Short-Term TLE Uncertainty Estimation Using an Artificial Neural Network Model

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ABSTRACT

A growing number of space activities have created an orbital debris environment that poses increasing impact risks to existing space systems and human space flight. Accurate knowledge of orbit propagation errors of space debris is essential for many types of analyses, such as space surveillance network tasking, conjunction analysis etc. Unfortunately, for two-line elements (TLEs) this is not available. In this paper, a new short-term TLE uncertainty estimation method based on an artificial neural network model is proposed. Object properties, orbit type, space environment and prediction time-span are considered as the input of the network, the propagation errors in the direction of downrange, normal and conormald are as the output of the network. In order to assure the chosen orbit for training is not for an object using station keeping, only debris and R/B are used. The network's efficiency is demonstrated with some objects with high ephemeris data. Overall, the method proves accurate, computationally fast, and robust, and is applicable to any object in the satellite catalogue, especially for those newly launched objects.

1. INTRODUCTION

A growing number of space activities have created an orbital debris environment that poses increasing impact risks to existing space systems and human space flight [1]. In order to avoid the on-orbit collision events, accurate orbital positions are needed, so does the need to improve the knowledge of orbital states and associated covariance. The covariance describing the accuracy of a satellite state is an important input for exercises, such as conjunction analysis and re-entry predictions, which are increasingly important for operating in today's space environment. Through error propagation, the probability of potential collisions can be calculated and a spread of impact locations and times anticipated. These efforts help significantly in managing and mitigating the problem of space debris.

Two-line elements (TLEs) present the most comprehensive and up-to-date source of Earth-orbiting objects and are key in many monitoring and analysis activities. Despite the importance of TLEs, they have many drawbacks: limited accuracy, miss maneuvers, and perhaps most importantly, lack covariance information. The lack of covariance information of TLEs has initiated numerous studies.

A wide range of methods [2-5] has been proposed to estimate the uncertainty information. These approaches differ greatly in complexity, accuracy and applicability. However, they can be divided into two classes: methods using only TLEs and methods relying on additional data. Unfortunately, methods relying on external data have many limitations, such as data are not available for the far majority of objects. Moreover, uncertainties derived for a few objects are hard to extrapolate across the population or time due to their dependency on object properties (shape, size, etc.), orbit type (semi-major axis, eccentricity, inclination, etc.), variability of the environment (solar radio flux, etc.), and the models and determination routines of TLEs.

In this paper, a new short-term TLE uncertainty estimation method based on an artificial neural network model is proposed. An artificial neural network (NN) [6] is a parallel-distributed system consisting of massively interconnected simple processing units, also referred to as artificial neurons. It is a type of nonlinear model representation inspired by biological neural networks. Object properties, orbit type, space environment and prediction time-span are considered as the input of the network, the propagation errors in the direction of downrange, normal and conormald are as the output of the network. A multilayer perceptron neural network with two layers of neurons is used in this work. The hidden layer consisting of 11 artificial neurons and the output layer has three artificial neurons. The number of neurons in each layer is fixed. For each set of input data (semi-major axis, eccentricity, inclination, B-Star, solar radio flux, the predicted time-span), the network provides a set of position uncertainties (the propagation errors in the direction of downrange, normal and conormald), which corresponds to a nonlinear function. Since the problem under investigation is a nonlinear process, the activation function applied to the hidden neurons is the hyperbolic tangent sigmoid function. For the output layer, a linear function was considered. The inputs are object properties, orbit type, space weather and prediction time-span.

Usually, object properties can be calculated with SEM model. Three months TLE data are picked-up for orbit calculation. In order to assure the chosen orbit for training is not for an object using station-keeping, only debris and R/B are used. TLEs are used for covariance estimation analysis, which are ‘‘mean” values obtained by removing periodic variations in a particular way. In order to obtain good predictions, these periodic variations must be reconstructed in exactly the same way they were removed by the model suitable for TLEs. The corresponding space weather data are downloaded from the public website. We use pairwise-differencing method [5] to generate the uncertainties as the corresponding outputs of the neural network model. We assumed that the state vector given is accurate and used it as a reference. We propagated the preceding element set to the epoch of the reference TLE data, and compared the position and its trivariate components: downrange, normal and conormal. We can get trivariate components errors. 90-percent of the data will be used for training and the left data will be used for network validation. The network's efficiency is also validated with some objects with high ephemeris data. Overall, the method proves accurate, computationally fast, and robust, and is applicable to any object in the satellite catalogue, especially for those newly launched objects.

2. NEURAL NETWORK MODEL

An artificial neural network (NN) is a parallel distributed system consisting of massively interconnected simple processing units, also referred to as artificial neurons [7]. It is a type of nonlinear model representation [6] inspired by biological neural networks.

In the neuron model, signal x_i at the input of the synapse i connected to neuron j is multiplied by the synaptic weight w_{ji}. This network is, therefore, trained by an iterative adjustment of the synaptic weights using both known input and output data. This kind of network have the ability to learn and generalize, that is, they are able to provide reasonable outputs for inputs not used during the training process [7]. They are composed by interconnected layers of neurons, in which the output y_j of a single neuron j with m inputs is given by the nonlinear weighted sum

$$y_j = \phi\left(\sum_{i=1}^{m} w_{ji}x_i + b_j\right) \tag{1}$$

where b_j is the bias, $x_1, x_2, \ldots, x_m$ are the input signals, $w_{j1}, w_{j2}, \ldots, w_{jm}$ are the synaptic weights of neuron j; ϕ is the activation function and y_j is the output signal of neuron j [6]. Fig. 1 provides a graphic representation of the neuron model described by Eq. (1).

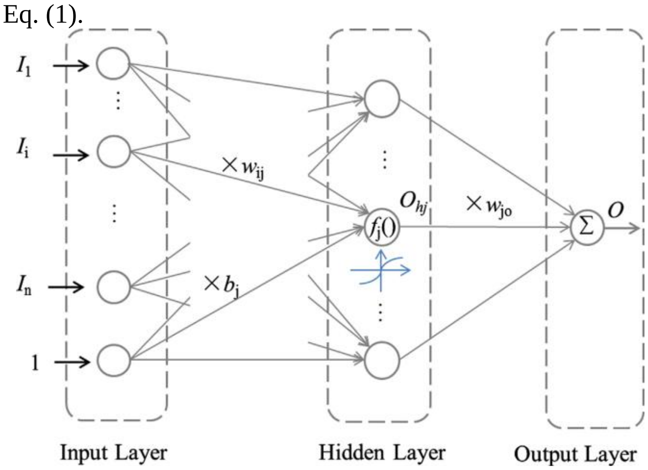

Fig. 1. The structure of a neural network. It consists of an input layer, a hidden layer performing hyperbolic tangent function of the weighted inputs and an output layer that sums the weighted outputs from the hidden neurons.

Since the NN is composed of different layers of neurons, the output of a single neuron, as given in Eq. (1), is connected to the input of another neuron. In this case, the output of a NN with a single node in the output layer and a single hidden layer is a nonlinear function with the following structure

$$y_o(k) = \phi_o \left\{ b_o + \sum_{j=1}^{N_j} w_j^o \phi_j \left(b_j + \sum_{i=1}^{N_i} w_{ji}^h x_i(k) \right) \right\} \tag{2}$$

where $y_o(k)$ is the output of the NN at instant k; x_i is the *i*th input, w_{ji}^h indicates a weight of the hidden layer that connects the *i*th input (which is the *i*th output of the previously layer) to the *j*th neuron of the hidden layer. N_i is the number of input signals and N_j is the number of neurons in the hidden layer. The biases and the activation functions are represented by b and u, respectively. Finally, the variables indicated by an 'o' are related to the output neuron [8]. The parameters of the proposed multilayer NN are estimated using the backpropagation algorithm [6].

3. NETWORK TRAINING

An illustrative scheme of the NN model proposed in this work is shown in Fig. 2. A multilayer perceptron neural network with two layers of neurons is used in this work. The hidden layer consisting of 11 artificial neurons and the output layer has only one artificial neuron.

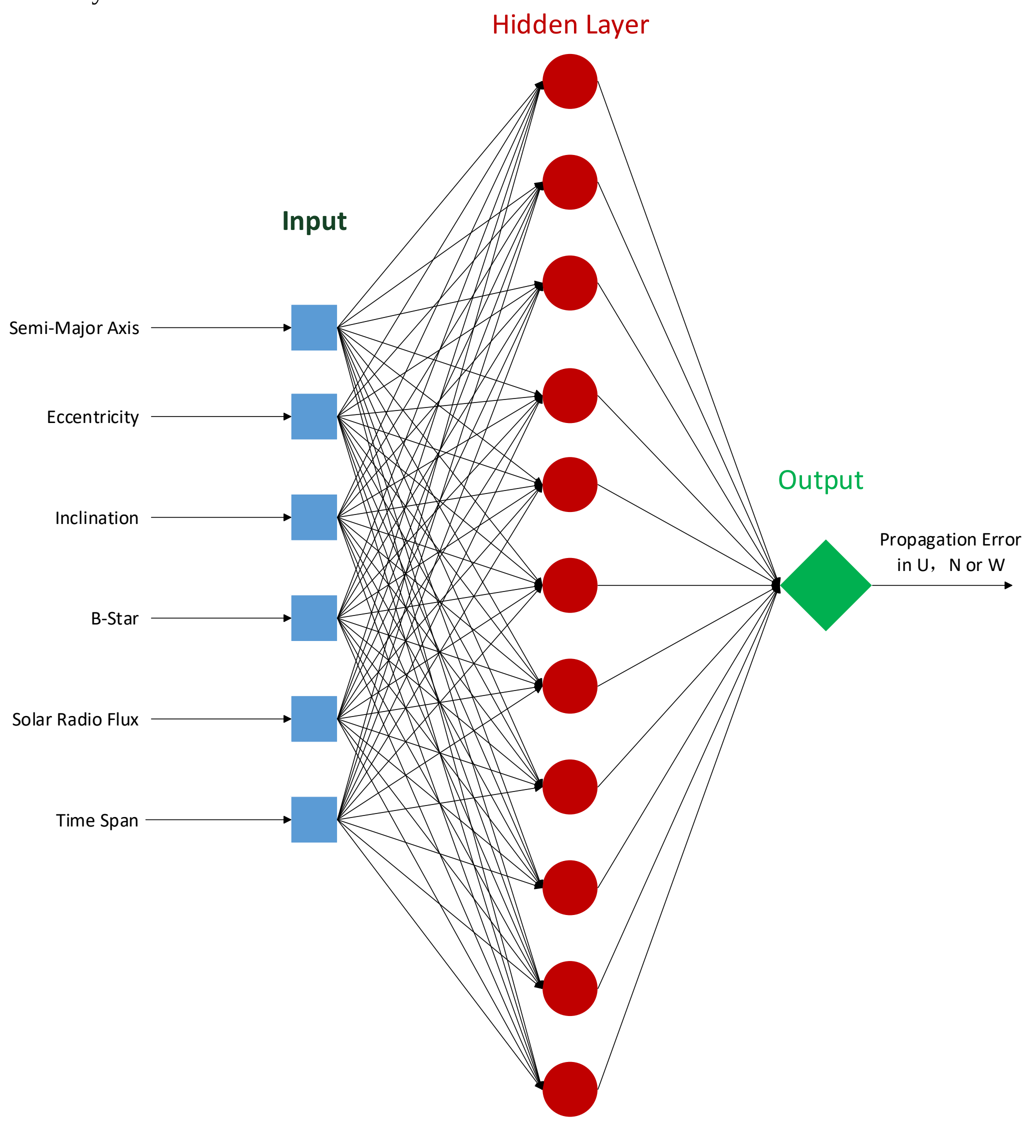

Fig. 2. Schematic representation of the proposed NN model.

The number of neurons in each layer is fixed. For each set of input data (Semi-Major Axis, eccentricity, inclination, B-Star, solar radio flux, and Time-span), the network provides a propagation error in S, T or W direction, which corresponds to $y_o(k)$ described in Eq. (2). Since the problem under investigation is a nonlinear process, the activation function applied to the hidden neurons is the hyperbolic tangent sigmoid function presented in Eq. (3).

$$\Phi(n) = \frac{1}{1+e^{-2n}} - 1 \tag{3}$$

For the output layer, a linear function was considered.

3.1 Inputs

Since TLE propagation errors are influenced by orbital parameters (semi-major axis, eccentricity, inclination and B-Star), predicted time-span and the solar activity, the input parameters of the proposed NN model are semi-major axis, eccentricity, inclination and B-Star, predicted time-span and radio flux at 10.7 cm.

3.1.1. Orbital Parameters

Orbital parameters are directly influence the propagation errors, especially the semi-major axis, eccentricity, inclination and B-Star. Orbital data used in this work were obtained from space-track website.

3.1.2. Predicted time-span

Prediction time-span is another important factor that influences TLE propagation errors. In order to account predicted time-span variability, a series of TLE data are considered in this work.

3.1.3 Solar radio flux

The 10.7 cm solar radio flux (F 10:7) is one of the most used indexes to interpret solar activity. Solar radio flux data used in this work were obtained from NOAA database, available online.

3.2 Training

In order to evaluate the performance of the NN model, the TLE data of all LEO objects from September 1, 2017 to September 30, 2017 are investigated. For each object, the TLE data in the first 20 days are selected to provide training data to the NN network and the data in the last ten days are used to test the network and verify its performance.

Known input and output data are required to train the network. Input vector consists of semi-major axis, eccentricity, inclination and B-Star, predicted time-span and solar radio flux, and the output is a propagation error in U, N or W direction. In training process, for a known input vector, the NN provides an estimated output. This output is then compared with the expected output value, and the error for each training pattern is sent back to the hidden layers by the Back-propagation algorithm, updating the NN weights.

In order to avoid overfitting or overtraining, considering the data available for both periods, 90% of the training set was used to the training procedure and 10% was used to validate the model. This procedure is important since the network may lose its generalization ability if over-trained [7]. The Levenberg-Marquardt algorithm was used to set the NN weights.

4. RESULT AND DISCUSSION

The assessment of the proposed NN model performance is done in terms of average relative error. Absolute error is defined as the absolute value of the difference between NN estimated error NN_{err} and calibrated error C_{err}, and the relative error is the ratio of the absolute error and calibrated error. Average relative error ϵ is calculated according to Eq. (4).

$$\epsilon = \frac{|NN_{err} - C_{err}|}{C_{err}} \times 100 \tag{4}$$

Figure 3 shows the comparison of NN model fitted data and the prediction data of object OPS 6582 is 15 day, which shows that the NN model fitted well with the prediction data, which also verified the validation of the proposed model in the work.

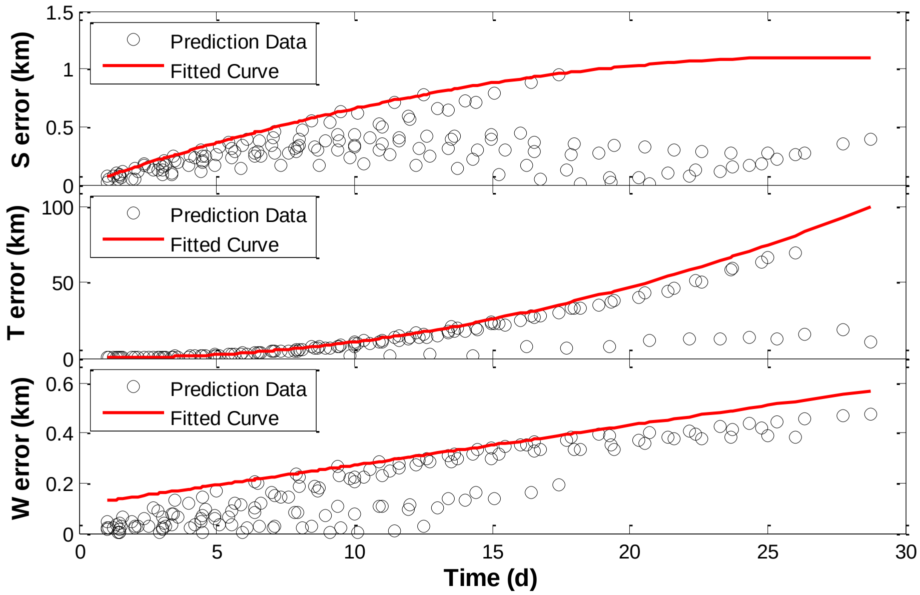

Fig. 3. STW residual variation of OPS 6582

5. CONCLUSION

The results indicate that the use of the proposed Neural Network model for TLE uncertainty estimation can provide good estimations for space objects. It is worth mentioning that the proposed NN model does not have the ability to calibrate TLE by itself, relying on data provided by the calibration technique. Therefore, more work should be done in the future research.

6. REFERENCES

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