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An Adaptation of Deep Learning Technique In Orbit Propagation Model Using Long Short-Term Memory

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Nor'asnilawati Salleh
Razak Faculty of Technology and Informatics
Universiti Teknologi Malaysia
Kuala Lumpur, Malaysia
Engineering and Space Technology Division
Malaysian Space Agency
Selangor, Malaysia
norasnilawati@gmail.com

Nurulhuda Firdaus Mohd Azmi
Razak Faculty of Technology and Informatics
Universiti Teknologi Malaysia
Kuala Lumpur, Malaysia
huda@utm.my

Siti Sophiayati Yuhaniz
Razak Faculty of Technology and Informatics
Universiti Teknologi Malaysia
Kuala Lumpur, Malaysia
sophia@utm.my

***Abstract*—The orbit propagation model is used to predict the position and velocity of the satellites. It is crucial to obtain accurate predictions to ensure that satellite operation planning is in place and detects any possible disasters. However, the model's accuracy decreases as the propagation span increases if the input data are not updated. Therefore, to minimize these errors while still maintaining the model accuracy, a study is conducted. The Simplified General Perturbations-4 (SGP4) model and two-line elements (TLE) data are selected to perform this study. The problem is analyzed, and the deep learning technique is the proposed method to solve the issue. Next, the enhanced model is validated. The study aims to produce a reliable orbit propagation model and assist the satellite's operational planning. Also, the improved model can provide vital information for space-based organizations and anyone who may be affected.**

Keywords—Orbit Propagation, SGP4, Deep Learning, Recurrent Neural Network, Long Short-Term Memory

I. Introduction

The operational planning for a satellite is essential as the life span is limited depending on its mission and design. For LEO satellite, the life span is typically five (5) years [1][2]. Thus, the satellite's operational planning must be well planned and accurate to carry out its mission. It would be disruptive and problematic for the user if they failed to perform the task due to improper planning. For example, the desired image unable to capture due to incorrect satellite position and timing.

Meanwhile, the increasing number of space objects has indirectly increased the number of conflicts between them [3][4]. The space object also includes the debris in orbit around the Earth, which also can be dangerous. Therefore, for collision cases, preventive measures can be made even better if the problem can be detected earlier. Several incidents involving space objects have occurred, such as the February 2009 incident involving a U.S. Iridium communications satellite and Russian communications satellite Cosmos 2251 [5]. One of the major causes of this incident is the orbit propagation model's ability to obtain accurate information about the satellite position [6][7]. Besides that, the relevant information is only available after the incident happened. Therefore, it is necessary to have an accurate orbit propagation model for optimal satellite operation planning and oversee space catalog object growth to prepare and prevent space incidents.

Many researchers have conducted various studies to improve the orbit propagation model. The Holt-Winters technique can increase accuracy up to 90.03% during a 30-day propagation span [8]. Later, a support vector machine (SVM) increased the orbit propagation's accuracy by 97.7%. However, if the propagation span is more than 28 days, the capability of SVM is reduced [9]. Further study has been done and shows that the machine learning approach can significantly improve the orbit prediction accuracy for the space objects' position and velocity. The increasing training data size can lead to a better performance until adequate data is used [7]. Therefore, in this study, the current problems are assessed, and a new solution to improve the current orbit propagation model by using the deep learning technique is the target.

This paper is structured as follows. Section 2 discusses the related works of the orbit propagation model and the prediction technique used. The proposed method and the study results are described in Section 3 and Section 4, respectively. Section 5 discusses the findings and study limits. Finally, the last section concludes the paper and points out the future work of this study.

II. Related Work

The orbit propagation model's characterization is according to the perturbations, equation motion formulation, and the integration method [8]. Three (3) different orbit propagation models are analytical, semi-analytical, and numerical [10][11][12][13]—Fig. 1 shown the illustration of the orbit propagation model types.

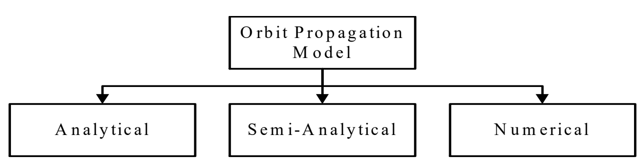

Fig. 1. Types of Orbit Propagation Model.

An analytical propagator used a closed-form solution to provide satellites position and velocity at a particular time by estimating object movement [14][15]. It is ideal for modeling a maintained orbit without maintenance maneuvers. This propagator's advantage is its less computational, but it is less accurate than other propagators [16][17].

Next, semi-analytical used several closed-form approaches and numerical integration [18][19]. The semi-analytical technique constitutes a combined approach. The complex perturbing effects values are included in the formulation and then transferred through analytical methods [8]. This propagator provides a quicker result compare to the total numerical integrations, and it is beneficial for long-term perturbation analysis [16][17].

Lastly, the numerical propagators used numerical methods to integrate motion equations for space objects [15][20]. This technique is conducive to higher accuracy because it allows complex perturbation models, although the need for small integration steps translates into long computational time [8]. The advantage of this type is it can give higher accuracy and used more cases than the other approach. But the disadvantage is that it requires more computational effort [17].

Chen et al. had studied the difference of each orbit propagation model and identified that the most selected model used is Simplified General Perturbations-4 (SGP4) model, a semi-analytical model [21]. It is because the SGP4 model is the most complete, which includes various elements and orbit perturbations value compared to other models [17][22][23].

A. *Simplified General Perturbations-4 (SGP4) Model*

Lane in 1965 has developed this SGP4 model, and it became operational in the early 1970s [22][24]. It is known as the most advanced space surveillance system with regular missions of space objects catalog, maintaining the catalog data, tracking the space objects, and updating the orbit elements [17][21][22].

However, to use the SGP4 model, the Two-Line Element (TLE) data must be used as input data to the model. TLE data ensure the maximum prediction accuracy obtained by the SGP4 model [22]. The TLE data is known as the most comprehensive space object cataloging system in which the information is updated every 1-2 days for the expected target. Meanwhile, for the critical target, it is updated 2-3 times every day. The TLE is an open-source data provided by NORAD, and it is accessible worldwide except for military data of the United States and its alliances [21].

Nevertheless, the accuracy of the SGP4 model decreased if the propagation span increased. The decrease happened because the period of validity of TLEs is limited to a specific period [8]. As a result, the current system based on TLEs and SGP4 is becoming insufficient for satellite operation planning and Space Situational Awareness (SSA) growing demands. Also, TLE data does not include the orbital error information [25][26]. It only contains the mean orbital elements; thus, another method needs to be applied to calculate the orbit error covariance [27].

B. *Orbit Propagation Method*

Various methods have been used in the orbit propagation model. Table I lists the overview of these methods.

TABLE I. PROPAGATION METHOD OVERVIEW

Technique	Year	Advantages	Disadvantages
Linear Propagator (LinCow/ CADET) [3]	1970-2006	Simple, high computation efficiency	Inaccurate for nonlinear system
Nonlinear Propagator [3]	1995-2016	High computation efficiency.	Complex and curse of dimensionality.
Coordinates Transformation [3]	1996-2015	To avoid complex uncertainty propagators.	Nonlinearity is not applicable for mapping.
Hybrid Method [3, 8]	2015-Present	High computation efficiency.	Complex.

From the list, the hybrid method is the latest method used. This hybrid method combines classical integration methods with prediction techniques such as time series technique, learning technique, etc. [8]. The hybrid method can improve computational efficiency, but due to the limitations of the prediction technique used, additional improvement is required [15]. Therefore, appropriate prediction techniques need to be selected and explored.

C. *Prediction Techniques*

In orbit propagation, errors during the initial control interval often show a systematic pattern repeated in each orbiter revolution [8]. Thus, to identify the suitable technique for this study, all related methods are investigated.

In their proposition [28], Jeffrey and Aubrey used the Runge-Kutta method to deal with nonlinear equations that occur over time. This method can handle nonlinear equations with longer time steps and reduce orbit propagation's computational cost. However, it is not straightforward and rarely used. Bradley [29] had developed a new way for diverse orbit determination applications known as Bandlimited Collocation Implicit Runge-Kutta (BLC-IRK). This method can minimize computational costs and achieve various levels of accuracy.

Besides that, the machine learning techniques had also adopted in the orbit propagation model. The learning techniques used are neural networks, Kalman filters, and support vector machines (SVM) [7][9][30][31]. Neural networks improve the position accuracy and velocity of space objects with perturbation theory [30]. The results show that combining these techniques reduces orbiter position errors and improves the accuracy of orbit propagation. Through this study, the use of learning techniques proved effective and appropriate for the orbit propagation model. Subsequently, the Kalman Filter was used with a focus on data mining and extracting unknown power information. While the extended Kalman filter (EKF) estimates the orbital reproduction [31]. As a result, the position's accuracy increases and satisfies the position's accuracy.

San-Juan et al. [32] have proposed a hybrid method that combines a simplified general perturbation theory and an additive Holt-Winters technique called the statistical time series model-based. This approach increased the orbit propagation's accuracy; however, they have not considered the higher-order terms and other external forces during the modeling. Later, San-Juan et al. [8] proposed a hybrid methodology to extend TLE validity with minimal changes to the SGP4 model. They use the Holt winters technique to model the error time series into the

Hybrid TLE (HTLE). This hybrid method allows the extension of the validity of TLE with little complexity and computational burden for the end-user [8]. However, the propagator's accuracy still decreased when the time horizon increased.

Also, distribution regression techniques and transfer learning methods have been presented [33]. The results show that this method is better than conventional methods. SVM has also demonstrated an excellent ability to improve the accuracy of orbital predictions [7]. SVM performance improves after sufficient data used, but it is not suitable for handling limited or large amounts of data. Therefore, other techniques need to be used to address this problem.

The selection of this study's technique depends on several criteria, namely root-mean-square error (RMSE) and accuracy. The RMSE is the average deviation of the predicted value quantity and represents the error that occurred during the forecast. The performance of the model will be better if the RMSE value is lower. While the accuracy value is to determine how well this technique can improve the model. The higher the accuracy value is, the better. The description of the selected methods is in the following sections.

III. Proposed Method

The study used the operational framework to guide the whole process. It contains the structure of activities to achieve the objectives of this study. There are four (4) main phases of this study's operational framework: the investigation, analysis and problem formulations, design and modeling, and evaluation. Several steps are adapted to realize this study in each phase. Fig. 2 shows the operational framework of the study.

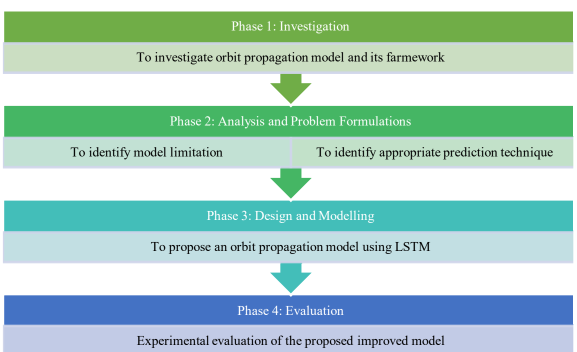

Fig. 2. Operational Framework.

A. Phase 1: Investigation

The most similar study is investigated in this phase to obtain the studies' gaps. I. Perez et al. [34] and H. Peng and X. Bai [7] had improved the orbit propagation model by using learning techniques. I. Perez et al. [34] had studied fitting techniques, while H. Peng and X. Bai [7] studied on SVM technique. Recently, I. E. Dawoodjee and M. Rajeswari [35] used nonlinear regression (NLR) to solve this issue. In this sense, our study is different from theirs as we plan to use deep learning techniques to capture periodic data patterns by memorizing and learn from the historical data. The proposed method is also required to solve the limitations of the previous methods used.

B. Phase 2: Analysis And Problem Formulation

In Phase 2, the analysis and problem formulation executed to identify the best techniques used. Holt Winter, SVM, and NLR have improved the orbit propagation model [7][8][35]. This study shows that although the researchers may not know to make physics-based predictions, they can apply learning techniques to get the space object's information through historical data. Then, the gathered information can develop an accurate orbit propagation model [8]. These include state estimates, measurement data, and errors for space object details and spatial environment [8][35].

Deep learning approaches have become one of the fastest-growing teaching and learning areas for data analysis [36]. It also demonstrates the effectiveness and efficiency of real-time detection [37]. Thus, in this study, the deep learning approach is explored to determine its suitability to improve the orbit propagation model's performance or vice versa.

The categories under deep learning are unsupervised learning, supervised learning, and deep hybrid networks [38]. The unsupervised learning captures high-order correlations of data and analyzes unlabelled data patterns [38][39]. The techniques for this category are Deep Belief Networks, Stacked Denoising Autoencoders, Deep Boltzmann Machine, Recurrent Neural Network (RNN), etc. [40][41][42]. Meanwhile, supervised learning can classify patterns by characterizing the classroom's posterior distribution on visible data [38]. The techniques used under this category are conditional random fields, convolutional neural networks (CNN), time-delay neural networks, etc.[43]. Lastly, hybrid networks which applied for deep network optimization [38].

In this study, techniques that can address time series problems identified and the RNN can do so in different architectures and approaches [44]. RNN is a type of neural network used in predictive modeling with random input sequences and an ideal technique for complex tasks [45]. However, RNN was affected by their gradients either growing or shrinking at each step [45]. Therefore, to correct this problem, long short-term memory (LSTM) has been introduced to overcome fatigue or explosion [46]. LSTM uses hidden units with natural behaviors that memorize long-term inputs and learn at long-distance dependencies [45]. Also, LSTM is more accurate than RNN and proved in a study conducted on space shuttle time-series data [47]. LSTM has again proven better than RNN in memory as it can handle thousands of discrete time steps [44]. For this study, the orbit propagation model needs to be improved to perform a longer orbit propagation span. Therefore, the proposed technique has to deal with the long-term data to give the solution. LSTM can remember the inputs over a long time, making it possible to recognize a sequence of data [48]. Therefore, the LSTM was selected to identify and accurately predict the long sequential orbital data.

C. Design And Modelling

For this study, the proposed model needs to minimize error and maintain propagator accuracy despite a longer propagation span. The new method is combining the SGP4 Model and LSTM module. The LSTM module will work as the extended predictive module of the SGP4 model.

LSTM is a repetitive neural network architecture. It consists of three layers: the input layer, the hidden layer, and the output layer [49]. The hidden layer connects to the input and output layers. The inner layer of the LSTM consists of blocks, and each block has three gates: input, output, and forget gates. This gate decides whether to let new inputs in or not, deletes information because it is not vital (forget gate) or the output at the current time step (output gate).

The expansion of the LSTM input layer requires reorganization of the data. A layer of ReLu activation function and dropout method needs to be added to the model to improve its performance. In our proposed model, dropout occurs between two hidden layers and between the hidden layer and the output layer. The dropout value is 20%. It is a type of regularization technique used to prevent overfitting and increase exercise time in some cases [50]. The last layer (dense layer) defines the output that represents the various activities and anomalies. Fig. 3 shows the development of the LSTM architecture.

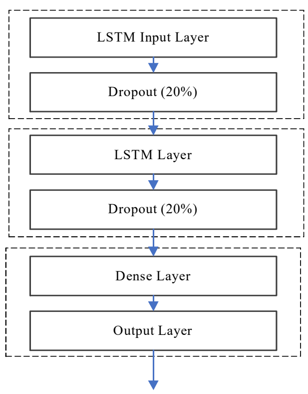

Fig. 3. LSTM Module

For time series prediction, the training data set typically consists of single-column data frame values. In this study, the values are position (ro_x, ro_y, ro_z) and velocity (vo_x, vo_y, vo_z). Each value are formulated as sequence such as, ro_x = [ro_x$_1$, ro_x$_2$, ro_x$_3$, ..., ro_x$_n$]. After entering the input, the error is calculated through the loss function and then propagated through the network to update the remaining iterations' weights. Then, the model is compiled using 'adam optimizer,' and the error is calculated with the loss function 'mean squared error.' This LSTM module developed using Python and Keras.

D. Phase 4: Evaluation

The evaluation of the proposed model is by comparing the results with the actual output. The methods used to evaluate and validate the improved model's performance are the root mean squared error (RMSE), mean absolute percent error (MAPE), and accuracy (ACC). The following equation is for the RMSE calculation.

$$RMSE = \sqrt{\frac{\sum|A_t-F_t|^2}{n})} \tag{9}$$

Whereby, A_t is the actual output; F_t is predicted output, and n is the number of samples used. These functions also can be used as an optimization criterion of the improved model. Meanwhile, equation (10) and equation (11) are used to evaluate the enhanced model's accuracy.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{A_t-F_t}{A_t}\right| \; x \; 100\% \tag{10}$$

$$ACC = 1 - \frac{1}{n}\sum_{i=1}^{n}\frac{|F_t-A_t|}{|A_t|} \; x \; 100\% \tag{11}$$

The smaller the RMSE and MAPE score, the better the model performance. While the ACC is different as a result is higher, the better the performance of the model. At the end of this phase, the result will determine whether the enhanced SGP4 model with the LSTM module is achievable or not.

IV. EXPERIMENTAL SETUP AND RESULTS

This section explains the experimental setup of this study. For the dataset preparation, the TLE data from the NORAD website, and real-time observation data from the Ground Station, Malaysia Space Centre are used. The TLE data collected is processed in the SGP4 model. Then, it is compared with the real-time observation data to ensure it is valid and usable for this study. Table II shows the results.

TABLE II. COMPARISON RESULTS BETWEEN REAL-TIME DATA AND THE SGP4 MODEL

TLE Age	Satellite Tracking Time		Performance Evaluation	
	Real-time	**SGP4**	**RMSE**	**Accuracy (%)**
1 day	4:16:05	4:16:16	0.0001	99.93
7 day	3:39:05	5:21:02	0.0708	53.46
13 days	3:02:51	4:41:21	0.0684	46.13

Based on the result shown in Table II, the TLE data from the SGP4 model is valid for 1-day prediction. The error is increasing when the propagation span increased. It also contributes to the RMSE value. Meanwhile, in terms of accuracy, the value is decreased when the propagation span increased. Therefore, this study is valuable if we can minimize error while maintaining the accuracy even though the propagation span increased and the TLE data is not updated.

Next, the collected data is processed and trained. The trained result is analyzed and evaluated to check whether it can give a solution for this study. Fig. 4 shows the process flow of this study.

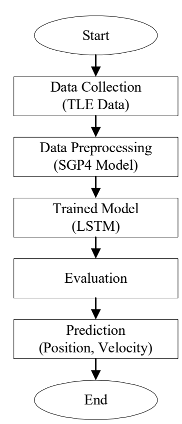

Fig. 4. LSTM-SGP4 model Process Flow.

The dataset consists of 43200 data sampling per minute for one (1) specific satellite and six (6) variables for 30 days. Then, the dataset is divided into train data (70%) and test data (30%) for further analysis. Fig. 5 shows a periodic pattern of X position (ro_x), which only the first 1440 observations plotted as it is difficult to see detailed features for all data samples.

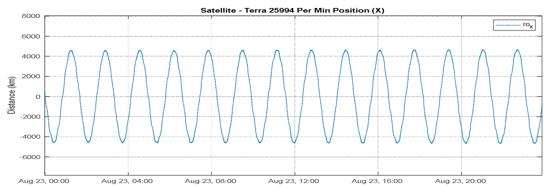

Fig. 5. X Position (ro_x) for one day.

Once the developed model is trained, the model's performance is evaluated, and the achievement results of the model listed in Table III.

TABLE III. SUMMARY OF EVALUATION RESULTS

Position/ Velocity	RMSE(km, km/s)	MAPE (%)	Accuracy (%)
ro_x	133.15	9.61	90.39
ro_y	69.07	6.14	93.86
ro_z	133.61	4.46	95.54
vo_x	0.12	3.91	96.09
vo_y	0.05	5.48	94.52
vo_z	0.08	8.35	91.65

Fig. 6 shows the comparison results between predicted and actual X position (ro_x) for the first 1440 observations.

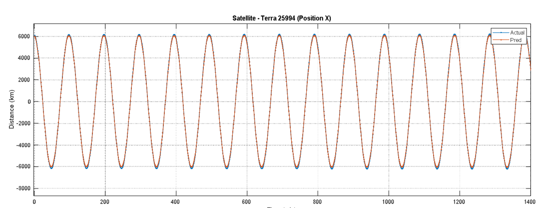

Fig. 6. Comparison between predicted and actual X Position

Next, Fig. 7 illustrates the predicted and actual X position (ro_x) of one (1) satellite pass for day-30, and Table III listed the result of the trained model for 30 days propagation span.

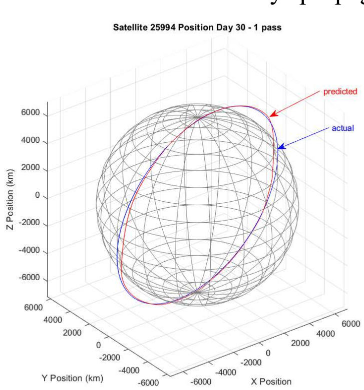

Fig. 7. X Position (ro_x) for one day.

TABLE IV. 30 DAYS PROPAGATION SPAN RESULTS

Position/ Velocity	RMSE(km, km/s)	MAPE (%)	Accuracy (%)
ro_x	170.64	7.47	92.53
ro_y	10.92	5.54	94.46
ro_z	59.08	5.65	94.35
vo_x	0.21	9.90	90.10
vo_y	0.02	5.91	94.09
vo_z	0.07	5.34	94.66

V. DISCUSSION

Based on the experiment conducted, the proposed orbit propagation model can minimize the error and maintain the accuracy even though there is an increase in propagation span. The accuracy is more than 90.03%, including the 30-day propagation span compared to previous studies [8]. However, this cannot be a fact or a basis because the data configuration and dataset details might differ from this study. Nevertheless, the results indicate various techniques can be considered to provide an improved orbit propagation model. The LSTM technique's recommendation is due to its flexibility to deal with long-term time-series data and proven to provide accurate and reliable results. The performance of the model also maintains even though the propagation span increase and more data are used.

VI. CONCLUSION AND FUTURE WORK

In conclusion, through adapting the LSTM technique, the deep learning method can enhance the SGP4 model for orbit propagation, even though the data input is not updated and for a longer propagation span. The main contributions of this work include the following fold. First, we developed the LSTM-SGP4 model to learn the complex data distribution from the TLE dataset. Second, the deep learning model training and selection strategy reduce the orbit propagation model's error. Finally, this study solves the issue which is challenging to be solved by other technique. In the future, this approach will analyze with multiple inputs and multiple outputs for a different class of satellites with other parameter values.

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