A HYBRID RECURRENT NEURAL NETWORK AND LONG SHORT-TERM MEMORY FOR SIMPLIFIED GENERAL PERTURBATIONS-4 MODEL IN ORBIT PROPAGATION

NOR'ASNILAWATI BINTI SALLEH

A thesis submitted in fulfilment of the
requirements for the award of the degree of
Doctor of Philosophy

Razak Faculty of Technology and Informatics
Universiti Teknologi Malaysia

JULY 2022

DEDICATION

This thesis is dedicated to my late parent, my beloved husband Mohd Nazrul Hanif, and my beautiful children Aqeela, Ameena, and Haqeel.

ACKNOWLEDGEMENT

In the name of Allah, Most Gracious, Most Merciful,

All praises and thanks to Allah S.W.T, who allowed me to complete this thesis with His will. I want to express my most tremendous appreciation to my supervisor, Assoc. Prof. Dr. Siti Sophiayati Binti Yuhaniz and Dr Nurulhuda Firdaus Binti Mohd. Azmi, for the guidance and encouragement during the completion of my project. Only Allah can repay for their kindness.

I owe my loving thanks to my family, especially my husband and my children, for supporting me all the time. It would have been impossible to finish this project without their encouragement and understanding.

Also, I offer my regards and blessings to all my friends, especially my colleagues at Malaysia Space Centre and the Ground Station Team, that supported me in any respect during the completion of this project. Finally, my special thanks to Malaysian Space Agency for realizing this project. May Allah bless them all.

ABSTRACT

Orbit propagation is one of the critical science tasks used to determine and forecast the position and velocity of orbiting space objects such as satellites, mission-related debris, rocket bodies, and others. Developing an accurate orbit propagation model is vital to ensure uninterrupted operational planning and prevent any disrupted collisions or disasters. However, using the current orbit propagation model has limitations, and these reduce the ability for long-term forecasting. It has errors depending on various aspects like measurement error, space environment information that constantly changes, inherent uncertainty in the data used, and errors in the data processing. Although classical time series methods such as Holt-Winters can improve the orbit propagator's accuracy and efficiency, it requires changes in the components' probability distribution, causing complexity and computational burden for end-user. However, this method can achieve maximum performance through integration with other approaches. Deep learning techniques, the new field of research within machine learning, are recently explored to analyse and improve the Simplified General Perturbations-4 (SGP4) Model, the orbit propagation model commonly used by space operators. The improved model should minimize errors and maintain accuracy even if the propagation span increases. Therefore, this study examined the Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) technique, a deep learning approach dealing with long-term time-series data. It can learn tasks and deal with complicated problems. Additionally, these learning techniques are a time series forecasting method that can improve models by capturing periodic data patterns by memorizing and learning from historical data. Thus, a hybrid RNN-LSTM SGP4 Model was developed. The performance and effectiveness of the improved model were evaluated and validated. As a result, this hybrid RNN-LSTM SGP4 Model improved more than 27% better than the SGP4 Model alone. It was also capable of being a reliable long-term time series forecasting model for space object data.

ABSTRAK

Penyebaran orbit adalah merupakan salah satu tugasan sains kritikal yang digunakan untuk menentukan dan meramalkan kedudukan dan halaju objek angkasa yang mengorbit seperti satelit, serpihan berkaitan misi, badan roket dan lain-lain. Membangunkan model ramalan orbit yang tepat sangat penting untuk memastikan perancangan operasi tidak terganggu dan mencegah sebarang perlanggaran atau bencana berlaku. Walau bagaimanapun, penggunaan model penyebaran orbit semasa mempunyai kekangan dan mengurangkan keupayaan untuk ramalan jangka panjang. Kekangan ini adalah disebabkan oleh pelbagai aspek, termasuk kesalahan pengukuran, maklumat persekitaran angkasa yang sentiasa berubah, ketidakpastian pada data yang digunakan, dan kesalahan dalam pemprosesan data. Walaupun kaedah ramalan siri masa klasik seperti Holt-Winters dapat meningkatkan ketepatan dan kecekapan penyebaran orbit, kaedah ini memerlukan perubahan pada taburan kebarangkalian komponen yang menyebabkan kerumitan dan beban pengiraan kepada pengguna akhir. Selain itu, kaedah ini boleh mencapai prestasi maksimum melalui integrasi dengan pendekatan lain. Terkini, teknik pembelajaran mendalam, iaitu satu bidang penyelidikan baharu dalam pembelajaran mesin telah diterokai untuk menganalisa dan menambah baik Model *Simplified General Perturbations-4* (SGP4). Model ini adalah model penyebar orbit yang biasa digunakan oleh operator angkasa. Model yang ditambah baik ini perlu meminimumkan ralat di samping dapat mengekalkan ketepatan walaupun di dalam jangka masa penyebaran yang meningkat. Oleh itu, penyelidikan ini mengkaji teknik Rangkaian Neural Berulang (RNN) dan Memori Jangka Pendek Panjang (LSTM), iaitu pendekatan pembelajaran mendalam yang boleh memproses data siri masa jangka panjang. Ia dapat mempelajari tugas dan menangani masalah yang rumit. Selain itu, teknik pembelajaran ini adalah kaedah ramalan siri masa yang dapat menambah baik model dengan menangkap corak data berkala dengan menghafal dan belajar daripada data sejarah. Oleh itu, Model RNN-LSTM SGP4 hibrid dibangunkan. Prestasi dan keberkesanan model yang dipertingkatkan ini dinilai dan disahkan. Hasilnya, prestasi Model RNN-LSTM SGP4 hibrid ini meningkat 27% lebih baik daripada Model SGP4. Ia juga mampu menjadi model ramalan siri masa jangka panjang yang boleh dipercayai untuk data objek angkasa.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ANN	-	Artificial Neural Network
ARIMA	-	Auto-Regressive Integrated Moving Average
BLC-IRK	-	Bandlimited Collocation Implicit Runge-Kutta
CADET	-	Covariance Analysis Describing Function Technique
CNN	-	Convolutional Neural Network
CPU	-	Central Processing Unit
DBM	-	Deep Boltzmann Machine
DBN	-	Deep Belief Network
DSST	-	Draper Semi-Analytical Satellite Theory
ECEF	-	Earth-Centred, Earth-Fixed
ECI	-	Earth Centred Inertial
EKF	-	Extended Kalman filter
ETS	-	Error, Trend, Seasonal
GA	-	Genetic Algorithm
GEO	-	Geostationary Orbits
GPU	-	Graphics Processing Unit
HEO	-	High Ellipticity Orbits
JLNELN	-	Joint Linear-Nonlinear Extreme Learning Network
LEO	-	Low Earth Orbit
LR	-	Linear Regression
LSTM	-	Long Short-Term Memory
MAPE	-	Mean Absolute Percentage Error
MEO	-	Medium Earth Orbit
NCA	-	Neighbourhood Component Analysis
NLR	-	Nonlinear Regression
NORAD	-	North American Aerospace Defense Command
ODEM	-	Orbit Determination for Extended Manoeuvres
PCE	-	Polynomial Chaos Expansions
P_{DL}	-	Performance of Deep Learning
RAAN	-	Right Ascension of the Ascending Node

RMSE	-	Root-Mean-Square Error
RNN	-	Recurrent Neural Network
RSO	-	Resident Space Object
RQ	-	Research Question
SDPSO-ELM	-	Switching Delayed Particle Swarm Optimization
SGP4	-	Simplified General Perturbations-4
SSA	-	Space Situational Awareness
SST	-	State Transient Tensors
STK	-	Satellite Toolkit
SVM	-	Support Vector Machine
TDNN	-	Time-Delay Neural Network
TEME	-	True Equator Mean Equinox
TLE	-	Two-Line Element
UKF	-	Unscented Kalman Filter
UTM	-	Universiti Teknologi Malaysia

LIST OF SYMBOLS

a_E	-	The equatorial radius of the Earth
$B*$	-	The SGP4 type drag coefficient
D, d	-	Diameter
e_o	-	The "mean" eccentricity in epoch
F	-	Force
i_o	-	The "mean" inclination at epoch
J_2	-	The second gravitational zonal harmonic of the Earth
J_3	-	The third gravitational zonal harmonic of the Earth
J_4	-	The fourth gravitational zonal harmonic of the Earth
I	-	Moment of Inertia
M_o	-	The "mean" mean anomaly at epoch
p	-	Pressure
r	-	Radius
ro	-	Position
Re	-	Reynold Number
vo	-	Velocity
$XKMPER$	-	kilometres/Earth radii
Δ	-	Minimal error
ω_o	-	The "mean" argument of perigee at epoch
Ω_o	-	The "mean" longitude of ascending node at epoch
$\dot{n}_o$	-	The time rate of change of "mean" motion at epoch
$\ddot{n}_o$	-	The second time rate of change of "mean" motion at epoch

LIST OF APPENDICES

CHAPTER 1

INTRODUCTION

1.1 Overview and Motivation

Space situational awareness (SSA) is a critical issue affecting the space industry and national security. SSA refers to the ability to observe, characterize and forecast the properties of natural and artificial objects that orbit the Earth. It also aims to prevent collisions, identify untracked objects, and ensure security for future missions (Oltrogge and Cooper, 2020; Pelton, 2019; Choi *et al.*, 2017). One of the critical technical discussions in the SSA is that space objects propagate state uncertainties due to dynamic and nonlinear environmental factors (Park, 2016). Besides that, the lack of information such as the space environment information and space object characteristics causes the current orbit propagation model unable to achieve the accuracy required for proper operational planning and avoid space object collisions (Tarran, 2021; Peng and Bai, 2018a).

Every year, the number of resident space objects (RSOs) orbiting the Earth increases and indirectly increases the conflict between RSOs (Lu *et al.,* 2020; Luo and Yang, 2017; Pelton and Jakhu, 2017; Park, 2016). It consists of satellites, mission-related debris, rocket bodies, etc. The growth is due to many countries scrambling to explore space for various purposes such as communications, remote sensing, scientific mission, security, defence, and many more. The number of space objects larger than 10cm is now approaching 21,000, an object of between 1 and 10cm is estimated to be around 500,000, and for objects smaller than 1cm, it is to be over 100 million (Peng and Bai, 2018a). Moreover, there is a large amount of debris in the orbits around the Earth, all of which endanger space assets and society (Tarran, 2021; Gambi *et al.*, 2018; San-Juan *et al.,* 2017; Lim, 2015). Figure 1.1 shows the number of objects in Earth Orbit by object type increasing yearly.

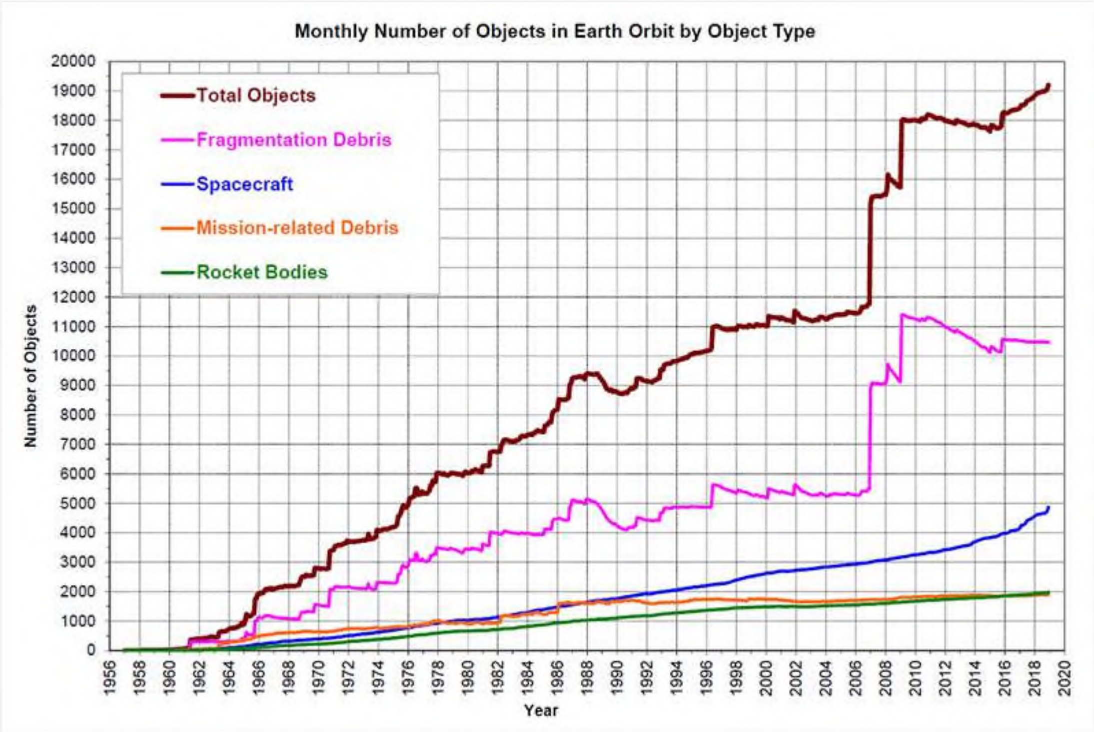

Figure 1.1 Yearly Number of Objects in Earth Orbit by Object Type (Source: https://orbitaldebris.jsc.nasa.gov/modeling/legend.html)

Some incidents involving space objects have also occurred, such as the February 2009 collision involving the U.S. Iridium communication satellite and Russian Cosmos 2251 communication satellite, as well as the threat of RED threshold late notice conjunction with the International Space Station (ISS) from the "25090 PAM-D" debris (Seong et al., 2017; Kelso, 2012; Jakhu, 2010; Bergin, 2009). One of the leading causes of these incidents is the orbit propagation model's ability to obtain accurate information about the satellite's position (Peng and Bai, 2019). The physics-based prediction failure also arises from a lack of information such as the space object's state, the initial time, the environment information, the intent information, etc. Figure 1.2 shows the Iridium 33 and Cosmos 2251 collision illustration view, which created more debris.

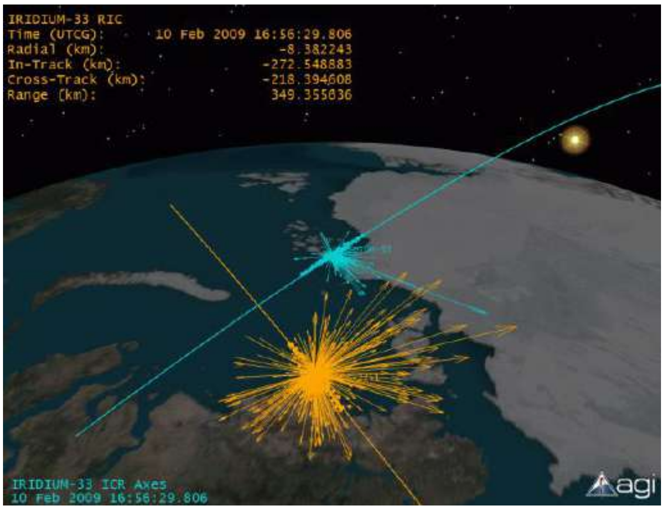

Figure 1.2 Illustration view of Iridium 33 and Cosmos 2251 Collision (Source: https://celestrak.com/events/collision/)

On April 2, 2018, the Chinese space station Tiangong-1 (Heavenly Palace) was declared out of control by Chinese authorities and re-entered the atmosphere (Goswami, 2018; Danner, 2018). Later, the incident involved a Long March 5B Rocket, also owned by China, had entered atmospheric space out of control (Zannoni, 2022). Therefore, the authorities should continuously track this space object to ensure its re-entry into the atmosphere can be immediately detected to prevent any accident from happening. Unfortunately, the related information is usually only obtained after the incident occurred. Thus, having the orbit propagation model that can forecast for long-term horizon will help affected parties have proper planning operations and take extra precautions to prevent collisions and observe the space objects orbiting the Earth. This orbit propagation model will also help identify possible crash locations to ensure no casualties. Countries with no space object information details can also take preventive measures using this orbit propagation model. Therefore, further analysis needs to ensure that no adverse events occur, especially collisions between the operating satellites resulting in the loss of millions of dollars.

Besides that, an accurate orbit propagation model is crucial to maintain catalogue objects' growth, conduct collision prevention assessments, and address satellite missions currently operating in orbit (Reiland *et al.*, 2021; Bradley, 2015; Bennett *et al.*, 2013). These also drive the need to improve the current orbit propagation model.

The need for high accuracy and efficiencies prompted various studies to renew the orbit propagation method (Petit *et al.*, 2021; San-Juan *et al*., 2017). One of the methods proposed is to propagate uncertainty by capturing the absence of dynamic information. Hence, it remains a challenge to forecast space objects. Among the challenges is our understanding of the space environment is limited. The information about the space object is not accurately updated, manoeuvring of a spacecraft could be unavailable, surveillance resources are expensive, and measurements are sparse and noisy.

The Simplified General Perturbations-4 (SGP4) Model is the orbit propagator model commonly used by the satellite operator as its code and input data; the Two-Line Elements (TLE) are publicly available and accessible by everyone (Driedger and Ferguson, 2021; Peng and Bai, 2020; San-Juan *et al.*, 2017). However, the TLE data must be updated to have an accurate result, or else the SGP4 Model error can be 1 km and grow ~1–3 km per day (Romano *et al.*, 2021; Riesing, 2015; Vallado *et al.*, 2006a). The North American Aerospace Defense Command (NORAD) provides the TLE data daily, but its accuracy is valid for 2- 3 days (Abay *et al.,* 2021; Romano *et al.*, 2021). Therefore, the SGP4 Model is unreliable for long-term forecasting horizons, and it shall be improved to increase its performance with minimal risk and cost.

1.2 Background of the Problem

The growth of space objects increases the risk of collision among those objects and, at the same time, poses a danger to space assets and humans. Also, the satellite communication window, especially in the Low Earth Orbit (LEO), is concise at about 7 to 12 minutes. This limited time is valuable for scheduling satellite operations such as satellite health checks, uploading schedules, and downloading mission data. The planning of this satellite schedule is prepared based on the time determined by the orbit propagator. However, there are distortions and noise in the orbit propagation caused by orbit perturbations such as earth gravity, atmospheric drag, multi-body gravity, and solar radiation pressure. Therefore, the orbit propagator becomes inaccurate and needs to be improved to minimize the error, reduce this risk, and ensure future mission safety. Figure 1.3 illustrates the overview of the orbit propagation approaches used.

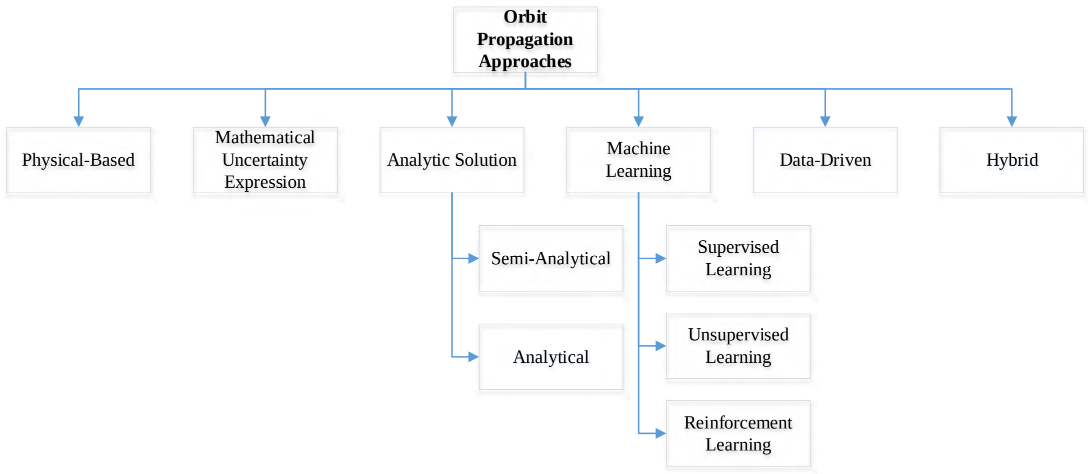

Figure 1.3 Overview of the Orbit Propagation Approaches

The satellite operation typically uses the physical-based approaches for orbit propagation. However, this approach's success requires knowing the space object at the beginning of trajectory calculations, environmental information, and manoeuvre the objects (Peng and Bai, 2018a). Meanwhile, the understanding of the space environment is limited. Furthermore, the information on space objects is not updated accurately; for example, a satellite owned by another country is not accessible if the owner is unwilling to share the information. Also, the current surveillance resources are limited and costly (Peng and Bai, 2018a).

There are various mathematical uncertainty expressions used for SSA, such as Gaussian, Polynomial Chaos Expansions (PCEs), State Transient Tensors (STTs), and Taylor Series Polynomial (Park, 2016). However, these expressions are inconsistent with substantial uncertainties with various perturbations such as earth gravity, atmospheric drag, multi-body gravitation, solar radiation pressure, or longer propagation time (Park, 2016; Shou, 2014).

Later, researchers proposed an analytic solution to solve the problem. Many researchers have explored analytical and semi-analytical solutions to explain the orbital motion with additional perturbation values (Park, 2016). In addition, analytical and semi-analytical solutions can provide an in-depth view of classifying variations in an object's orbital motion. This fact inspires a new perspective to explain uncertainty's evolution and implies new orbit propagation methods.

Machine learning approaches present different modelling capabilities and forecasting than physics-based methods (Gonzalo and Colombo, 2021). The forecasting process can be performed without explicitly modelling space objects and limited space environment information. Instead, the models are studied based on the observed data. There are various types of machine learning approaches. The most common types are; supervised, unsupervised, and reinforcement learning (Jo, 2021; Abu-Mostafa *et al.*, 2012). Supervised learning is a method that studies the function or mapping of labelled data (Xie and Huang, 2021; Huang *et al.*, 2014). Yet, unsupervised learning is a learning method from unlabelled data (Wang *et al.*, 2021; Novotny *et al.*, 2018). It uses to find patterns and structure data such as cluster data into different groups without providing output to describe groups. Besides, reinforcement learning is used to make decisions (Leng *et al.*, 2021; Abu-Mostafa *et al.*, 2012). Thus, supervised learning is ideal for increasing orbit propagation accuracy based on historical measurements. In addition, it is more straightforward and not complicated compared to other methods.

Also, using the data-driven approach for orbit propagation allows the prediction process through data processing to aid decision-making (Jiménez-Luna *et al.*, 2021). The data-driven approach can produce a precise orbit propagation model, although there are elements that mathematical models cannot determine. For example, identifying perturbation value through data approaches (Jiménez-Luna *et al.*, 2021; Jäggi and Arnold, 2017). Peng and Bai (2017) used the data-driven approach to reduce orbit prediction errors from historical data and increase orbit propagation accuracy.

Recently, the hybrid propagation method has improved the accuracy of the orbit propagator (Lopez *et al.*, 2021; San-Juan *et al.*, 2017). This method combines classical integration methods with a forecasting technique based on either statistical time series or machine learning techniques. It can model the difference between the integrated solution and natural behaviour. The hybrid propagation method also enhances orbit propagation by refining the analytic approach and improving computational efficiency (Park, 2016). San-Juan *et al.* (2017) improved 90.03% over 30 days of the SGP4 Model by using this hybrid method with statistical technique. However, it also causes complexity and computational burden for the end-user (San-Juan *et al.*, 2017). Later, Peng and Bai (2017) improve orbit propagator accuracy by up to 96.1% using a support vector machine (SVM) for medium-term forecasting. Therefore, further study is required to explore the recent method used and appropriate learning techniques to accomplish this study.

1.3 Problem Statement

The SGP4 Model is the orbit propagator model commonly used and known as the most advanced space surveillance system. However, this SGP4 Model has an error of ~1 km and grows at ~1–3 km per day. Besides that, the TLE data used in conjunction with the SGP4 Model for space operations can be forecasted with accuracy valid for 2- 3 days. It needs to be updated periodically to minimize the error. The increased propagation span caused the position error to rise to 270.7km for 30 days. Thus, the operation planning will disrupt and create problems for the user, such as the desired image cannot be taken due to an incorrect satellite position. In case of collision, accident detection may be too late for prevention. Recently, the hybrid propagator method has improved the orbit propagator. The hybrid propagator method extends the validity of TLE data and reduces the error in the SGP4 Model. The Holt-Winters technique was used in this hybrid propagator, and it improves 90.03% over 30 days of propagation. However, this method requires changes in the components' probability distribution, causing complexity and computational burden for the end-user. Later, the SVM can reduce error and improve orbit propagator accuracy up to 96.1%. However, this technique's correction capability is limited and adequate after 28 days. Its ability reduces for long-term forecasting. In the literature, it has been found that ANN has the most regression capability due to its more flexible structure. Thus, this study explores deep learning techniques as they are scalable and suitable for complex data. The Recurrent Neural Network (RNN) and long short-term memory (LSTM) are deep learning methods ideal for time series forecasting and can remember patterns for long-term forecasting. Therefore, an improved orbit propagation model can be developed through the hybrid of the RNN-LSTM with the SGP4 Model. This hybrid RNN-LSTM is proposed because integrating these two techniques can assist in long-term forecasting with minimal error as they complement each other and overcome their weaknesses. Also, it can reduce the reliance on external inputs in performing forecasting. It also provides a solution to sequence and time series-related problems. Furthermore, the forecasting only required initial TLE data for long-term forecasting. Thus, it avoids relying on updated TLE data and enhances the current SGP4 Model capabilities.

1.4 Research Aim

This research project aims to improve the SGP4 Model for orbit propagation using the deep learning approaches. As a result, the improved SGP4 Model will overcome the limitations of orbit propagation for long-term forecasting and handle complex satellite data information. Furthermore, the enhanced SGP4 Model will validate. Hence, the results can be evaluated and discussed.

1.5 Research Questions

A set of research questions is formulated to find the solution for this research study. The following are the research questions used to guide the research accomplishment:

(a) **(RQ1):** What are the essential features in the space object data to form the SGP4 Model?

(b) **(RQ2):** How to design the SGP4 Model framework for identifying elements involved in improving the SGP4 Model?

(c) **(RQ3):** How to develop a hybrid RNN-LSTM SGP4 Model for minimizing errors and maintaining accuracy in long-term forecasting?

(d) **(RQ4):** How to validate the improved SGP4 Model based on error rate forecast measurements?

1.6 Research Objectives

Following are the research objectives of the study to achieve the aim of the research:

(a) **(RO1):** To identify essential features in the space object data for pre-processing to form the SGP4 Model.

(b) **(RO2):** To design the SGP4 Model Framework in identifying the elements involved in improving the SGP4 Model.

(c) **(RO3):** To develop a hybrid RNN-LSTM SGP4 Model for minimizing errors and maintaining accuracy in long-term forecasting.

(d) **(RO4):** To validate the improved SGP4 Model based on error rate forecast measurements.

1.7 The Scope of The Study

The research is bounded by:

(a) The space object data used in this study is a Low Earth Orbit (LEO) space object data. The selection of The LEO space object for this study is because it is this space object that is tracked by the Ground Station, Malaysia Space

Centre. Therefore, the results of this study will be able to assist the monitoring and operation of the satellite operators. In addition, LEO space object data is the most abundant data in orbit. Its increasing number poses a danger to the surroundings because they can collide, and its position is close to the Earth compared to other space objects. Therefore, LEO space object tracking is crucial compared to other space objects, such as in Medium Earth Orbit (MEO) and Geostationary orbit (GEO).

(b) The forecasting analysis is focused on the learning-based process approach. This approach is used because it is less complicated than other approaches, such as the statistical-based approach or mathematical approach, which requires mastery of mathematical formulations that are more complex and complicated. In this study, a learning-based approach that uses machine learning techniques through deep learning can optimize the use of historical data. The method is also less complicated and suitable for dealing with the development of a long-term forecasting model.

(c) The space object data used in this study is text type. The selection of text type data was made because the forecasting results for this study will also be in the form of text. In addition, the enhanced model developed is a regression model, and text-type data can assist in long-term forecasting. Although there are other types of space object data, such as images, for this study, such data will not be used and will be unsuitable for solving the long-term forecasting issues.

(d) The algorithm used in this study will also focus on appropriate techniques for time series data only. This is because the data features selected to be trained in this study, namely position and velocity space object data, are time-series data.

(e) This research does not investigate the privacy issues or the security issues related to orbit propagation. These privacy and security issues include tracking a spy satellite used by certain parties for intelligence purposes, warfare, and so on. Therefore, the results of this study will only help the parties involved in terms of governance of space object data only.

1.8 The Significance of the Study

The significance of this study can be gained through practicality and theoretically as follow.

1.8.1 Practicality

(a) Nation

The study will play an essential role in the space industry and assist the regulatory authorities in monitoring the space asset and public safety. In addition, it will provide additional inputs to the international regulatory authorities monitoring space object issues such as NORAD and other related international organizations. Thus, it will prevent unwanted events from happening. In turn, it helps speed up the prevention process in any incident.

(b) Space Agency

The study's outcome will allow the space agency that cannot afford the related facilities to benefit at a worthwhile cost. Subsequently, it will assist in administering the operational management of the ground station activity. As a result, space-based organizations can have their orbit propagation system without relying on other space agencies. Also, this orbit propagation model system can be designed based on their requirements and needs.

(c) Researcher

The ideas presented may be used as reference data to conduct new space data analytics research and improve current research. The researcher or analyst can make the right decision based on the deep learning approach despite their lack of expertise and facilities.

(d) Individual

The study will produce a reliable orbit propagation model and provide vital information for individuals or anyone affected without gathering the information from the authorities or any related organization.

1.8.2 Theoreticality

(a) The study helps to improve the method for the long-term forecasting horizon of space object data.

(b) The improved model is more robust and resilient to the effects of the space environment as the modelling does not require the latest space environment data as it is based on the historical data used.

(c) The improved model framework can assist in having systematic rules when processing and preparing the raw space object until the data is ready to be used for the modelling process.

(d) The improved model framework can assist in future modification of the orbit propagation model and dealing with space object data.

1.9 Thesis Organization

The thesis's organization is structured as follows;

- **Chapter 1** presents the research work's introduction, describing the research's overview and motivation, the background of the problem, problem statement, research aim, scope, and significance of the study. The problem statement highlights the need for an orbit propagation model for long-term forecasting. Also, to provide an accurate result-based deep learning approach to overcome the current SGP4 Model limitation.

- **Chapter 2** reviews related works and evaluate the previous study and results that led to the research gap. Then, based on the literature investigation, the way forward of the research is discussed.

- **Chapter 3** describes the research methodology and deliverables for the activities involved in achieving the research aims. The research plan contains five (5) phases that are: 1) Preliminary Study, which aims to analyse the problem and limitation of the current orbit propagation model and identify an approach that can improve the SGP4 Model's performance; 2) Data Collection, which explains how the collection of data is executed; 3) Data Analysis and Pre-Processing, which to pre-process the space object data; 4) Design and Modelling which to design and model-based deep learning approach to overcome the SGP4 Model limitation which is the integration between the SGP4 Model and the RNN-LSTM module, and 5) Validation Phase which aims to validate the improved model through experimental simulation and analyse the performance in terms of error rate forecast measurement.

- **Chapter 4** presents the data analysis and pre-processing for the study. Firstly, the analysis of data is conducted. Secondly, the space object data collection is explained. Next, the space object data is studied to understand more about the data. Then, the execution of pre-processing of the data. A suitable sampling interval is proposed based on the analysis conducted. Then, identify the essential features in the space object to form the SGP4 Model, and present the behaviour of the data patterns. This chapter addresses the first research objective **(RO1)** of the thesis, which identifies the essential features in the space object data for pre-processing to form the SGP4 Model. With that, this chapter provides the first contributions of this study.

- **Chapter 5** explains the design of the SGP4 Model Framework. This chapter also addresses the thesis's second research objective **(RO2),** which is to design the SGP4 Model framework to identify the elements involved in improving the SGP4 Model. In addition, this chapter contributes to the second contribution of the study.

- **Chapter 6** addresses the third and fourth research objectives **(RO3, RO4)** to contribute to the thesis. First, it will explain the RNN-LSTM module development contribute to the integration model's development. Next, the integration model is validated to ensure this study's accomplishment. Thus, this chapter contributes to the third and fourth contributions of the thesis.

- **Chapter 7** addresses the last research objective **(RO4)** of the thesis. On top of that, it will elaborate the experiments' results and discussion of findings in detail. Thus, this chapter contributes to the final contribution of the study.

- **Chapter 8** summarizes the achievement of the thesis, the research contributions, limitations of proposed approaches, research outcomes, and future works.

REFERENCES

Abay, R., Balage, S., Brown, M., & Boyce, R. (2021). Two-Line Element Estimation Using Machine Learning. *The Journal of the Astronautical Sciences*, 68(1), 273-299.

Abdel-Nasser, M., & Mahmoud, K. (2019). Accurate photovoltaic power forecasting models using deep LSTM-RNN. *Neural Computing and Applications*, 31(7), 2727-2740.

Abrol, A., Fu, Z., Salman, M., Silva, R., Du, Y., Plis, S., & Calhoun, V. (2021). Deep learning encodes robust discriminative neuroimaging representations to outperform standard machine learning. *Nature communications*, 12(1), 1-17.

Abu-Mostafa, Y.S., Magdon-Ismail, M. and Lin, H.T. (2012). *Learning from Data*. (4th ed). New York: NY, USA. AML Book.

Aghelpour, P., Mohammadi, B., & Biazar, S. M. (2019). Long-term monthly average temperature forecasting in some climate types of Iran, using the models SARIMA, SVR, and SVR-FA. *Theoretical and Applied Climatology*, 138(3), 1471-1480.

Ahmad, T., & Chen, H. (2018). Potential of three variant machine-learning models for forecasting district level medium-term and long-term energy demand in smart grid environment. *Energy*, 160, 1008-1020.

Alessi, E. M., Schettino, G., Rossi, A., & Valsecchi, G. B. (2018). Natural highways for end-of-life solutions in the LEO region. *Celestial Mechanics and Dynamical Astronomy*, 130(5), 1-22.

Almonacid, E., Fernandeza, E.F., Mellit, A. and Kalogirouc, S. (2017). Review of Techniques Based On Artificial Neural Networks for the Electrical Characterization of Concentrator Photovoltaic Technology. J*ournal of Renewable and Sustainable Energy Reviews*. 75, 938-953. doi: 10.1016/j.rser.2016.11.075.

Alzahrani, A., Shamsi, P., Dagli, C. and Ferdowsi, M. (2017). Solar Irradiance Forecasting Using Deep Neural Networks. *Journal of Procedia Computer Science*. 114, 304-313. doi: 10.1016/j.procs.2017.09.045.

Al Sadeque, Z., & Bui, F. M. (2020). A Deep Learning Approach to Predict Weather Data Using Cascaded LSTM Network. *2020 IEEE Canadian Conference on Electrical and Computer Engineering (CCECE)* (pp. 1-5). IEEE.

Arantes Gilz, P.R., Bréhard, F. and Gazzino, C. (2018). Validated Semi-Analytical Transition Matrix for Linearized Relative Spacecraft Dynamics via Chebyshev Polynomials. *2018 Space Flight Mechanics Meeting*. 1960.

Araya, S., Rakesh, N., & Kaur, M. (2021). Smart Home Load Analysis and LSTM-Based Short-Term Load Forecasting. In Innovations in Information and Communication Technologies (IICT-2020) (pp. 123-131). Springer, Cham.

Aristoff, J.M., Horwood, J.T. and Poore, A.B. (2014). Orbit and uncertainty propagation: a comparison of Gauss–Legendre-, Dormand–Prince-, and Chebyshev–Picard-based approaches. *Celestial Mechanics and Dynamical Astronomy*. 118(1), 13-28.

Armaghani, D. J., & Asteris, P. G. (2021). A comparative study of ANN and ANFIS models for the prediction of cement-based mortar materials compressive strength. *Neural Computing and Applications*, 33(9), 4501-4532.

Armellin, R. and San-Juan, J.F. (2017). Optimal Earth's Reentry Disposal of The Galileo Constellation. *Advances in Space Research*. 61(4), 1097-1120. doi: 10.1016/j.asr.2017.11.028.

Arnas, D., & Linares, R. (2021). A set of orbital elements to fully represent the zonal harmonics around an oblate celestial body. *Monthly Notices of the Royal Astronomical Society*, 502(3), 4247-4261.

Bagirov, A. M., Mahmood, A., and Barton, A. (2017). Prediction of Monthly Rainfall In Victoria, Australia: Clusterwise Linear Regression Approach. *Atmospheric Research*. 188, 20-29. doi: 10.1016/j.atmosres.2017.01.003.

Bai, X. and Junkins, J.L. (2012). Modified Chebyshev-Picard Iteration Methods for Solution of Initial Value Problems. *The Journal of the Astronautical Sciences.* 59(1-2), 327-351.

Bandara, K., Bergmeir, C., & Smyl, S. (2020). Forecasting across time series databases using recurrent neural networks on groups of similar series: A clustering approach. *Expert systems with applications*, 140, 112896.

Bengio, Y., Simard, P. and Frasconi, P. (1994). Learning Long-Term Dependencies with Gradient Descent Is Difficult. *IEEE Transactions on Neural Networks*. 5 (2), 157-166.

Bennett, J.C., Sang, J., Smith, C.H. and Zhang, K. (2013). Accurate Orbit Predictions for Debris Orbit Manoeuvre Using Ground-Based Lasers. *Advances in Space Research*. 52(11), 1876-1887.

Bergin, C. (2009). RED Threshold Late Notice Conjunction Threat Misses ISS. Unpublished note, NASA.

Bhatta, B. (2021). Global Navigation Satellite Systems: New Technologies and Applications. CRC Press.

Binbusayyis, A., & Vaiyapuri, T. (2021). Unsupervised deep learning approach for network intrusion detection combining convolutional autoencoder and one-class SVM. *Applied Intelligence*, 1-15.

Bock, S., Goppold, J., & Weiß, M. (2018). An improvement of the convergence proof of the ADAM-Optimizer. *arXiv e-prints*, arXiv-1804.

Bounoua, Z., Chahidi, L. O., & Mechaqrane, A. (2021). Estimation of daily global solar radiation using empirical and machine-learning methods: a case study of five Moroccan locations. *Sustainable Materials and Technologies*, 28, e00261.

Bradley, B.K. (2015). Numerical Algorithms for Precise and Efficient Orbit Propagation and Positioning. Ph.D. Thesis, University of Colorado, Boulder.

Bui, V., Le, N. T., Nguyen, V. H., Kim, J., & Jang, Y. M. (2021). Multi-Behavior with Bottleneck Features LSTM for Load Forecasting in Building Energy Management System. *Electronics*, 10(9), 1026.

Buizza, R. (2019). Introduction to the special issue on “25 years of ensemble forecasting”. *Quarterly Journal of the Royal Meteorological Society*, 145, 1-11.

Capderou, M. (2014). *Handbook of Satellite Orbits: From Kepler to GPS*. Springer Science & Business. ISBN: 3319034162, 9783319034164.

Carrico, T., Carrico, J., Policastri, L. and Loucks, M. (2008). Investigating Orbital Debris Events Using Numerical Methods with Full Force Model Orbit Propagation. *Adv. Astronaut. Sci*. 130, 407-426.

Cazabonne, B., & Cefola, P. J. (2021). Towards Accurate Orbit Determination using Semi-analytical Satellite Theory. *AAS Paper*, 21-309.

Celan, M. and Lep, M. (2017). Bus Arrival Time Prediction Based on Network Model. *Journal of Procedia Computer Science*. 113, 138-145. doi: 10.1016/j.procs.2017.08.331.

Chandra, R. and Chand, S. (2016). Evaluation of Co-Evolutionary Neural Network Architectures for Time Series Prediction with Mobile Application in Finance. *Journal of Applied Soft Computing.* 49, 462-473. doi: 10.1016/j.asoc.2016.08.029.

Chandran, V., K Patil, C., Karthick, A., Ganeshaperumal, D., Rahim, R., & Ghosh, A. (2021). State of charge estimation of lithium-ion battery for electric vehicles using machine learning algorithms. *World Electric Vehicle Journal*, 12(1), 38.

Chen, L., Bai, X.-Z., Liang, Y.-G. and Li, K. -B. (2017). *Orbital Data Applications for Space Objects Conjunction Assessment and Situation Analysis*. Springer. ISBN: 978-981-10-29639.

Chen, X., Chen, X., She, J. and Wu, M. (2017). A Hybrid Time Series Prediction Model Based on Recurrent Neural Network and Double Joint Linear-nonlinear Extreme Learning Network for Prediction of Carbon Efficiency in Iron Ore Sintering Process. *Journal of Neurocomputing.* doi: 10.1016/j.neucom.2017.03.069.

Chen, Z., Zhao, H., Shu, X., Zhang, Y., Shen, J., & Liu, Y. (2021). Synthetic state of charge estimation for lithium-ion batteries based on long short-term memory network modeling and adaptive H-Infinity filter. *Energy*, 228, 120630.

Chernick, M., & D'Amico, S. (2021). Closed-form optimal impulsive control of spacecraft formations using reachable set theory. *Journal of Guidance, Control, and Dynamics*, 44(1), 25-44.

Chihabi, Y., & Ulrich, S. (2021). Analytical spacecraft relative dynamics with gravitational, drag and third-body perturbations. *Acta Astronautica.*

Cho, H. and Udwadia, F. (2010). Explicit Analytic Solution to the Satellite Formation-Keeping Problem. In Earth and Space 2010: *Engineering, Science, Construction, and Operations in Challenging Environments*. 1849-1864.

Choi, E. J., Cho, S., Jo, J. H., Park, J. H., Chung, T., Park, J., ... & Lee, Y. (2017). Performance analysis of sensor systems for space situational awareness. *Journal of Astronomy and Space Sciences*, 34(4), 303-314.

Clynch, J. R. (2006). Earth coordinates. Electronic Documentation, February.

Comini, M. (2017). Orbit Determination with Simplified General Perturbation Model. Master Thesis. Politecnico Di Milano. *Aerospace Science and Technology*.

Correa, P.N. and Correa, A.N. (2007). The Gravitational Aether, Part II: Gravitational Aetherometry (7)-Antigravity Lift and Exotic Flight (II): Critical Overview of Theories and Technologies. *Aetherometric Theory of Synchronicity*. 2(9), 1-97.

Cui, Z., Ke, R., Pu, Z., & Wang, Y. (2018). Deep bidirectional and unidirectional LSTM recurrent neural network for network-wide traffic speed prediction. *arXiv preprint arXiv:1801.02143*.

Cunio, P.M., Bantel, M., Flewelling, B.R., Therien, W., Jeffries Jr, M.W., Montoya, M., Butler, R. and Hendrix, D. (2017). Photometric and Other Analyses of Energetic Events Related to 2017 GEO RSO Anomalies. *Conference in Advanced Maui Optical and Space Surveillance (AMOS) Technologies*.

Dahl, G. E. (2015). Deep Learning Approaches to Problems in Speech Recognition, Computational Chemistry, And Natural Language Text Processing. Ph.D. Thesis. University of Toronto, Canada.

Danner, L.K. (2018). Military Case Studies. In China's Grand Strategy. 151-191. Palgrave Macmillan, Cham. Springer.

Daquin, J., Alessi, E. M., O'Leary, J., Lemaitre, A., & Buzzoni, A. (2021). Dynamical properties of the Molniya satellite constellation: long-term evolution of the semi-major axis. *arXiv preprint.* arXiv:2103.06251.

Dargan, S., Kumar, M., Ayyagari, M. R., & Kumar, G. (2019). A survey of deep learning and its applications: A new paradigm to machine learning. *Archives of Computational Methods in Engineering*, 1-22.

de Iaco Veris, A. (2018). The Central Gravitational Force and Its Perturbations. Practical Astrodynamics. 323-569. Springer, Cham.

Decker, B.L. (1986). World Geodetic System 1984. *Defense Mapping Agency Aerospace* Center St Louis Afs Mo.

Deepak, G., Rooban, S., & Santhanavijayan, A. (2021). A knowledge centric hybridized approach for crime classification incorporating deep bi-LSTM neural network. *Multimedia Tools and Applications*, 1-25.

Dell'Elce, L., Arnst, M. and Kerschen, G. (2014). Probabilistic Assessment of The Lifetime of Low-Earth-Orbit Spacecraft: Uncertainty Characterization. *Journal of Guidance, Control, and Dynamics.* 38(5), 900-912.

Demina, N.Y., Andreev, A.O., Demin, S.A. and Nefedyev, Y.A. (2017). The Method for Celestial Bodies' Center Of Mass Position Relative To Their Figures Determination On The Basis Of Harmonic Analysis Of The Expansion In

Spherical Functions In Order To Refine The Physical Libration Parameters. *Journal of Physics: Conference Series*. 929(1), 012013. IOP Publishing.

Deng, L. and Yu, D. (2014). Deep Learning Methods and Applications. *Foundations and Trends® in Signal Processing*, 7(3–4), 197-387.

Di Carlo, M., da Graça Marto, S., & Vasile, M. (2021). Extended analytical formulae for the perturbed Keplerian motion under low-thrust acceleration and orbital perturbations. *Celestial Mechanics and Dynamical Astronomy*, 133(3), 1-39.

Diab Pascual, O. V. (2020). *Analysis of Perturbation incidence in the calculation of trajectories in Ephemeris Model*. Master thesis. Universitat Politècnica de Catalunya, Spain.

Disse, E., Ledoux, S., Bétry, C., Caussy, C., Maitrepierre, C., Coupaye, M., Laville, M., and Simon, C. (2017). An Artificial Neural Network to Predict Resting Energy Expenditure in Obesity. *Journal of Clinical Nutrition*. doi: 10.1016/j.clnu.2017.07.017.

Dong, W. and Chang-yin, Z. (2010). An Accuracy Analysis of The SGP4/SDP4 Model. *Chinese Astronomy and Astrophysics.* 34(1), 69-76.

Driedger, M., & Ferguson, P. (2021). Feasibility Study of an Orbital Navigation Filter Using Resident Space Object Observations. *Journal of Guidance, Control, and Dynamics*, 44(3), 622-628.

Edel, M. and Köppe, E. (2015). An advanced method for pedestrian dead reckoning using BLSTM-RNNs. *International Conference on Indoor Positioning and Indoor Navigation* (IPIN), 2015. 1-6. IEEE.

El-Bar, S.A. and El-Salam, F.A. (2018). Modelling of charged satellite motion in Earth's gravitational and magnetic fields. *Astrophysics and Space Science.* 363(5), 89.

Fan, C., Xiao, F. and Zhao, Y. (2017). A Short-Term Building Cooling Load Prediction Method Using Deep Learning Algorithms. *Journal of Applied Energy*. 195, 222-233. doi: 10.1016/j.apenergy.2017.03.064.

Fan, J., Zhang, K., Huang, Y., Zhu, Y., & Chen, B. (2021). Parallel Spatio-temporal attention-based TCN for multivariate time series prediction. *Neural Computing and Applications*, 1-10.

Feng, Z. K., & Niu, W. J. (2021). Hybrid artificial neural network and cooperation search algorithm for nonlinear river flow time series forecasting in humid and semi-humid regions. *Knowledge-Based Systems*, 211, 106580.

Fernandez, O. R., Utzmann, J., & Hugentobler, U. (2019). SPOOK-A comprehensive Space Surveillance and Tracking analysis tool. *Acta Astronautica*, 158, 178-184.

Flohrer, T., Krag, H. and Klinkrad, H. (2008). Assessment and Categorization of TLE Orbit Errors for the US SSN Catalogue. *Proceedings of the Advanced Maui Optical and Space Surveillance Technologies Conference.* September 17-19. Wailea, Maui, Hawaii, Ed.: S. Ryan, The Maui Economic Development Board., 53.

Flores, R., Burhani, B. M., & Fantino, E. (2021). A method for accurate and efficient propagation of satellite orbits: A case study for a Molniya orbit. *Alexandria Engineering Journal*, 60(2), 2661-2676.

Fono, A., Thiele, G., Klein, M., & Krüger, J. (2021, May). Assistance Method for the Application-Driven Design of Machine Learning Algorithms. *IOP Conference Series: Materials Science and Engineering* (Vol. 1140, No. 1, p. 012018). IOP Publishing.

Gambi, J.M., del Pino, M.L.G. and Rodríguez-Teijeiro, M.C. (2018). Non-linear Post-Newtonian Equations for the Motion of Designated Targets with Respect to Space Based APT Laser. *Progress in Industrial Mathematics* at ECMI 2016. 26, 467.

Ganorkar, S. S., Tiwari, N., & Namdeo, V. (2021). Analysis and Prediction of Student Data Using Data Science: A Review. Smart Trends in Computing and Communications: *Proceedings of SmartCom 2020*, 443-448.

Gazzola, S., Hansen, P. C., & Nagy, J. G. (2019). IR Tools: a MATLAB package of iterative regularization methods and large-scale test problems. *Numerical Algorithms*, 81(3), 773-811.

Gondelach, D. J. (2019). *Orbit prediction and analysis for space situational awareness.* Ph.D. Thesis. University of Surrey, United Kingdom.

Gong, B., Ergu, D., Cai, Y., & Ma, B. (2021). Real-Time Detection for Wheat Head Applying Deep Neural Network. *Sensors*, 21(1), 191.

Gonzalo Gòmez, J. L., & Colombo, C. (2021). On-Board Collision Avoidance Applications Based on Machine Learning and Analytical Methods. 8*th European Conference on Space Debris*, ESA/ESOC (pp. 1-6). ESA.

Gorgolis, N., Hatzilygeroudis, I., Istenes, Z., & Gyenne, L. G. (2019, July). Hyperparameter optimization of LSTM network models through genetic algorithm. *2019 10th International Conference on Information, Intelligence, Systems and Applications (IISA)* (pp. 1-4). IEEE.

Goswami, A., Ahmed, M. W., Rajesh, D., Alam, M. I., Imam, H., & Perveen, A. (2017). Disease pattern discover in institutional data via cluster analysis. *Journal of Medicinal Plants,* 5(2), 143-147.

Goswami, N. (2018). China in Space: Ambitions and Possible Conflict. *Strategic Studies Quarterly*. 12(1), 74-97.

Greff, K., Srivastava, R. K., Koutník, J., Steunebrink, B. R. and Schmidhuber, J. (2017). LSTM: A Search Space Odyssey. *IEEE Transactions on Neural Networks and Learning Systems.* 28(10), 2222-2232.

Hanada, T., Hinagawa, H., Chen, H., Hamada, H. and Ikemura, S. (2015). Attitude Motion Under Full Orbit Perturbations. *Transactions of The Japan Society for Aeronautical and Space Sciences, Aerospace Technology Japan.* 13,.45-50. doi: 10.2322/tastj.13.45.

Hatipoglu, P. U. (2016). *Time Series Classification Using Deep Learning.* Master Thesis. Middle East Technical University.

Hartikainen, J., Sepp¨anen, M. and S¨arkk¨a, S. (2012). State-Space Inference for Non-Linear Latent Force Models with Application to Satellite Orbit Prediction. *Proceedings of the 29th International Conference on Machine Learning (ICML-12).* 903–910.

Hautesserres, D., San-Juan, J.F. and Lara, M. (2018). A Parametric Study of the Orbital Lifetime of Super GTO and SSTO Orbits Based on Semi-analytical Integration. *Stardust Final Conference.* 85-98. Springer, Cham.

Heaton, J. B., Polson, N. G. and White J. H. (2016). Deep Learning in Finance. *Computer Science Journals.* CoRR. arXiv: 1602.06561.

Hemdan, E.E.D. and Manjaiah, D.H. (2017). Digital Investigation of Cybercrimes Based on Big Data Analytics Using Deep Learning. *Deep Learning Innovations and Their Convergence With Big Data*.79.

Hinton, G. E., Osindero, S. and Teh, Y.-W. (2006). A Fast Learning Algorithm for Deep Belief Nets. *Neural Computation*. 18. 1527-1554.

Hochreiter, S. and Schmidhuber, J. (1997). Long Short-Term Memory. N*eural Computation*. 9(8), 1735-1780.

Hoots, F. R. and Roehrich, R. L. (1980). *Spacetrack Report #3: Models for Propagation of the NORAD Element Sets*. Unpublished note. U.S. Air Force Aerospace Defense Command, Colorado Springs, CO.

Hoots, F.R., Schumacher Jr, P.W. and Glover, R.A. (2004). History of Analytical Orbit Modeling In the US Space Surveillance System. *Journal of Guidance, Control, and Dynamics*. 27(2), 174-185.

Huang, G., Song, S., Gupta, J.N. and Wu, C. (2014). Semi-Supervised and Unsupervised Extreme Learning Machines. *IEEE Transactions on Cybernetics*. 44(12), 2405-2417.

Huerta, E. A., & Zhao, Z. (2021). Advances in Machine and Deep Learning for Modeling and Real-time Detection of Multi-Messenger Sources. *arXiv preprint.* arXiv:2105.06479.

Idrees, S. M., Alam, M. A., & Agarwal, P. (2019). A prediction approach for stock market volatility based on time series data. *IEEE Access*, 7, 17287-17298.

Jäggi, A. and Arnold, D. (2017). *Precise Orbit Determination*. Springer International Publishing AG.

Jakhu, R.S. (2010). Iridium-Cosmos collision and its implications for space operations. In Yearbook on Space Policy 2008/2009. 254-275. Springer, Vienna. ISBN: 978-3-7091-0317-3. doi: 10.1007/978-3-7091-0318-0.

Jeffrey, A. and Aubrey, P. (2012). Implicit Runge-Kutta Methods for Orbit Propagation. *AIAA/AAS Astrodynamics Specialist Conference*. 4880. doi: 10.2514/6.2012-4880.

Jiménez-Luna, J., Grisoni, F., Weskamp, N., & Schneider, G. (2021). Artificial intelligence in drug discovery: *Recent advances and future perspectives. Expert Opinion on Drug Discovery*, 1-11.

Jo, T. (2021). Machine Learning Foundations: Supervised, Unsupervised, and Advanced Learning. Springer Nature.

Jones, B. (2012). Orbit Propagation Using Gauss-Legendre Collocation. *AIAA/AAS Astrodynamics Specialist Conference.* 4967.

Jones, B. and Anderson, R. L. (2012). A Survey of Symplectic And Collocation Integration Methods for Orbit Propagation. *AAS/AIAA Spaceflight Mechanics Conference.* 1-20.

Jung, O., Seong, J., Jung, Y., & Bang, H. (2021). Recurrent neural network model to predict re-entry trajectories of uncontrolled space objects. *Advances in Space Research*.

Kardol, S. (2018). *An interactive, web-based, near-Earth orbit visualization tool*. Master Thesis. Delft University of Technology

Karpathy, A., Johnson, J., & Fei-Fei, L. (2015). Visualizing and understanding recurrent networks. *arXiv preprint.* arXiv:1506.02078.

Kelso, T. (2012). *Iridium 33/Cosmos 2251 Collision.* Unpublished note. NORAD.

Kennefick, D. (2016). Traveling at The Speed of Thought: Einstein and The Quest for Gravitational Waves. Princeton University Press. ISBN: 1400882745, 9781400882748.

Khayyam, H., Jamali, A., Bab-Hadiashar, A., Esch, T., Ramakrishna, S., Jalili, M., & Naebe, M. (2020). A novel hybrid machine learning algorithm for limited and big data modeling with application in industry 4.0. *IEEE access*, 8, 111381-111393.

Kidder, S. Q., Kidder, R. M., & Haar, T. H. V. (1995). *Satellite meteorology: an introduction*, Academic Press, San Diego, 15-46. ISBN: 9780124064300. doi: 10.1016/B978-0-08-057200-0.50006-7.

Kim, S., Jo, B. U., Choi, E. J., Cho, S., & Ahn, J. (2021). Procedure and methodologies for managing the risk of space object reentry. *Advances in Space Research*, 67(6), 1844-1858.

Kuhn, M., & Johnson, K. (2013). *Applied predictive modeling* (Vol. 26). New York: Springer.

Kuleshov, V. and Ermon, S. (2017). Deep Hybrid Models: Bridging Discriminative and Generative Approaches. UAI.

Kulsrud, R. M. (2020). *Plasma physics for astrophysics.* Princeton University Press.

Kumar, K., Hekma, E., Agrawal, A. and Topputo, F. (2017). Effect of Perturbations on Debris-To-Debris Orbital Transfers: A Quantitative Analysis. *Advances in Space Research*. 59(5), 1289-1303.

Kuznetsov, E., & Safronova, V. (2018). Application of metrics in the space of orbits to search for asteroids on close orbits. *Planetary and Space Science*, 157, 22-27.

Kwon, D., Kim, H., Kim, J., Suh, S. C., Kim, I., & Kim, K. J. (2019). A survey of deep learning-based network anomaly detection. *Cluster Computing*, 22(1), 949-961.

Lara, M., Moraes, R. V., Sanchez, D. M. and Prado, A.F. B. A. (2015). Propagation of Space Objects. *J. Aerosp. Technol. Manag.*, São José dos Campos. 7(1), 5-6, Jan.-Mar., 2015. doi: 1 0.5028/jatm.v7i1.469.

Larson, W. J., & Wertz, J. R. (1992). *Space mission analysis and design* (No. DOE/NE/32145-T1). Torrance, CA (United States); Microcosm, Inc. ISBN: 1-881883-01-9; 0-7923-2998-2.

LeCun, Y., Bengio, Y. and Hinton, G. (2015). Deep Learning. *Nature.* 521(7553). 436. doi: 10.1038/nature14539.

Leick, A., *Surveying,* G. S., & Wiley, J. (2004). Sons.

Leng, J., Ruan, G., Song, Y., Liu, Q., Fu, Y., Ding, K., & Chen, X. (2021). A loosely-coupled deep reinforcement learning approach for order acceptance decision of mass-individualized printed circuit board manufacturing in industry 4.0. *Journal of cleaner production,* 280, 124405.

Li, S., Li, W., Cook, C., Zhu, C., & Gao, Y. (2018). Independently recurrent neural network (indrnn): Building a longer and deeper rnn. *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 5457-5466).

Li, W., Wang, X., Bian, Y. and Zhang, Y. (2017). Study on orbit control error propagation characteristics by covariance technique. *2017 IEEE International Conference on Cybernetics and Intelligent Systems (CIS) and IEEE Conference on Robotics, Automation and Mechatronics* (RAM). 446-451. IEEE.

Li, X., Chen, S., Hu, X., & Yang, J. (2019). Understanding the disharmony between dropout and batch normalization by variance shift. *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 2682-2690).

Lim, D. (2015). Rethinking the Vital Role of Smallsats in the Space Ecosystem. A*IAA SPACE 2015 Conference and Exposition*. 4598. doi: 10.2514/6.2015-4598.

Lipa, J.A., Wang, S., Nissen, J., Kasevich, M. and Mester, J. (2007). Detecting Lorentz Invariance Violations in the 10-20 Range. *International Journal of Modern Physics D.* 16(12b), 2393-2398. doi: 10.1142/S0218271807011528.

Liu, C., Liu, Ch., Shang, Y., Chen, S., Cheng, B. and Chen, J. (2017). An Adaptive Prediction Approach Based on Workload Pattern Discrimination in the Cloud. *Journal of Network and Computer Applications*. 80, 35-44. doi: 10.1016/j.jnca.2016.12.017.

Liu, L., Jiang, H., He, P., Chen, W., Liu, X., Gao, J., & Han, J. (2019, September). On the Variance of the Adaptive Learning Rate and Beyond. I*nternational Conference on Learning Representations*.

Long, Y., Na, T., & Mukhopadhyay, S. (2018). ReRAM-based processing-in-memory architecture for recurrent neural network acceleration. *IEEE Transactions on Very Large Scale Integration (VLSI) Systems*, 26(12), 2781-2794.

Loossens, T., Tuerlinckx, F., & Verdonck, S. (2021). A comparison of continuous and discrete time modeling of affective processes in terms of predictive accuracy. *Scientific reports*, 11(1), 1-11.

Losacco, M., Principe, G., Pirovano, L., Gondelach, D., Armellin, R., San Juan, J. F., ... & Urdampilleta, I. (2021). Differential Algebra-Based Orbit Determination With The Semi-Analytical Propagator Sada. 8*th European Conference on Space Debris*, Darmstadt, Germany, published by ESA Space Debris Office.

Lopez-Jimenez, S., Pastor, A., & Escobar, D. (2021). Improving orbital uncertainty realism through covariance determination. *Acta Astronautica*, 181, 679-693.

Lu, W., Xu, Q., Lan, C., Lyu, L., Zhou, Y., Shi, Q., & Zhao, Y. (2020). Microservice-based platform for space situational awareness data analytics. *International Journal of Aerospace Engineering*, 2020.

Lu, Y. (2021). *Positioning, Coordinate System, and Time Standard*. In BDS/GPS Dual-Mode Software Receiver (pp. 1-35). Springer, Singapore.

Luo, Y.Z and Yang, Z. (2017). A Review of Uncertainty Propagation in Orbital Mechanics. *Progress in Aerospace Sciences*. 89, 23-19. doi: 10.1016/j.paerosci.2016.12.002.

Ma, L., Xu, X. and Pang, F. (2016). Accuracy Assessment of Geostationary-Earth-Orbit with Simplified Perturbations Models. *Artificial Satellites.* 51(2), 55-59. doi: 10.1515/arsa-2016-0005.

Ma, Y., Peng, W., Yu, W., Su, J., Wu, C., & Zhao, G. (2013, July). A distributed routing algorithm for LEO satellite networks. 2*013 12th IEEE International Conference on Trust, Security and Privacy in Computing and Communications* (pp. 1367-1371). IEEE.

Macdonald, M. (2014). *Introduction to Astrodynamics.* The International Handbook of Space Technology, 61-98. Springer, Berlin, Heidelberg.

Malhotra, P., Vig, L., Shroff, G., & Agarwal, P. (2015, April). Long short term memory networks for anomaly detection in time series. *Proceedings* (Vol. 89, pp. 89-94).

Mejia, J., Avelar-Sosa, L., Mederos, B., Ramírez, E. S., & Roman, J. D. D. (2021). Prediction of time series using an analysis filter bank of LSTM units. *Computers & Industrial Engineering*, 157, 107371.

Mercado, R., Rastemo, T., Lindelöf, E., Klambauer, G., Engkvist, O., Chen, H., & Bjerrum, E. J. (2021). Graph networks for molecular design. *Machine Learning: Science and Technology,* 2(2), 025023.

Miura, N.Z. (2009). Comparison and design of Simplified General Perturbation Models (SGP4) and code for NASA Johnson Space Center. Orbital debris program office.

Moghar, A., & Hamiche, M. (2020). Stock market prediction using LSTM recurrent neural network. *Procedia Computer Science*, 170, 1168-1173.

Montgomery, D. C., Peck, E. A., & Vining, G. G. (2021). *Introduction to linear regression analysis.* John Wiley & Sons.

Muzaffar, S., & Afshari, A. (2019). Short-term load forecasts using LSTM networks. *Energy Procedia*, 158, 2922-2927.

Najafi, G., Ghobadiana, B., Moosavian, A., Yusaf, T., Mamat, R., Kettner, M. and Azmi, W. H. (2016). SVM and ANFIS for Prediction of Performance and Exhaust Emissions of a SI Engine with Gasoline–Ethanol Blended Fuels. *Applied Thermal Engineering.* 95, 186-203. doi: 10.1016/j.applthermaleng.2015.11.009.

Namasudra, S., Dhamodharavadhani, S., & Rathipriya, R. (2021). Nonlinear neural network based forecasting model for predicting COVID-19 cases. *Neural Processing Letters,* 1-21.

Narmadha, S., & Vijayakumar, V. (2021). Spatio-Temporal vehicle traffic flow prediction using multivariate CNN and LSTM model. *Materials Today: Proceedings.*

NASA Orbital Debris Program Office. *Astromaterials Research & Exploration Science.* [Online] Available at:

https://orbitaldebris.jsc.nasa.gov/modeling/legend.html [Accessed 13 February 2022].

Nielsen, A. (2019). Practical time series analysis: Prediction with statistics and machine learning. O'Reilly Media.

Nisha, S. S., Sathik, M. M., & Meeral, M. N. (2021). *Application, algorithm, tools directly related to deep learning*. In Handbook of Deep Learning in Biomedical Engineering (pp. 61-84). Academic Press.

Niu, X., Yang, C., Wang, H. and Wang, Y. (2017). Investigation of ANN and SVM Based on Limited Samples for Performance and Emissions Prediction of a CRDI-Assisted Marine Diesel Engine. *Applied Thermal Engineering.* 111, 1353-1364. doi: 10.1016/j.applthermaleng.2016.10.042.

Novotny, D., Albanie, S., Larlus, D. and Vedaldi, A. (2018). Self-supervised Learning of Geometrically Stable Features Through Probabilistic Introspection. *arXiv preprint arXiv.* 1804.01552.

Nwankwo, V. U., Denig, W., Chakrabarti, S. K., Ajakaiye, M. P., Fatokun, J., Akanni, A. W., ... & Anekwe, P. I. (2021, May). Atmospheric drag effects on modelled low Earth orbit (LEO) satellites during the July 2000 Bastille Day event in contrast to an interval of geomagnetically quiet conditions. *Annales Geophysicae* (Vol. 39, No. 3, pp. 397-412). Copernicus GmbH.

Oh, S. L., Ng, E. Y., San Tan, R., & Acharya, U. R. (2018). Automated diagnosis of arrhythmia using combination of CNN and LSTM techniques with variable length heart beats. *Computers in biology and medicine*, 102, 278-287.

Oltrogge, D., & Cooper, J. (2020). Space Situational Awareness & Space Traffic Management. *Space Debris Peril: Pathways to Opportunities,* 9.

Pang, Z., Niu, F., & O’Neill, Z. (2020). Solar radiation prediction using recurrent neural network and artificial neural network: A case study with comparisons. *Renewable Energy,* 156, 279-289.

Panigrahi, S., Pattanayak, R. M., Sethy, P. K., & Behera, S. K. (2021). Forecasting of Sunspot Time Series Using a Hybridization of ARIMA, ETS and SVM Methods. *Solar Physics,* 296(1), 1-19.

Park, I. (2016). *Dynamical Realism and Uncertainty Propagation.* Ph.D. Thesis. University of Colorado, Boulder.

Parvathi, S.P. and Ramanan, R.V. (2018). An Iterative Analytical Technique for The Design of Interplanetary Direct Transfer Trajectories Including Perturbations. *Advances in Space Research*. doi: 10.1016/j.asr.2018.03.034.

Patera, R.P. (2005). Calculating Collision Probability for Arbitrary Space Vehicle Shapes Via Numerical Quadrature. *Journal of Guidance, Control, And Dynamics*. 28(6), 1326-1328.

Pearce, L. A., Kraus, A. L., Dupuy, T. J., Mann, A. W., Newton, E. R., Tofflemire, B. M., & Vanderburg, A. (2020). Orbital parameter determination for wide stellar binary systems in the age of Gaia. *The Astrophysical Journal*, 894(2), 115.

Pelton, J. N. (2019). A path forward to better space security: Finding new solutions to space debris, space situational awareness and space traffic management. *Journal of Space Safety Engineering,* 6(2), 92-100.

Pelton, J.N. and Jakhu J. S. (2017). *Global Space Governance: An International Study*. Springer International Publishing AG. Springer, Cham. ISBN: 978-3-319-54363-5. doi: 10.1007/978-3-319-54364-2.

Peng, H. and Bai, X. (2017). Limits of Machine Learning Approach on Improving Orbit Prediction Accuracy using Support Vector Machine. *Advanced Maui Optical and Space Surveillance Technologies Conference* (AMOS).

Peng, H. and Bai, X. (2018a). Improving Orbit Prediction Through Supervised Machine Learning. *Advances in Space Research.* doi: 10.1016/j.asr.2018.03.001.

Peng, H., & Bai, X. (2018b). Artificial neural network–based machine learning approach to improve orbit prediction accuracy. *Journal of Spacecraft and Rockets*, 55(5), 1248-1260.

Peng, H., & Bai, X. (2019). Comparative evaluation of three machine learning algorithms on improving orbit prediction accuracy. *Astrodynamics,* 3(4), 325-343.

Peng, H., & Bai, X. (2020). Machine learning approach to improve satellite orbit prediction accuracy using publicly available data. *The Journal of the Astronautical Sciences*, 67(2), 762-793.

Peng, H., & Bai, X. (2021). Fusion of a machine learning approach and classical orbit predictions. *Acta Astronautica*, 184, 222-240.

Pertseva, M., Gao, B., Neumeier, D., Yermanos, A., & Reddy, S. T. (2021). Applications of Machine and Deep Learning in Adaptive Immunity. *Annual Review of Chemical and Biomolecular Engineering,* 12.

Petit, A., Rossi, A., & Alessi, E. M. (2021). Assessment of the close approach frequency and collision probability for satellites in different configurations of large constellations. *Advances in Space Research.*

Pérez, I., San-Juan, J. F., San-Martín, M. and López-Ochoa, L. M. (2013). Application of Computational Intelligence in Order to Develop Hybrid Orbit Propagation Methods. *Mathematical Problems in Engineering.* 631628. doi: 10.1155/2013/631628.

Pérez, I., San-Martín, M., López, R., Vergara, E. P., Wittig, A. and San-Juan, J. F. (2017). Forecasting Satellite Trajectories by Interpolating Hybrid Orbit Propagators. *International Conference on Hybrid Artificial Intelligence Systems*. Springer. 650-661. doi: 10.1007/978-3-319-59650-1_55.

Pérez, I., San-Martín, M., López, R., Vergara, E. P., Wittig, A., & San-Juan, J. F. (2019). Extending the hybrid methodology for orbit propagation by fitting techniques. *Neurocomputing,* 354, 49-60.

Portnov, A. M. (2021, January). Coordinate basis adaptation of cataloging of unified immovable complexes included into the Russian-Chinese initiative project “One Belt–One Way”(by example railway transport). *In Journal of Physics: Conference Series* (Vol. 1715, No. 1, p. 012054). IOP Publishing.

Qian, J., Zhu, S., Wong, W. K., Zhang, H., Lai, Z., & Yang, J. (2021). Dual robust regression for pattern classification. *Information Sciences*, 546, 1014-1029.

Qu, L., Lyu, J., Li, W., Ma, D., & Fan, H. (2021). Features injected recurrent neural networks for short-term traffic speed prediction. *Neurocomputing*, 451, 290-304.

Reiland, N., Rosengren, A. J., Malhotra, R., & Bombardelli, C. (2021). Assessing and minimizing collisions in satellite mega-constellations. *Advances in Space Research,* 67(11), 3755-3774.

Riesing, K. (2015). Orbit Determination from Two Line Element Sets Of ISS-Deployed Cubesats. *29th Annual AIAA/USU Conference on Small Satellites.*

Rivas, P. (2020). *Deep Learning for Beginners: A beginner's guide to getting up and running with deep learning from scratch using Python*. Packt Publishing Ltd.

Rodríguez, E., Otero, B., Gutiérrez, N., & Canal, R. (2021). A Survey of Deep Learning Techniques for Cybersecurity in Mobile Networks. *IEEE Communications Surveys & Tutorials.*

Romano, M., Muciaccia, A., Trisolini, M., Colombo, C., Di Lizia, P., Di Cecco, A., & Salotti, L. (2021). PUZZLE Software for the Characterisation of In-Orbit Fragmentations. *8th European Conference on Space Debris*, ESA/ESOC (pp. 1-14). ESA.

Rovetto, R.J. (2016). An Ontological Architecture for Orbital Debris Data. *Earth Science Informatics.* 9(1), 67-82.

Sabzi, H. Z., King, J. P. and Abudu, S. (2017). Developing an Intelligent Expert System for Streamflow Prediction, Integrated In a Dynamic Decision Support System for Managing Multiple Reservoirs: A Case Study. *Journal of Expert Systems with Applications.* 83, 145-163. doi: 10.1016/j.eswa.2017.04.039.

Sahoo, B. B., Jha, R., Singh, A., & Kumar, D. (2019). Long short-term memory (LSTM) recurrent neural network for low-flow hydrological time series forecasting. *Acta Geophysica*, 67(5), 1471-1481.

Sak, H., Senior, A. and Beaufays, F. (2014). Long Short-Term Memory Recurrent Neural Network Architectures For Large Scale Acoustic Modeling. *Fifteenth Annual Conference of The International Speech Communication Association*.

Salakhutdinov, R. and Hinton, G. (2009). Semantic hashing. *International Journal of Approximate Reasoning*. 50(7). 969-978.

Salakhutdinov, R. (2015). Learning Deep Generative Models. *Annual Review of Statistics and Its Application.* 2. 361-385.

San-Juan, J.F., San-Martín, M., Pérez, I., López, R. (2016). Hybrid Perturbation Methods Based on Statistical Time Series Models. *Advances in Space Research.* PII: S0273-1177 (15), 00365-8. doi: 10.1016/j.asr.2015.05.025.

San-Juan, J. F., Pérez, I., San-Martín, M. and Vergara, E. P. (2017). Hybrid SGP4 Orbit Propagator. *Acta Astronautica.* 137, 254-260.

San-Martin, M., Pérez, I., Lopez, R. and San-Juan, J. F. (2016). Hybrid SGP4: Tools and Methods. *6th International Conference on Astrodynamics Tools and Techniques* (ICATT). Darmstadt.

Sang, J., Bennett, J.C. and Smith, C.H. (2013). Estimation of Ballistic Coefficients of Low Altitude Debris Objects from Historical Two-Line Elements. *Advances in Space Research.* 52(1), 117-124.

Sangrody, H., Zhou, N., Tutun, S., Khorramdel, B., Motalleb, M., & Sarailoo, M. (2018, February). Long term forecasting using machine learning methods. In *2018 IEEE Power and Energy Conference at Illinois* (PECI) (pp. 1-5). IEEE.

Sarker, I. H. (2021). Machine learning: Algorithms, real-world applications and research directions. *SN Computer Science*, 2(3), 1-21.

Sazonov, V. V., & Samylovskiy, I. A. (2021, May). Optimization-based method for interplanetary spacecrafts passive navigation. *Journal of Physics: Conference Series* (Vol. 1864, No. 1, p. 012129). IOP Publishing.

Schmidhuber, J. (2015). Deep Learning in Neural Networks: An Overview. *Neural Networks*. 61, 85-117. doi: 10.1016/j.neunet.2014.09.003.

Seong, J.D., Kim, H.D. and Choi, H.Y. (2017). A Study of a Target Identification Method for An Active Debris Removal System. Proceedings of the Institution of Mechanical Engineers, Part G. *Journal of Aerospace Engineering*. 231(1), 180-189. doi: 10.1177/0954410016662065.

Setty, S.J., Cefola, P.J., Montenbruck, O., Fiedler, H. and Lara, M. (2014). Investigating the Suitability of Analytical and Semi-Analytical Satellite Theories for Space Object Catalogue Maintenance in Geosynchronous Regime. *Adv. Astronaut. Sci.* 150, 1027-1042.

Setty, S. J., Cefola, P.J., Montenbruck, O. and Fiedler, H. (2016). Application of Semi-Analytical Satellite Theory Orbit Propagator to Orbit Determination for Space Object Catalog Maintenance. *Advances in Space Research*. 57(10), 2218-2233. doi: 10.1016/j.asr.2016.02.028.

Shah, D., Campbell, W., & Zulkernine, F. H. (2018, December). A comparative study of LSTM and DNN for stock market forecasting. *2018 IEEE International Conference on Big Data* (Big Data) (pp. 4148-4155). IEEE.

Shahriar, S. A., Kayes, I., Hasan, K., Hasan, M., Islam, R., Awang, N. R., ... & Salam, M. A. (2021). Potential of ARIMA-ANN, ARIMA-SVM, DT and CatBoost for Atmospheric PM2. 5 Forecasting in Bangladesh. *Atmosphere*, 12(1), 100.

Shai, S. S. and Shai, B. D. (2014). *Understanding Machine Learning: From Theory to Algorithms.* Cambridge University Press New York. ISBN: 1107057132 9781107057135.

Shams, S. R., Jahani, A., Kalantary, S., Moeinaddini, M., & Khorasani, N. (2021). Artificial intelligence accuracy assessment in NO 2 concentration forecasting of metropolises air. *Scientific Reports*, 11(1), 1-9.

Sharadga, H., Hajimirza, S., & Balog, R. S. (2020). Time series forecasting of solar power generation for large-scale photovoltaic plants. *Renewable Energy*, 150, 797-807.

Sharma, S. and Cutler, J. W. (2015). *Robust Orbit Determination and Classification: A Learning Theoretic Approach.* IPN Progress Report 42-203. Jet Propulsion Laboratory.

Shewalkar, A. (2019). Performance evaluation of deep neural networks applied to speech recognition: RNN, LSTM and GRU. *Journal of Artificial Intelligence and Soft Computing Research*, 9(4), 235-245.

Shi, H., Li, Y., Bai, X., Wang, Z., Zou, D., Bao, Z., & Wang, Z. (2021). Investigation of the orbit-spinning behaviors of the outer ring in a full ceramic ball bearing-steel pedestal system in wide temperature ranges. *Mechanical Systems and Signal Processing*, 149, 107317.

Shou, H. N. (2014). Orbit Propagation and Determination of Low Earth Orbit Satellites. *International Journal of Antennas and Propagation.* 12. doi: 10.1155/2014/903026.

Silva, E. G., Cavalcanti, G. D., de Oliveira, J. F. L., & de Mattos Neto, P. S. (2020, July). On the evaluation of dynamic selection parameters for time series forecasting. *2020 International Joint Conference on Neural Networks (IJCNN)* (pp. 1-7). IEEE.

Singh, R., Ojha, S. P., Puviarasan, N., & Singh, V. (2019). Impact of GNSS signal delay assimilation on short range weather forecasts over the Indian region. *Journal of Geophysical Research: Atmospheres*, 124(17-18), 9855-9873.

Skinner, M. A., Sorge, M. M. E., Bernstein, M. D., & Muelhaupt, M. T. (2021). *The Aerospace Corporation's Space Traffic Management Research Program*.

Souriau, R., Lerbet, J., Chen, H., & Vigneron, V. (2021). A review on generative Boltzmann networks applied to dynamic systems. M*echanical Systems and Signal Processing*, 147, 107072.

Srivastava, N (2017). *Deep Learning Models for Unsupervised and Transfer Learning.* Ph.D. Thesis. University of Toronto, Canada.

Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I., & Salakhutdinov, R. (2014). Dropout: a simple way to prevent neural networks from overfitting. *The journal of machine learning research*, 15(1), 1929-1958.

Srivastava, V. K., Mishra, P., & Ramakrishna, B. N. (2021). Satellite ephemeris prediction for the Earth orbiting satellites. *Aerospace Systems,* 1-12.

Stepchenko, A., Chizhov, J., Aleksejeva, L. and Tolujew, J. (2017). Nonlinear, Non-stationary and Seasonal Time Series Forecasting Using Different Methods Coupled with Data Preprocessing. *Journal of Procedia Computer Science*. 104, 578-585. doi: 10.1016/j.procs.2017.01.175.

Stodden, D.Y. and Galasso, G.D. (1995). Space system visualization and analysis using the Satellite Orbit Analysis Program (SOAP). *Conference in Aerospace Applications. Proceedings* IEEE. 1, 369-387. IEEE.

Sujatha, R., Abhyankar, V., Gehlot, A., Gupta, P., & Subramaniam, S. (2021). Stock Market Trend Prediction Using Regression Model, RNNs, and Sentiment Analysis. *Advances in Automation, Signal Processing, Instrumentation, and Control*: Select Proceedings of I-CASIC 2020, 700, 291.

Sullivan, J., Koenig, A. W., Kruger, J., & D'Amico, S. (2021). Generalized Angles-Only Navigation Architecture for Autonomous Distributed Space Systems. Jo*urnal of Guidance, Control, and Dynamics,* 44(6), 1087-1105.

Suzuki, K., Mori, H., & Ogata, T. (2021). Compensation for undefined behaviors during robot task execution by switching controllers depending on embedded dynamics in RNN. *IEEE Robotics and Automation Letters,* 6(2), 3475-3482.

Takane, H., Ryoichiro, A., Tsuyoshi, I., Kohei, F., Takuma, Y., & Takeshi, I. (2021). High-fidelity elastic Green's functions for subduction zone models consistent with the global standard geodetic reference system. Earth, Planets and Space (Online), 73(1).

Tarran, B. (2021). Prepare for impact: Space debris and statistics. *Significance*, 18(3), 18-23.

Terna, P., D'Acunto, G. and Caselle, M. (2016). *A Deep Learning Model to Forecast Financial Time-Series.* Master Thesis. University Degli Studi DiTorino.

Tietjen, G. L. (2017). The analysis and detection of outliers. *Goodness-of-fit techniques* (pp. 497-522). Routledge.

Tommasi, T., & Fiorino, D. (2021). Using Deep Generative Models for Representation Learning with Applications to AI Explainability. Master Thesis. Politecnico di Torino, Italy.

Valk, S., Lemaître, A. and Anselmo, L. (2008). Analytical and Semi-Analytical Investigations of Geosynchronous Space Debris with High Area-To-Mass Ratios. *Advances in Space Research.* 41(7), 1077-1090.

Vallado, D. A., and Cefola, P. J. (2012). Two-Line Element Sets–Practice and Use. *63rd International Astronautical Congress.* Naples, Italy.

Vallado, D. and Crawford, P. (2008). SGP4 Orbit Determination. *AIAA/AAS Astrodynamics Specialist Conference and Exhibit*. 6770. American Institute of Aeronautics and Astronautics.

Vallado, D. A., Crawford, P., Hujsak, R. and Kelso, T. S. (2006a). Revisiting Spacetrack Report #3: Rev 1. AIAA 2006-6753-Rev 1. *AIAA/AAS Astrodynamics Specialist Conference and Exhibit.* American Institute of Aeronautics and Astronautics.

Vallado, D. A., Crawford, P., Hujsak, R. and Kelso, T. S. (2006b). Revisiting Spacetrack Report #3: Rev 2. AIAA 2006-6753-Rev 2. *AIAA/AAS Astrodynamics Specialist Conference and Exhibit.* American Institute of Aeronautics and Astronautics.

Vallado, D.A., Virgili, B.B. and Flohrer, T. (2013). Improved SSA Through Orbit Determination of Two-Line Element Sets. *ESA Space Debris Conference.* doi: 10.13140/2.1.4644.2241

Vargas, R., Mosavi, A., & Ruiz, R. (2017). Deep learning: a review. *Advances in intelligent systems and computing.*

Varsha, M., Poornima, B., Vinutha, H. P., & Pavan Kumar, M. P. (2021). Predictive Model for Rice Blast Disease on Climate Data Using Long Short-Term Memory and Multi-Layer Perceptron: An Empirical Study on Davangere District. *Annals of the Romanian Society for Cell Biology*, 25(6), 4703-4722.

Vincent, P., Larochelle, H., Bengio, Y. and Manzagol, P.-A. (2008). Extracting and Composing Robust Features with Denoising Autoencoders. *Proceedings of the 25th International Conference on Machine Learning*. 1096-1103.

Vincent, P., Larochelle, H., Lajoie, I., Bengio, Y. and Manzagol, P.-A. (2010). Stacked Denoising Autoencoders: Learning Useful Representations in A Deep Network with A Local Denoising Criterion. *Journal of Machine Learning Research.* 11. 3371-3408.

Vishwajeet, K., Singla, P. and Jah, M. (2014). Nonlinear Uncertainty Propagation for Perturbed Two-Body Orbits. *Journal of Guidance, Control, and Dynamics.* 37(5), 1415-1425.

Vitart, F., & Robertson, A. W. (2018). The sub-seasonal to seasonal prediction project (S2S) and the prediction of extreme events. *npj Climate and Atmospheric Science*, 1(1), 1-7.

Voyant, C., Notton, G., Kalogirou, S. Nivet, M. L., Paoli, C. Motte, F. and Fouilloy, A. (2016). Machine Learning Methods for Solar Radiation Forecasting: A Review. *Journal of Renewable Energy*. doi: 10.1016/j.renene.2016.12.095.

Wang, F., Xuan, Z., Zhen, Z., Li, K., Wang, T., & Shi, M. (2020). A day-ahead PV power forecasting method based on LSTM-RNN model and time correlation modification under partial daily pattern prediction framework. *Energy Conversion and Management*, 212, 112766.

Wang, H., Czerminski, R., & Jamieson, A. C. (2021). *Neural networks and deep learning*. In The Machine Age of Customer Insight. Emerald Publishing Limited.

Wang, N., Zhou, W., Song, Y., Ma, C., Liu, W., & Li, H. (2021). Unsupervised deep representation learning for real-time tracking. *International Journal of Computer Vision*, 129(2), 400-418.

Wang, P., Zhang, H., Qin, Z. and Zhang, G. (2017). A Novel Hybrid-Garch Model Based on ARIMA and SVM for PM2.5 Concentrations Forecasting. *Journal of Atmospheric Pollution Research.* 8(5), 850-860. doi: 10.1016/j.apr.2017.01.003.

Wang, S., Mu, L., & Liu, D. (2021). A hybrid approach for El Niño prediction based on Empirical Mode Decomposition and convolutional LSTM Encoder-Decoder. *Computers & Geosciences*, 149, 104695.

Weigend, A. S. (2018). Time series prediction: forecasting the future and understanding the past. Routledge.

Weiß, C. H. (2018). An introduction to discrete-valued time series. John Wiley & Sons.

Wittig, A., Colombo, C. and Armellin, R. (2017). Long-Term Density Evolution Through Semi-Analytical and Differential Algebra Techniques. *Celestial Mechanics and Dynamical Astronomy*. 128(4), 435-452.

Wu, X., Shi, B., Dong, Y., Huang, C., Faust, L., & Chawla, N. V. (2018). Restful: Resolution-aware forecasting of behavioral time series data. *Proceedings of the 27th ACM International Conference on Information and Knowledge Management* (pp. 1073-1082).

Xia, Z., & Qahouq, J. A. A. (2019, March). Adaptive and fast state of health estimation method for lithium-ion batteries using online complex impedance and artificial neural network. *2019 IEEE Applied Power Electronics Conference and Exposition* (APEC) (pp. 3361-3365). IEEE.

Xiao, Y., Yin, H., Zhang, Y., Qi, H., Zhang, Y., & Liu, Z. (2021). A dual-stage attention-based Conv-LSTM network for spatio-temporal correlation and multivariate time series prediction. *International Journal of Intelligent Systems*, 36(5), 2036-2057.

Xie, M. K., & Huang, S. J. (2021). Partial multi-label learning with noisy label identification. *IEEE Transactions on Pattern Analysis and Machine Intelligence*.

Xu, X. and Xiong, Y. (2018). Orbit Error Characteristic and Distribution of TLE Using CHAMP Orbit Data. *Astrophysics and Space Science*. 363, 31. doi: 10.1007/s10509-018-3251-z.

Yalçın, M. A., Elmqvist, N., & Bederson, B. B. (2017). Keshif: Rapid and expressive tabular data exploration for novices. *IEEE transactions on visualization and computer graphics*, 24(8), 2339-2352.

Yan, H., & Wu, C. (2021, January). Analysis of A Mixed Neural Network Based on CNN and RNN for Computational Model of Sensory Cortex. *2021 International Conference on Electronics, Circuits and Information Engineering* (ECIE) (pp. 245-249). IEEE.

Yang, C., & Wang, X. (2021). A steam injection distribution optimization method for SAGD oil field using LSTM and dynamic programming. *ISA transactions*, 110, 198-212.

Ye, J., Pan, G., & Alouini, M. S. (2021). Earth Rotation-Aware Non-Stationary Satellite Communication Systems: Modeling and Analysis. *IEEE Transactions on Wireless Communications.*

Yu, W., Kim, I. Y., & Mechefske, C. (2021). Analysis of different RNN autoencoder variants for time series classification and machine prognostics. *Mechanical Systems and Signal Processing*, 149, 107322.

Yucesan, M., Pekel, E., Celik, E., Gul, M., & Serin, F. (2021). Forecasting daily natural gas consumption with regression, time series and machine learning based methods. *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, 1-16.

Yulita, I. N., Abdullah, A. S., Helen, A., Hadi, S., Sholahuddin, A., & Rejito, J. (2021, January). Comparison multi-layer perceptron and linear regression for time series prediction of novel coronavirus covid-19 data in West Java. *Journal of Physics: Conference Series* (Vol. 1722, No. 1, p. 012021). IOP Publishing.

Yurong, H., Zhi, L. and Lei, H. (2016). Covariance Propagation of Two-Line Element Data. *Control and Decision Conference (CCDC)*. 3836-3841. IEEE.

Zeckl, J., Wastian, M., Brunmeir, D., Rappelsberger, A., Arseniev, S. B., & Adlassnig, K. P. (2021). From machine learning to knowledge-based decision support—a predictive-model-markup-language-to-Arden-syntax transformer for decision trees. Soft Computing for Biomedical Applications and Related Topics (pp. 89-99). Springer, Cham.

Zannoni, D. (2022). Out of sight, out of mind? The proliferation of space debris and international law. *Leiden Journal of International Law*, 1-20. doi: https://doi.org/10.1017/S0922156522000152.

Zeng, N., Zhang, H., Liu, W., Liang, J. and Alsasdi, F. E. (2017). A Switching Delayed PSO Optimized Extreme Learning Machine for Short-Term Load Forecasting. *Journal of Neurocomputing*. 240, 175-182. doi: 10.1016/j.neucom.2017.01.090.

Zhang, Q., Wang, H., Dong, J., Zhong, G., and Sun, X. (2017). Prediction of Sea Surface Temperature Using Long Short-Term Memory. *IEEE Geoscience and Remote Sensing Letters*. 14(10), 1745-1749.

Zhao, J., Wu, J., Guo, X., Han, J., Yang, K., & Wang, H. (2019). Prediction of radar sea clutter based on LSTM. *Journal of Ambient Intelligence and Humanized Computing*, 1-8.

Zhou, L., Pan, S., Wang, J., and Vasilakos, A. V. (2017). Machine Learning on Big Data: Opportunities and Challenges. *Journal of Neurocomputing.* 237, 350-361. doi: 10.1016/j.neucom.2017.01.026.

Zhu, C., Li, Y., Zhang, M., Wang, Q., & Zhou, W. (2020, May). An Optimization Method for the Gateway Station Deployment in LEO Satellite Systems. *2020*

IEEE 91st Vehicular Technology Conference (VTC2020-Spring) (pp. 1-7). IEEE.

Ziat, A., Delasalles, E., Denoyer, L., & Gallinari, P. (2017, November). Spatio-temporal neural networks for space-time series forecasting and relations discovery. *2017 IEEE International Conference on Data Mining* (ICDM) (pp. 705-714). IEEE.

Zulqarnain, M., Ghazali, R., Hassim, Y. M. M., & Aamir, M. (2021). An Enhanced Gated Recurrent Unit with Auto-Encoder for Solving Text Classification Problems. *Arabian Journal for Science and Engineering*, 1-15.

LIST OF PUBLICATIONS

Indexed Journals

1. **Salleh, N.**, Yuhaniz, S.S., Sabri, S.F., & Azmi, N.F. (2020). Enhancing Prediction Method of Ionosphere for Space Weather Monitoring Using Machine Learning Approaches: A Review. International Journal on Advanced Science, Engineering and Information Technology, 10, 9-15. **(Indexed by SCOPUS)**
2. **Salleh, N**., Yuhaniz, S.S., Sabri, S.F., & Azmi, N.F. (2022). Modeling Orbital Propagation Using Regression Technique and Artificial Neural Network. International Journal on Advanced Science, Engineering and Information Technology. **(Indexed by SCOPUS)**

Indexed Conferences Proceedings

1. **Salleh, N.** A., Yuhaniz, S. S., Azmi, N. F. M., & Sabri, S. F. (2019, February). Enhancing Simplified General Perturbations-4 Model for Orbit Propagation Using Deep Learning: A Review. In Proceedings of the 2019 8th International Conference on Software and Computer Applications (pp. 27-32). **(Indexed by SCOPUS)**
2. **N. Salleh**, N. F. Mohd Azmi and S. S. Yuhaniz, "An Adaptation of Deep Learning Technique In Orbit Propagation Model Using Long Short-Term Memory," 2021 International Conference on Electrical, Communication, and Computer Engineering (ICECCE), 2021, pp. 1-6, DOI: 10.1109/ICECCE52056.2021.9514264. **(Indexed by SCOPUS)**