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Research Article

Predicting Spacecraft Telemetry Data by Using Grey–Markov Model with Sliding Window and Particle Swarm Optimization

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Predicting telemetry data is vital for the proper operation of orbiting spacecraft. The Grey–Markov model with sliding window (GMSW) combines Grey model (GM (1, 1)) and Markov chain forecast model, which allows it to describe the fluctuation of telemetry data. However, the Grey–Markov model with sliding window does not provide better predictions of telemetry series with the pseudo-periodic phenomenon. To overcome this drawback, we improved the GMSW model by applying particle swarm optimization (PSO) algorithm a sliding window for better prediction of spacecraft telemetry data (denoted as PGMSW model). In order to produce more accurate predictions, background-value optimization is specially carried out using the particle swarm optimization technique in conventional GM (1, 1). For verifying PGMSW, it is utilized in the prediction of the cyclic fluctuation of telemetry series data and exponential variations therein. The simulation results indicate that the PGMSW model provides accurate solutions for prediction problems similar to the pseudo-periodic telemetry series.

1. Introduction

Spacecrafts are massive systems with an intricate design and purpose [1], high reliability requirements, and huge potential risks. A growing field of investigation in the control of orbiting spacecrafts is satellite prognosis and health management [2]. The sole means by which the ground management system may assess the functionality and state of health of orbiting spacecrafts is through the transmission of telemetry data, which are typically gathered through sensors and transferred through telemetry lines [3]. Main components of satellite prognosis and health management include deterioration predictions and evaluation, which decides whether spacecrafts can function safely and effectively in orbit. Utilizing the satellite's online telemetry data to determine the state of the satellite is one method of keeping track of its health [4]. Telemetry data seem to be the sole source of information used by ground personnel in aeronautical engineering to assess the health of orbiting spacecrafts [5]. Accurate telemetry data prediction for expensive spacecrafts with complicated systems may enhance fault-response effectiveness, lower aerospace risk, and guarantee their safety, which offers significant advantages for the economy, society, and the military [1]. Through contrasting their true values with the acceptable boundaries of telemetry data, this prediction-based technique was used to identify anomalies [5]. In-orbit operations strategy and decision-making could therefore benefit greatly from accurate forecast and interpretation of telemetry data [2].

Telemetry measurements made onboard spacecraft ensure that accurate information is collected regarding the functioning of onboard subsystems in-flight so that in order to deal with the off-nominal circumstances onboard satellites, the appropriate control can be used. Ground controllers can keep an eye over the satellite via satellite telemetry data, e.g., when they separate following orbital entry from the rocket. They can also monitor satellite orientation and dynamics, the status of onboard subsystems, the functioning of control programs, and command execution. These capabilities can reveal malfunctions in the onboard subsystems and allow operators to monitor satellite instruments and the temperature of structural elements of the satellite [4]. Telemetry data are thus the only available indicators of satellite performance and subsystem health. The simplest and most widely used algorithm for analyzing telemetry data is limit checking, whereby the sensor measurements are checked to determine whether they fall within predefined ranges [6]. The technique requires setting the proper range for each parameter (e.g., temperature, voltage, and current) so that observing variance of each parameter permits the detection of out-of-range events. This algorithm's benefit is the ease that it provides by enabling ranges to be specified and changed to track spacecraft performance.

However, the multitask, in-orbit operation of satellites in the complex and constantly varying environment of space makes it extremely difficult to assess and predict satellite degradation in the long term [2]. During satellite operation, temperature is an important parameter that is indicative of satellite health. The temperature of a satellite's operating side, which is strongly exposed to sunlight and could attain above 100°C, could be as little as 100 to 200°C because the spacecraft is in space [2]. The various satellite instruments, however, must operate at appropriate temperatures. Thus, a significant variance in forecasting telemetry data is caused by seasonal fluctuation and heteroscedasticity of status-related telemetry data. Simple curves employed in conventional threshold baseline for satellite assessment are unable to identify the satellite status based on degradation data [2].

Given the spacecraft orbits are relatively regular and the operating conditions vary periodically, this work focuses on analog telemetry series and pseudo-periodic phenomena. Utilizing online satellite telemetry to evaluate the spacecraft status is a method of keeping track of a satellite's health. The operators can utilize the forecast of telemetry characteristics to identify potential impending satellites modes, that becomes helpful when making decisions quickly. This issue is vital because an urgent situation may lead to the complete loss of a satellite [4]. Monitoring trends in telemetry parameters can sound alarms to warn of possible failure [4]. Predicting the values of a single term then using a limit check is one straightforward way to put this concept into practice, which would warn of potential failure. When the predicted value falls outside the allowable error defined by the satellite operator or designer, a related subsystem may enter a faulty state, which can degrade the satellite system. The operator must therefore take precautions to avoid this situation [4].

Correctly predicting satellite telemetry data is thus vital for the proper operation of orbiting satellites. Scholars have proposed some prediction methods, such as an online reviews-driven method [7], multicriteria decision-making methods [8], an artificial wavelet neural network method [9], a Bayesian theory-based forecast [10], and the grey method [11]. Considering the complex nonlinear characteristics of telemetry data and after analyzing various methods to predict telemetry data, we selected the Grey model GM (1, 1) proposed by Deng in 1989 [12]. A significant and popular forecasting technique derived from Grey prediction theory is GM (1, 1) model [13]. Numerous scientific fields, including sociology, stock market analysis, economics, agriculture, autos, finance, meteorology, medicine, hydrology, geology, the military, and transportation, have extensive use for grey theory [14]. GM (1, 1) provides accurate predictions when raw data follow a slow exponential variation [13]. However, in practical problems, the raw data may oscillate as they increase and/or follow a rapid exponential [13].

Significant research has been devoted to enhancing the forecasting precision of GM (1, 1) [15]. Unfortunately, a single model cannot comprehensively describe a data sequence. Thus, previous research has focused on improving the GM (1, 1) model by combining it with other methods or by expanding it [16]. Given that a combined model can well solve this problem [17], researchers have recently combined two to three models to increase prediction precision of telemetry data [14].

Combination modeling which incorporates the Grey model in other models were developed to further boost the effectiveness of conventional Grey models [18]. In particular, Markov theory was included in Grey model to address wide fluctuations [18]; Due to its straightforward theory and superior performance, the resultant Grey–Markov model is a data-driven model that is frequently used to forecast the outcome of systems having unclear structure and attributes [19]. Since the GM (1, 1) curve behaves exponentially, it is unable to match the naturally occurring randomly changing data patterns. However, Markov processes can simulate such data because they are stochastic processes whose future value differs greatly based on present value. Thus, we use a combined Grey–Markov model to describe satellite telemetry data: GM (1, 1) describes the improvement of raw data, and Markov model describes the modified prediction of residual sequence [14]. Thus, GM (1, 1) and Markov models are combined to produce Grey–Markov model [20].

We now review the few applications in the field of space of GM (1, 1) and of other models combined. The existing studies of GM (1, 1) mainly focus on two aspects. In theoretical areas, some scholars focused on constructing expansion models by combining the GM (1, 1) model with other methods. Wang et al. predicted the moving trajectory of spacecrafts using the Grey approach [21]. The regular value of gold requests (2019), the level of cotton spider mite infections (2017), product demand (2017), and carbon dioxide index detection (2011) are only a few areas where the Grey–Markov approach has been used [22]. A Grey–Markov model was applied by Edem and Oke to predict fire accidents [20]. Others focused on developing new grey forecasting models by improving the selection of the background value with a sliding window mechanism or adaptive period grey models. Jiang et al. suggested the Grey–Markov prediction model with sliding window to forecast the degradation of mechanical equipment [18]. Jia et al. then improved the Grey–Markov chain model for predicting coal's intake in Gansu Province and obtained a reliable forecast of greater accuracy than the original model [12]. Govindan et al. enhanced Grey–Markov model to improve forecasts of traffic volume [14]. There are also some researches based on Grey–Markov model. For example, Ye et al. presented an adaptive Grey–Markov prediction model for incomplete and complex dynamic systems [23]. Finally, Zou et al. forecasted gross domestic product by using a Grey–Markov model with artificial neural network error correction [24]. To increase prediction accuracy, the model continuously adds the most recent information, eliminates the oldest information, and dynamically builds the forecasting sequence [25].

However, the above methods do not consider the pseudo-periodic phenomena of telemetry series on the spacecraft. Few scholars have researched the optimal background value by applying particle swarm optimization (PSO) algorithm in the GM (1, 1) model and how to increase new information's effect. Using a fixed formula to deal with the pseudo-periodic changes of data set cannot produce accurate predictions. The purpose of this work is to develop the modified Grey–Markov telemetry data model PGMSW, a prediction tool to help the assessment of health of orbiting spacecrafts. The predicted values are compared with the actual values to identify the future values (either normal or abnormal state). The main novelty addressed in this paper is to improve prediction precision of the pseudo-periodic telemetry series by applying the new model. The grey background values are reconstructed using the particle swarm optimization (PSO) technique. It creates a new residual modified model using an improved background value Grey–Markov model and a sliding window algorithm. It is believed that the development of the PGMSW as a prediction tool will provide early warnings to the ground staffs for judging the state of orbiting spacecraft. The present study uses a hybrid telemetry data forecasting method for spacecraft based on a sliding window and the Grey–Markov model. The Grey–Markov method is a prediction algorithm that can predict telemetry points and is used herein to predict satellite telemetry data. Thus, this paper uses a Grey–Markov model with sliding window to address the limitations outlined above regarding predicting telemetry data and increases the precision and accuracy of predicting satellite telemetry data.

This article's structure is as follows: Section 2 presents the basic concepts of GM (1, 1), the particle swarm optimization (PSO) algorithm, and the Grey–Markov model. Section 3 uses these models to predict spacecraft telemetry data. Section 4 provides the discussion. Finally, a conclusion is given in Section 5.

2. Model Principle

2.1. Building the GM (1, 1) Model. The general steps of GM (1, 1) are given below [12].

Step 1. Assume all actual data can be written as follows:

$$X^{(0)} = \left(x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)\right). \tag{1}$$

Step 2. Based on the original series $X^{(0)}$ and the accumulated generating operator, a new series $X^{(1)}$ can be generated as an $X^{(0)}$ one-cumulative sequence.

$$X^{(1)} = \left(x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(n)\right), \tag{2}$$

where

$$x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(k), \quad k = 1, 2, \ldots, n. \tag{3}$$

Step 3. The GM (1, 1) whitening equation is as follows [18]:

$$\frac{\mathrm{d}x^{(1)}}{\mathrm{d}t} + ax^{(1)} = b, \tag{4}$$

and its difference equation is as follows:

$$x^{(0)}(k) + az^{(1)}(k) = b, \quad k = 2, 3, \ldots, n, \tag{5}$$

where a represents the development coefficient and b represents the driving coefficient, which are two constants found by the original data sequence.

Step 4. $z^{(1)}(k)$ is the average value of the following adjacent data [26]:

$$z^{(1)}(k) = \frac{1}{2}\left(x^{(1)}(k) + x^{(1)}(k-1)\right), \quad k = 2, 3, \ldots, n, \tag{6}$$

$$z^{(1)}(k) = \lambda x^{(1)}(k) + (1-\lambda)x^{(1)}(k-1), \quad k = 2, 3, \ldots, n, \tag{7}$$

where $z^{(1)}(k)$ is the background value. This demonstrates that this generating technique only determines the mean of $x^{(1)}(k)$ and $x^{(1)}(k-1)$ by taking $\lambda = 0.5$. λ is not considered. The precise formula for calculating the background/reference value $z^{(1)}(k)$ needs to be clarified in equation (7).

Step 5. Parameters a and b can be estimated by the least square method as follows:

$$(a, b)^T = \left(B^T B\right)^{-1} B^T Y, \tag{8}$$

where

$$Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix}, B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix}. \tag{9}$$

Step 6. Based on equation (5), the solution of $x^{(1)}(k)$ is as follows:

$$\hat{x}^{(1)}(k) = \left[x^{(0)}(1) - \frac{b}{a}\right]e^{-a(k-1)} + \frac{b}{a}, \quad k = 1, 2, \ldots, n, \tag{10}$$

where $\hat{x}^{(1)}(k)$ is the predicted value of $x^{(1)}(k)$ at time k.

Finally, with the subtraction operation, the predicted value of $x^{(0)}(k)$ at time k is derived as follows:

$$\begin{aligned}\hat{x}^{(0)}(k) &= \hat{x}^{(1)}(k) - \hat{x}^{(1)}(k-1)\\ &= \left[x^{(0)}(1) - \frac{b}{a}\right](1-e^{a})e^{-a(k-1)}.\end{aligned} \quad (11)$$

2.2. Background Value Optimized GM (1, 1) Model. GM (1, 1)'s essential parameters, development coefficient a, and driving coefficient b, were obtained by fitting background value with the least squares approach. Enhancing the selection of background values is mostly responsible for raising GM (1, 1) model's predictive performance [27]. Thus, optimizing the method of generating background values is vital for improving the forecast precision of GM (1, 1) through searching for the ideal λ^* value within equation (7) [17]. The PSO algorithm of Kennedy and Eberhart (1995) is a population-based algorithm that randomly adjusts the velocity of a population of individuals to search a multidimensional space for a global optimum [28]. It converges faster and requires fewer adjustable parameters. Therefore, we utilize PSO algorithm in calculating background value. The target preset minimizes the mean absolute percentage error (MAPE). The steps of the PSO algorithm are summarized as follows [25].

Assume there are N particles to form a population in a D-dimensional targeted search area, where particle $i\,(i = 1, 2, \cdots, N)$ is a D-dimensional vector denoted by the following equation:

$$X_i = (x_{i1}, x_{i2}, \ldots x_{iD}), \quad i = 1, 2, \ldots, N. \quad (12)$$

The position of each particle is a potential solution, and X_i can be substituted into the objective function to determine its adapted value.

Speed of particle i is a D-dimensional vector and is represented as follows:

$$V_i = (v_{i1}, v_{i2}, \ldots v_{iD}), \quad i = 1, 2, \ldots, N. \quad (13)$$

The best position for particle i is as follows:

$$P_{\text{Best}} = (p_{i1}, p_{i2}, \ldots p_{iD}), \quad i = 1, 2, \ldots, N, \quad (14)$$

and the global extreme value is as follows:

$$G_{\text{Best}} = (g_{i1}, g_{i2}, \ldots g_{iD}), \quad i = 1, 2, \ldots, N. \quad (15)$$

The PSO method updates the particle velocity and position using the following formulae if the two ideal values are not obtained [25]:

$$\begin{aligned}v_{ij}(t+1) &= \omega v_{ij}(t) + \eta_1 r_1(t)\left[p_{ij}(t) - x_{ij}(t)\right] + \eta_2 r_2(t)\left[g_{ij}(t) - x_{ij}(t)\right],\\ x_{ij}(t+1) &= x_{ij}(t) + v_{ij}(t+1),\end{aligned} \quad (16)$$

where ω denotes inertia factor, η_1 and η_2 denote acceleration constants, r_1 and r_2 represent random numbers in range [0, 1], p_{ij} and g_{ij} represent the optimal available particle location as well as the best flocking location globally, and v_{ij} is the particle speed. Optimized background values are acquired from the best fit-line to exponential-function which reduces bias of conventional GM (1, 1) models [29].

2.3. Grey–Markov Model. Markov procedure is a kind of stochastic process in which system communicates with a specific probability of transitioning from a state to the other [3]. It has been applied widely in a host of real applications [26]. The state of future time t_{n+1} is solely connected to current state at time t_n and is not associated with any past states [12]. To more accurately predict telemetry data, the Markov chain is introduced into the GM (1, 1) model, which proves especially helpful for describing times series data that fluctuations significantly in time [24]. Consequently, the Grey–Markov model is created by combining these two models [30].

Markov model is represented by the following equation [31]:

$$x_{k+n} = x_k P^n. \quad (17)$$

For the prognostic series $(\hat{x}^{(0)}(1), \hat{x}^{(0)}(2), \ldots, \hat{x}^{(0)}(k))$ produced by the GM (1, 1) model, relative error between the predicted and actual values is as follows [14]:

$$e_k = \frac{x^{(0)}(k) - \hat{x}^{(0)}(k)}{x^{(0)}(k)}, \quad k = 1, 2, \ldots, n. \quad (18)$$

The remaining sequence predictions can be altered using the Markov model [31]. Range of relative error may be used to classify the variance into S states through using relative error of the GM (1, 1) model for both the predicted and the original value: $[\min e_k, \max e_k]$. This range can be divided into S intervals of equal length [12]. There are no strict rules on the number of state divisions, and it is generally appropriate to divide them into three to five categories [12]. Each state E_j is expressed as follows [18]:

$$e_k \in E_i = [E_{i-}, E_{i+}], \quad i = 1, 2, \ldots, S, \quad (19)$$

where E_{i-} and E_{i+} are the lower and upper bounds of states, respectively.

The probability of an m-step transition from state E_i to the next state E_j is the state transition probability $P_{ij}^{(m)}$ [12].

$$P_{ij}^{(m)} = \frac{M_{ij}(m)}{M_i}, \quad i, j = 1, 2, \ldots, S, \quad (20)$$

where $M_{ij}(m)$ indicates the ratio's sample size while shifting from state E_i to E_j in step m, and M_i represents the ratio's sample size of E_i.

Thus, the state transition probability from E_i to E_j after m steps is denoted $P^{(m)}$ and expressed as follows [20]:

$$P^{(m)} = \begin{bmatrix} P_{11}^{(m)} & P_{12}^{(m)} & \cdots & P_{1l}^{(m)} \\ P_{21}^{(m)} & P_{22}^{(m)} & \cdots & P_{2l}^{(m)} \\ \vdots & \vdots & \cdots & \vdots \\ P_{l1}^{(m)} & P_{l2}^{(m)} & \cdots & P_{ll}^{(m)} \end{bmatrix}. \tag{21}$$

According to the middle value of the residual interval $[E_{i-}, E_{i+}]$ of state E_i with Grey predictive value $\widehat{x}^{(0)}(k)$, the value predicted by the Grey–Markov chain model is $\widehat{y}^{(0)}(k)$ [12]:

$$\widehat{y}^{(0)}(k) = \widehat{x}^{(0)}(k)\left[\frac{1 + (E_{i-} + E_{i+})}{2}\right]. \tag{22}$$

2.4. Grey–Markov Model Based on Sliding Window Algorithm and Background Value Optimization. Grey–Markov model incorporates the sliding window approach to dynamically-update the prediction models using the most recent data [32]. The Grey–Markov model featuring sliding window and PSO algorithm (denoted PGMSW) increases the accuracy of long-term predictions. Further enhancing computing efficiency is the adjustable parameter for the sliding window (i.e., step size), which is useful for performing multistep prediction [19]. In other words, it is impossible to make accurate forecasts using a fixed formula to handle the dynamic changes in a data set [33]. To increase forecast accuracy, the model continuously incorporates the most recent data, eliminates the most outdated data, and builds the prediction series dynamically [25]. We integrate the PGMSW model and backdrop value optimization to increase predictive performance.

The window size m of the model does not vary. This system functions similarly to a sliding window during the identifying process [34]. The total count of raw data equals the window size. The window advances following a reading cycle, which can be seen in Figure 1. The sliding window approach and the background value optimization method are incorporated into the Grey–Markov model to further enhance the prediction model and raise the accuracy of measurements. In several respects, the combination prediction models presented in this study diverge significantly from the current models. First, the PGSW model adopts a structure that embeds the Markov process' change of predicted values into the GM (1, 1) model in a single iteration to forecast future values. It predicts without sample size restrictions and solves issues with insufficient training samples. Second, the conventional GM (1, 1) model is a linear grey forecasting model, and the Markov chain primarily adapts to stationary objects, but the PGSW model extends linear grey forecasting to nonlinear forecasting and can also cope with nonstationary objects. Thirdly, the PGSW model may minimise the noise in forecasts. Since the sequence being modeled is continuously updated with the changing values, it is possible to further adjust the influence of data fluctuations; this has the unique advantage of improving measurement accuracy over a large time scale. Consequently, PGSW is a more effective model for long-term forecasting. The new method maximises their particular advantages. GM (1, 1), Markov, and PSO may enlarge the applicable scopes to nonlinear dynamic information prediction and improve the accuracy of predicted information.

Figure 2 displays a flow chart outlining the stages involved in using the PGMSW model. These steps are as follows [32]:

Step 1. Assume that $(x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n))$ represents all actual telemetry data, and $x^{(0)}(n)$ is the telemetry data at time n. The original sequence series $(x^{(0)}(n-m+1), x^{(0)}(n-m+2), \ldots, x^{(0)}(n))$ is then chosen based on window size m. A fixed-length sliding window is applied.

Step 2. Input the original sequence series $(x^{(0)}(n-m+1), x^{(0)}(n-m+2), \ldots, x^{(0)}(n))$ into the GM (1, 1) model, which will output the predicted value $\widehat{x}^{(1)}(n+1)$ at time $n+1$. The GM(1, 1) model is constructed based on the data available in the sliding window [35].

Step 3. Remove the oldest data $x^{(0)}(n-m+1)$ in the original sequence $(x^{(0)}(n-m+1), x^{(0)}(n-m+2), \ldots, x^{(0)}(n))$, and $x^{(0)}(n+1)$ is added at the end of the original sequence $(x^{(0)}(n-m+1), x^{(0)}(n-m+2), \ldots, x^{(0)}(n))$ to build a new original sequence $(x^{(0)}(n-m+2), \ldots, x^{(0)}(n+1))$. Finally, continue to build the PGMSW model until the prediction goal is attained. This approach increases predictive performance by fully utilizing the additional data.

3. Case Study

We use actual satellite in-orbit data as a research topic to assess all capabilities of the suggested Grey–Markov forecasting model. Core telemetry series are often pseudo-period sequences influenced by regular orbits and operating mode, recorded by sensors aboard orbiting spacecraft [3]. The mean absolute error (MAE), mean squared error (MSE), and MAPE are used as test criteria for evaluating the prediction accuracy. They are expressed as follows [27]:

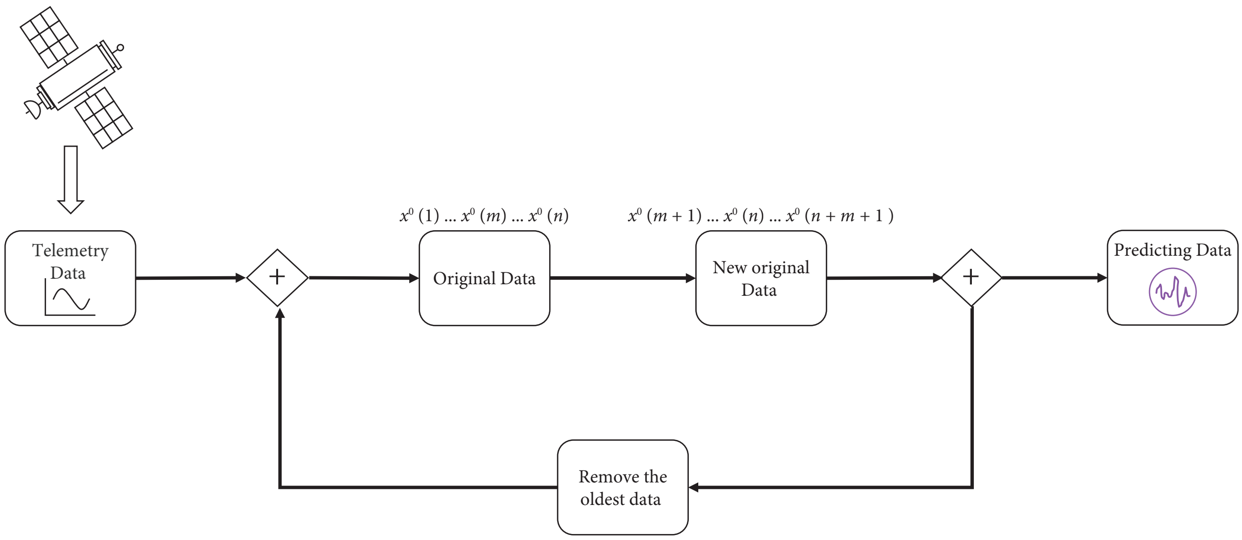

Figure 1: Sliding window mechanism.

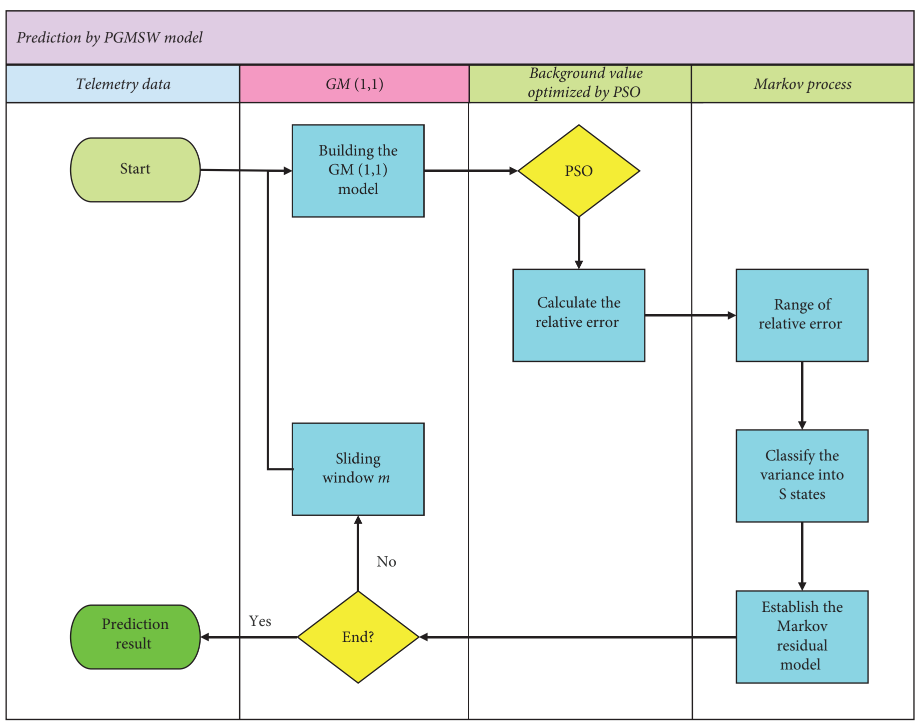

Figure 2: Flow chart of prediction by PGMSW model.

$$\begin{aligned}
\mathrm{MAE} &= \frac{\sum_{k=1}^{n}\left|x^{(0)}(k)-\hat{x}^{(0)}(k)\right|}{n},\\
\mathrm{MSE} &= \frac{\sum_{k=1}^{n}\left(x^{(0)}(k)-\hat{x}^{(0)}(k)\right)^2}{n},\\
\mathrm{MAPE} &= \frac{1}{n}\sum_{k=1}^{n}\left(\frac{\left|x^{(0)}(k)-\hat{x}^{(0)}(k)\right|}{x^{(0)}(k)}\right)\times 100\%.
\end{aligned} \tag{23}$$

While operating the spacecraft, temperature can be considered as a critical term. There are several temperature parameters with identical properties on each spacecraft [2]. The solar array and batteries provide all of the power the spaceship needs. A widely-utilized solar array subsystem is a shunt regulator because of its superior efficiency's small mass, simplicity, and high reliability [36]. The shunt regulator (SR) can be considered as the heart for delivering the spacecraft's power system; it works when sunshine is available to provide the mandatory energy for the bus through solar arrays and shunts unnecessary current produced via solar arrays to ground [37]. Ground staff are typically very concerned about variations in SR temperature during orbit, so predicting its temperature is of engineering importance. The variable used for this study is "temperature of shunt regulator," also referred to as "temperature." In detail, telemetry series of SR temperature from a spacecraft tends to assess operation of this suggested approach considering an actual applicable scenario.

As shown in Figure 3, the SR temperature has two recurring states, the shadow state and the sunlight state, and the temperature cycles between the two states. The temperature data seem to decay nonlinearly, whereas the growth may be exponential. The temperature transitions between these two recurring states as the SR moves from the shadow to the sunlight or vice versa. The influence of the orbit and working modes imparts a pseudo-period on these telemetry series. Only a pseudo-periodic data series may be used by the ground monitoring system to assess a spacecraft's operational efficiency and overall condition [3]. The value and duration of these telemetry series are, however, subject to significant ambiguity due to the space environment. Apparently, it cannot be predicted with any degree of accuracy and may result in some erroneous alerts during the transition period. 180 specimens in total are included in each cycle's raw data. Resample the original data set and permit 30 samples for every cycle in the trials to increase the algorithm's effectiveness. It is very challenging to find the ideal size of the sliding window for various data series and forecasting algorithms. The sliding window was utilized to continually update the data points while most recent five data points are being used to anticipate the subsequent data points. Finally, we divide GM (1, 1)'s relative error sequence to 4 equal stages.

Figure 4 shows the findings of three prediction models, with MAPE of each given in Table 1. Figure 4 plots the estimates foreseen using the same models, which indicates how closely-related the estimated values by proposed model are to the actual ones. In this case study, the sliding window size is 1, and the number of state divisions is classified into 4 types. The outcome of GM (1, 1) cannot trace the original data's variations. The values anticipated with PGMSW model more accurately track the fluctuations in the telemetry data than the values predicted by GM (1, 1). Here, MAPE is utilized for comparing telemetry data with predicted values and thereby assess the models' accuracy.

Figure 5 shows the telemetry data and the values predicted by the PGMSW model. In our model, the most recent data points are used to forecast the next data point, and a sliding widow is utilized to continually update data points. These results show that the prediction accuracy was upgraded by the dynamic updating of the modeling sequence with modified values. The predicted temperature is thus very close to the actual temperature given in Figure 5 and Table 2.

Figure 6 displays the MAPE evolution with a boost in the window size from 1–6. However, an excessive window size may not be a good choice because of low precision and weak correlation. Table 1 and Figure 6 provide performance comparisons for the three models, and Figure 4 displays the outcomes of the predictions.

Table 1 shows the error between values predicted by different models and the telemetry data. The PGMSW model produces the best precise predictions. Considering the outcomes given in Table 1, we conclude that PGMSW model performs better than GM (1, 1) in terms of MAE, MSE, and MAPE. Comparing the outcomes to GM (1, 1) and GMSW models, the forecast error of PGMSW was significantly reduced.

Comparing the outcomes to GM (1, 1), the MAPE-determined forecast precision of PGMSW model with window size 1–6 improves by 21.2% (from 2.22% to 1.75%), 25% (from 3.28% to 2.46%), 10.8% (from 4.07% to 3.63%), 33.6% (from 5.99% to 3.98%), 12.2% (from 7.38% to 6.48%), and 29% (from 11.76% to 8.35%), respectively. In addition, a single window size for the PGMSW may decrease the computational efficiency.

4. Discussion

Pseudo-cycle telemetry data are significantly challenging to accurately predict. To predict telemetry data, we show herein that PGMSW makes better predictions than GM (1, 1) and GMSW models. The PGMSW model also offers a wide range of practicality and universality. Table 1 shows quantitative verification indexes that demonstrate the superior PGMSW accuracy, where the outcomes presented in Figure 4 confirm these results. Each error-verification index is minimal for the PGMSW model. In this study, the models GM (1, 1), GMSW, and PGMSW are chosen, and the model parameters are acquired by comparative experiment analysis. In this section, two data sets with increasing trend and decreasing trend are utilized to assess the proposed PGMSW. In the simulation, PGMSW is compared to GM (1, 1) and GMSW. Sliding windows are introduced with lengths of 1/2/3/4/5/6 on the basis of the GM (1, 1) model, the GMSW model, and the PGMSW model. Prediction errors of PGMSW model with different sliding window sizes are shown in Figure 6. When the window size is larger, the prediction accuracy is lower. To confirm the accuracy of the suggested model, the prediction accuracy of other regression models is compared. The outcomes of the predictions are compared in detail in Table 1.

The prediction accuracy is highest when the sliding window size is 1. In addition, the accuracy of predicting one value in the sliding window is greater than that of predicting three values. Thus, the acceptable sliding window size for accurate predicting of telemetry data is 1, which allows for

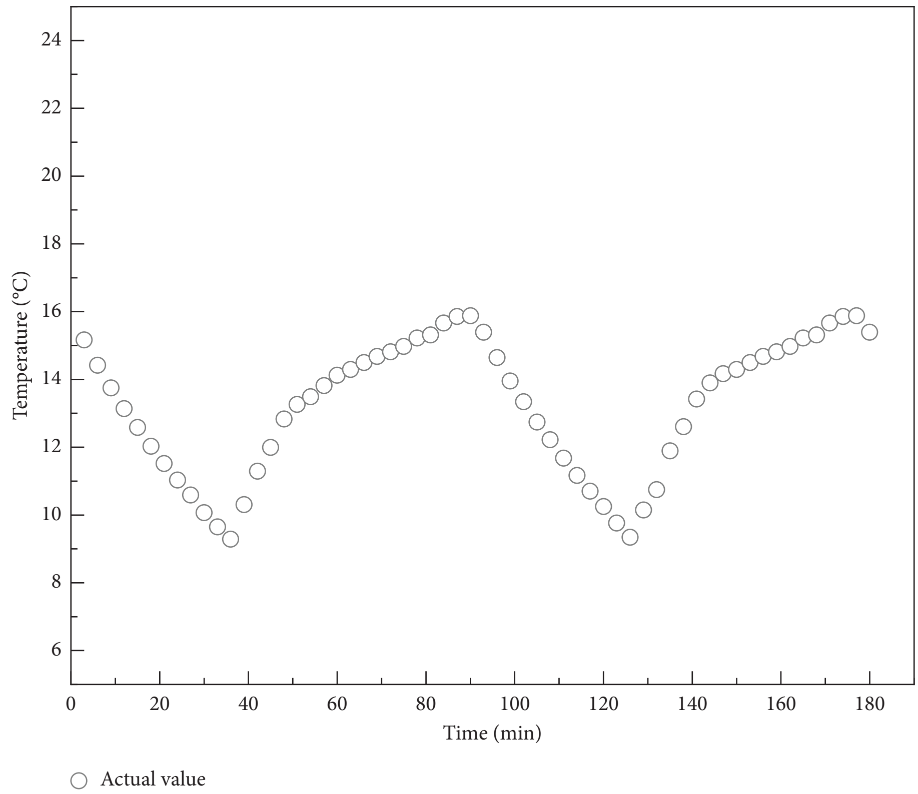

Figure 3: Measured SR temperature.

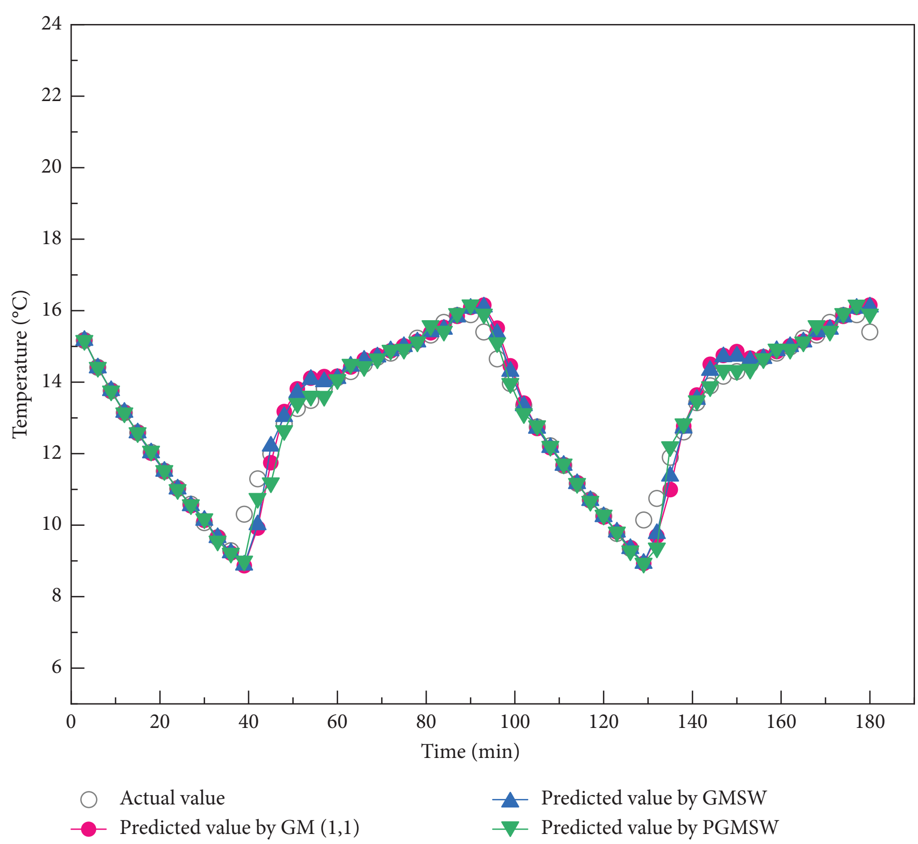

Figure 4: Comparison of three models for predicting SR temperature data (window size = 1).

Table 1: Comparison of different prediction models.

Prediction models	MAE	MSE	MAPE	MAE	MSE	MAPE	MAE	MSE	MAPE	MAE	MSE	MAPE	MAE	MSE	MAPE	MAE	MSE	MAPE
	Window size 1			Window size 2			Window size 3			Window size 4			Window size 5			Window size 6		
GM (1,1)	0.28	0.22	2.22%	0.41	0.49	3.28%	0.52	0.76	4.07%	0.78	1.56	5.99%	0.96	2.53	7.38%	1.56	5.97	11.76%
GMSW	0.24	0.17	1.94%	0.37	0.37	2.91%	0.50	0.73	3.94%	0.75	1.48	5.72%	0.93	2.41	7.16%	1.55	5.95	11.73%
PGMSW	0.21	0.14	1.75%	0.30	0.32	2.46%	0.45	0.69	3.63%	0.50	0.78	3.98%	0.83	1.81	6.48%	1.07	3.94	8.35%

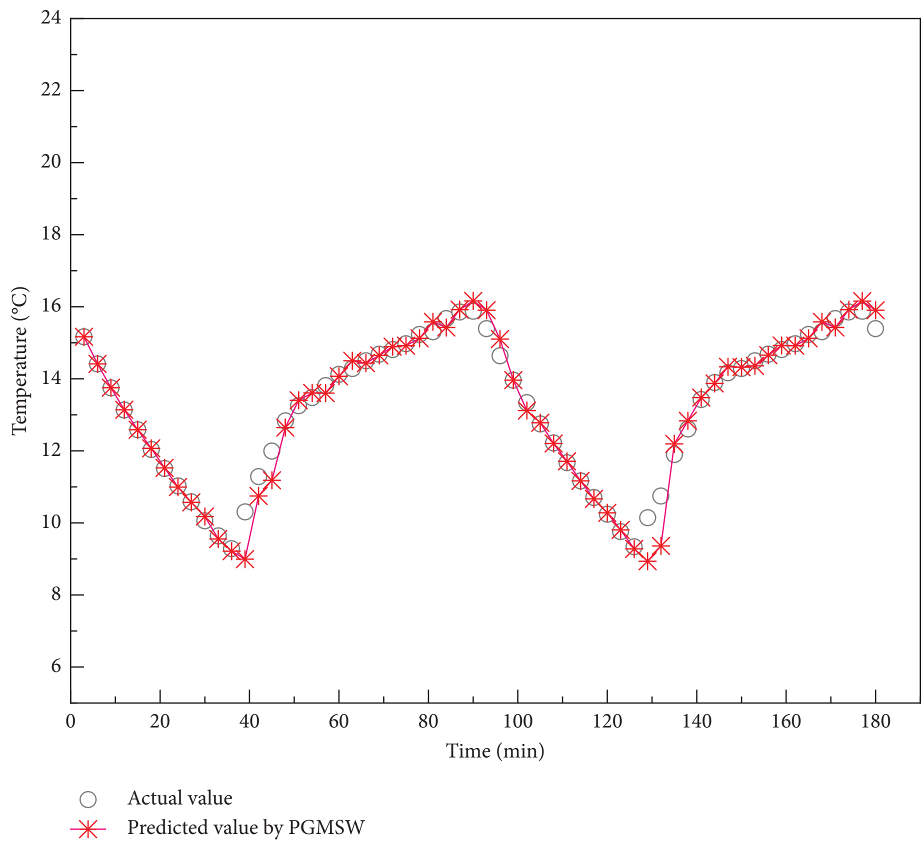

Figure 5: Fitting of values predicted by PGMSW model to telemetry data (window size = 1).

more accurate reproduction of randomly fluctuating sequences. In general, adding various sliding windows improves the forecast accuracy of the three models. When the sliding window size is 6, the predictive accuracy of GMSW in Figure 6 is essentially identical to that of GM (1, 1). PGMSW provides more accurate predictions than GM (1, 1) and GMSW.

These results are useful for real aerospace applications. Accurate prediction of spacecraft telemetry data can provide mission-critical information and can offer early warnings to the ground staff for in-orbit operational management of spacecraft.

Figure 7 displays MAE of the proposed method over the entire 180 min experiment. The minimum/maximum MAE for PGMSW model are 0.01 and 1.38, respectively. The PGMSW model provides more accurate predictions than the other two methods. In addition, the prediction outcomes shown in Figures 4, 6, and 7 demonstrate that GMSW and the traditional GM (1, 1) model are generally stable, but create greater errors. In contrast, the majority of data points in the PGMSW model contain minimal errors.

The MAE of the PGMSW model is only 75.0% and 87.5% of that for GM (1, 1) and GMSW models, respectively (see Table 1), and the MSE of the PGMSW model is only 63.6% and 82.4% of that for GM (1, 1) and GMSW models, respectively (see Figure 8). In contrast, because of the intrinsic flaw of the GM (1, 1) theory, the forecast accuracy in the original series with broad variations is quite poor. Furthermore, our future work will focus on reducing the inherent flaws of the GM (1, 1) theory and broadening its field of application.

Sometimes (especially at the transition points), the GMSW model produces large MAE and MSE than the GM (1, 1) model (e.g., see transition from shadow-sunlight period). However, the MAE and MSE of GMSW decrease during the shadow and sunlight period. The GMSW model better reflects the fluctuations in temperature at 51 minutes, 53 minutes, 57 minutes, 144 minutes, 147 minutes, and 150 minutes during the shadow period. Once the prediction results are modified by incorporating the PSO method, the prediction error decreases significantly, especially during the transition between sunlight and shade.

The MAPE of the PGMSW model is only 1.75% (Table 1), which is only 78.8% and 90.2% of that of GM (1, 1) and GMSW, respectively. This minimal MAPE indicates that the PGMSW model produces the most stable predictions. Figure 9 shows that the PGMSW model surpasses others in MAPE, which reflects the capacity of the PGMSW model to accurately predict real-time fluctuating telemetry data from spacecraft. However, the computational efficiency of the PGMSW model is slightly less than that of the other two models. This modest restriction might be seen as a worthwhile trade-off for the model's improved forecast accuracy. Superior predictive precision denotes the ability of the approach to confidently tell ground workers of future values (normal/abnormal condition). The PGMSW model is thus

Table 2: Comparison of telemetry data and predicted data by PGMSW model.

Time (min)	Temperature (°C)	PGMSW model	Time (min)	Temperature (°C)	PGMSW model	Time (min)	Temperature (°C)	PGMSW model
3	15.166	15.166	63	14.291	14.499	123	9.765	9.809
6	14.416	14.416	66	14.499	14.437	126	9.346	9.281
9	13.754	13.754	69	14.686	14.651	129	10.145	8.938
12	13.138	13.138	72	14.811	14.891	132	10.746	9.359
15	12.586	12.586	75	14.978	14.918	135	11.895	12.195
18	12.037	12.072	78	15.229	15.124	138	12.606	12.835
21	11.511	11.527	81	15.313	15.578	141	13.425	13.481
24	11.027	10.995	84	15.670	15.424	144	13.898	13.872
27	10.585	10.571	87	15.860	15.921	147	14.167	14.334
30	10.065	10.179	90	15.881	16.159	150	14.291	14.322
33	9.645	9.553	93	15.397	15.901	153	14.499	14.362
36	9.287	9.215	96	14.644	15.101	156	14.686	14.657
39	10.305	8.994	99	13.960	13.960	159	14.811	14.923
42	11.289	10.750	102	13.343	13.117	162	14.978	14.918
45	11.997	11.182	105	12.749	12.781	165	15.229	15.124
48	12.831	12.646	108	12.220	12.205	168	15.313	15.578
51	13.261	13.402	111	11.673	11.711	171	15.670	15.424
54	13.486	13.607	114	11.168	11.165	174	15.860	15.921
57	13.816	13.603	117	10.706	10.668	177	15.881	16.158
60	14.126	14.072	120	10.245	10.279	180	15.397	15.901

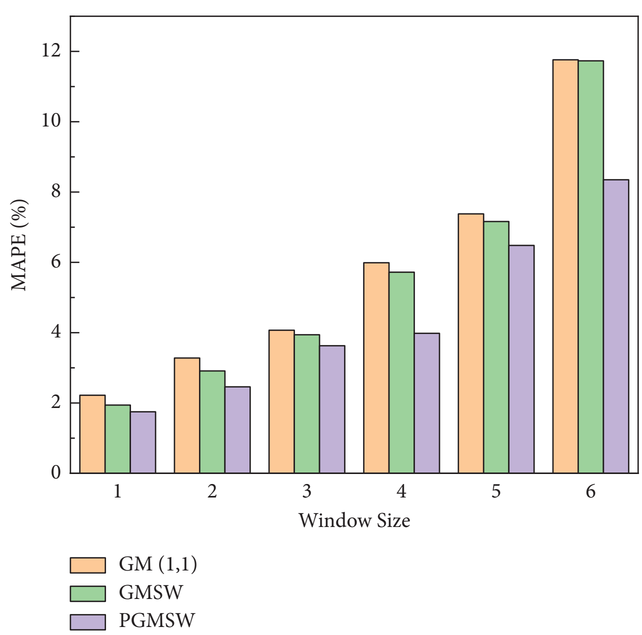

Figure 6: Comparison of MAPE of all results (window size from 1 to 6).

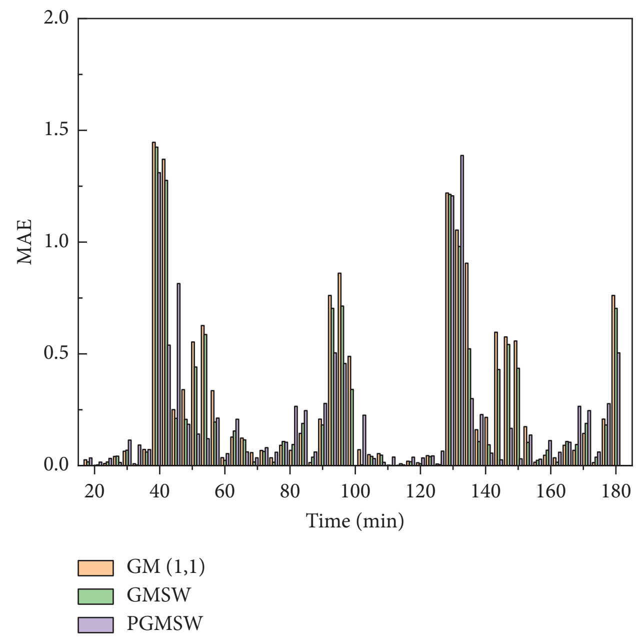

Figure 7: MAEs of the three models (window size = 1).

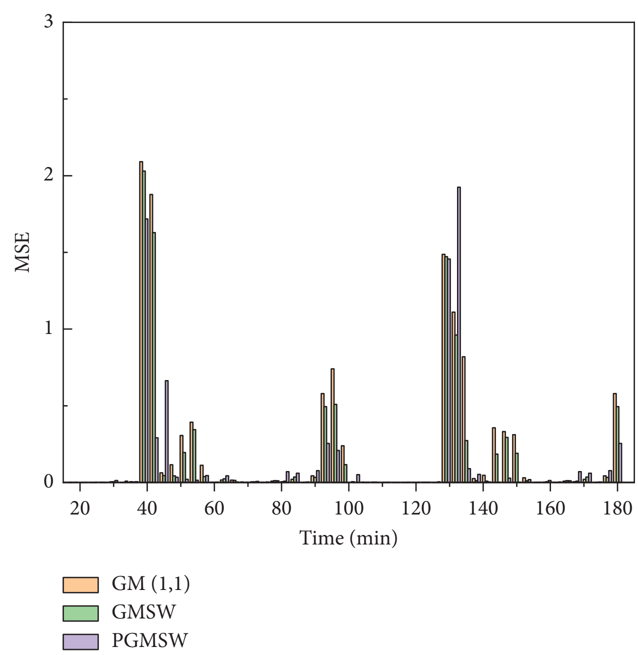

Figure 8: MSEs of the three models (window size = 1).

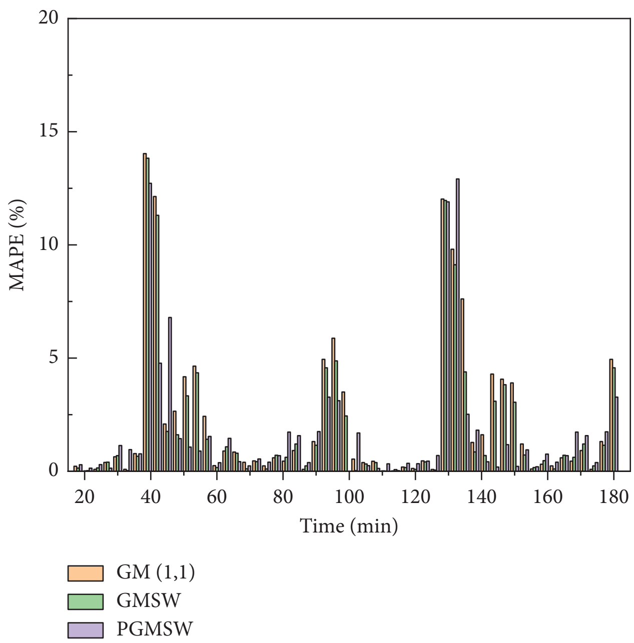

Figure 9: MAPEs of the three models (window size = 1).

suitable for predicting pseudo-periodic spacecraft telemetry data.

5. Conclusions

Forecasting spacecraft telemetry data is quite difficult due to multitasking and in-orbit operations in a complex and changing outer space. By analyzing pseudo-periodic spacecraft temperature telemetry data, this paper proposes a model PGMSW for predicting future operational trends. PGMSW is adapted to treat telemetry data by combing a Markov chain, GM (1, 1) model, and PSO algorithm. PGMSW minimizes the MAPE among expected value and actual telemetry data. In addition, the Markov chain is introduced into GM (1, 1), and we enhance GM (1, 1)'s starting value and add a sliding window to increase precision and flexibility. In contrast to conventional Grey–Markov model, PGSWM embraces new structures for optimizing the background value via the PSO algorithm, which is then used in the Grey modeling process with sliding window.

Spacecraft temperature telemetry data from 3 minutes to 180 minutes are used as a case study to examine whether the suggested PGMSW model with respect to the GM (1, 1) and GMSW models. Furthermore, we use the three test criteria MAE, MSE, and MAPE to quantify the forecast accuracy. Experiments showed that PGMSW proposed herein provides the most accurate predictions. The PGMSW model can thus improve the accuracy of predicting spacecraft telemetry data, which should greatly simplify the problem of predicting fluctuating data. Finally, PGMSW may be used to resolve comparable forecasting issues involving pseudo-periodic telemetry series. In order to increase accuracy and flexibility, we also optimize the GM (1, 1) model's background value and add a sliding window. However, there are some limitations and further research that need to be conducted in the future. First, the method is based on the traditional GM (1, 1), with further research using the fractional-order Grey model (FGM (1, 1)). Second, the sliding window size has a great impact on the prediction results that should be improved by combining the optimization algorithms. Prediction outcomes demonstrate that the proposed method performs better on two data sets with a declining trend and a rising trend. Moreover, predicting pseudo-periodic telemetry series for the proper operation of orbiting spacecraft deserves a comprehensive study in the future.

Data Availability

All data generated or used during the study are available within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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