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Manoeuvre Prediction for GEO Satellites Based on AI Algorithms

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Abstract

Collision avoidance in space missions is crucial for preventing potential risks involving space debris and other active satellites with maneuvering capabilities. Normally, manoeuvre plans are not available for active objects, making it harder to predict close encounters for this type of satellites. This paper explores the application of Artificial Intelligence (AI) techniques to predict manoeuvre plans for active GEO satellites, aiming to reduce false positives and improve collision avoidance operations.

The study utilizes a historical database of two years of satellite ephemeris and applies various AI methods, including time series models (ARIMA, SARIMAX, Prophet), neural networks (LSTM) and transformers (informer). These algorithms learn from data patterns and generate alternative propagation models that include the effect of identified manoeuvre patterns. The AI models can accurately forecast the limits in longitude, providing reliable predictions for active satellites within their respective windows.

Integrating AI-predicted orbits into GMV's operational collision avoidance service, Focusoc, is expected to reduce false positives in GEO by over 90% and predict active-active events for collocated objects with greater anticipation. Future developments will extend these techniques to the LEO regime, addressing the challenges posed by diverse manoeuvre strategies and the higher number of objects.

Acronyms/Abbreviations

18SDS	18th Space Defence Squadron
19SDS	19th Space Defence Squadron
AI	Artificial Intelligence
AR	Auto Regressive
ARIMA	Auto Regressive Integrated Moving Average
GEO	Geostationary Orbit
LEO	Low Earth Orbit
LSTF	long Sequence Time-Series Forecasting
LSTM	Long Short-Term Memory
MA	Moving Average
RNN	Recurrent Neural Networks
SARIMAX	Seasonal AutoRegressive Integrated Moving Average with eXogenous factors

1. Introduction

Collision avoidance in space missions is a critical aspect of ensuring the safety and longevity of satellites. Predicted risk events can be broadly classified into two categories: encounters involving space debris and encounters with other active satellites possessing maneuvering capabilities. While the former is relatively straightforward, involving the propagation of the orbit and the uncertainty of the secondary object, the latter presents significant challenges. The trajectory of manoeuvering satellites can be altered through planned manoeuvres, complicating the prediction process.

Traditionally, the best approach to mitigate collision risks between manoeuvering satellites involves sharing manoeuvre plans between satellite operators. However, this is often impractical due to the classified nature of manoeuvre planning information and various restrictions on sharing such data. Consequently, encounters with other manoeuvering objects are frequently false positives, or the final geometry of the encounter is modified, complicating decision-making processes. Additionally, real events might be overlooked if operational manoeuvre plans are not considered in the propagation models.

1.1 Objectives

The primary objective of this work is to develop and apply Artificial Intelligence (AI) techniques to predict the manoeuvre plans of active GEO satellites. By integrating these AI-based predictions into GMV's operational collision avoidance service, ***Focusoc***, the aim is to:

1. Significantly reduce false positives in collision predictions, cutting unnecessary alerts by over 90%.
2. Improve the accuracy of predicting active-active events for collocated objects.
3. Enhance the overall efficiency and safety of collision avoidance operations.

1.2 Background

Active GEO satellites typically operate within a defined longitude window, and station-keeping efforts aim to maintain the satellite within this window. Without considering manoeuvre plans, propagating the orbit of active secondary objects often results in false conjunctions, predicting that the neighboring object will enter the adjacent window of the primary satellite.

The predictions within the ***Focusoc*** system are based on the high-accuracy SP catalogue provided by the 18th and 19th Space Defence Squadrons (18SDS/19SDS), which includes high-quality ephemeris for all non-classified objects but lacks manoeuvre plans. By analyzing the historical trends of satellite behavior, including past manoeuvres, AI models can identify patterns and extend these into the future to predict manoeuvre plans. This study utilizes a historical database of two years of satellite ephemeris and applies various AI methods, including time series models (ARIMA, SARIMAX, and Prophet), neural networks (LSTM) and transformers (informer).

These AI algorithms do not directly consider orbital mechanics or physics but instead learn from data patterns and extrapolate them, generating alternative propagation models that include the effect of identified manoeuvre patterns. The primary advantage observed in GEO is that AI models can accurately forecast the limits in longitude, generating reliable predictions for active satellites within their respective windows. Although some aspects, such as the amplitude of daily longitude oscillations, require further refinement, these AI-based predictions are generally more reliable than classical propagation methods for manoeuvering objects, with significantly smaller prediction errors.

By integrating AI-predicted orbits for active satellites, Focusoc aims to reduce false positives in GEO by over 90% and predict active-active events for collocated objects with greater anticipation. This represents a substantial reduction in the effort required for collision avoidance operations and contributes to the overall safety of space missions. Future developments will extend these techniques to the LEO regime, where manoeuvre strategies are more diverse, and the higher number of objects necessitates processing vast amounts of data. Despite the challenges, the potential benefits for LEO collision avoidance operations are significant.

2. Material and methods

2.1 Data Collection

The orbital information used in this study was sourced from the 19SDS Special Perturbations (SP) catalogue, which provides high-quality ephemeris for all non-classified objects. This catalogue is known for its accuracy and reliability, making it an ideal foundation for predicting satellite manoeuvres.

2.2 Data Processing

The collected orbital data was processed using GMV's ***Focussuite*** flight dynamics software. ***Focussuite*** is a comprehensive tool designed for precise orbit determination and prediction, ensuring that the processed data maintains its integrity and accuracy throughout the analysis.

2.3 AI Analysis

For the AI analysis, Python and its extensive libraries were employed. Python is a versatile programming language widely used in data science and machine learning due to its robust ecosystem of libraries. The following libraries were particularly instrumental in this study:

- **NumPy:** Used for numerical computations and handling large datasets.
- **Pandas:** Utilized for data manipulation and analysis.
- **Matplotlib:** For plotting and presenting results.
- **Scikit-learn:** For Machine Learning algorithms.
- **Statsmodels:** Employed for statistical modeling, including time series analysis.
- **Prophet:** Used for forecasting time series data.
- **TensorFlow/Keras:** Implemented for building and training neural network models.
- **GluonTS:** Used for probabilistic time series modelling and data transformations
- **Transformers:** Utilized for configuring the Informer model’s hyperparameters, as well as for training and evaluation.

These tools enabled the application of various AI methods, including time series models, neural networks and transformers, to predict the manoeuvre plans of active GEO satellites.

3. Theory and calculation

3.1 Data Processing and Conversion

The initial step in the analysis involves processing and converting the orbital data obtained from the 19SDS SP catalogue. This high-quality ephemeris data is processed using GMV's ***Focussuite*** flight dynamics software, which ensures reliable frame conversions and handling of orbital information. The steps involved in data processing and conversion are as follows:

1. Data Ingestion:
    - The raw orbital data from the 19SDS SP catalogue is ingested into the ***Focussuite*** software.
    - The data includes parameters such as position, velocity, and time stamps for each satellite.
2. Data Cleaning:
    - Any anomalies or missing values in the data are identified and addressed.
    - Outliers are removed or corrected to ensure the integrity of the dataset.
3. Data Transformation:
    - The cleaned data is transformed into a format suitable for AI analysis, in this case, a Pandas DataFrame.
    - SP catalogue is updated in a daily basis, and orbit files include a span of several days into the future. In order to extract historical trend including manoeuvre effect, first day of ephemeris is taken from each catalogue update, and these days are put sequentially into a 2-year ephemeris evolution.
4. Ephemeris conversion:
    - Relevant magnitudes are extracted from the transformed data, such as longitude, latitude, altitude, and positions in Earth-fixed frame.
    - Additional features, such as the rate of change of these parameters, are computed to enhance the predictive power of the AI models.

3.2 AI Algorithms for Data Analysis

Once the data is processed and converted, various AI algorithms are applied to analyze the data and predict the manoeuvre plans of active GEO satellites. The AI methods used in this study include time series models and neural networks, each with its unique approach to forecasting.

1. **ARIMA (AutoRegressive Integrated Moving Average):**
    - **Theory:** ARIMA models are used for analyzing and forecasting time series data. They combine autoregressive (AR) terms, integrated (I) terms, and moving average (MA) terms to capture different aspects of the data.

   - **Calculation:** The ARIMA model is defined by three parameters (p, d, q), where p is the number of lag observations, d is the degree of differencing, and q is the size of the moving average window. The model is fitted to the time series data, and future values are predicted based on the identified patterns.
2. **SARIMAX (Seasonal AutoRegressive Integrated Moving Average with eXogenous factors):**
   - **Theory:** SARIMAX extends ARIMA by incorporating seasonal effects and external variables (exogenous factors). This allows the model to capture periodic patterns and the influence of external factors on the time series.
   - **Calculation:** The SARIMAX model is defined by parameters (p, d, q) for the non-seasonal part and (P, D, Q, s) for the seasonal part, where s is the length of the seasonal cycle. The model is fitted to the data, and predictions are made by considering both seasonal and non-seasonal components.
3. **Prophet:**
   - **Theory:** Prophet is a forecasting tool designed for time series data with strong seasonal effects and missing data. It uses an additive model where non-linear trends are fit with yearly, weekly, and daily seasonality, plus holiday effects.
   - **Calculation:** The Prophet model decomposes the time series into trend, seasonality, and holiday components. It then fits these components to the data and generates future predictions by extrapolating the identified patterns.
4. **LSTM (Long Short-Term Memory):**
   - **Theory:** Neural networks, particularly recurrent neural networks (RNNs) such as long short-term memory (LSTM) networks, are used for modeling sequential data. They are capable of capturing complex, non-linear relationships and long-term dependencies in the data.
   - **Calculation:** The neural network is trained on the time series data, where the input is a sequence of past observations, and the output is the predicted future value. The network learns the underlying patterns through multiple layers of interconnected neurons, adjusting the weights and biases to minimize the prediction error.
5. **Informer:**
   - **Theory:** Transformer is a deep learning model architecture designed to improve the long sequence processing capabilities of its predecessors, becoming fundamental in fields such as Natural Language Processing. Its high parallelizability leads to faster training. In particular, Informer is a Transformer-based model for long sequence time-series forecasting (LSTF). This model offers probabilistic and multi-variable predictions for multiple time series.
   - **Calculation:** The neural network is trained on the time series data, where the input is a sequence of past observations, and the output is the predicted future value. The network learns the underlying patterns through multiple layers of interconnected neurons, adjusting the weights and biases to minimize the prediction error. Informer follows an Encoder-Decoder architecture, where each token being processed is a timestep.

4. Results

Figure 1 represents the predictions in longitude for a GEO active satellite using ARIMA and SARIMAX models. Predictions are also compared against the classical physical propagation not accounting for manoeuvres, to illustrate the drift in longitude if manoeuvres are not included. In the same way, Figure 2 represents the prediction results for different prophet models.

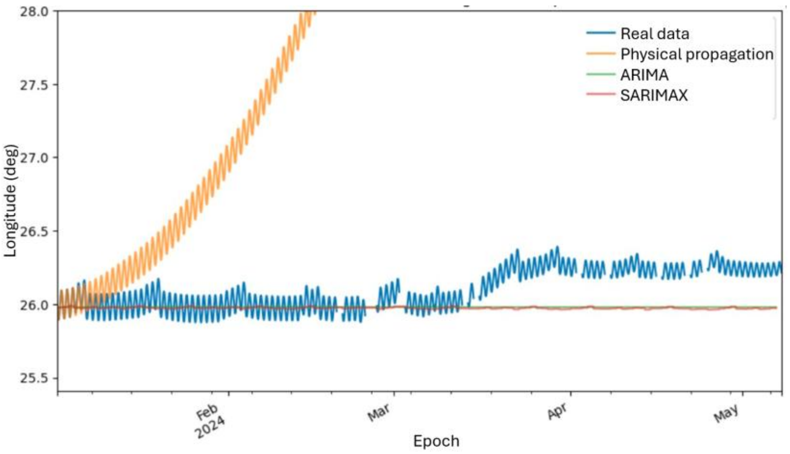

Fig. 1. Longitude predictions for ARIMA and SARIMAX models

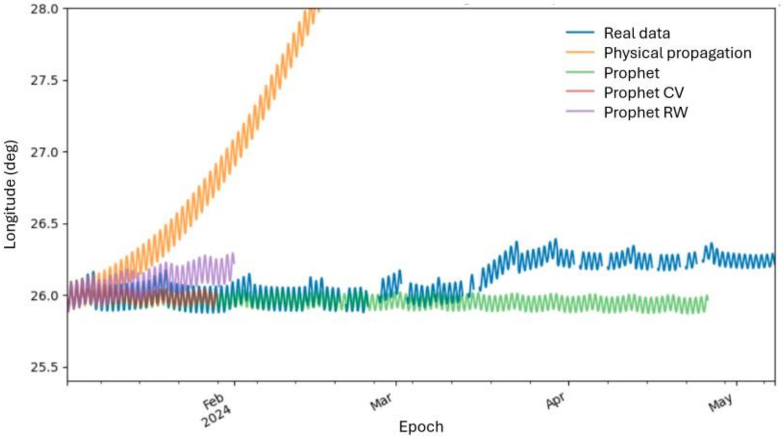

Fig. 2. Longitude predictions for Prophet models

Figure 3 represents the prediction of the longitude using LSTM (neural networks).

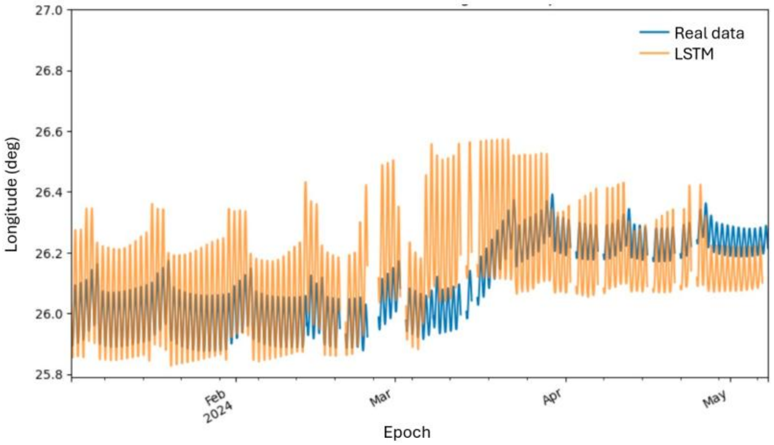

Fig. 3. Longitude predictions for LSTM model

Figures 4, 5 and 6 represent, respectively, the prediction for longitude, latitude and altitude computed using informer, the selected transformer for this study.

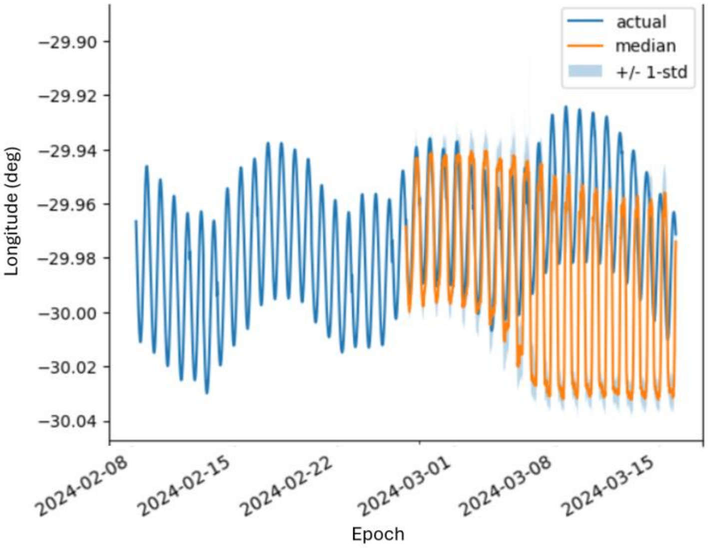

Fig. 4. Longitude predictions for informer method

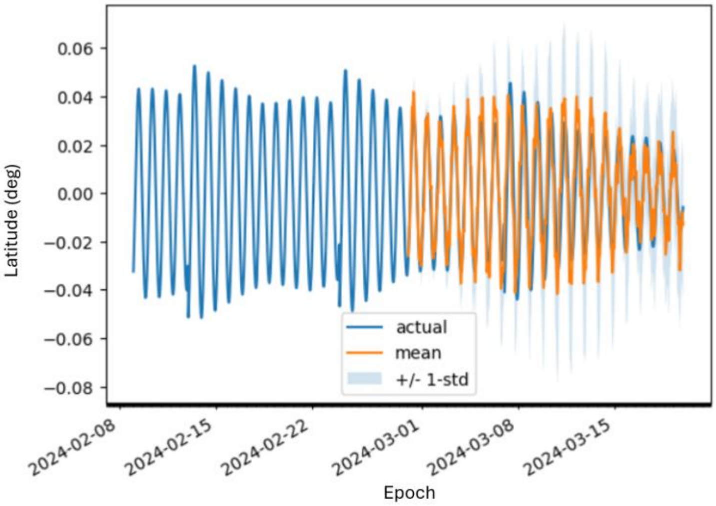

Fig. 5. Latitude predictions for informer method

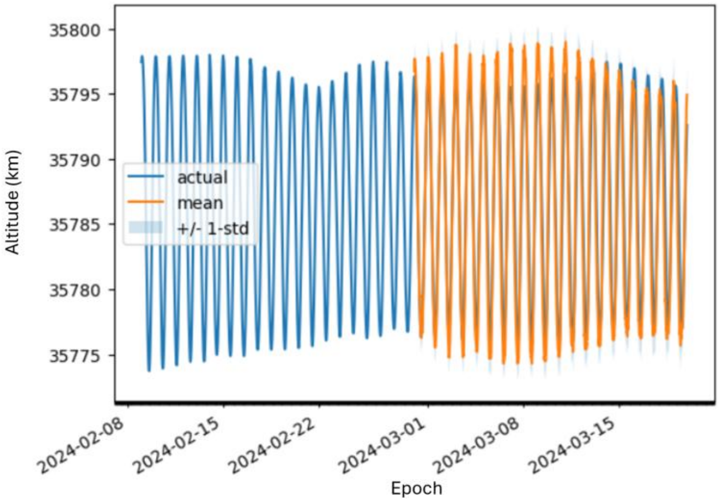

Fig. 5. Altitude predictions for informer method

5. Discussion

The application of various AI methods to predict the manoeuvre plans of active GEO satellites has yielded promising results. This section compares the performance of different AI models and discusses their effectiveness in predicting satellite behavior within their longitude windows.

5.1 Comparison of AI Methods

The AI methods applied in this study include time series models (ARIMA, SARIMAX, Prophet), neural networks (LSTM) and transformers (Informer). Each method has its strengths and limitations, which are highlighted below:

1. **ARIMA and SARIMAX:**
    - **Strengths:** ARIMA SARIMAX models are capable of predicting average values for longitude trend. They require a short training time.
    - **Limitations:** They struggle with capturing short-term oscillations in longitude, making predictions inaccurate for osculating elements.
    - **Results:** ARIMA & SARIMAX provided reasonable results for mean longitude, but oscillating longitude is not correctly modelled. These models could be used for initial predictions of mean longitude for approximate positioning of satellites.
2. **Prophet:**
    - **Strengths:** Prophet is designed for handling time series data with strong seasonal effects and missing data. It is user-friendly and requires minimal tuning. In this case, they provided reasonable results for the average trend of longitude, capturing two-week cycles in the data trend and daily longitude short-term cycles.
    - **Limitations:** While robust, Prophet may not capture all nuances in highly irregular data.
    - **Results:** Prophet demonstrated strong performance in predicting periodic manoeuvre patterns, making it a reliable choice for forecasting satellite behavior within longitude windows.
3. **LSTM:**
    - **Strengths:** Neural networks, particularly recurrent neural networks (RNNs) and long short-term memory (LSTM) networks, excel at capturing complex, non-linear relationships and long-term dependencies in data. They are capable of predicting more irregular trends.
    - **Limitations:** They require substantial computational resources and large datasets for training. Overfitting can be a concern if not properly managed. Additionally, amplitude of the longitude oscillations is not accurately captured.
    - **Results:** Neural networks provided accurate predictions of long-term trends, effectively capturing intricate manoeuvre patterns and long-term trends.
4. **Informer:**
    - **Strengths:** These models can predict complex patterns, presenting a good fitting to the real data in general terms. They capture longitude oscillation amplitude quite accurately and detect long-period oscillations, even though they do not follow the long-term trend that accurately.
    - **Limitations:** They require substantial computational efforts and a bigger dataset for training. In some cases, they do not capture the trend accurately after some abrupt changes.
    - **Results:** This model provides a reliable 20-day prediction, with some limitations but enough for the operational purposes of discarding false positives.

5.2 Practical Implications

Despite the inherent limitations of each method, the AI-based predictions have proven to be highly useful in predicting trajectories of GEO satellites within their designated longitude windows. The integration of AI-predicted orbits into the ***Focusoc*** system can significantly reduce the number of false positives in collision predictions, enhancing the efficiency and reliability of collision avoidance operations.

The AI models' ability to forecast the limits in longitude with high accuracy ensures that active satellites remain within their operational windows, minimizing the risk of unintended conjunctions. Although some aspects, such as the amplitude of daily longitude oscillations or relocations, require further refinement, the overall performance of the AI methods is satisfactory.

5.3 Future Work

Future developments will focus on refining the AI models to address their current limitations and extending these techniques to the LEO regime. The diverse manoeuvre strategies and higher number of objects in LEO present additional challenges, but the potential benefits for collision avoidance operations are substantial. Continued research and development in this area will further enhance the safety and efficiency of space missions.

Other methods will be explored for both GEO and LEO regimes, aiming to reduce training time and enhance accuracy of the results, for instance, physics-informed neural networks techniques.

6. Conclusions

This study demonstrates the effectiveness of applying Artificial Intelligence (AI) techniques to predict the manoeuvre plans of active GEO satellites. By utilizing a historical database of satellite ephemeris and employing various AI methods, including time series models (ARIMA, SARIMAX, Prophet), neural networks (LSTM) and transformers, the predictions have shown significant improvements in predicting trajectories of satellites within their designated longitude windows.

The integration of AI-predicted orbits into GMV's collision avoidance service, ***Focusoc***, has resulted in a substantial reduction of false positives in GEO. This enhancement not only improves the accuracy of predicting active-active events for collocated objects but also reduces the effort required for collision avoidance operations, contributing to the overall safety of space missions.

While the AI models are not perfect and some aspects, such as the amplitude of daily longitude oscillations, require further refinement, the overall performance is satisfactory. The AI-based predictions are generally more reliable than classical propagation methods for manoeuvering objects, with significantly smaller prediction errors.

Future developments will focus on extending these techniques to the LEO regime, where the diverse manoeuvre strategies and higher number of objects present additional challenges. Despite these challenges, the potential benefits for LEO collision avoidance operations are substantial, promising further advancements in the safety and efficiency of space missions.

References

[1] L. Herrera, Strategy Optimization for Collision Risk Mitigation in Earth-Centered Orbits (*Originally in Spanish: "Optimización de Estrategias para Mitigación de Riesgo de Colisión en Órbitas Terrestres"*), Madrid, 2024.

[2] 18th and 19th Space Defence Squadrons, Spaceflight Safety handbook for Satellite Operators, California, 2023.

[3] GMV, ***Focusoc*** safety of flight and collision avoidance service, https://www.gmv.com/en-es/products/space/focusoc, (accessed 04.04.2025)