Maneuver prediction for constellation satellites based on the Informer model

Han Liu [1,2], Shengxian Yu [1], Xin Wang [1]

[1] *Purple Mountain Observatory, Chinese Academy of Sciences*
Nanjing, China
Email:hanliu@pmo.ac.cn

[2] *School of Astronomy and Space Science, University of Science and Technology of China*
Hefei, China

***Abstract* – In order to solve the problem of poor orbit prediction accuracy during frequent maneuvers of constellation satellites, this paper proposes a maneuver prediction method based on deep learning algorithm. The method takes the ephemeris data of the constellation satellites as the dataset, and first extracts the period information during maneuvering and the interaction characteristics among the three satellites in the constellation as inputs. Then, the maneuver is predicted using the informer model. Numerical results show that the method can effectively realize the prediction of maneuver moments and amplitudes.**

***Keywords*: satellite maneuver, orbit prediction, Informer, constellation satellites**

I. INTRODUCTION

In recent years, the trend towards launching and utilizing small satellites in bulk has become dominant, e.g., LEO mega-constellation satellites. This has led to an increasingly complex space environment. The new space environment is requiring higher levels of Space Situational Awareness (SSA) with tougher challenges. To ensure the safety of space activities, the future position of each satellite must be accurately forecast. At present, orbital prediction involving frequent maneuvers remains a challenging task, and its accuracy may degrade rapidly if maneuvers are not accurately forecasted.

Traditional orbital prediction methods are mainly based on dynamical models, modeling various forces by analytical or numerical methods, such as the Earth's non-spherical gravity, atmospheric drag, solar radiation pressure, and so on. However, in order to achieve better forecasting accuracy, both methods face the problem of maneuver prediction. In contrast to natural perturbations, the maneuvers of constellation satellites, which involve pre-set maneuver procedures and accidental collision avoidance maneuvers, are hard to model and predict. Nevertheless, there are certain rules for the constellation satellites while the constellation configuration is maintained by pre-set maneuver procedures.

Machine learning methods excel at capturing nonlinear relationships and trends in complex problems, with the ability to learn features and patterns between inputs and outputs automatically, providing a forward-looking approach to refining orbit prediction. At present, some of the models widely used in the field of orbit prediction include Support Vector Machines (SVMs) and Artificial Neural Networks (ANNs)[1], etc.

However, current orbit prediction models extended by machine learning are typically grounded on the error compensation method, which mainly improves prediction accuracy by correcting the prediction errors of existing models. When dealing with frequent and discontinuous maneuvers of LEO satellites, the applicability of these methods would be limited. Moreover, most of them are designed based on short-term predictions, the performance may continue to degrade with a longer forecasting sequence. Given the need to predict LEO satellite maneuvers for the next day, models must perform well in long-series prediction tasks.

To address the above problems, this paper proposes a maneuver prediction method in the case of frequent maneuvers from the perspective of time series prediction algorithms. Based on the time-series characteristics of maneuver variations of constellation satellites, the historical maneuver characteristics of multiple satellites in the constellation are modeled. By introducing the informer model in the deep learning approach for training, the final maneuver prediction is achieved. The publicly available ephemeris data of Starlink satellites is used to verify the effectiveness of the maneuver prediction method.

In this paper, Section 2 will describe the calculation of the orbital mean element based on raw precision ephemeris data. Section 3 will present the structure of the designed Informer neural network. In Section 4, a case study applying the algorithm to LEO satellite maneuver prediction is given to validate the performance of the proposed model. Finally, conclusions are presented in Section 5.

II. MANEUVER DATA ANALYSIS

For Starlink satellites, the orbital maneuver magnitude is much smaller than the orbital short-period amplitude, so it is difficult to obtain their orbital maneuver information by direct calculation. In this section, we first obtain the raw precision ephemeris data and mean it through analytical methods. By eliminating the short-period variations in it, the amount of orbital maneuvers and maneuver moments can be accurately derived when performing maneuver detection. The Two-Line-Element(TLE) set downloaded from the North American Air Defence Command (NORAD) is used as the base data(https://www.space-track.org).

For orbits of space objects, Kepler's orbital elements are generally expressed as (a,e,i,Ω,ω,M). However, it is not quite suitable for cases where the orbital eccentricity is very small, thus requiring the adoption of the equinoctial elements (a,i,Ω,ξ,η,λ). Their relationship to the Kepler's orbital elements is as follows:

$$\begin{aligned} \xi &= e\cos\omega, \\ \eta &= e\sin\omega, \\ \lambda &= \omega + M. \end{aligned} \tag{1}$$

Since orbital variations caused by orbital maneuvers are coupled with orbital variations caused by various perturbations, it is necessary to distinguish which is the main factor contributing to the orbital variations, thus enabling maneuver detection. Among these perturbations, the biggest one is the Earth's oblateness perturbation. Therefore, in studying this problem, the first step is to remove the short-period variation of the orbital elements caused by the Earth's oblateness perturbation, as follows for Kepler's orbital elements[2]:

$$\begin{aligned}
a_s &= \frac{J_2 a_E^2}{a}\left(1-\frac{3}{2}\sin^2 i\right)\left[\left(\frac{a}{r}\right)^3-(1-e^2)^{-3/2}\right] \\
&\qquad + \frac{3J_2 a_E^2}{2a}\sin^2 i\left(\frac{a}{r}\right)^3\cos 2(f+\omega), \\
i_s &= \frac{C_E}{4}\sin 2i\left[\cos 2(f+\omega)+e\cos(f+2\omega)+\frac{e}{3}\cos(3f+2\omega)\right], \\
e_s &= \frac{1-e^2}{e}\left(\frac{1}{2a}a_s-\tan i\, i_s\right), \\
\Omega_s &= -C_E\cos i\Big\{(f-M+e\sin f) \\
&\qquad -\frac{1}{2}\left[\sin 2(f+\omega)+e\sin(f+2\omega)+\frac{e}{3}\sin(3f+2\omega)\right]\Big\}, \\
M_s &= C_E\sqrt{1-e^2}\Big\{-\left(1-\frac{3}{2}\sin^2 i\right)\left[\left(\frac{1}{e}-\frac{e}{4}\right)\sin f+\frac{1}{2}\sin 2f+\frac{e}{12}\sin 3f\right] \\
&\qquad +\sin^2 i\Big[\left(\frac{1}{4e}+\frac{5e}{16}\right)\sin(f+2\omega)-\left(\frac{7}{12e}-\frac{e}{48}\right)\sin(3f+2\omega) \\
&\qquad -\frac{3}{8}\sin(4f+2\omega)-\frac{e}{16}\sin(5f+2\omega)-\frac{e}{16}\sin(f-2\omega)\Big]\Big\}, \\
\omega_s &= -\cos i\,\Omega_s-\frac{1}{\sqrt{1-e^2}}M_s+C_E\left(1-\frac{3}{2}\sin i\right)(f-M+e\sin f), \\
&\qquad +C_E\sin^2 i\left[\frac{3}{4}\sin 2(f+\omega)+\frac{3e}{4}\sin(f+2\omega)+\frac{e}{4}\sin(3f+2\omega)\right].
\end{aligned} \tag{2}$$

where $C_E = \frac{3J_2 a_E^2}{2a^2(1-e^2)^2}$, J_2 is the Earth's oblateness perturbation coefficient, a_E is the equatorial radius of the Earth's reference ellipsoid, f is the orbital true anomal, and $r = \frac{a(1-e^2)}{(1+e\cos f)}$. Using the above formula, the short-period variation of the equinoctial elements can be further obtained as follows:

$$\begin{aligned} \xi_s &= e_s\cos\omega - \omega_s e\sin\omega, \\ \eta_s &= e_s\sin\omega + \omega_s e\cos\omega, \\ \lambda_s &= \omega_s + M_s. \end{aligned} \tag{3}$$

The amount of a single maneuver of a Starlink satellite is small, on the order of a hundred meters. Therefore, in addition to the above short-period variations, it is necessary to further eliminate the higher-order effects of the Earth's non-spherical gravitational perturbations. After obtaining the instantaneous orbital elements of the space object, the mean elements applicable to maneuver detection can be obtained by subtracting the above period term from it [3].

III. MODELS AND METHODS

In this paper, we model the orbital maneuver characteristics of spacecraft based on the Informer framework. The Informer model was proposed by Zhou[4] recently based on the improvement of Transformer in long sequence time-series forecasting(LSTF). It is able to accurately capture long-term dependencies and interactions in sequence data and has been shown to be well applicable to LSTF problems. The model structure is shown in Fig.1.

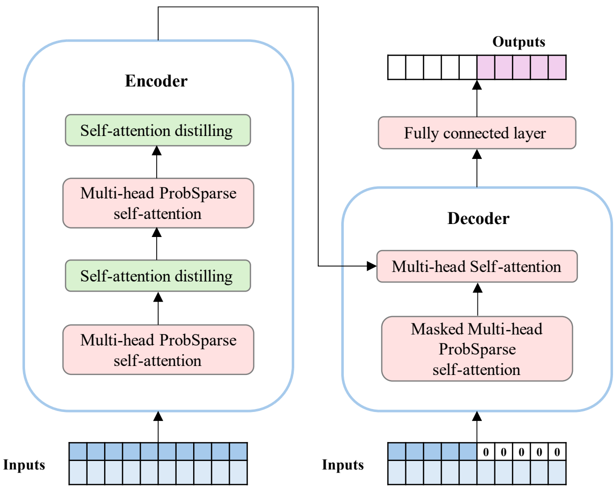

Fig. 1. The framework of Informer.

Informer uses an Encoder-Decoder structure, in which the encoder achieves feature-learning mapping on long sequence data through a *ProbSparse* attention mechanism instead of the traditional self-attention mechanism. The original self-attention uses *(Query, Key)* and scaled dot-product operations to compute the attention score, but since the distribution of self-attention probabilities is sparse, i.e., a small number of dot-product constitute the main attention, the contribution of the other dot-product can be ignored, and the Kullback-Leibler (KL) divergence can be used to evaluate the sparsity of the *Query*. The evaluation formula corresponding to the *i*-th query is[4]:

$$M(\boldsymbol{q}_i, \boldsymbol{K}) = \ln \sum_{j=1}^{L_K} e^{\frac{\boldsymbol{q}_i \boldsymbol{k}_j^\top}{\sqrt{d}}} - \frac{1}{L_K} \sum_{j=1}^{L_K} \frac{\boldsymbol{q}_i \boldsymbol{k}_j^\top}{\sqrt{d}} \qquad (4)$$

where, the first term is the Log-Sum-Exp (LSE) of $\boldsymbol{q}_i$ on all the keys; the second term is the arithmetic mean on them. Based on this analysis, the *ProbSparse* self-attention result can be calculated as follows [4]:

$$A(\boldsymbol{Q}, \boldsymbol{K}, \boldsymbol{V}) = Softmax\left(\frac{\overline{\boldsymbol{Q}}\boldsymbol{K}^\top}{\sqrt{d}}\right)\boldsymbol{V} \qquad (5)$$

where softmax is the activation function, *d* is the input dimension, and $\boldsymbol{Q} \in \mathbb{R}^{L_Q \times d}$, $\boldsymbol{K} \in \mathbb{R}^{L_K \times d}$, $\boldsymbol{V} \in \mathbb{R}^{L_V \times d}$. $\overline{\boldsymbol{Q}}$ is a sparse matrix of the same size of $\mathbf{q}$ and it only contains the Top-u queries under the sparsity measurement $M(\boldsymbol{q},\boldsymbol{K})$.

The distillation operation is performed to privilege the superior ones with dominating features and make a focused self-attention feature map in the next layer. The distillation process from layer *j* to layer *j+1* is as follows [4]:

$$\boldsymbol{X}_{j+1}^t = \text{MaxPool}\left(\text{ELU}\left(\text{Conv1d}\left(\left[\boldsymbol{X}_j^t\right]_{AB}\right)\right)\right) \qquad (6)$$

where $\left[\mathbf{X}_\mathrm{j}^\mathrm{t}\right]_{AB}$ contains the attention block and the multi-head *ProbSparse* self-attention, conv1d is the one-dimensional convolution, and ELU is the activation function. Finally, the maximum pooling downsampling is performed through the MaxPool layer.

The decoder mainly focuses on interacting with the higher-order feature information learned from the input data as well as outputting the forecast results. A traditional Decoder structure is used in Informer, consisting of a stack of two identical multi-head attention layers [4]:

$$\boldsymbol{X}_{\text{de}}^t = \text{Concat}(\boldsymbol{X}_{\text{token}}^t, \boldsymbol{X}_0^t) \in \mathbb{R}^{(L_{\text{token}}+L_y)\times d_{\text{model}}} \qquad (7)$$

Finally, the prediction results are output through the fully connected layer.

IV. MANEUVER PREDICTION

To validate the performance of the Informer model in maneuver prediction, the experiment is tested with an LEO satellite 46534 as the prediction target, while two satellites, 46545 and 46538, which are in phase and close to it, are selected as auxiliary targets. The specific information of the test cases is listed in Table 1. Figure 2 presents the variation of the orbital semimajor axis with time for satellite 46534.

To improve the prediction accuracy and reduce the dimension of features, we chose the Random Forest (RF) algorithm to evaluate the importance of features, all of which include six orbital elements $(\mathrm{a}, \mathrm{e}, \mathrm{i}, \Omega, \omega, \mathrm{M})$ and $\Delta\lambda$ for the three satellites, as well as the differences in λ of the target satellite 46534 from the other two satellites(46545,46538), $\delta\lambda_A$ and $\delta\lambda_B$, respectively. The feature importance ranking is shown in Figure 3. The prediction experiment finally selects the top three important features a_2, $\Delta\lambda_1$, and a_3 along with the target satellite's (46534) semimajor axis as inputs.

Table 1. Information of the experimental satellites.

NORAD ID	*a* /km	*i*	Ω
46534	6925.6880	53.1329	146.7932
46538	6925.6440	64.1912	146.8296
46545	6925.6480	49.5591	146.8222

Four metrics, Mean Absolute Error(*MAE*), Root Mean Square Error (*RMSE*), *Precison*, and *Recall*, are chosen to evaluate the predictive performance of the model

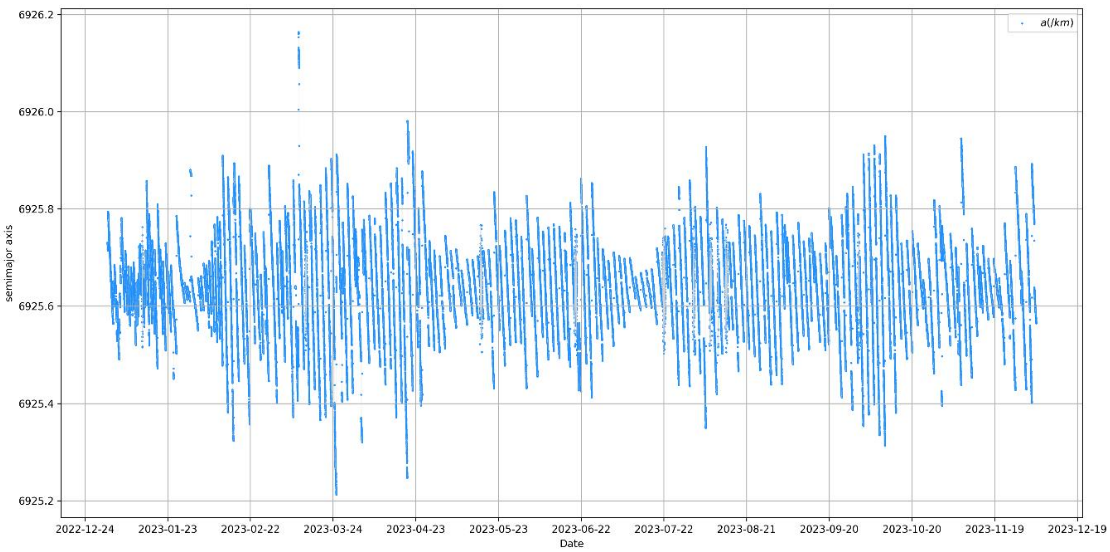

Fig. 2 Variation of the orbital semimajor axis of Starklink satellite 46534 versus time.

The formulas are listed below:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y - \hat{y}_i|$$
$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y - \hat{y}_i)^2} \quad (8)$$

where y represents the actual value, $\hat{y}_i$ is the predicted value, and n is the total number of predicted points.

$$Precision = \frac{TP}{TP + FP}$$
$$Recall = \frac{TP}{TP + FN} \quad (9)$$

where, TP (true positive) refers to the model predicting that there is a maneuver when it occurs; FP (false positive) refers to the model predicting that there is a maneuver when it does not occur; and FN (false negative) refers to the model not predicting that there is a maneuver when it occurs.

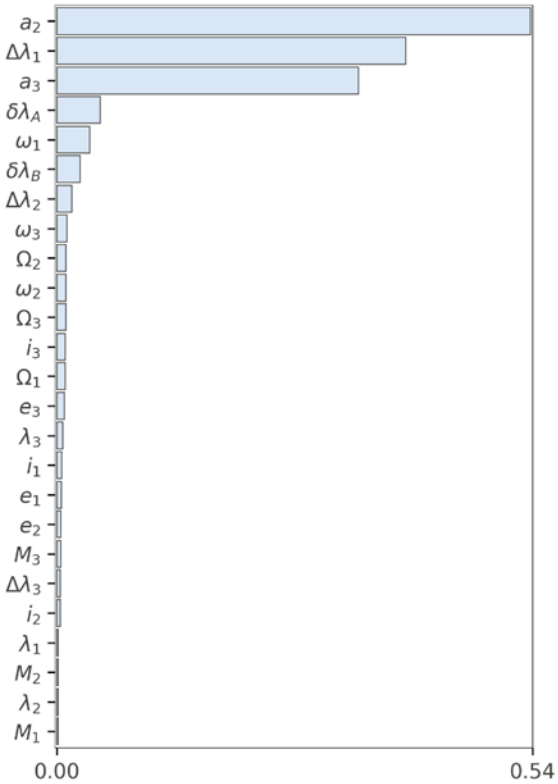

Fig. 3 Feature importance ranking results. (satellites 46534, 46545, and 46538 correspond to subscripts 1, 2, and 3, respectively, and $\delta\lambda_A$, $\delta\lambda_B$ correspond to the λ -difference between 46534 and 46545, and the λ -difference between 46534 and 46538)

Table 2. Results of different evaluation metrics for the Informer model

metric	*MAE*	*RMSE*	**Precision**	**Recall**
	0.0427	0.0540	91.35%	82.09%

The prediction results are shown in Table 2. Among them, the distribution of maneuver moments and magnitude errors in the samples with correct maneuver predictions are shown in Fig. 4 and Fig. 5. Fig. 6 and Fig. 7 gives two examples of the prediction results for the maneuvers, where the actual maneuver characteristics and predicted maneuver characteristics are marked in green and red, correspondingly.

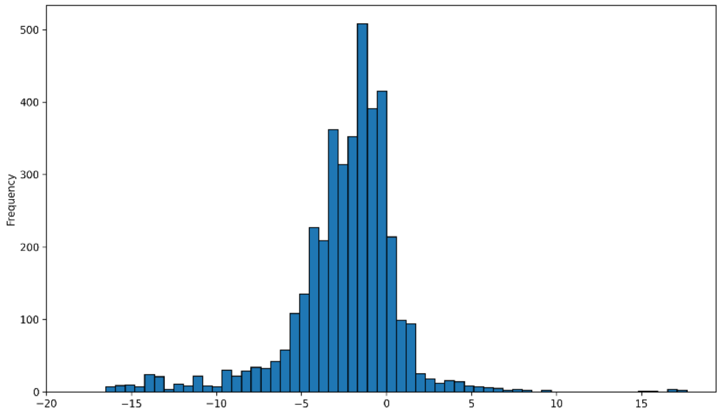

Fig. 4 The Maneuver moments prediction error (hours).

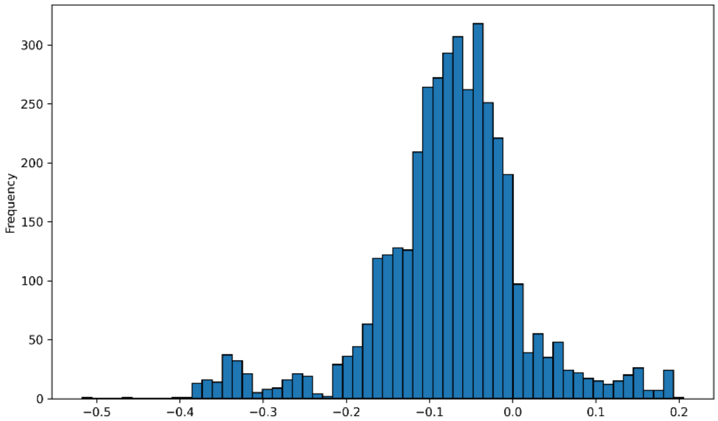

Fig. 5 The Maneuver magnitudes prediction error (/km).

For example 1, the predicted maneuver moment is 30 min earlier and the maneuver magnitude is 0.046 km smaller compared to the real maneuver. For example 2, the predicted maneuver moment is 40 min earlier and the maneuver magnitude is 0.033 km smaller compared to the real maneuver.

It can be seen that the model we constructed is able to predict the majority of future maneuvers. At the same time, it can also give more accurate information about the characteristics of the future maneuver, including the size of the maneuver magnitude and the moment of the maneuver. In addition, it is worth noticing that the results perform better when the input data is more periodic.

V. Conclusion

The problem of orbital prediction in the case of frequent maneuvers of constellation satellites is briefly studied. A method is proposed to realize maneuver prediction based on the Informer model. The maneuver prediction experiment is performed using the Starlink satellite 46534 as an example. Results show that the prediction accuracy of maneuver moment and maneuver amplitude is well, which proves the feasibility of the method. This method can fit the maneuver well while avoiding the tedious formula derivation. We are trying to apply the method to actual orbit prediction to evaluate its application.

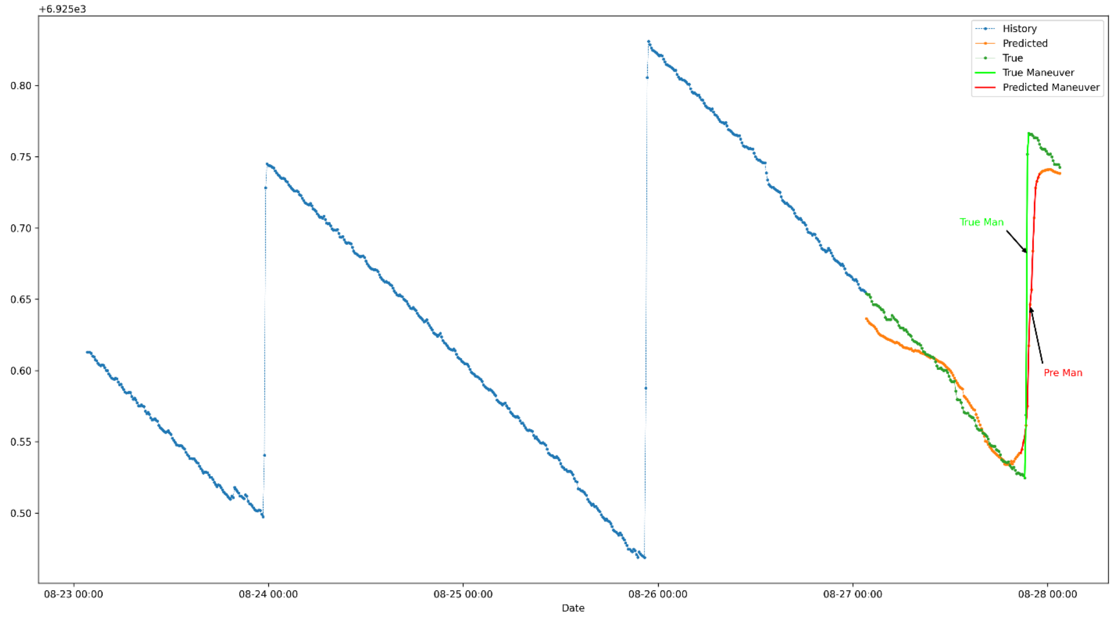

Fig. 6 example 1 of the prediction results for the maneuver.

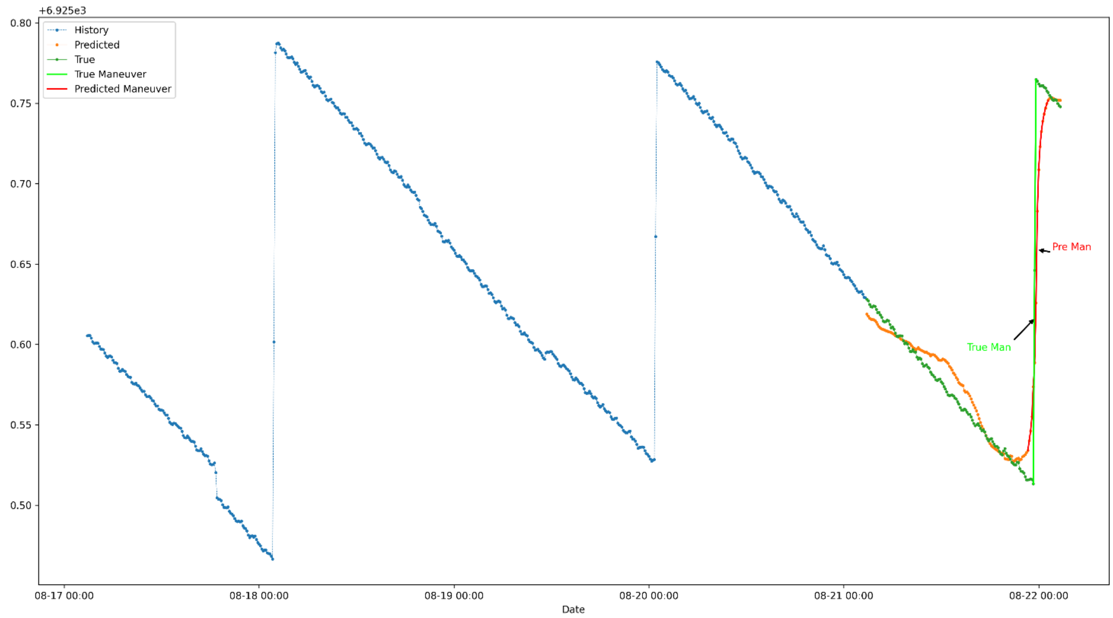

Fig. 7 example 2 of the prediction results for the maneuver.

Acknowledgement: Our work was funded by the National Natural Science Foundation of China (Grant No. 12073082).

VI. REFERENCES

[1] Peng, H.; Bai, X. "Improving Orbit Prediction Accuracy through Supervised Machine Learning". *Advances in Space Research*, vol. 71,pp. 2628–2646, 2018.

[2] Kozai, Y. "The Motion of a Close Earth Satellite". *The Astronomical Journal*, vol. *64*, pp. 367,1959.

[3] Liu,L. *Orbit Theory of Spacecraft*. Beijing: National Defense Industry Publishing House, 2000.

[4] Zhou, H.; Li, J.; Zhang, S.; Zhang, S.; Yan, M.; Xiong, H. "Expanding the Prediction Capacity in Long Sequence Time-Series Forecasting". *Artificial Intelligence*, vol. *318*, pp. 103886. 2023