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Comparison and Precision Analysis of Several BDS Satellite Clock Bias Prediction Algorithms

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Abstract: *In order to analyze the influence of different data amounts on the accuracy and stability of BDS satellite clock bias prediction model, BDS satellites of different systems were randomly selected in this paper, and post-event precision satellite clock bias data released by Wuhan University was used. The prediction accuracy and stability of quadratic polynomial model, grey prediction model and autoregressive moving average model are compared and analyzed in detail by using different modelling schemes. The experimental results show that the prediction accuracy and stability of quadratic polynomial model are the highest, followed by the autoregressive moving average model and the grey prediction model, and the quadratic polynomial model and the autoregressive moving average model are more sensitive to the amount of data involved in modelling. In addition, the autoregressive moving average model has the highest prediction accuracy and stability for BDS-2 system satellite clock bias, and the grey prediction model has the highest prediction accuracy and stability for BDS-3 system satellite clock bias.*

Keywords: *BeiDou satellite navigation system; satellite clock bias; prediction model; accuracy analysis*

1. Introduction

With the wide application of the Global Navigation Satellite System (GNSS), especially in the field of high-precision positioning, navigation and timing (PNT), the accurate modelling and prediction of the satellite clock bias (SCB) has become one of the key factors to enhance the system performance [1]. In Precise Point Positioning (PPP) technology, in order to obtain centimeter-level positioning service requirements, precision satellite orbits and precision SCB need to be substituted into the equations as known values for positioning solution. China's BeiDou Navigation Satellite System (BDS), as one of the world's four major satellite navigation systems, has provided high-precision PNT services on a global scale. Therefore, high-precision prediction of SCB is particularly important for achieving centimeter-level PPP [2-3].

In recent years, with the rapid development of BDS, its service scope and application fields are expanding, and the requirements for the accuracy of BDS SCB prediction are getting higher and higher. Many scholars at home and abroad have carried out extensive and in-depth research on BDS SCB prediction, and proposed a series of SCB prediction algorithms, such as Quadratic Polynomial Model (QPM), Grey Model (GM (1,1)), Kalman Filter (KF), Auto-Regressive Integrated Moving Average (ARIMA) and Spectrum Analysis (SA), and so on [4-18]. Each of these methods has its own advantages and disadvantages and is suitable for different prediction situations.

In order to compare the prediction effect of different algorithms and analyze their accuracy, this paper adopts the after-the-fact precision SCB products released by the GNSS Analysis Center of Wuhan University as the experimental data, and establishes the QPM, the GM(1,1) and the ARIMA model by different modelling methods, and carries out the analysis of a large number of BDS SCB data, and sums up the advantages and deficiencies of them, with a view to improving the overall accuracy of BDS SCB prediction. We summarize their advantages and shortcomings in order to improve the overall accuracy of the BDS SCB prediction, and provide theoretical basis and technical support for the research of BDS SCB prediction and the selection of optimal algorithms for practical applications.

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2. Principle of SCB Prediction Algorithm

2.1 Quadratic Polynomial Model

Let a set of SCB time series be $y_1, y_2, ..., y_n$, whose corresponding time is $t_1, t_2, ..., t_n$, for which the following quadratic polynomial model [4] is built as:

$$y_i = a_0 + a_1 t_i + a_2 t_i^2 + \varepsilon_i \tag{1}$$

Where, $t_i \left(i = 1, 2, \cdots, n\right)$ is the time and $\varepsilon_i \left(i = 1, 2, \cdots, n\right)$ is the residual.

The optimal polynomial coefficients a_0, a_1 and a_2 , i.e., the sum of squares of the residuals S is minimized, can be determined by the least square method:

$$S = \sum_{i=1}^{n} {\varepsilon_i}^2 = \sum_{i=1}^{n} \left\{ y_i - \left(a_0 + a_1 t_i + a_2 {t_i}^2 \right) \right\}^2 \tag{2}$$

By taking the partial derivatives of S with respect to a_0, a_1 and a_2 making them equal to zero, a set of linear equations can be obtained as:

$$\begin{cases} \dfrac{\partial S}{\partial a_0} = -2\sum_{i=1}^{n}\left(y_i - a_0 - a_1 t_i - a_2 {t_i}^2\right) = 0 \\ \dfrac{\partial S}{\partial a_1} = -2\sum_{i=1}^{n}\left(y_i - a_0 - a_1 t_i - a_2 {t_i}^2\right) t_i = 0 \\ \dfrac{\partial S}{\partial a_2} = -2\sum_{i=1}^{n}\left(y_i - a_0 - a_1 t_i - a_2 {t_i}^2\right) {t_i}^2 = 0 \end{cases} \tag{3}$$

Collating the above linear equations gives:

$$\begin{cases} \sum_{i=1}^{n} y_i = n a_0 + a_1 \sum_{i=1}^{n} t_i + a_2 \sum_{i=1}^{n} {t_i}^2 \\ \sum_{i=1}^{n} y_i t_i = a_0 \sum_{i=1}^{n} t_i + a_1 \sum_{i=1}^{n} {t_i}^2 + a_2 \sum_{i=1}^{n} {t_i}^3 \\ \sum_{i=1}^{n} y_i {t_i}^2 = a_0 \sum_{i=1}^{n} {t_i}^2 + a_1 \sum_{i=1}^{n} {t_i}^3 + a_2 \sum_{i=1}^{n} {t_i}^4 \end{cases} \tag{4}$$

Expressing equation (4) as a matrix equation as:

$$\begin{bmatrix} n & \sum_{i=1}^{n} t_i & \sum_{i=1}^{n} t_i^2 \\ \sum_{i=1}^{n} t_i & \sum_{i=1}^{n} t_i^2 & \sum_{i=1}^{n} t_i^3 \\ \sum_{i=1}^{n} t_i^2 & \sum_{i=1}^{n} t_i^3 & \sum_{i=1}^{n} t_i^4 \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \\ a_2 \end{bmatrix} = \begin{bmatrix} \sum_{i=1}^{n} y_i \\ \sum_{i=1}^{n} y_i t_i \\ \sum_{i=1}^{n} y_i {t_i}^2 \end{bmatrix} \tag{5}$$

Estimates of the coefficients of the equation (1), a_0, a_1 and a_2, can be calculated using the least squares method by substituting them into equation (1) to obtain the estimates $\hat{a}_0, \hat{a}_1$ and $\hat{a}_2$:

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$$y_i = \hat{a}_0 + \hat{a}_1 t_i + \hat{a}_2 t_i^2 + \varepsilon_i \tag{6}$$

The model can be used to predict the SCB at any point in the future.

2.2 Grey Prediction Model

A set of SCB time series is given as $X^{(0)} = \left\{x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(n)\right\}$, and a new data series $X^{(1)}$ is generated by one accumulation:

$$X^{(1)} = \left\{x^{(0)}(1), \sum_{t=1}^{2} x^{(0)}(t), \cdots, \sum_{t=1}^{n} x^{(0)}(t)\right\} \tag{7}$$

A first order differential equation [4,8] is built for the cumulative sequence $X^{(1)}$:

$$\frac{dX^{(1)}}{dt} + aX^{(1)} = u \tag{8}$$

Where, a is the development coefficient and u is the amount of grey action. The discretization of equation (8) leads to:

$$Y = GA \tag{9}$$

Among them:

$$Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix}, G = \begin{bmatrix} -\frac{\left[x^{(1)}(2) + x^{(1)}(1)\right]}{2} & 1 \\ -\frac{\left[x^{(1)}(3) + x^{(1)}(2)\right]}{2} & 1 \\ \vdots & \vdots \\ -\frac{\left[x^{(1)}(n) + x^{(1)}(n-1)\right]}{2} & 1 \end{bmatrix}, A = \begin{bmatrix} a \\ u \end{bmatrix}$$

The least squares solution to the matrix equation (9) can be obtained by the least squares method as:

$$\hat{A} = [\hat{a} \quad \hat{u}] = \left(G^T G\right)^{-1} G^T Y \tag{10}$$

Substituting equation (10) into equation (8) gives:

$$\frac{dX^{(1)}}{dt} + \hat{a}X^{(1)} = \hat{u} \tag{11}$$

The solution to the time response function (10) is

$$\hat{x}^{(1)}(k+1) = \left[x^{(0)}(1) - \frac{\hat{u}}{\hat{a}}\right] \cdot e^{-\hat{a}k} + \frac{\hat{u}}{\hat{a}}, \qquad k = 1, 2, \cdots, n-1. \tag{12}$$

Since $X^{(1)}$ is the sequence formed by the accumulation of $X^{(0)}$, the forecast model of $X^{(0)}$ can be obtained by accumulating equation (12):

$$\begin{cases} \hat{x}^{(0)}(1) = \hat{x}^{(1)}(1) \\ \hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) = (1-e^{\hat{a}}) \cdot \left[x^{(0)}(1) - \dfrac{\hat{u}}{\hat{a}} \right] \cdot e^{-\hat{a}k} \end{cases} \tag{13}$$

Where, k is the number of raw data series involved in the prediction. The model can be used to predict the SCB at any time in the future.

2.3 Auto-Regressive Integrated Moving Average model

The ARIMA(0,2,q) model [15] is a simplified form of the ARIMA model, which does not contain an autoregressive component, but does contain a second-order differencing and q order moving average component, and the Bayesian Information Criterion (BIC) was used to determine the values of the parameters of the model's optimal q [6,14,15].

Let there be a set of SCB time series as X_t , and the second-order differencing of this set of SCB time series is processed as:

$$\nabla^2 X_t = \nabla(\nabla X_t) = \nabla(X_t - X_{t-1}) = (X_t - X_{t-1}) - (X_{t-1} - X_{t-2}) = X_t - 2X_{t-1} + X_{t-2} \tag{14}$$

The second order difference sequence of the SCB is obtained as Y_t:

$$Y_t = \nabla^2 X_t \tag{15}$$

For the second order difference series of SCB Y_t ARIMA (0,2, q) model is built as:

$$Y_t = \mu + \varepsilon_t + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} \tag{16}$$

Where, μ denotes the mean value of the SCB series, ε_t denotes the white noise error term of the SCB, and θ_j denotes the moving average coefficient.

The maximum likelihood estimation is used to estimate the parameter θ_j, and the objective function is:

$$L(\theta) = -\frac{T}{2}\ln(2\pi) - \frac{T}{2}\ln(\sigma^2) - \frac{1}{2\sigma^2}\sum_{t=1}^{T}\varepsilon_t^2 \tag{17}$$

Finding the maximizing log-likelihood function $\ln L(\theta)$ is equivalent to finding the minimizing negative log-likelihood function $-\ln L(\theta)$, which in turn is equivalent to minimizing $\frac{1}{2\sigma^2}\sum_{t=1}^{T}\varepsilon_t^2$.

Find the derivative of the negative log-likelihood function $-\ln L(\theta)$ and let its derivative be zero:

$$\frac{\partial[-\ln L(\theta)]}{\partial\theta_k} = 0 \text{, namely } \sum_{t=1}^{T}\varepsilon_t \frac{\partial\varepsilon_t}{\partial\theta_k} = 0 \tag{18}$$

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Where, $\frac{\partial \varepsilon_t}{\partial \theta_k} = -\varepsilon_{t-k}$.

The parameter estimate θ_k can be found by solving equation (18).

The optimal order of the model can be determined using the BIC criterion q, the BIC criterion is calculated using the following formula:

$$BIC = \ln\left(\text{sum of squared residuals}\right) + \frac{q\ln\left(n\right)}{n} \tag{19}$$

Where, $\ln\left(\text{sum of squared residuals}\right)$ is the negative of the log-likelihood function, q is the required order, and n is the sample size.

The estimated parameters are used to make predictions of future values, assuming that the known observations $Y_t = \left\{Y_1, Y_2, \cdots, Y_T\right\}$, for the future observations $\hat{Y}_{T+h}$, the predicted values are:

$$\hat{Y}_{T+h} = \hat{\mu} + \varepsilon_{T+h} + \sum_{j=1}^{q} \hat{\theta}_j \cdot \varepsilon_{T+h-j} \tag{20}$$

Where, $\ln\left(\text{sum of squared residuals}\right)$ is the estimated parameter.

$$\hat{Y}_{T+h} = \hat{\mu} + \varepsilon_{T+h} + \sum_{j=1}^{q} \hat{\theta}_j \varepsilon_{T+h-j} \tag{21}$$

Where, $\hat{\mu}$, $\hat{\theta}_j$ are the estimated parameters and ε_{T+h} is the future error term (usually assumed to be zero because we cannot observe the future error term).

Finally, the predicted difference sequence $\hat{Y}_{T+h}$ is back differentiated back to the original sequence X_t:

$$\hat{X}_{T+h} = \hat{Y}_{T+h} + 2X_{T+h-1} - X_{T+h-2} \tag{22}$$

The model can be used to predict the SCB at any point in the future.

3. Tests and Analysis

3.1 Sources of Experimental Data

In order to fully analyze the prediction accuracy and stability of these prediction models, this study uses the precision hindcast SCB data from BDS satellites released by the GNSS Analysis Centre of Wuhan University. The data for 11 August 2024 were selected, and the data sampling interval was 5 minutes. During this time period, more than 40 BDS satellites were in orbit, and their on-board clocks mainly included the following five types: the BLOCK GEO-Rb clock, the BLOCK IGSO-Rb clock, the BLOCK MEO-Rb clock, the BLOCK MEO-H clock and the BLOCK IGSO-H clock. The clock bias data of six satellites with different orbits, clock types, systems and launch ages were randomly selected for the prediction test, specifically including BDS-2 GEO-7-Rb PRN03, BDS-2 GEO-4-Rb PRN04, BDS-2 IGSO-6-Rb PRN13, BDS-3 MEO-3-Rb PRN21, BDS-3 MEO-16-H PRN35, and BDS-3 IGSO-H PRN39, and information on the above selected satellites is shown in Table 1:

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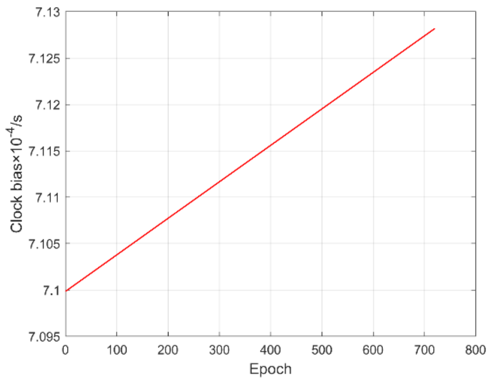
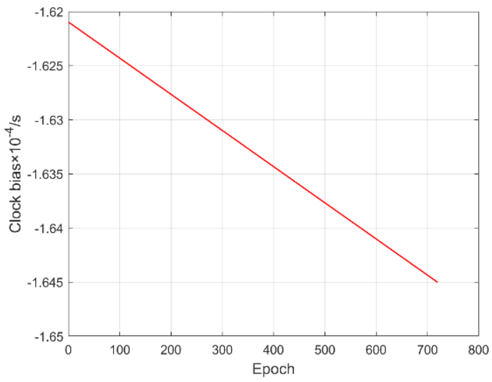
Table 1: Selected satellite related information.

Satellite number	Clock type	System type	Launch time	Trends in clock bias	Linear property
PRN 03	GEO-7-Rb	BDS-2	Jun 12, 2016	monotonically increasing positive values	high linearity
PRN 09	IGSO-4-Rb	BDS-2	July 27, 2011	monotonically decreasing negative values	high linearity
PRN 13	IGSO-6-Rb	BDS-2	30th March 2016	monotonically decreasing positive values	poor linearity
PRN 21	MEO-3-Rb	BDS-3	February 12, 2018	monotonically increasing negative values	high linearity
PRN 35	MEO-16-H	BDS-3	15th November 2018	monotonically decreasing positive values	high linearity
PRN 39	IGSO-H	BDS-3	25th June 2019	monotonically decreasing negative value	poor linearity

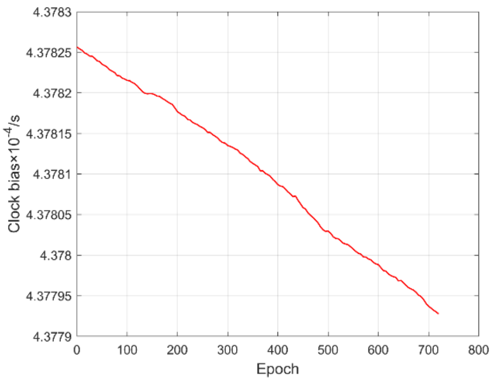
The variation of the time series of SCB for the first 12 hours of the day of 11 August 2024 for these six satellites is shown in figure 1.



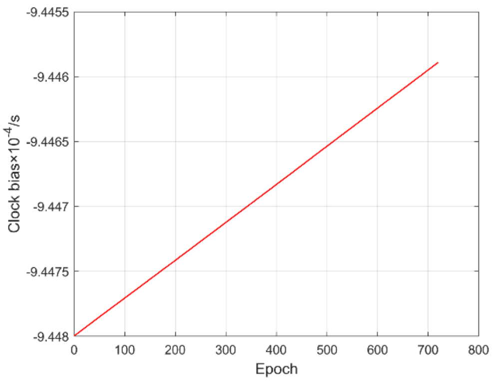
(a) PRN03



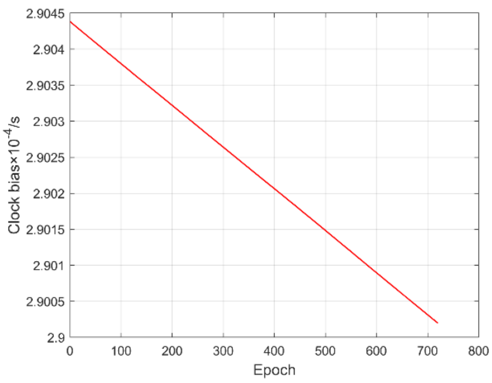
(b) PRN09



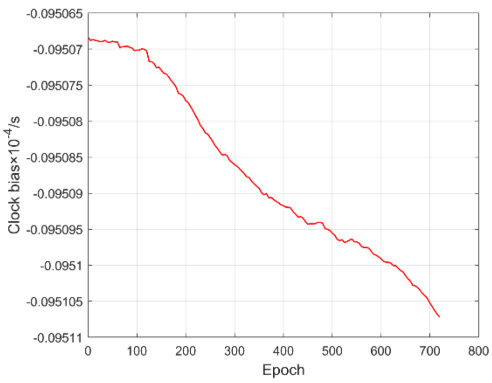
(c) PRN13



(d) PRN21



(e) PRN35



(f) PRN39

Figure 1: Variation of clock bias for satellites PRN03, PRN09, PRN13, PRN21, PRN35 and PRN39

3.2 Prediction results and analyses

In order to comprehensively assess the performance of the SCB prediction algorithm in this study, the precision hindcast SCB data of the BDS satellite on 11 August 2024 were used to construct the

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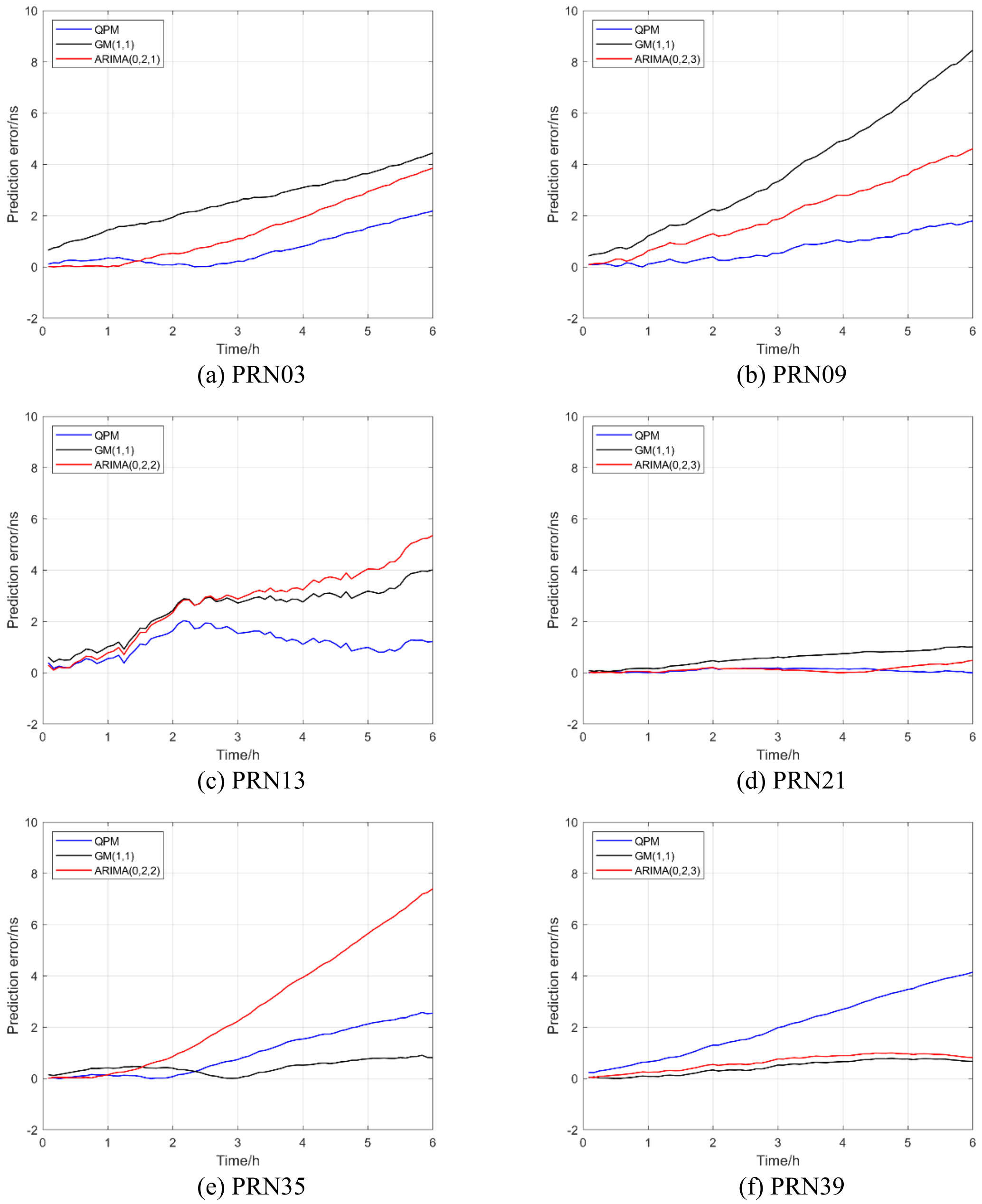
QPM model, the GM (1,1) model and the ARIMA (0,2, q) model, respectively, for the first 6 hours and 12 hours before the day, and to predict the SCB for the next 6 hours. The prediction results are compared with the precise SCB data released by the GNSS Analysis Centre of Wuhan University for the same time period, and the prediction errors of each model are calculated. The error of the precision SCB data released by the GNSS Analysis Centre of Wuhan University is less than 0.1 ns, so it can be regarded as the "true value", and the Root Mean Square Error (RMS) and Range are calculated to evaluate and compare the prediction accuracy and stability of each model. The formulae for the evaluation indexes are as follows:

$$RMS = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2} \tag{23}$$

$$Range = \max\left(y_i - \hat{y}_i\right) - \min\left(y_i - \hat{y}_i\right) \tag{24}$$

The relevant results are shown in Figure 2-4 and Table 2-3.



(a) PRN03 (b) PRN09

(c) PRN13 (d) PRN21

(e) PRN35 (f) PRN39

Figure 2: Comparison chart of errors in forecasting 6-hour SCB using 6-hour

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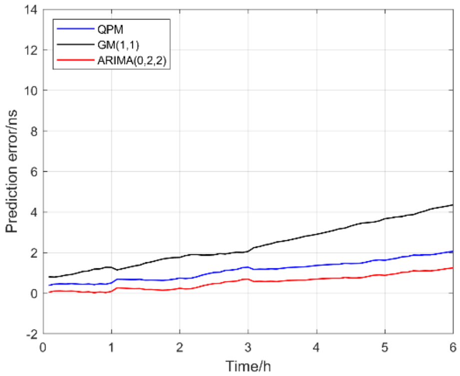
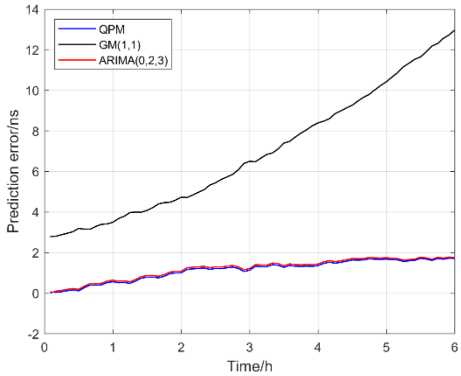
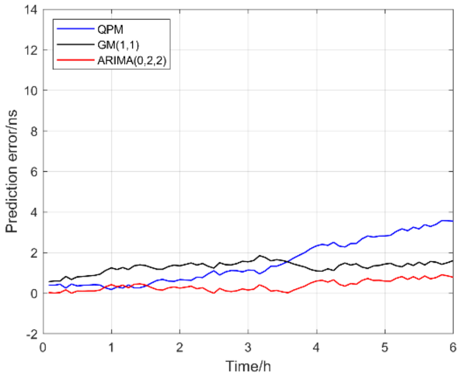


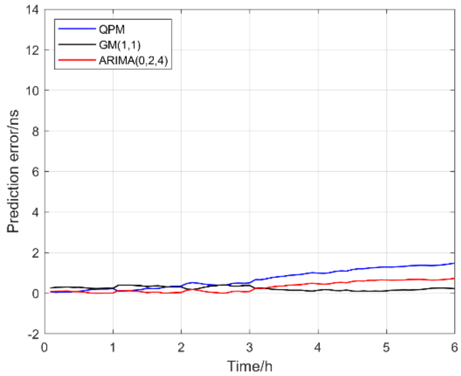
(a) PRN03



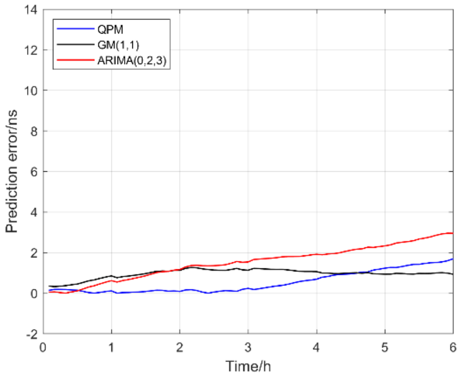
(b) PRN09



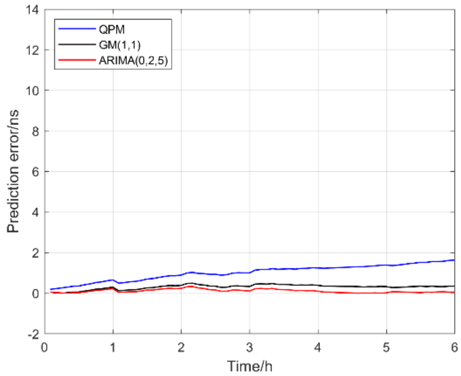
(c) PRN13



(d) PRN21
7



(e) PRN35



(f) PRN39

Figure 3: Comparison chart of errors in forecasting 6-hour SCB using 12-hour

Table 2: Statistical results of 6h forecast 6h SCB (unit: ns)

Model	Evaluation indicators	PRN 03	PRN 09	PRN 13	PRN 21	PRN 35	PRN 39	Average
QPM	RMS	0.96	0.91	1.24	0.12	1.35	2.39	1.16
	Range	2.18	1.79	1.86	0.19	2.58	3.91	2.09
GM (1,1)	RMS	2.75	4.49	2.64	0.64	0.51	0.52	1.93
	Range	3.79	8.03	3.60	0.96	0.90	0.78	3.01
AMIRA (0,2, q)	RMS	1.89	2.50	3.09	0.18	3.67	0.71	2.01
	Range	3.85	4.52	5.25	0.49	7.39	0.96	3.74

Table 3: Statistical results of 12h forecast 6h SCB (unit: ns)

Method	Evaluation indicators	PRN 03	PRN 09	PRN 13	PRN 21	PRN 35	PRN 39	Average
QPM	RMS	1.23	1.24	1.89	0.84	0.75	1.09	1.17
	Range	1.68	1.69	3.40	1.44	1.70	1.45	1.89
GM (1,1)	RMS	2.62	7.57	1.33	0.26	0.99	0.33	2.18
	Range	3.56	10.17	1.29	0.32	0.94	0.49	2.80
AMIRA (0,2, q)	RMS	0.65	1.31	0.45	0.40	1.73	0.14	0.78
	Range	1.22	1.79	0.91	0.73	2.95	0.33	1.32

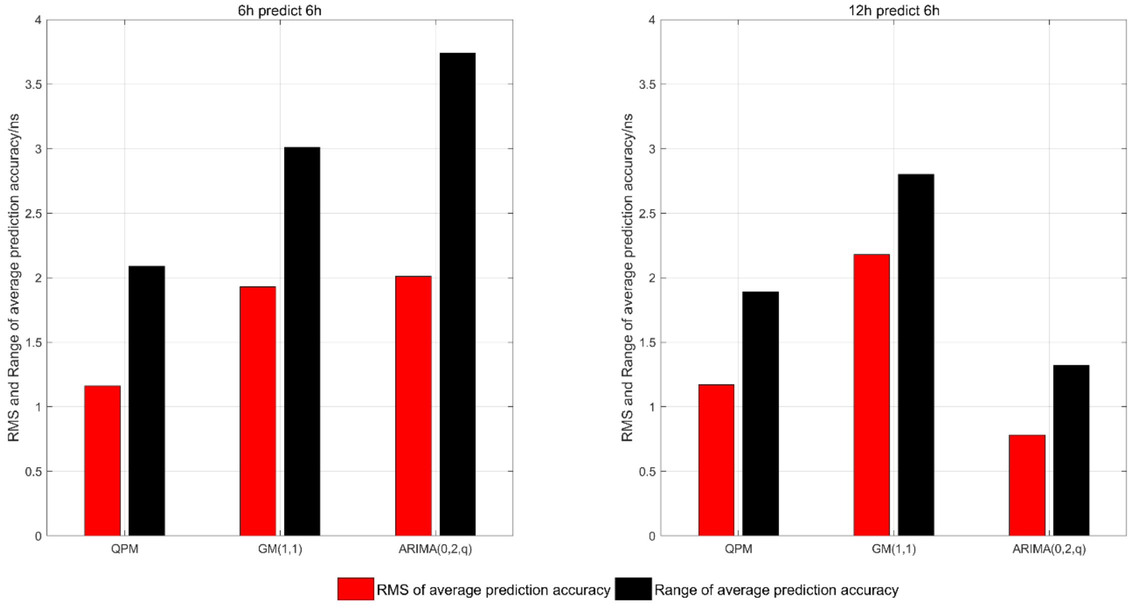


Figure 4: Comparison of average prediction accuracy

According to Figure 2-4 and Table 2-3:

(1) When forecasting the future 6-hour clock bias using 6-hour clock bias modelling, the average prediction accuracy and stability of the QPM model are 1.04ns and 1.94ns for BDS-2 satellites and 1.29ns and 2.23ns for BDS-3 satellites, respectively; the average prediction accuracy and stability of the GM(1,1) model for BDS-2 satellites are 3.29ns and 5.14ns for BDS-3 satellites, and 0.57ns and 0.88ns for BDS-3 satellites; the average prediction accuracy and stability of AMIRA(0,2,q) model are 2.49ns and 4.54ns for BDS-2 satellites, and 1.52ns and 2.95ns.

(2) When 12-hour clock bias modelling is used to predict the next 6-hour clock bias, the average prediction accuracy and stability of the QPM model are 1.45ns and 2.26ns for BDS-2 satellites and 0.89ns and 1.53ns for BDS-3 satellites. The average prediction accuracy and stability of the GM(1,1) model are 3.84ns and 5.01ns for BDS-2 satellites and 0.53ns and 0.58ns for BDS-3 satellites. The average prediction accuracy and stability of AMIRA(0,1) model are 0.53ns and 0.58ns for BDS-3 satellites, respectively. Models are 3.84ns and 5.01ns, and the average prediction accuracy and stability for BDS-3 satellites are 0.53ns and 0.58ns, respectively. The average prediction accuracy and stability of AMIRA (0,2, q) model for BDS-2 satellites are 0.80ns and 1.31ns, and the average prediction accuracy and stability for BDS-3 satellites are 0.76ns and 1.34ns.

(3) Overall, the highest average prediction accuracy and stability of the QPM model, followed by the GM (1,1) model, and then the AMIRA (0,2, q) model, are observed when the 6-hourly clock bias are modelled to predict the future 6-hourly clock bias. The highest average prediction accuracy and stability of the SCB prediction for the BDS-2 system are from the QPM model, followed by the AMIRA (0,2, q) model, and then the GM (1,1) model. The highest average prediction accuracy and stability prediction of SCB for the BDS-3 system is the GM (1,1) model, followed by the QPM model and again the AMIRA (0,2, q) model. When the amount of modelling data is increased, the AMIRA (0,2, q) model has the highest average prediction accuracy and stability, followed by the QPM model, and then the GM (1,1) model, when the 12-hourly clock bias is used for modelling the prediction of the next 6-hourly clock bias. The highest average prediction accuracy and stability of prediction of SCB for

the BDS-2 system were obtained from the AMIRA (0,2, q) model, followed by the QPM model and then the GM (1,1) model. The highest average prediction accuracy and stability prediction of SCB for the BDS-3 system is the GM (1,1) model, followed by the AMIRA (0,2, q) model, and again by the QPM model.

4. Conclusion

In order to analyze the effects of different data volumes on the accuracy and stability of the BDS SCB prediction algorithm, this paper randomly selects BDS satellites of different systems, and adopts different modelling schemes to compare and analyze in detail the prediction accuracy and stability of the QPM model, the GM (1,1) model and the AMIRA (0,2, q) model. The results show that the average prediction accuracy and stability of the QPM model are almost unchanged when the amount of modelled data is increased, which indicates that the model has little effect on the prediction accuracy when the amount of modelled data is increased; the average prediction accuracy and stability of the GM(1,1) model have slight changes, and its average prediction accuracy improves by 11.40% when modelled with 6 h data compared to 12 h data, but it has a higher accuracy than 12 h. The results of the GM (1,1) and AMIRA (0,2, q) models are compared and analyzed in detail. 11.40%, but its average prediction stability decreases by 6.90%; on the contrary, the AMIRA (0,2, q) model has significantly better average prediction accuracy and stability when modelled with 12-hour data than when modelled with 6-hour data, with an increase of 61.2% and 64.7% in average prediction accuracy and stability, respectively. In addition, the QPM model has the highest mean prediction accuracy and mean prediction stability when modelled with 6-hour clock bias, followed by the GM (1,1) model and then the AMIRA (0,2, q) model. When the amount of modelling data is increased and modelled with 12-hourly clock bias, the mean prediction accuracy and stability of the QPM model and GM(1,1) model are almost unchanged, which indicates that the model has less impact on the prediction accuracy and stability of the model when the amount of modelling data is increased, whereas the mean prediction accuracy and stability of the AMIRA(0,2,q) model are significantly improved with the increase in the amount of modelling data, which indicates that the model has a greater impact on the prediction accuracy of the model when increasing the amount of modelling data.

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References

[1] Li M, Huang T, Li W, et al. Precise point positioning with mixed single- and dual-frequency GNSS observations from Android smartphones considering code-carrier inconsistency[J]. Advances in Space Research, 2024, 74(6): 2664-2679.
[2] Wang J M, Li T, Xie D P, et al. Study on short-term prediction of clock bias of BeiDou precision satellites[J]. Surveying and Mapping Science, 2020, 45(01): 33-41.
[3] Yu Y, Huang M, Wang C, et al. A New BDS-2 Satellite Clock Bias Prediction Algorithm with an Improved Exponential Smoothing Method[J]. Applied Sciences, 2020, 10(21): 7456.
[4] Yi L, Xiong Y L, Xu L H. Comparison and accuracy analysis of two GPS satellite clock bias prediction models[J]. Surveying and Mapping Geographic Information, 2013, 38(02): 17-19.
[5] Guo Z C, Sun P, Li Z C, et al. A study on the effects of forecast model and modelling sequence length on the accuracy of short-term forecasts of orographic aberration[J]. Astronomical Research and Technology, 2020, 17(03): 299-307.
[6] Zhang G C, Han S H, Ye J, et al. A method for precisely predicting satellite clock bias based on robust fitting of ARMA models[J]. GPS Solutions, 2021, 26(1): 1-15.
[7] Yu Y, Huang M, Wang X Q, et al. Clock bias prediction of navigation satellites using the least-squares improved grey model[J]. Surveying and Mapping Bulletin, 2019, (04): 1-6.
[8] Yu Y, Huang M, Duan T, et al. Particle swarm optimization of weighted grey regression combination for satellite clock bias forecast[J]. Journal of Harbin Institute of Technology, 2020,

ISSN 2706-655X Vol. 7, Issue 2: 23-33, DOI: 10.25236/IJFET.2025.070204

52(10): 144-151+182.

[9] Fu W, Wang J, Wang L, et al. A Kalman filter-based online fractional cycle bias determination method for real-time ambiguity-fixing GPS satellite clock estimation[J]. Measurement, 2022, 205: 112207.

[10] Wang X, Chai H Z, Shi M C, et al. Analysis and comparison of satellite clock bias prediction models[J]. Journal of Surveying and Mapping Science and Technology, 2021, 38(04): 350-354.

[11] Tan X R,Xu J N,He H Y,et al.Optimisation of initial conditions of GM(1,1) model and its application to GNSS clock bias forecasting[J]. Geodesy and Geodynamics, 2022, 42(09): 919-924.

[12] TAN X R, Xu J N, LI F N, et al. A new GM (1,1) model suitable for short-term prediction of satellite clock bias[J]. IET Radar, Sonar & Navigation, 2022, 16(12): 2040-2052.

[13] Yu Y, Huang M, Duan T, et al. Enhancing Satellite Clock Bias Prediction Accuracy in the Case of Jumps with an Improved Grey Model[J]. Mathematical Problems in Engineering, 2020, 20.

[14] Jiang S Q,Li B F.Application of ARIMA model in short-term forecasting of satellite clock bias[J]. Journal of Navigation and Positioning, 2019, 7(04): 118-124.

[15] Xu J Y, Zeng A M.Application of ARIMA(0,2,q) model in satellite clock bias forecast[J]. Geodesy and Geodynamics Science, 2009, 29(05): 116-120.

[16] Lina H, Hairui Z, Shaolin Z, et al. An Improved QZSS Satellite Clock Offsets Prediction Based on the Extreme Learning Machine Method[J]. IEEE ACCESS. 2020, 8: 156557-156568.

[17] Yan K, Chang G B, Zhou T, et al. Study on a Sparse Autoregressive Prediction Model of Satellite Clock Bias [J]. Ocean Mapping, 2021, 41(04): 28-32+37.

[18] Yang X, Wang Q X, Lu W C, et al. Kalman filter-based short-term clock bias prediction with consideration of inter-satellite correlation[J]. Journal of Navigation and Positioning, 2022, 10(03): 59-68.