Relevance of Machine Learning Models in Orbital Prediction

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Abstract - *Orbital prediction is one of the important aspects of Space Domain Awareness (SDA) that mainly deals with predicting the nature of Resident Space Objects (RSO's) such as satellites, asteroids and space debris that reside on the gravity of earth or other space objects such as planets and stars. This prediction was done so far using a physics-based model that was time consuming and required more physical computation. Also, due to lack of sufficient information on the space environment condition and status of RSOs, the prediction often failed to meet the required accuracy. So, to overcome the drawbacks of the physics-based model, use of Machine Learning models that automate prediction with less physical interaction resulting in more accuracy and increased efficiency of prediction is investigated here.*

***Key Words*: Orbital prediction, Space Domain Awareness (SDA), Machine Learning, Resident Space Object (RSO).**

1. INTRODUCTION

Space Domain Awareness (SDA), also known as Space Situational Awareness (SSA) has gained more importance now-a-days with growing space related activities by many countries. It gives detailed knowledge of space objects and space events. In the early days, knowing the detailed and updated information about space events was not an easy task. With improvements in technology, knowing the detail information of space events in a short time is possible by SDA. One of the biggest challenges for Space Domain Awareness (SDA) is orbital determination. Orbital determination deals with the prediction, movements, and status of RSOs in space.

RSOs are the natural or artificial objects such as asteroids, comets, space debris and artificial satellites, that orbit on the gravity of earth or other space objects. According to recent research, the number of RSOs and their collision alarms are increasing rapidly. Hence, increasing the efficiency of orbital prediction is a major responsibility of the SDA team. For many years, orbital prediction was done using physics-based models, but the accuracy rate was quite less due to insufficient availability of data for predictions such as, prediction parameters of space objects, space environment condition, updated information of RSOs, etc.

The success of prediction requires sufficient information about the state of the space object and RSOs at the beginning of the trajectory computation and requires space environment information such as earth gravity, atmospheric drag, and solar radiation pressure at different levels. However, understanding of the space time variation of atmospheric density is quite limited, and information about the space condition is not updated regularly. For example, the detailed features of a spacecraft that belongs to some other nation may not be available when orbital prediction is conducted by a nation. Moreover, current surveillance resources of space environment are limited and expensive; and space-tracking measurements are mostly noisy data. All these are issues that lead to the fact that physics-based predictions could result in lesser accuracy of prediction. To overcome these drawbacks, an attempt is made here to investigate application of Machine Learning (ML) models for prediction.

According to NASA's latest research [1], the number of space objects that are above 10cm in size are about 21000, those below 10cm are about 500000, and those less than 1cm exceeds 100 million. In the past, many major incidents have happened, such as collision of an US Iridium communication Satellite and a Russian Cosmos 2251communication satellite in February 2009 that led to a red alert notice to the International Space Station (ISS) as "25090 PAM-D" debris [2]. This was due to the limitations in the prediction models that were used.

In order to protect critical space assets such as space objects where human life and human resources exists, it is important to observe, understand, and study the condition, behaviour, and functionality of the RSOs around such space objects. Physics-based models that analyse the behaviour of RSOs can consider only the information about the trajectory of RSOs. To enhance the characteristics of RSOs for analysis by other models, Space Object Ontology (SOO) is developed to enhance the SDA [3]. SOO is a domain that mainly deals with locating the space objects in outer space, their behaviour in space, and the interaction of different entities like launch vehicles, launch sites, and space vehicles with such space objects. SOO covers many aspects including RSOs, which is further classified as natural and artificial RSOs, subsystems and modules of different spacecraft's, spacecraft design specification, orbital design, orbital elements and other entities that are involved in spacecraft operation. The space object data are collected through ontology and dynamically stored in a Resource Description Framework (RDF) that can be used for SDA. This data can then be used as the parameters for prediction.

Machine Learning is a technique that enables systems the ability to automatically learn a task and improve performance from experience without being explicitly programmed. Machine learning concepts mainly involves supervised learning, unsupervised learning, reinforcement learning and deep learning. Supervised learning mainly deals with learning the model from the labelled data or mapping from defined data. Unsupervised learning is used to find different patterns and classify data as output based on models such as clustering and so on. Deep learning deals with prediction and classification using neural network methodologies. Reinforcement learning is mainly used for decision making problems [4]. The training data involve input which in fact is the output of Experience data. According to research done, supervised learning is an efficient technique to improve orbital prediction [8] and can correct errors of prediction based on previous output and errors. Machine learning models avoid the extraction of information from the large amount of data. Instead they analyse the dataset and predict the output based on experience, which is quite similar to a person analysing from experience and predicting the future events. The ML models have given wide range of capabilities for many space applications. Various neural network models also have a great influence on prediction.

2. SIMULATION ENVIRONMENT

The simulation of Machine learning model for orbital prediction is shown in figure 1, where the Data collection is done and are given as input to the machine learning model.

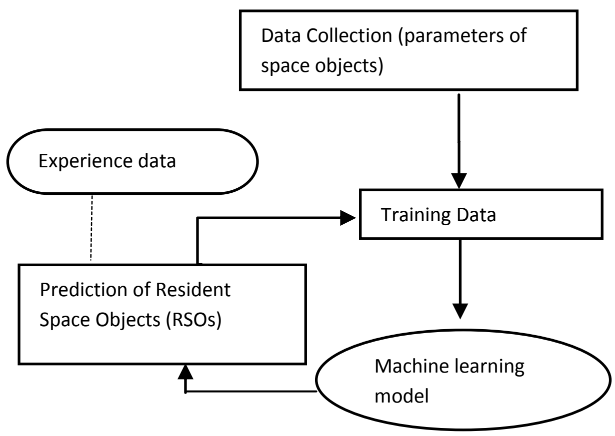

Fig -1 Simulation Model

2.1 Data collection (Parameters of RSO)

Measurement models are used for data collection. Optical stations and ground based radars are used to obtain RSO measurements. Dataset contains parameters of the RSO. Dynamic model is used to generate orbit and RSO details. It includes:

- Gravitational force
- External Perturbation
- Solar Radiation pressure
- Characteristics of RSO

Time also influences selection of dynamic model for data collection.

2.2 Training Data

Training data is given as features to the model. Based on that the RSO is predicted. The predicted models are stored as an experience data and used for future prediction.

2.3 Experience Data

The output of a model is the prediction of RSO, the prediction is sent back to the model in the form of experience data. If the same RSO with same nature is encountered, then prediction is done directly based on experience data.

3. MACHINE LEARNING MODEL FOR PREDICTION

The Machine Learning approaches used for orbital prediction is designed as one of the data-driven methodology, which is used to explore the potential relationship between the learning mechanism and target values by using advanced machine learning algorithms. An ML approach is different from computational analysis and numerical modelling technique. There are different ML models used for different applications. ML models provide output in very less time. ML approach is a statistical model algorithm that automatically learns from Experience data and gives the output with respect to input. Both input and output contain some noise. So sometimes, it may lead to less accuracy of prediction than the physical model. Hence data pre-processing (to select only required data for prediction) is done in order to overcome this issue. But the advantage is that it can avoid the assumption made in the analytical model [5].

As the ML model learns from the training data, choosing the learning variables and the quality of the data set is of utmost importance in the performance of the model. Some factors may also affect the performance of the model, namely:

- The training data may not be adequate.
- The numerical implementations in the model may require some improvements.
- The target values, learning variable and input are too noisy.
- If no relationship exists between the designed model and the target value.

Even though the machine learning algorithm helps to increase the prediction accuracy, there are some additional concern from the operational point of view including:

- The machine learning model should not be prone to overfit of the data.
- As specific ML algorithm is used for a specific type of problem. The designed ML approaches should be capable of achieving similar output by using different ML algorithms with common features.

The ML models being investigated here are the following:

3.1 Artificial neural network (ANN)

Artificial Neural Network is the computational model thatis inspired by the biological neural model but not as identical to it. ANN is based on the collection of artificial nodes that are known as artificial neurons which receive input and combine the input data with the weights and perform internal operations and provide the output. Each of the connection among these neurons is like synapses in a biological brain that can connect from one neuron to another. One of the important features of artificial neural network is its layered architecture with a feed forward network which helps to achieve the parallel computing techniques. In the present scenario, many sub branches are attached to ANN like deep convolution neural network that is mainly used for image recognition. Figure 2 shows the ANN with L number of layers that includes both the input and output layers. Hence there are L-2 hidden layers. The circle at the input contains an arrow that corresponds to the learning variables that are also known as weights and the circle at the output also contains the arrow that corresponds to the target values or desired output. The hidden layer contains artificial neurons, and each neuron generates a value and passes it on to the corresponding connection, finally reach the last layer and give the desired output. Then an activation function is activated to govern the neuron with corresponding input [6].

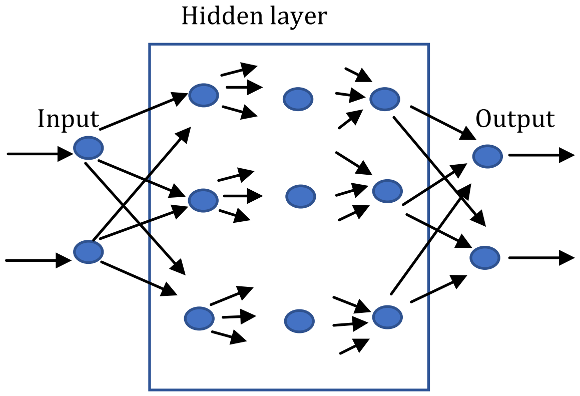

Fig -2 ANN Model

Once the structure is ready, the neural network is trained by reducing the cost function, also known as the Mean Square Error (MSE), given by the equation:

$$C_{MSE} = 1/N \sum_{i=1}^{N} ||eTi - aLi||$$

where, N belongs to the training data size and aLi is the ANN's i-th output. The time complexity of the training data in artificial neural network is O(n^3). Even the structure and implementation of the model influence the complexity [7].

3.2 Support Vector Machine (SVM)

Support Vector Machine is one of the efficient supervised machine learning algorithms that is mainly used for nonlinear regression problems. It uses a technique known as kernel trick that is used to transform the input data into the feature space using a kernel function. Hence a regression model can be constructed based on feature space and based on this transformation an optimal boundary can be found between the possible outputs. On the other hand, support vector machine has capability of solving both classification and regression problems. Support vector machine perform the classification by finding the hyperplane that is used to maximize the margin between the two classes, and here the vectors are the hyperplane.

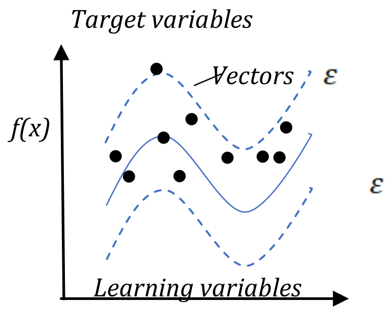

Fig -3 SVM Model

The requirement is that ||w||, which represents the weight of the regression model must be minimized. When SVM is completely trained it leads to the convex optimization problem that helps the dual problem to be simplified and to be solved numerically. Figure 3 shows the support vector representation on a function. A soft margin ε around the real function f(x) is used in support vector machine, so the support vectors which are black circle that are on the boundary of a marginal boundary are used to construct the regression model, and the other support vector that are inside the margin boundary are not used for calculation. Hence, data with small noise is allowed by soft boundary. Simultaneously we can observe some support vectors that are outside the boundary which are called as penalty team for borders in the training data. The training complexity of the support vector machine is approximately $O(mn^2)$ where n is the size of training data and m is represented as the dimension of the learning variable.

The support vector machine is likely to capture the most general pattern in the given dataset rather than trying to fit all the data from the dataset. But at some point of time it may miss some of the details like prior information within the ε margin, if ε is too large [8].

Based on the experience of data or from the cross validation and grid searching experiment, the marginal width that is represented as ε and other hyperparameters are determined.

3.3 Supervised Learning

A supervised learning structure is an efficient model which learns a function and gives the output with respect to the input. The supervised model is one the efficient approaches for improving the orbital prediction accuracy based on previous measurements and error information. The improvement in the model can be explicitly done without modelling space objects, spacecraft movements, and space condition, under the assumption that the trained ML models are applied to prediction are similar enough to those used during the training [9].

3.4 Learning

The learning task and target variables of a machine learning model are designed based on the physics of the problem and available data for that model. In many cases it has to be determined by trial and error experiments. Reducing the error is one of the reasons for using the ML model in prediction, so that the previous errors are kept as the target variable. Then the ML model is well trained with the data set. Usually some part of the dataset is taken as training data and some part is taken as the testing data. Once the ML model is completely trained with the dataset, the output is generated for each set of learning variables. Then the output of the machine learning model is compared with the target variable to get the true error of the model which is then used to measure the efficiency of the model. The main aim is to reduce the true error.

4. COMPUTATIONAL ANALYSIS

The analysis of ML model for orbital prediction is illustrated in Figure 4. It represents the prediction analysis on Space Objects. The two circles around space objects represent the prediction state. The doted circle is the estimated prediction and the other is the true state of RSO. When observed, there is a small gap between true state of the RSO and the estimated state of the RSO and that is the error of the model. To improve the accuracy of prediction this error must be decreased. The error in prediction models is mainly due to the improper dataset of any new RSO or could also be due to the overfitting. Hence the error can be reduced by updating the dataset based on the RSO and using efficient ML models suitable for the RSO.

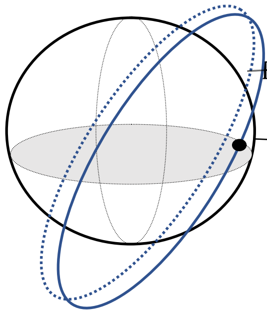

Fig -4 Prediction model

5. CONCLUSION

In this paper, the need of Machine learning models for orbital prediction and review of different ML models to overcome the drawback of physics-based models are discussed. The main motivation is to increase the accuracy of prediction and to decrease the error rate compared to the physic-based models. ML models learn from previous experience and predict the output. But accuracy of prediction is important. Many researches are being done in order to improve the efficiency of prediction.

ACKNOWLEDGMENT

The author would like to thank George Philip C who is the co-author, for the support and guidance and thank the researcher from Rutgers University for the research papers on orbital prediction.

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