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Orbit-centered atmospheric density prediction using artificial neural networks

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ABSTRACT

At low Earth orbits, drag force is a significant source of error for propagating the motion of a spacecraft. The main factor driving the changes on the drag force is neutral density. Global atmospheric models provide estimates for the density which are significantly affected by bias due to misrepresentations of the underlying physics and limitations on the statistical models. In this work a localized predictor based on artificial neural networks is presented. Localized refers to the focus being on a specific orbit, rather than a global prediction. The predictor uses density measurements or estimates on a given orbit and a set of proxies for solar and geomagnetic activities to predict the value of the density along the future orbit of the spacecraft. The performance of the localized predictor is studied for different neural network structures, testing periods of high and low solar and geomagnetic activities and different prediction windows. Comparison with previously developed methods show substantial benefits in using artificial neural networks, both in prediction accuracy and in the potential for spacecraft onboard implementation. In fact, the proposed neural networks are computationally efficient and would be straightforward to integrate into onboard software.

1. Introduction

Due to their ease of accessibility, low Earth orbits (LEO) contain the majority of artificial satellites currently in operation. At LEO below 700 km, atmospheric drag is the most significant force acting on spacecraft after gravity. Given that atmospheric drag is not easy to estimate, it constitutes the largest source of error force models. The drag force is a function of several time varying factors, such as atmospheric winds, drag coefficient, and density. However, the largest variations in the drag force are caused by changes in the atmospheric density, as the spacecraft flies through different regions of the thermosphere with different densities, and also as those densities fluctuate in response to solar and geomagnetic activity. Consequently, precise models for the density are necessary for accurately estimating the drag force, which in turn is necessary for precise onboard orbit determination. Reliable onboard orbit determination will be a key factor in the development of better methods for maneuver planning and coverage calculations. Furthermore, in the past 30 years starting with the work of Leonard et al. in Ref. [1] there has been an increasing body of work focusing on using the drag

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force for maneuvering spacecraft in LEO [2–5]. Accurate onboard estimation of the density can be used to improve some of the methods proposed for maneuvering with the drag force, since it will provide the controllers with an accurate estimate of the control force.

Over the past 50 years several different global atmospheric models have been developed for calculating the main characteristics of the thermosphere including density (a summary of the different models available is presented by Vallado in [6] chapter 8.6.2.). Global models can be classified into empirical and physics-based models. The seminal work for empirical global atmospheric models is Jacchia's 1960 [7] model, which uses an empirical formula that estimates the density as a function of the geometric height, the 20-cm solar flux (F_{20}) and the angular distance to the center of the diurnal solar bulge. Further improvements of this approach include Jacchia models from 1971[8], 1977 [9], and up to Jacchia–Bowman 2006 (JB2006) [10] and 2008 (JB2008) [11]. The High Accuracy Satellite Drag Model (HASDM) uses calibration data from up to 75 inactive satellites and a Dynamic Calibration of the Atmosphere (DCA) method to correct older models such as the Jacchia models [12]. DCA methods use available current measurements to correct the current density estimate; an example of one of these methods developed by two of the authors can be seen in ref [13]. Another highly used empirical global model is the Mass Spectrometer and Incoherent Scatter Radar model (MSIS-77) [14]. MSIS-77 uses data from satellites and also from ground-based measurements from incoherent scatter radars to estimate density. Several improvements to the original MSIS from 1977 have been made, including MSIS-86 [15], MSISE-90 ([16]), and NRLMSISE-00 developed by the U.S. Naval Research Laboratory [17]. An additional empirical model is the Drag Temperature Model (DTM) [18] developed in terms of spherical harmonics, using data covering nearly two solar cycles. This model has been further developed as DTM-94 [19] and DTM-2000 [20].

Global circulation models (physics-based models) are an alternative to the global empirical models for predicting the density. Among these is the thermosphere–ionosphere–mesosphere–electrodynamics General Circulation Model (TIME-GCM) [21]. This model calculates the global circulation, temperature and compositional structure with coupled electrodynamics. An additional global circulation model is the Coupled Thermosphere–Ionosphere–Model (CTIM) [22]. CTIM is a time dependent, nonlinear model that consists of the union of two elements: a neutral thermospheric model and a mid and high latitude ionospheric convection model. CTIM was further developed by including a model of the plasmasphere and low latitude ionosphere, thus producing the Coupled Thermosphere–Ionosphere–Plasmasphere model (CTIP) [23]. Later on the Coupled Thermosphere–Ionosphere–Plasmasphere Electrodynamic model (CTIPE), presented in Refs. [24] and [25], was created by combining an electrodynamic model with CTIP. The Coupled Middle Atmosphere and Thermosphere model (CMAT) [26] and its updated version (CMAT-2), first applied in [27], are extensions of CTIP developed at the University College London. Another global circulation model is the Global Ionosphere–Thermosphere Model (GITM) [28], developed at the University of Michigan. GITM consists of a three dimensional spherical code that solves the energy, momentum and continuity equations.

Global atmospheric models are often designed to estimate much more than just the density, which unfortunately results in longer computation times and less accurate results for a specific quantity such as density. Furthermore, the physics can be misrepresented in the case of the physical models, while the data used for generating the empirical ones can be limited. These three factors result in errors in the prediction of the local density. Furthermore, the physics based models are computationally expensive and require several real-time inputs, which hampers onboard calculations. For these reasons it is desirable to use a different approach for designing a density predictor capable of running onboard a satellite.

An alternative originally proposed by Stastny et al. in Ref. [29] is a localized density model. Such an approach consists of limiting the model to estimate only the density along the orbit of a single spacecraft. By introducing these restrictions, the ability of the model to accurately estimate the density is greatly enhanced. Provided that measurements or estimates of the density of the medium around the spacecraft are available on-board, time series forecasting techniques can be used to predict the future density along the orbit of the spacecraft. In their work, Stastny et al. [29] used a linear model as the predictor and showed that such a model provided accurate results, with less bias than two of the latest empirical models (HASDM and JB2006) for predicting one orbit into the future.

A similar approach to that of Stastny et al. is used in this work. However, instead of using a linear model as the predictor, artificial neural networks (ANNs) are used. A neural network is capable of forecasting nonlinear behaviors since it contains nonlinearities in its neurons, and therefore it has the potential to accurately model the nonlinear behavior of the density along the orbit of the spacecraft. To train, validate, and test the neural networks, density data from the CHAllenging Minisatellite Payload (CHAMP) [30], mission was used.

The foremost contributions of this work are

1) Development of neural network-based localized models for the density that are capable of forecasting the density to be encountered by a spacecraft along its orbit for prediction windows of one, eight and 32 orbits into the future (i.e. approximately 90 min, 12 h and two days respectively).
2) Appropriate design of the neural network structure using different parameters such as the sampling rate of the data, the number of neurons in the hidden layer and the number of delays of the input.
3) Tests of the neural network predictors over periods of high and low solar and geomagnetic activities.
4) Comparison of the results of the neural network predictors with a simple persistence model, a linear model, JB2006, and HASDM (the latter three obtained from Ref. [29]) for the one-orbit forecast.

The paper is organized as follows: Section 2 presents the concept of atmospheric drag and density. Section 3