Low-Orbit Satellite Solar Array Current Prediction Method Based on Unsupervised Learning

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Abstract. With the continuous development of the space industry, the role of satellite become more and more important in China's national economic construction, disaster prevention and mitigation. Power system is one of the important sub-systems that directly impact the in-orbit safe and affection of satellites. Satellite solar array determine the current output of whole satellite. The paper shows the solar array current prediction method based on unsupervised learning which can solve the low-orbit satellite solar array current prediction problem. This method introduces the competition elements that establish the mapping relation between the historical data and the competition element, obtains the best sample through the competition between the competition elements in the prediction processes, the relation functions take the best sample data as the benchmark which can realize the prediction of solar cell array output. Through competition the information of temperature, earth reflection, conversion efficiency and attenuation factors in the sample data are introduced effectively, and the description of such factors in the prediction process is avoided. Through the actual data analysis, we realize the extrapolation of the one-year current mean error is not more than 0.4 a, and the maximum error is not more than 0.5 a. The prediction algorithm for the solar cell array of low orbit satellites without the mathematical description of temperature, earth reflection, conversion efficiency and attenuation factors can predict the reasonable introduction of the above factors.

Keywords: Current · Prediction · Reflection · Solar array

1 Introduction

In order to satisfy the needs of current voltage of the primary power in power system, the satellite solar array is usually composed of a series of photovoltaic cell patches in parallel. The output of Photovoltaic is impacted by temperature, solar incident intensity, space environment, earth light and so many other factors. In document 1, the max power of solar array output is described as:

$$P_{BOL} = S_0 * X * X_s * X_e * A_c * N * F_b * \eta * F_c\left(\beta_p \Delta T + 1\right) \cos\theta$$

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S_0 is the space solar constant, θ is the angle of the right amount of the normal sun sail, X is the correction factor for oblique shooting, X_s is the seasonal change factors, X_e is the earth albedo gain factor, A_c is the battery array nominal area, N is the total number of individual solar cells, F_b is the testing calibration of loss factors, η is the transfer efficiency, F_c is the combined loss factor, β_p is the power temperature coefficient, ΔT is the differences between operating temperatures and nominal temperatures.

In all the factors, only the solar incident intensity can describe by mathematics, the other factors are difficult to be described by accuracy mathematics mode. For example, solar array working temperature, in the document 2 the solar array temperature is determined by the following energy equation:

sunlight + earthlight +earth thermal radiation +the heat from the neighbor components of satellite = output electric power+ heat of radiation back to the space.

The equation is described the battery array temperature because it caused by the earth reflection, thermal radiation, self-dissipating heat and so on is difficult to describe the temperature of the battery array more accurately.

Thus, the prediction of solar array output has to consider many factors based on model method and some of the factors cannot express accurately by data method. It is difficult to calculate the output of low-orbit satellite solar array using a general method for the analytical parameters often different to suit different satellite solar array. This paper proposes a prediction method of low-orbit solar array current based on unsupervised learning to these problems shown above. The advantages of this method are best matching samples through the competition between layers and to calculate the result in form of output function with the best matching samples to obtain the output current of solar array which effectively avoid the impact factors such as earth light, temperature and the difference between different satellites analyze model. The low-orbit satellite solar array output can use the unify algorithm.

2 Algorithm Design

The basic idea of this algorithm is to sample the historical current telemetry data according to certain rules and slice the data to form different sample data. The sample data are cleaned according to the cleaning rules to form a pure sample. The mapping of the sample and the solar cell array output influence factors are established. Each sample corresponds to the influence factors according to the mapping relationship, and the influence factors form the competitive layers of the data. When the currents are predicted, the influence factors corresponding to the period which will be predicted are calculated as the input of the prediction. The matching degree of competitions and inputs between each competition element in the competition layers. The historical data which are mapped by the winning competition elements are the benchmark sample, and the benchmark sample are calculated according to the prescribed functional relationship to form the prediction data. At the same time, the differences between the predicted data and the actual data are calculated and introduced into the next stage of current calculation as the correction coefficients. The basic flow is shown in Fig. 1. In this algorithm, the key link is sample cleaning, because the sample purity directly affects the accuracy of the prediction data. It is necessary to establish reasonable cleaning rules for the sample data to ensure the purity of the sample data.

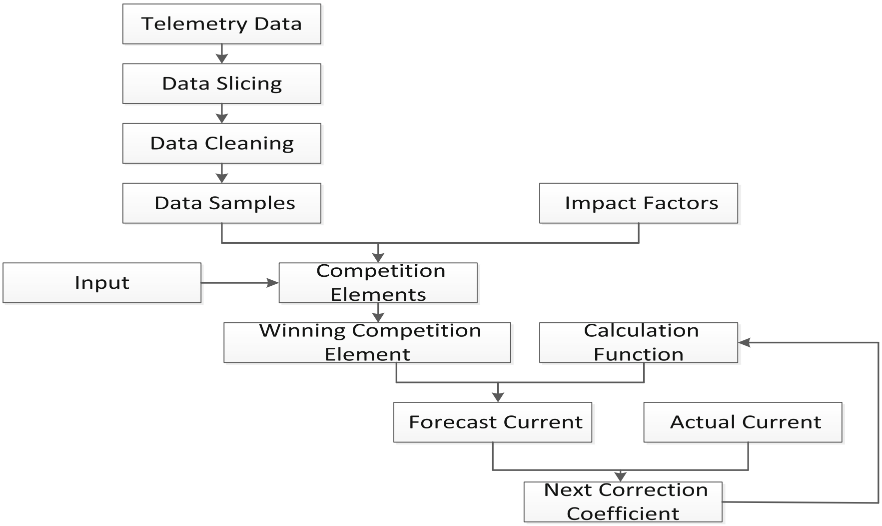

Fig. 1. Algorithm flow

2.1 Data Selection

In addition to the above factors, the output of satellite solar array is also affected by the working state and the working mode of the satellite. For example, in the side-swing mode, the relationship between the normal sail and the right amount of the sun is changed, and at the same time, it may cause the solar cell array shielding by the satellite body and the space-borne equipment. And the output of solar cell array will change. Because of the change of the load, the working point of the solar cell array is changed. According to the data analysis, the working point of the solar cell array of a remote sensing satellite is shifted to the right under the condition of load operation, resulting in the output current dropping about 0.5 a from the normal working point. In order to ensure the purity of sample data. different modes of sample data cause the output of its solar cell array change, which lead to the error in the prediction process. In the process of data selection, the data need to be cleaned to eliminate the interference of the satellite working state, working mode and so on.

The data of satellite battery array are extracted from the database which are combined with the satellite orbit cycle, and the ground shadow is taken as the starting time of the slice until the next point before the ground shadow, which is used as a slice of the satellite telemetry data. If there is no ground shadow, the data are extracted from the changing characteristics of the data and the satellite orbit cycle. the current data set as $I = (I_1, I_2, \ldots, I_n)$. Slice the I according to the rules of orbital period, illumination region, full illumination region, etc. To form different sets of slices $I_i'(i = 1, 2, \ldots, K)$ the current set corresponding to each slice $I'_i = (I'_{i1}, I'_{i2}, \ldots, I'_{ij})$.

Each current value of the satellite solar array output corresponds to each working state of the satellite. It is necessary to distinguish the satellite working state corresponding to the satellite current. There is only the expected state in the sample. for the undesired state in the slice, the fragment in the slice should be removed. for each data slice I'_i, the current data domain working state data needs to be aligned. Because of the telemetry sampling rate differences, the two are out of sync in time, so it is necessary to react to the satellite working state according to different parameters, so that the current output can be well approximated to the desired satellite working state. The corresponding cleaning rule set $C = (C_1, C_2, \ldots, C_m)$ is established for slice I'_i,. If the corresponding state of each data in the I'_i satisfies the set c, all the data is selected as the element of the I'_i set. If there is a situation that the I'_{ij} and I'_{ij+k} does not meet the c, the data needs to be cleaned. the elements in the I'_{ij} to I'_{ij+k} does not meet the rules. if the time interval is greater than 5 min, this sample is culled; the time interval is less than or equal to 5 min, the data between the I'_{ij} and the I'_{ij+k} is culled, and the rest of the sample data is retained. After slice cleaning, the elements in the slice I'_i are output of satellite solar cell array in the desired state, and the purity of slice data is guaranteed.

2.2 Sample Establishment

For the clean satellite solar cell array current output is set as i'. The angle of incidence is calculated as:

$$\beta = \sin^{-1}(\cos\partial_s * \sin R_i * \sin(\Omega - \alpha_s) + \sin\partial_s * \cos R_i)$$

As shown above, Ω is the rising point of red longitude, α_s is the sun red longitude, ∂_s is the sun red latitude, R_i is satellite orbit inclination. The distance factor is calculated by the ratio of the current daily distance to the standard daily distance. The current daily distance is R_1, the standard distance is R_2, then the distance factor $R = R_1/R_2$. pi each R, β is defined as an impact factor P, and each impact factor P_i will correspond uniquely to the current sample I'_i, the impact factor P_i will map one-to-one with the sample I'_i to form a mapping f: $P_i \rightarrow I'_i$.

Make the R_i, β_i as a point P_i on the plane in three-dimensional space, the corresponding relationship between the P_i and the sample I'_i is shown in Fig. 2 below, and the corresponding elements of each sample are set as $I'_I = (x_1, x_2, \ldots, x_k)$. the influence factor is defined on the Rβ plane, where point P_i mapped to the sample I'_i. the influence factor corresponding to the current period to be predicted is set as P_0 on the Rβplane. in this way, the most matching sample P_0 with the target point will be obtained and converted to the best match between the mapping influence factor P_i and the input influence factor on the Rβ plane. the point P_i on the Rβ plane is used as the competition element, and the matching degree between them. The P_0, and the winning point P_i in the corresponding sample will be used as the base sample to participate in the calculation of the predicted current.

2.3 Self Organization Mapping

The method based on Euclidean distance is used for the competition between points P_i on the Rβ plane. the euclidean distance between the j unit of the competition layer and the input influence factor P_0 is shown below.

$$d_j = P_0 - P_j = \sqrt{(\beta_j - \beta_0)^2 + (R_j - R_0)^2}$$

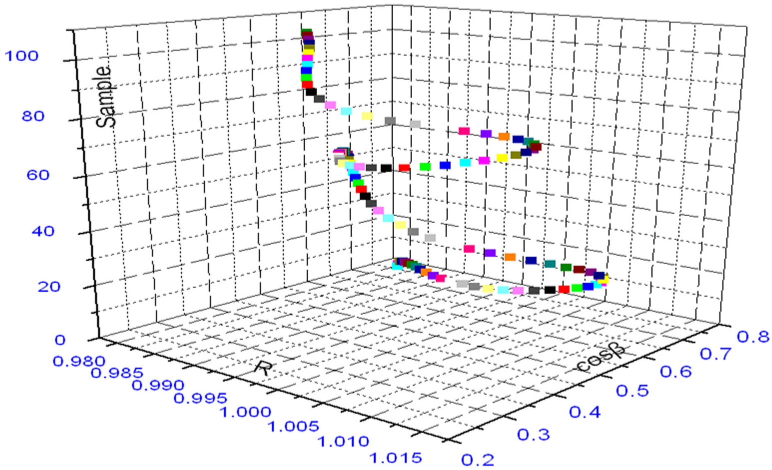

Fig. 2. The relationship of samples and parameters

To randomly select a competitive element P_j for any P_0, calculate its distance with the P_0 and write it as d_j the initial value of the competition. To the next unit of the competition layer, calculate its distance and write as d_{j+1}, if $d_j > d_{j+1}$, recorded as $d_j = d_{j+1}$, otherwise $d_j = d_j$, until the end of the competition, to obtain the minimum corresponding competition element is the winning unit.

According to the factors that affect the output of solar cell array described in reference 1, sample acquisition and cleaning proposes the best sample matching. we can make full use of the information of oblique correction factor, seasonal change factor, earth albedo gain factor, loss factor, conversion efficiency, power temperature coefficient and so on. The current value in the sample is highly similar to the above information contained in the current value of the target point to be predicted.

Mark the minimum distance unit after winning the competition as P_j, as the benchmark unit for data prediction. Take its corresponding data sample f:P → I", $P_j \rightarrow I'_j = (x_1, x_2, \ldots, x_n)$ according to the mapping relationship between the unit and the sample. Each of the corresponding elements in the I'_j will serve as a reference element for the current to be predicted. The predicted current is recorded as the calculation function f(x), then the predicted current value $I_a = f(x) * I'_j$.

3 Example Verification

3.1 Competition of Competition Elements

Two typical satellites with low orbit are selected for verification, which are recorded as S1 and S2 respectively. Two satellites were selected to slice the measured data of solar cell array in 2019, and more than 400 slices were formed. The cleaning rules for the above slice formation are.

c = (pose control state, load state, shunt state, load current). after cleaning, the number of S1 is 483, and the number of S2 is 409. Each sample is taken as a mapping unit, and the sample data time is 2019 to each sample, calculate its corresponding influence factors pi, define the pi on the rβ plane, and the S1 and S2 samples correspond to their influence factors one by one to form a mapping relationship. Select four different dates for s1 and S2 to predict current in 2020, that is, give four different inputs in the rβ plane of s1 and S2. The input parameters p the S1 and S2 input points are (0.984477, 0.613864), (0.991789, 0.686474), (1.011244, 0.984914), (0.990069, 0.973689), (0.985539, 0.966172), (1.012402, 0.973927). In the competition layer the influence factors compete with each other to match the input and the unit with the smallest distance win. Specific competition results are shown in Table 1 below.

Table 1. Result of competition

Input P_0	Label	S1	S2
Day1	The minimum distance The winning competition units	0.007566 P_3	0.064538 P_{317}
Day2	The minimum distance The winning competition units	0.006646 P_{35}	0.017800 P_{317}
Day3	The minimum distance The winning competition units	/ /	0.019589 P_{287}
Day4	The minimum distance The winning competition units	/ /	0.008997 P_{213}

After competition, winning competition units P_3, P_{35} of S1 win in day1, day2, winning competition units P_{317}, P_{317}, P_{287}, P_{213} of S_2 that win in day1 to day4. The corresponding samples of these units contain the factors that affect the output of the solar cell array most closely to the actual factors, and will obtain the right to participate in the current calculation.

3.2 Current Prediction

Table 1 shows that the predict current of satellite S1 and S2 are the sample i'3, i'35 and the sample i'317, i'317, i'287, i'213, respectively the corresponding elements of each sample are extracted separately and participate in the current calculation. To establish the calculation function.

$f(X) = \frac{\cos\beta}{\cos\beta_i} * \frac{R_i^2}{R_2^2} * K$, where k is the correction coefficient and the ratio of the actual value to the theoretical value in the previous stage. The predicted current is $I_a = f(X) * I'_j = \frac{\cos\beta}{\cos\beta_i} * \frac{R_i^2}{R^2} * K * I'_j$. The elements in the sample I'_j are calculated according to the function $f(X)$ to form a set of current I_a, and the elements in the set I_a are the predicted current values.

Using the above method, the S1 and S2 satellites are calculated to formulate the output current prediction of the solar array at any date, and the current values are shown in Fig. 3, 4, 5, 6, 7 and Fig. 8 below.

The satellite S1operates in different orbital positions, the angle between the solar cell formation line and the solar vector is constantly changing. At the same time, the

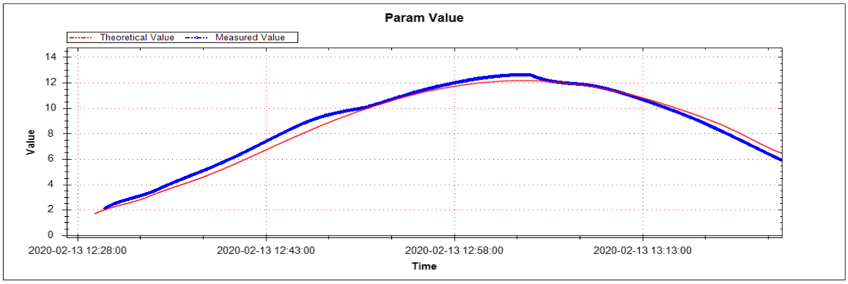

Fig. 3. S1 satellite current forecasting and actual results day1 (extrapolation for 1 year)

output of the satellite solar cell array is basically cosine curve due to the influence of the incident angle, the temperature of the battery array, the conversion efficiency and so on. Because the above factors are included in the sample information and are basically consistent with the state to be predicted, the predicted data can well reflect the actual state after competitive calculation. It can be seen from the Fig. 3 and Fig. 4 that the predicted value is in good agreement with the actual value. The predicted data can well track the output state of the battery array at different orbital positions, track the influence of the earth light on the output of the solar cell array, and reflect the current change of the satellite due to the change of incident conditions.

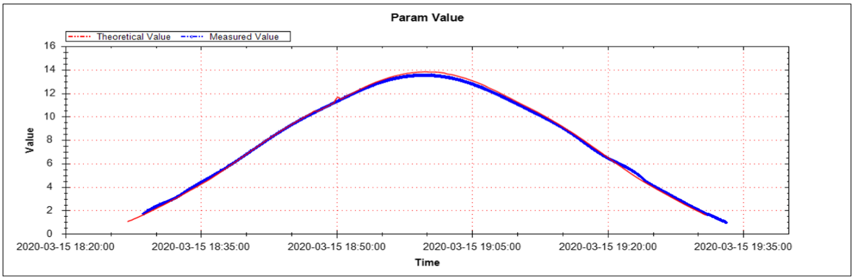

Fig. 4. S1 satellite current forecasting and actual results day2 (extrapolation for 1 year)

Figure 5, 6, 7 and 8 reflect the consistency between measured and predicted data from satellite S2. satellite S2 track solar mode for conventional solar cell arrays. the deviation of its solar cell formation line from the solar vector will remain within a certain range of requirements. in addition to the influence of incident angle, conversion efficiency, sail temperature and other factors during the operation of the satellite, there are also different orbital positions from the relationship between the solar cell formation line and the earth changes, it is can be known that in its output being affected by the earth albedo. Earth albedo is difficult to express mathematically, for the Earth albedo information is contained in the sample data, the predicted data can reflect the trend influencing of different factors on the output of solar array such as Earth albedo and so on.

Figure 7 predicts that there is no satellite shadowing process, because the shadowing data does not meet the cleaning rules c, and its data is cleaned during the sample

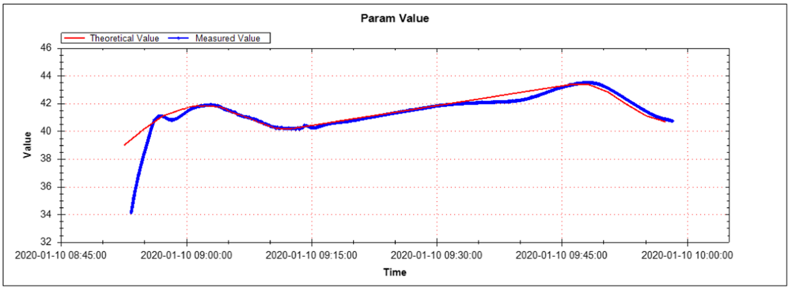

Fig. 5. S2 satellite current forecasting and actual results day1 (extrapolation for 1 year)

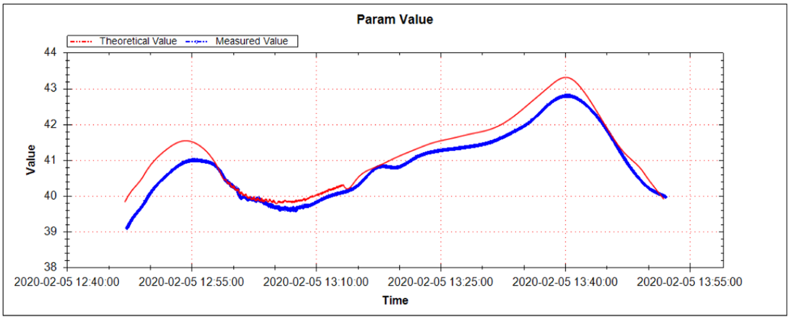

Fig. 6. S2 satellite current forecasting and actual results day2 (extrapolation for 1 year)

establishment. Through the actual data analysis, the satellite s2 due to the change of the satellite load, the working point of the solar cell array shifts to the right, which results in the phenomenon that the output of the solar cell array drops about 0.5 a. compared with the normal operation. If the sample data is not cleaned in model it will cause the prediction data to appear concave points, which will lead to prediction error.

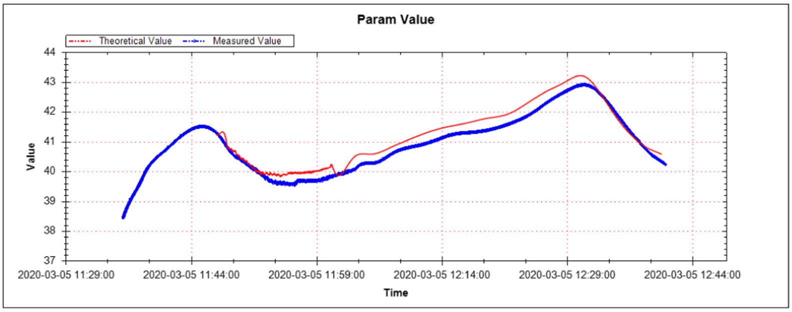

Fig. 7. S2 satellite current forecasting and actual results day3 (extrapolation for 1 year)

In one orbit period, after the satellite is completely out of the ground, the predicted current can be basically consistent with the measured data on the key information such

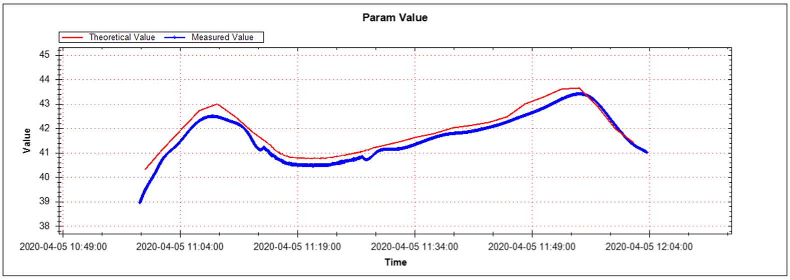

Fig. 8. S2 satellite current forecasting and actual results day4 (extrapolation for 1 year)

as curve shape amplitude, and energy supply state of the reaction satellite during the whole orbit period. Because of the short out-of-the-ground shadow process (usually tens of seconds), there is no special description of the out-of-the-ground shadow pattern in the process of sample establishment.

It can be seen that the prediction data of the solar cell array current can well reflect the trend of the solar cell array current in one orbit cycle except that the prediction data of the satellite out-of-ground shadow process can track the actual data well.

3.3 Precision Analysis

Analysis of the error between prediction data and measured data of satellite S1 is shown in Fig. 9 and Fig. 10. The error calculation method is to calculate the difference between the measured data and the predicted data frame by frame. The difference value is defined as absolute error, which can reflect the real-time tracking ability of the predicted data to the measured data. Where the day1 prediction error is approximately 0.7 a, that exceeds the expected result. The correction coefficient is calculated k, and the coefficient k is introduced into the calculation of day2. The absolute error of day2 is less than 0.5 a that is in line with the expectation.

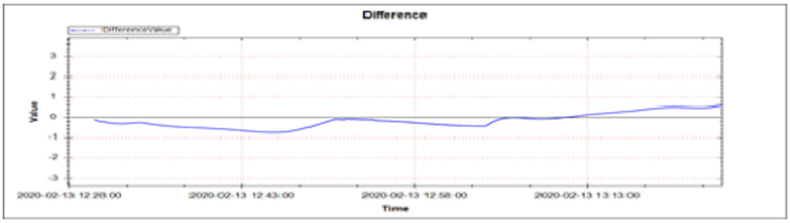

Fig. 9. The errors of S1 in Day1

An analysis of the error between prediction data and measured data of satellite s2 is shown in Figs. 11, 12, 13 and 14. In Fig. 11, Fig. 12 and Fig. 14, the error exceeds 0.7 a means satellite are part os its out-of-ground process. After the satellite is completely out of the ground, the predicted data can track the actual data change well. The error

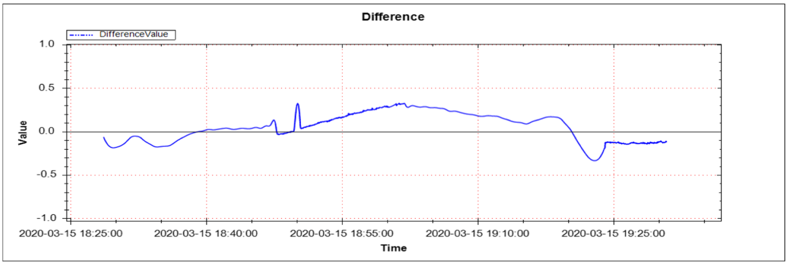

Fig. 10. The errors of S1 in Day2

can be controlled at about 0.5 a. The energy supply of satellite solar array is mainly concentrated in the light region. We need to pay more attention to the output current prediction of satellite in the sun illumination region. The process of entering or leaving the ground shadow, the output of solar cell array has little effect on satellite energy cannot be considered in prediction analysis.

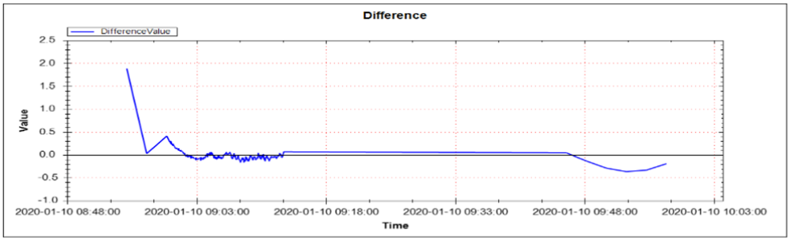

Fig. 11. The errors of S2 in Day1

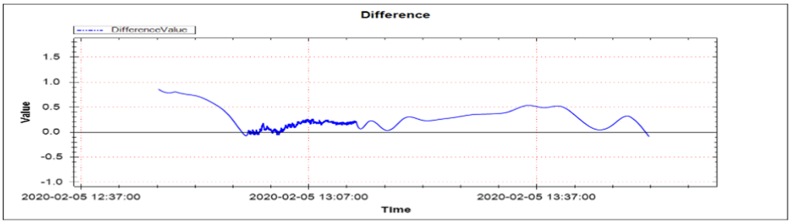

Fig. 12. The errors of S2 in Day2

The predict data and the measure data are statistically analyzed from three aspects: mean, median and maximum. The results are shown in Table 2 below. The main reason for selecting these three parameters is that the mean value can reflect the power supply capacity of the solar array in one orbital period, the median can reflect the central characteristic of the output current of the battery array in one orbital period, and the maximum value reflects the output characteristic of the battery array under the influence of the earth albedo. These three parameters are basically able to characterize the consistency between the predicted data and the actual data.

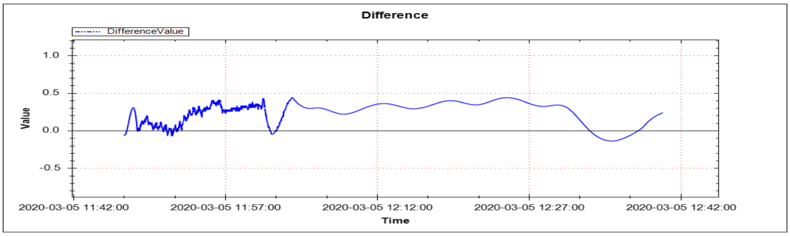

Fig. 13. The errors of S2 in Day3

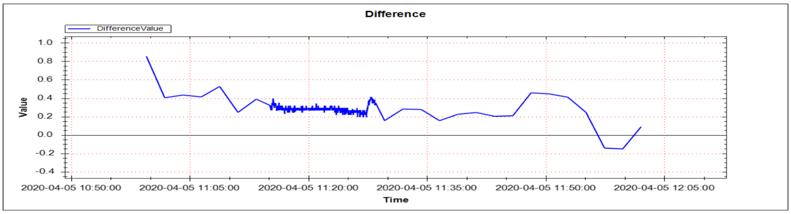

Fig. 14. The errors of S2 in Day4

Table 2. Statistical analysis of accuracy

Sat	Time	Ave (theory, measured)	Med (theory, measured)	Max (theory, measured)
S1	Day1	8.18, 8.16	8.65, 8.80	12.26, 12.63
	Day2	8.33, 8.23	8.78, 8.66	13.85, 13.55
S2	Day1	40.79, 41.47	40.89, 40.95	43.32, 43.52
	Day2	41.19, 40.89	41.13, 40.85	43.32, 42.84
	Day3	41.22, 40.94	41.24, 40.95	43.23, 42.92
	Day4	41.98, 41.65	41.90, 41.67	43.73, 43.42

After one year of extrapolation, the predict current can be basically consistent with the actual measured value on the statistical characteristics such as mean, median, maximum and so on. mean error of S1 is less than 0.2 a, median error is less than 0.2 a, maximum error is less than 0.4 a.. mean error of S2 is less than 0.4 a, median error is less than 0.3 a, maximum error is less than 0.5 a. In the above statistical characteristics, the mean value reflects the stability part of the output of the satellite solar cell array, which is generally the output state of the solar cell array after the earth shadow is basically constant, the working point is stable, and the earth albedo influence is small. The median value describes the central position data characteristics of the battery array output current data, reflecting the centralized trend of the data. The small median error can indicate that the prediction is in good agreement with the actual data in the trend of the data set. The maximum value mainly reflects the effect of the earth albedo on the output of the solar cell array, and the small error of the maximum value indicates that the predicted data can track the effect of the earth albedo well.

It can be seen from the above precision analysis that the method can be consistent with the measured data in absolute error and statistical characteristic error, and the long period prediction results can well reflect the change of the actual solar array current. It can be used in the prediction of the power supply capacity of the satellite solar array.

4 Conclusion

In this paper, the output of satellite solar cell array is predicted by unsupervised method. After one year of extrapolation, the accuracy and variation trend can keep good agreement with the measured data. This method can predict the output of solar cell array based on the historical data by establishing historical sample data and introducing competition elements. In the process of current prediction, the purity of sample data is the key to predict accurately. To establish pure samples, the appropriate sample cleaning rules must be selected. In the process of sample cleaning, it is necessary to fully consider the influence of satellites output of the solar cell array. Pure sample data information can reflect the output of solar cell array in different working states and working modes. The pure sample data information in different factors which can describe the effects of the output of the satellite solar cell array, the different factors in the current change. If the sample is not clear and clean, and the information of satellite working state is introduced, it will inevitably cause a large difference between the predicted data and the actual data. compared with the analytical model, we make full use of such a huge amount of influence factors contained in the historical output telemetry data of solar cell array that do not need to establish the model of temperature, earth albedo, conversion efficiency and other factors in the actual calculation process. through sample cleaning, competition between competing elements, the reasonable introduction of the above factors is realized. According to the actual situation of different satellites, this method can realize the unity of the algorithm. In the process of practical application, the mapping relationship between the output current and the influence factor can be formed by establishing the database of the output of the solar array output of different satellites. Through the precision analysis, it can be seen that the long-period extrapolation can meet the demand of low-orbit satellite solar array output prediction in terms of absolute error and statistical error. According to the demand of high-orbit satellite current prediction, adaptive modification is made in data sampling, cleaning and calculation.

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