Enhancing Simplified General Perturbations-4 Model for Orbit Propagation Using Deep Learning: A Review

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ABSTRACT
This paper studies the method used in orbit propagation in order to enhance the Simplified General Perturbations-4 (SGP4) model which is the common orbit propagation model used by the satellite operator. The orbit propagation is used to determine and predict the position and velocity of a satellite. The capability of making an accurate orbital prediction is important to ensure satellite operation planning will not be disrupted and prevent any disrupted collisions or disasters. However, the accuracy of the SGP4 model is decreased once the propagation horizon increased. Therefore, a study is done to identify a technique that can be applied to enhance the SGP4 model. The model needs to be improved in term of minimizing the error and increase the accuracy even though the propagation span is increased. The method used in this study is by comparing the techniques that have been used by other researchers for the orbit propagation model. From the review that has been done, a deep learning technique is found to be a suitable technique. It also produces an accurate model for time series data. The new framework of the SGP4 model is expected and able to become a reliable predictor model. In the future, the study will further analyze by using simulation tools and real-time data. The accuracy and effectiveness of the improved model will be evaluated and the results will be compared with actual observations.

CCS Concepts
• Theory of computation → Mathematical optimization

• Theory of computation → Machine learning theory

Keywords
Orbit Propagation; SGP4; Deep Learning.

1. INTRODUCTION
Space situational awareness (SSA) is one of the serious issues affecting the space industry. SSA refers to the ability to observe, characterize and predict the properties of natural and artificial objects that orbiting the earth. It also aims to prevent collisions, identify untracked objects, and ensure security for future missions. The number of resident space objects (RSOs) is increasing and it indirectly increases the quantity of conflict between RSOs [1]. In addition, there is a large amount of debris in the orbits that surround the Earth, where, all these will pose a danger to space assets and services to the community. Some incidents involving space objects have also occurred such as the February 2009 collision involving U.S. Iridium communication satellite and Russian Cosmos 2251 communication satellite [2]. One of the main causes of these incidents is due to the limitation of the current orbit propagation capability and the inherent uncertainty in the data used. In the event of any collision, the related information is only obtained after the occurrence as there is no detailed information on the space object. The need for accurate orbit propagation is identified to maintain the growth of catalogue objects, conducting assessments for collision prevention, handling of ongoing satellite missions that requiring orbital transmission which includes a wide range of accuracy and computational requirements. With that, various studies being carried out for the renewal of orbit propagation methods. However, there are a lot of challenges that need to face such as our understanding of the space environment is limited, the information about the space object is not accurately updated, maneuvering of a spacecraft could be unavailable, surveillance resources are expensive and measurements are sparse and noisy. Thus, the new solution of the orbit propagation needs to be derived to improve the current implementation despite its various challenges. In this study, the learning technique will be studied to see whether it can be applied and enhance the SGP4 model for orbit propagation.

This paper is divided into the following sections: Section 2 and 3 described the related works of orbit propagation model and the prediction technique used; Section 4 explained the methodology used and stated the results of the study; Section 5 discusses the findings including future work and study limits. Finally, Section 6 explains the conclusions of this study.

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2. RELATED WORKS
This section describes the related work of the orbit propagation model. There are different methods have been used by the researchers in order to improve the model. The physical-based approaches are mostly being used. However, the success of this approach requires a good knowledge of the space object at the beginning of trajectory calculations, and environmental information, as well as information of maneuver objects [3]. Nevertheless, the understanding of space is limited and information on space objects is not updated accurately. Besides that, the current surveillance resources are also limited and costly.

There are various mathematical expressions also have been used such as Gaussian, Polynomial Chaos Expansions (PCEs), State Transient Tensors (STTs) and Taylor Series Polynomial [4]. However, these expressions are inconsistent with actual uncertainties when there are various perturbations such as earth gravity, atmospheric drag, multibody gravitation and solar radiation pressure or when the propagation time is longer [4]. Later, the analytic solution to the problem has been proposed. Many researchers have explored analytical and semi-analytical solutions to describe the orbital motion with additional perturbation values [4]. In addition, analytical and semi-analytical solutions can provide an in-depth view as it can classify variations in the orbital motion of an object. This fact inspires a new perspective to explain the evolution of uncertainty and imply the possibility of developing new methods for orbit propagation.

Next, the machine learning approach presents different modelling capabilities and predictions. The prediction can be made without explicit modelling space objects and space environment information. Instead, the models are studied based on the observed data. There are three (3) types of machine learning approaches, namely; supervised learning, unsupervised learning and reinforcement learning. Based on that, supervised learning is the ideal approach to increase orbit propagation accuracy based on historical measurements and error information. Also, the use of the data-driven approach for orbit propagation started the emergence of artificial intelligence which allows prediction can be made through the learning process from the data that can help in the decision-making process. In addition, data-driven approach solutions have the potential to produce more precise orbital propagation due to the presence of elements that cannot be clearly defined by mathematical models such as the value of perturbations.

The hybrid propagation method is also used to improve the accuracy of orbit propagator. This method is combining classical integration methods with a prediction technique based on either statistical time series models or learning techniques. It is able to model the dynamics of the difference between the integrated approximate solution and real behavior. The hybrid propagation method also constitutes a non-intrusive technique that can be applied to enhance the orbit propagator by refining the analytic technique and improve computational efficiency [4].

Based on the review conducted, the hybrid method is the latest method used in the orbit propagation. However, there are certain deficiencies that need to be fixed due to the limitation of the current method used. Therefore, an appropriate prediction technique needs to be chosen. The technique that commonly been used is a statistical or learning technique. Meanwhile, in orbit propagation, the error during the initial control interval always shows a systematic pattern that repeats in every orbiter revolution and depending on each case. Consequently, the prediction technique based on time series is best suited to modelling this error. Thus, the hybrid method, as well as the alternative learning technique, is going to be explored. The various methods used in orbit propagation is illustrated in Figure 1.

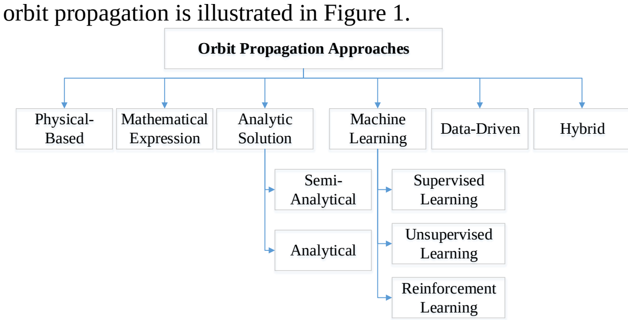

Figure 1. Orbit Propagation Approaches

3. PREDICTION TECHNIQUE

The Runge-Kutta technique has been used to deal with nonlinear equations at the time step. This method reduces orbit propagation computational cost with larger time steps but it is complex and rarely been used. Next, a study on fixed-step used on the eccentric orbit is done [5]. The Gauss-Legendre technique is used to deal with this issue. The time step varies over time and stability properties are improved compared with the classical method. It improved the numerical technique accuracy and computational efficiency for orbit propagation and uncertainty. However, it requires several user-defined tuning parameters [6].

The Kamel's theory and Draper Semi-Analytical Satellite Theory (DSST) has also been used to improve the orbital propagation model [7]. These theories are used to test the accuracies of the selected propagators compared with a numerical "truth" trajectory. In 2016, further analyzed has been done on the DSST Theory as a propagator for the space object catalogue maintenance [8]. The simulation result shows that the theory provides a balance between prediction accuracy and computation time. Whereby, the computation time was approximately 70% to 90% less while maintaining the required prediction accuracy. However, this technique is complex and suitable for certain orbit region [8].

Meanwhile, for machine learning technique, some configurations to the hybrid methodology for orbit propagation is analyzed. There are a few learning techniques have been used for propagating the orbital such as neural network, kalman filter and support vector machine (SVM). The neural network with perturbation theory is used to improve the accuracy of position and velocity of the space object [9]. This technique successfully improved the orbit propagator accuracy. The result shows that this combination of techniques reduce the orbiter position error and increase the accuracy of the prediction. With this study, the implementation of the learning technique is proven and applicable to be implemented in the orbit propagation model. Later, the method used focuses on the data mining aspect and extract information of unknown forces from historical data by using Kalman Filter. The technique improved the filtering efficiency but underlying Gaussian approximation to the state posterior. In addition, the Kalman filter (EKF) has also used to estimate orbit propagation and determination [10]. However, the study only covers the low earth orbit (LEO) satellite. The result shows the positioning accuracy is increased based on orbit mission requirements using EKF. It is able to satisfy the position accuracy and compute two indicators.

Besides that, a learning approach to do orbit determination based on distribution regression and transfer learning method has presented [11]. The result shows that the proposed machine learning approach is superior to the conventional methods such as the extended Kalman Filter. Moreover, the method is able to estimate significantly varying orbital parameters. The SVM shows a good capability to improve orbit prediction accuracy [12]. It is shown that including more data will improve the performance of a trained SVM model, but the performance will not further improve after adequate data has been used. The result also shows that the SVM model cannot be generalized for too much time ahead. Therefore, the orbit predictions cannot be made too far and the SVM model needs to be updated [12]. As the SVM method is not appropriate to deal with a large amount of data. Thus, the new technique needs to be explored to handle this issue.

4. COMPARISON ANALYSIS

In this study, the most accurate technique with high accuracy and minimum error will be chosen in order to improve the SGP4 model. Therefore, to ensure the most suitable technique is selected, there are a few criteria that have been specified to support the process namely root-mean-square error (RMSE) and accuracy. The RMSE is the measured average squared deviation of prediction values. It represents the error which occurred during prediction. The smaller the RMSE value, the better the performance of the model. Meanwhile, the accuracy is used to define how precise the technique can improve the model. Based on the previous review, there are various techniques that able to improve the orbit propagation model. The techniques that able to improve the accuracy with the highest result is Runge-Kutta which is 99% [13]. However, for the SGP4 model, the techniques that have been used are Holt Winter and SVM [12][14][15]. Therefore, in order to identify the best techniques, these techniques are compared with the same problem parameters. Table 1 shows the results of the prediction technique evaluation metric comparison.

Table 1. Prediction Technique Evaluation Metric Comparison

Criteria	Description	Propagation Span	Holt Winter	SVM
RMS Position Error	The position of the satellite in the orbit.	0.7 day	0.441[14]	N/A
		1 day	0.981[14]	N/A
		2 days	2.399[14]	N/A
		7 days	9.505[14]	0.4[3]
		30 days	27.005[14]	N/A
Accuracy (%)	The accuracy of the proposed model compared with the SGP4 Model	0.7 day	92.26% [14]	N/A
		1 day	87.74% [14]	N/A
		2 days	85.34% [14]	N/A
		7 days	83.71% [14]	N/A
		28 days	N/A	97.9% [12]
		30 days	90.03% [14]	N/A

Based on the analysis, the SGP4 model can perform better by using the SVM technique as compared with Holt Winter. Whereby, the RMS position error value is the smallest and the accuracy is the highest. However, this value is limited to a certain propagation span. Thus, in this study, further review will be done on the learning technique which is proved to perform better in improving the SGP4 model. This review will identify the most appropriate technique to be selected.

Recently, the deep learning techniques have become one of the fastest growing and most exciting areas of learning with large data. It can be simply viewed as neural networks with many large hidden layers, or deep-layered architecture with each layer applying a nonlinear transformation from its input to its output. The technique is trained along with the availability of more powerful computers such as high processing CPUs and the advent of general-purpose GPUs. Besides that, better software infrastructure has created great opportunities for deep learning research [16]. A deep neural network also demonstrates the effectiveness and efficiency in real-time detection [17]. Therefore, the deep learning technique is considered to be used in this study. However, prior to the selection of the technique, this technique needs to be studied further to ensure it is suitable to be implemented and to enhance the model or not.

4.1 Deep Learning

Deep learning is a learning technique which was first theorized in the early '80s and perhaps even earlier. It is again on the rise as it quite good at teaching computers to do what our brains can do naturally. In 2006, a deep belief network uses a strategy called greedy layer-wise pre-training breakthrough [18]. It appears as a new field of research within machine learning [19]. The deep learning approach is divided into three (3) major classes which are unsupervised or generative learning, supervised learning or discriminative and hybrid deep network [20]. Unsupervised learning is intended to capture the high-order correlation of the observed or visible data for pattern analysis or synthesis purposes when no information about target class labels is available [20]. It deals with the problem of finding structure in unlabeled data [21]. One of the earliest works that considered deep unsupervised learning is the Deep Belief Networks (DBNs) [18]. Later, a class of models called Stacked Denoising Autoencoders which also learn distributed representations of data using deep networks [22]. Unlike DBNs, this technique does not provide explicit parameterization for the probability density but it provides a fast deed-forward inference of latent representations [21]. Later, an efficient training algorithm for Deep Boltzmann Machine (DBM), which are fully undirected graphical models had been proposed [23]. It has typically been applied to modestly complex datasets such as handwritten digits, faces or small images.

The supervised learning is able to provide discriminative power for pattern classification purpose, often by characterizing the posterior distributions of classes conditioned on the visible data [20]. The data label is always available in direct or indirect forms. The techniques used under this category are conditional random fields, multilayer perceptron neural networks, deep stacking network, convolutional neural network (CNN), time delay neural network and hierarchical temporal memory [24].

Lastly, the hybrid networks are the outcomes of generative or unsupervised deep learning [20][25]. It can accomplish better optimization of the deep network in generative or supervised learning. Besides that, it is able to estimate the parameters in any of the supervised and unsupervised category. Figure 2 shows an overview of deep learning techniques.

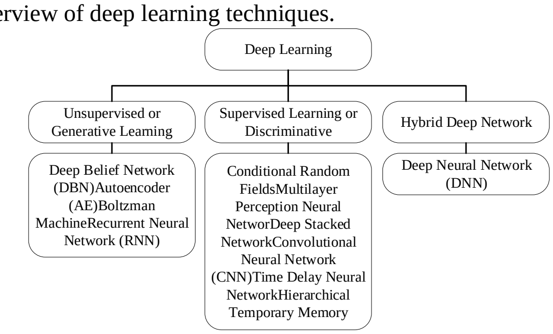

Figure 2. Overview of Deep Learning Techniques

From the review conducted, the technique that deals with time series problem is investigated. Several processing techniques were proposed such as Recurrent Neural Network (RNN), Time-Delay Neural Network (TDNN), Adaptive Extension and Nonlinear Auto-Regressive. Based on that, RNN is mostly been used and evolved with different architecture and approaches [26]. The RNN is a type of neural network used in predictive modelling where the output depends on the inputs. RNN able to predict input sequences randomly based on its own internal memory. RNN is a powerful dynamic technique and suitable for a complex task [27]. However, training of RNN has proved to be problematic due to gradients either grow or shrink at each time step, therefore it typically exploded or vanished [27]. Thus, it is difficult to learn and tract in long-term memorization when they use their connection for short-term memory [27]. In order to correct this limitation, the long short-term memory (LSTM) has been introduced to overcome vanishing or exploding gradient [28]. It used hidden units with natural behavior that memorized inputs for a long time and learning at long range dependencies [27]. In terms of accuracy, the LSTM is performed better than RNN by using same parameters which is anomaly detection in time series data of space shuttle [29]. Meanwhile, in term of memory, LSTM also has been improved and proved to be better than RNN as it is able to deal with thousands of discrete time steps [26].

In this study, the technique that able to work with a longer time lag is preferable as the SGP4 model need to be improved in order to do the orbit propagation in a longer time span. Therefore, LSTM proved to be more suitable to be used in this study. It will be used to deal with long-term time series data. The LSTM successfully overcome the fundamental of deep learning problem without any supervised pre-training and able to learn tasks without local sequence predictability and dealing with very deep problems [26].

4.2 Long Short-Term Memory (LSTM)

LSTM is capable to pass on information from previous time steps unchanged so that it can learn from the distant input. It consists of the hidden layer of memory blocks. Where, each block contains a recurrent memory cell and three multiplicative units: the input, output and forgets gates; the gates are trainable: each block can learn whether to keep information across time steps or not [30]. Figure 3 shows a memory block with a single cell of LSTM.

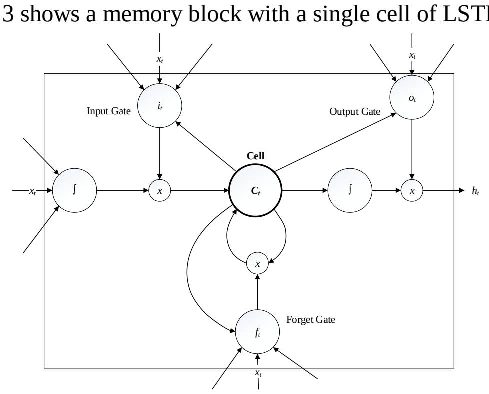

Figure 3. A Single of LSTM Memory Block

The cell state, C_t, is updated based on its current state and three sources of input at a time, t. These sources input are input gate (i_t), output gate (o_t) and forget gate (f_t). Input gate can decide how much input information enter the current cell. Output gate decides what information will be output from the current cell. While the forget gate decides how much information be forgotten for the previous memory vector. The LSTM memory cell stores a value for either long or short time periods. This is achieved by the activation function of the memory cell. The activation function can be computed by using the sigmoid function or hyperbolic tangent function. Following are the equations used to define the whole computation [31].

$$i = \sigma(W^i H + b^i) \quad (1)$$

$$f = \sigma(W^f H + b^f) \quad (2)$$

$$o = \sigma(W^o H + b^o) \quad (3)$$

$$c = tanh(W^c H + b^c)\text{^c)} \quad (4)$$

$$m' = f \odot m + i \odot c \quad (5)$$

$$h' = \tanh(o \odot m') \quad (6)$$

Where σ is the sigmoid function, W^i, W^f, W^o, W^c in $\mathbb{R}^{dx2d}$ are the recurrent weight matrices and the corresponding bias terms are b^i, b^f, b^o, b^c. Meanwhile, H in $\mathbb{R}^{2d}$ is the concatenation of the new input x_i and the previous hidden vector h_{i-1}. This can be presented by the following equation.

$$H = \begin{bmatrix} Ix_i \\ h_{i-1} \end{bmatrix} \quad (7)$$

The LSTM is the cell state which can remember long-term information has the ability to remove or add information to the cell state. Thus, it is can be regulated by the gate's structures and the whole function of LSTM also can be concluded as follow.

$$(h', m') = LSTM(\begin{bmatrix} Ix_i \\ h_{i-1} \end{bmatrix}, m, W) \quad (8)$$

Where W concatenates the four weight matrices W^i, W^f, W^o, W^c. In addition, there are different LSTM topologies allowed and some of its variants also used self-connections modification [26]. Therefore, the LSTM is recognized as the technique that appropriates with noisy input streams; robust storage of high precision real numbers across extended time intervals, arithmetic operations and long-time lag task [26].

5. ENHANCING SGP-4 MODEL

The SGP4-LSTM model is proposed to improve the current SGP4 model and allow the error correction to be made by using the LSTM technique. In this study, there are two (2) main objectives that need to be achieved which are minimizing the error and increase the accuracy of the propagator. Figure 4 illustrated the new framework of the SGP4 model which is a combination of the SGP4 module and LSTM module. This new model aims to do the error correction and improved the current SGP4 model.

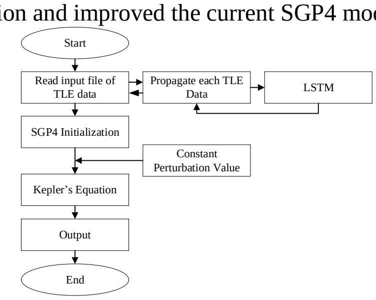

Figure 4. LSTM-SGP4 Model Block Diagram

In addition, the new framework of the SGP4 model will be evaluated by comparing the simulation result of the current SGP4 model and LSTM-SGP4 model. A few tests will be conducted by using different sets of data input which is the two-line element (TLE) that contains space object information such as satellite number, international designator, atmospheric drag and orbital elements in order to ensure the test result is valid. The methods that will be used to evaluate and validate the performance and the effectiveness of the improved model are the mean squared error (MSE), mean absolute error (MAE) and mean absolute percentage (MAPE). These methods can be calculated using the following equations:

$$MSE = \frac{1}{T}\sum_{t=1}^{T}(\varepsilon_t - \hat{\varepsilon}_t)^2 \quad (9)$$

$$MAE = \frac{1}{T}\sum_{t=1}^{T}|\,\varepsilon_t - \hat{\varepsilon}_t| \quad (10)$$

$$MAPE = \frac{1}{T}\sum_{t=1}^{T}|\frac{\varepsilon_t - \hat{\varepsilon}_t}{\varepsilon_t}|100 \quad (11)$$

Whereby, ε_t is the actual output, $\hat{\varepsilon}_t$ is the predicted output, and T is the number of samples used. These three (3) different error function also can be used as an optimization criterion of the improved model. The smaller the result will be the better. In addition, in order to evaluate the improved model accuracy, the following equation is used.

$$ACC = \frac{1}{n}\sum_{i=1}^{n} \frac{|prediction - true\ value|}{true\ value} \quad (12)$$

Where n is the prediction length and ACC are the accuracy results. The result of ACC is different from the previous measurement as the higher the result is the better.

The proposed model performance will also be evaluated by comparing the propagation result with the Satellite Toolkit (STK) software and real-time observation data. The real-time observation data can be obtained from the owner of the spacecraft or ground mission station that tracking the spacecraft. At the end of this phase, the results will determine whether the improved algorithm is able to enhance the SGP4 propagation model or otherwise.

6. CONCLUSION

As a conclusion, the LSTM technique will be used to enhance the SGP4 model for orbit propagation. It is recommended due to its flexibility to deal with long-term time series data and proven to provide accurate and reliable results. The SGP4 model and LSTM technique will be further studied in order to adapt it to the newly proposed model. This approach is believed to improve current SGP4 orbit propagation model in term of minimizing the error and high accuracy. A simulation will be done using Matlab and the new framework SGP4 model will be evaluated.

7. ACKNOWLEDGMENTS

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