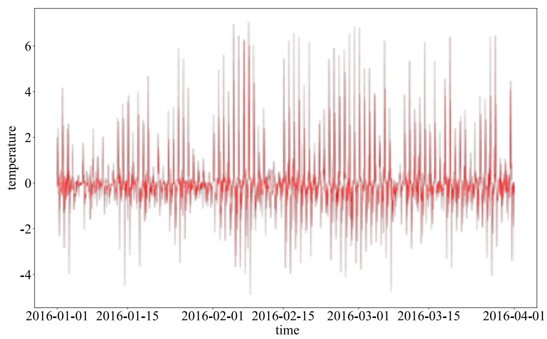

Fig. 4: trend diagram of a first-order difference sequence

Generally, there are two ways to determine the order p of autoregression and the order q of moving average in ARIMA model, namely, judging the trailing and cutting of the trailing according to autocorrelation graph and partial autocorrelation graph and judging by the minimum information criterion. This paper adopts the method based on AIC(An Information Criterion) to judge.

AIC criterion was put forward by Japanese statistician Akaike in 1973, and its full name is minimum information criterion. The guiding idea of this criterion is that the quality of a fitting model can be examined from two aspects: on the one hand, the likelihood function value which is very familiar and commonly used to measure the degree of fitting; The other is the number of unknown parameters in the model.

Generally, the larger the likelihood function value is, the better the model fitting effect is. The more unknown parameters in the model, the more independent variables included in the model, the more independent variables, the more flexible model changes, the higher the accuracy of model fitting. A high degree of model fitting is what we hope, but we cannot simply measure the quality of the model by the precision of fitting, because this will inevitably lead to the number of unknown parameters, the better. The more unknown parameters, the more independent variables in the model, the more unknown risks. Moreover, the more parameters, the more difficult the parameter estimation, the worse the accuracy of the estimation. Therefore, a good fitting model should be a comprehensive optimal configuration of fitting precision and the number of unknown parameters.

The AIC criterion, which is a weighting function of the fitting accuracy and the number of parameters, is put forward under this consideration: The AIC criterion, which is a weighting function of the fitting accuracy and the number of parameters, is put forward under this consideration:

$$\mathrm{AIC} = -2\ln\mathrm{L} + 2\mathrm{K} \tag{8}$$

In the above functions,L represents the maximum likelihood function value of the model, and K represents the number of unknown parameters in the model. The model that minimizes AIC function is considered to be the optimal model.

Therefore, the grid search method is used to fit the model with the original data to find the p and q values corresponding to the minimum AIC criterion value. The values of p_max and q_max are set to 6, and p_max and q_max are traversed from 0 respectively. TABLE Ⅱ shows the AIC information amount obtained by erasing models with different parameters.

Table 2: Different P and Q correspond to AIC value of model

AIC criterion value		**The order of the moving average**					
		0	***1***	***2***	***3***	***4***	***5***
The Order of autoregressive	***0***	7030.18	7021.29	7020.82	6772.11	6773.76	6733.98
	1	7020.24	6985.55	6928.76	6769.98	6767.5	6709.6
	2	7012.97	6966.92	6892.56	6727.67	6714.91	6711.6
	3	6831.34	6832.69	6804.3	6700.3	6394.62	6373.69
	4	6832.24	6833.24	6479.81	6664.33	6666.06	6352.84
	5	6816.74	6583.7	6433.84	6665.73	6385.99	6473.21

According to TABLE Ⅱ, when p is 4 and q is 5, the corresponding AIC information quantity value is 6352.84, The amount of information is the least in all of the above models. so the ARIMA model finally determined in this paper is ARIMA(4, 1, 5).

4. MODEL TESTING AND PREDICTION

The residual analysis of the built model shows that the residual sequence of the system model can be understood as the residual value after fitting the model, that is, the residual of the modified model is equal to the difference between the observed value and the corresponding fitting value. The residual sequence generated by a good prediction method should meet the requirement that the mean value of the residual is zero and the residual basically meets the normal distribution . It can be seen from the Fig. 5. that The residual sequence of the established ARIMA(4,1,5) model obeys two characteristics of zero mean and normal distribution, indicating that the model fits well.

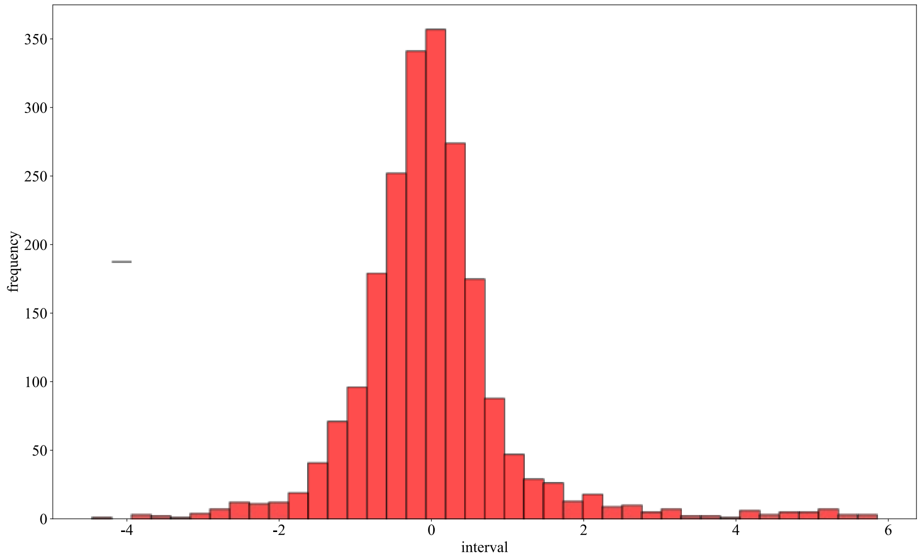

Fig. 5: ARIMA(4,1,5) Residual histogram of the model

The established ARIMA model was used to predict the surface temperature in the first 12 hours of March 30, 2016. The prediction results are shown in the Fig. 6. As can be seen from the figure, the prediction accuracy within 3 hours is less than 0.5 degrees Celsius, but with the increase of time, the prediction accuracy becomes worse and worse, and the temperature change trend cannot be displayed.

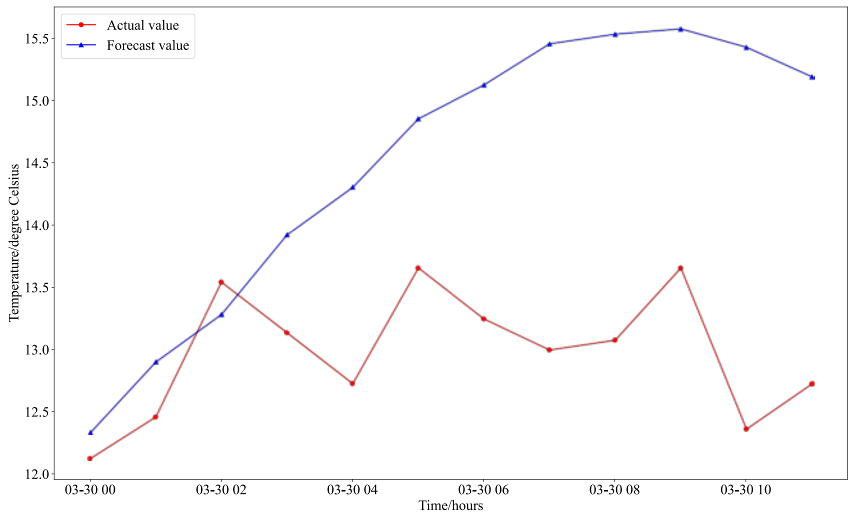

Fig. 6: Direct multi-step prediction results

Since the accuracy of multi-step prediction using ARIMA model is low, update prediction method is adopted here. The parameters determined in section 2 are still used in model fitting, but only a single step prediction is made each time. Each time a real data is added to the original data to predict the hourly average temperature of the next hour. The 24-step prediction is carried out, and the prediction results are shown in the Fig. 7.

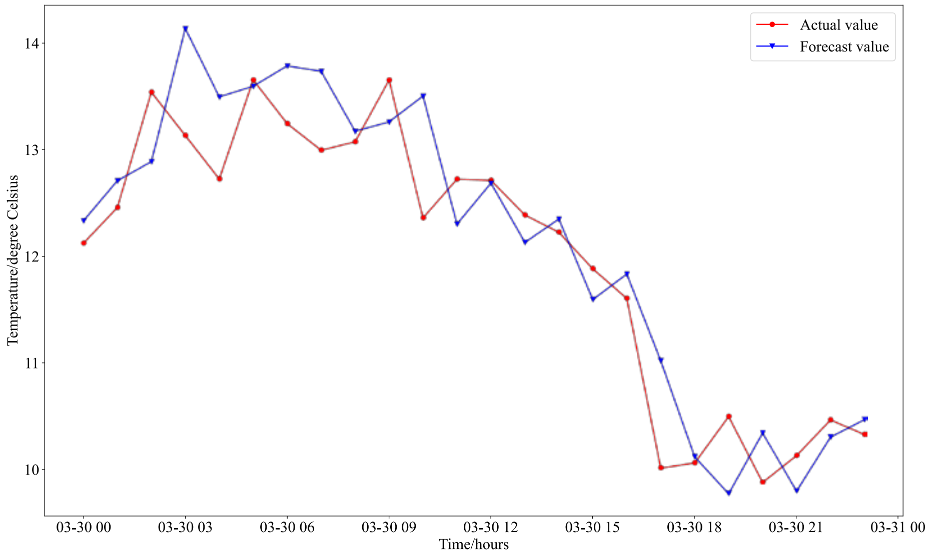

Fig. 7: Update prediction results in a single step

As can be seen from the Fig. 7, for the determined ARIMA model, the prediction accuracy of single-step update is high, and the single prediction error is not more than 0.4 degrees Celsius, indicating that the prediction accuracy of the temperature in the next 24 hours can be obtained by using this update prediction method.

In this paper, MAE,MSE and RMSE are used to evaluate the predictive performance of ARIMA model. MAE is the average of the absolute error between the observed and predicted values, while MSE and RMSE are used to calculate the prediction error, that is, to measure the degree of difference between the real sequence and the model predicted sequence. For MAE,MSE, and RMSE, a value of 0 indicates perfect predictive performance. Therefore, the lower MAE, MSE and RMSE values, the better the performance of the model.

The prediction errors of different predicted steps are shown in Table Ⅲ. As can be seen from the Table Ⅲ, the prediction effect of updated prediction is better than that of direct prediction. However, the updated prediction needs to provide new temperature data every time. When the temperature data is known and only one or less than four steps are needed for prediction each time, both the updated prediction and direct prediction can get good prediction results, but the accuracy of the updated prediction is higher. However, if the result of about 24 steps is to be predicted, the result of single-step update prediction is far better than that of direct prediction.

TABLE.3 PREDICTION ERROR OF DIFFERENT STEPS

Types of predictions	**Different types of mean error parameters**		
	MAE	***MSE***	***RMSE***
Direct prediction (4 steps)	0.5030	0.3810	0.6172
Direct prediction (24 steps)	1.5609	3.3062	1.8183
Single step update forecast (24 steps)	0.4196	0.2801	0.5292

5. Results

In this paper, a temperature prediction model based on ARIMA model is established based on the atmospheric temperature data in the analysis dataset of ERA5 downloaded from the European Center for Weather Forecasts (ECMWF), and the different prediction methods and step sizes are compared by setting the prediction modes and step sizes. The comparison results show that both ARIMA model and single-step update forecast can get better prediction effect in short-term prediction, but single-step update forecast can get better results in long-step prediction. It can be seen that the ARIMA atmospheric temperature prediction model established in this paper has good effect and has certain application value and practical significance.

6. References

[1] Hansen J, Ruedy R, Sato M, et al. Global surface temperature change[J]. Reviews of Geophysics, 2010, 48(4).J. Clerk Maxwell, A Treatise on Electricity and Magnetism, 3rd ed., vol. 2. Oxford: Clarendon, 1892, pp.68–73.

[2] Hansen J, Ruedy R, Glascoe J, et al. GISS analysis of surface temperature change[J]. Journal of Geophysical Research: Atmospheres, 1999, 104(D24): 30997-31022.

[3] Hansen J, Ruedy R, Sato M, et al. A closer look at United States and global surface temperature change[J]. Journal of Geophysical Research: Atmospheres, 2001, 106(D20): 23947-23963.

[4] Wolff S, O'Donncha F, Chen B. Statistical and machine learning ensemble modelling to forecast sea surface temperature[J]. Journal of Marine Systems, 2020, 208: 103347.

[5] Stockdale T N, Anderson D L T, Balmaseda M A, et al. ECMWF seasonal forecast system 3 and its prediction of sea surface temperature[J]. Climate dynamics, 2011, 37(3): 455-471.

[6] Kelly P M, Jones P D, Pengqun J I A. The spatial response of the climate system to explosive volcanic ruptions[J]. International Journal of Climatology: A Journal of the Royal Meteorological Society, 1996, 16(5): 537-550.

[7] Ho S L, Xie M. The use of ARIMA models for reliability forecasting and analysis[J]. Computers & industrial engineering, 1998, 35(1-2): 213-216.

[8] Senatore A, Furnari L, Mendicino G. Impact of high-resolution sea surface temperature representation on the forecast of small Mediterranean catchments' hydrological responses to heavy precipitation[J]. Hydrology and Earth System Sciences, 2020, 24(1): 269-291.

[9] Meyler A, Kenny G, Quinn T. Forecasting Irish inflation using ARIMA models[J]. 1998.

[10] Box G E P, Jenkins G M, Reinsel G C, et al. Time series analysis: forecasting and control[M]. John Wiley & Sons, 2015.

[11] Kalpakis K, Gada D, Puttagunta V. Distance measures for effective clustering of ARIMA series[C]//Proceedings 2001 IEEE international conference on data mining. IEEE, 2001: 273-280.