

Design of an Error Estimation Algorithm for Time Series Data Prediction in Attitude Controlled Systems

M. RAJA^{*,1,a}, Kokila VASUDEVAN^{1,b}, Kartikay SINGH^{1,c}, Aishwerya SINGH^{1,d},
Ayush GUPTA^{1,e}

*Corresponding author

¹Aeronautical Department, Hindustan Institute of Technology and Science,
Rajiv Gandhi Salai (OMR),
Padur, Kelambakam, Chennai -603103, Tamil Nadu, India,
rajavionics@gmail.com*, kokilaspv@gmail.com, kartikaysingh1297@gmail.com,
aishwerya1@gmail.com, ayush15499@gmail.com

DOI: 10.13111/2066-8201.2021.13.3.12

Received: 04 July 2020/ Accepted: 15 April 2021/ Published: September 2021

Copyright © 2021. Published by INCAS. This is an “open access” article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>)

Abstract: This research presents an error estimation approach with the combination of traditional multilevel techniques used to minimize errors for an accurate prediction and to investigate the behavior of such an algorithm for a satellite. The traditional techniques mentioned above are a combination derived from multiple regression techniques and perform a case study for data analysis. A linear plot can easily be predicted, however if a system tends to deviate toward non-linearity the overall result derived from such an algorithm can be non-reliable since each value would depict a completely different output at different levels. The stability of the fixed regression derived is used to determine the accuracy of the system.

Key Words: Neural Networks, Regression Analysis, Mean Absolute Error, Vector Auto regression

1. INTRODUCTION

In recent years, the use of Machine Learning has become popular and is now being used for obtaining high measurement to solve complex problems. Even though these values are not completely accurate as they do achieve some standard deviations as well as a high error in true values for a short time scale, they are highly accurate on a long time scale due to the increase in the size of the training data [1].

These errors may be caused by incorrect data analysis or by the fact that the model is unable to distinguish between over-fitted and under-fitted estimates. Thus, these errors can be overcome and the system can reduce the estimation error if neural networks are combined with some additional regression models and if different sets of algorithms are used and, in addition, if mixing, stacking and regularization techniques are utilized.

^a Associate Professor-Dr

^b Visiting Faculty

^c Student

^d Student

^e Student

In the proposed research work, the regression analysis of the Neural Networks will be approached using known examples of satellite attitude stabilization problems and hence that knowledge will be used to solve an unknown/new problem related to satellite stabilization and to generate a model to test the accuracy of such a system [2].

2. LITERATURE REVIEW

In [1], A. Ismailova, Karlyga Zhilisbayeva discuss about the Earth's magnetic field kept as reference; it is used to distinguish the trajectories and establish a proper stabilization system. Derivation of equations for electric and magnetic fields of Earth and their influence are studied. An idea of varying magnetic field lines simulation was established from this review.

A Neural network satellite attitude controller with error based reference trajectory [2] by Valdemir Carrara, Atair Rios Neto was reviewed to understand feed forward neural networks.

A back propagations algorithm with parallel processing structure to handle large amounts of data is established.

Elaborative training techniques were used in this paper. Moreover, it is expected that a more sophisticated algorithm for adjusting the different outcomes obtained by the system will be necessary than the simple dynamics detection, which also offers significant benefits in performance.

The result was a comparison between ANN (Non-Linear) methods and PD controllers. It was understood from this paper that very large training time was required for adaptive neural networks. Another research paper on artificial intelligence use in spacecraft [3] by Dario Izzo, Marcus Martens, Binfeng Pan describes a comparative study under the strong scientific influence for successful missions.

Highlighted game-changing and innovative techniques implied, deep learning and neural networks have been highlighted as key factors in making these techniques robust.

3. METHODOLOGY

The estimator is supposed to understand and interpret the data given by the satellite that are in terms of APM (Attitude Parameter Data); however the receiver must have a propagator that interprets these data to compute the current estimated attitude at a particular instance of time while considering the proper data. The APM is a combination of the following:

1. Header, 2. Metadata, 3. Categorical Explanations for Failsafe Measurements, 4. Attitude Data

The APM Header is composed of the short description and threshold values as well as the permissible values and the novelty of the data sent. The metadata however is a container that stores the existing data in case of refresh request from the center due to mismatch of information and henceforth.

The Categorical Data consist of the following labels as date month and day since operation [4].

The Attitude data consist of the current altitude and the Name of reference frame in xyz rotations as well as the rotation direction (in newer formats) and the rotation angles. Our approach is also similar as we use the ephemeris data and the attitude data in order to calculate the regression values to adjust the accuracy of the system.

The following estimators/repressors are used to compare each other in order to adjust the accuracy of the system. In addition, the Mean absolute error is projected with the over 1000 iterations.

A. Iteration Model for finding best-case individual

In order to find the best individual amongst the multiple regression in the system, the above process is followed by convergence in each of the system.

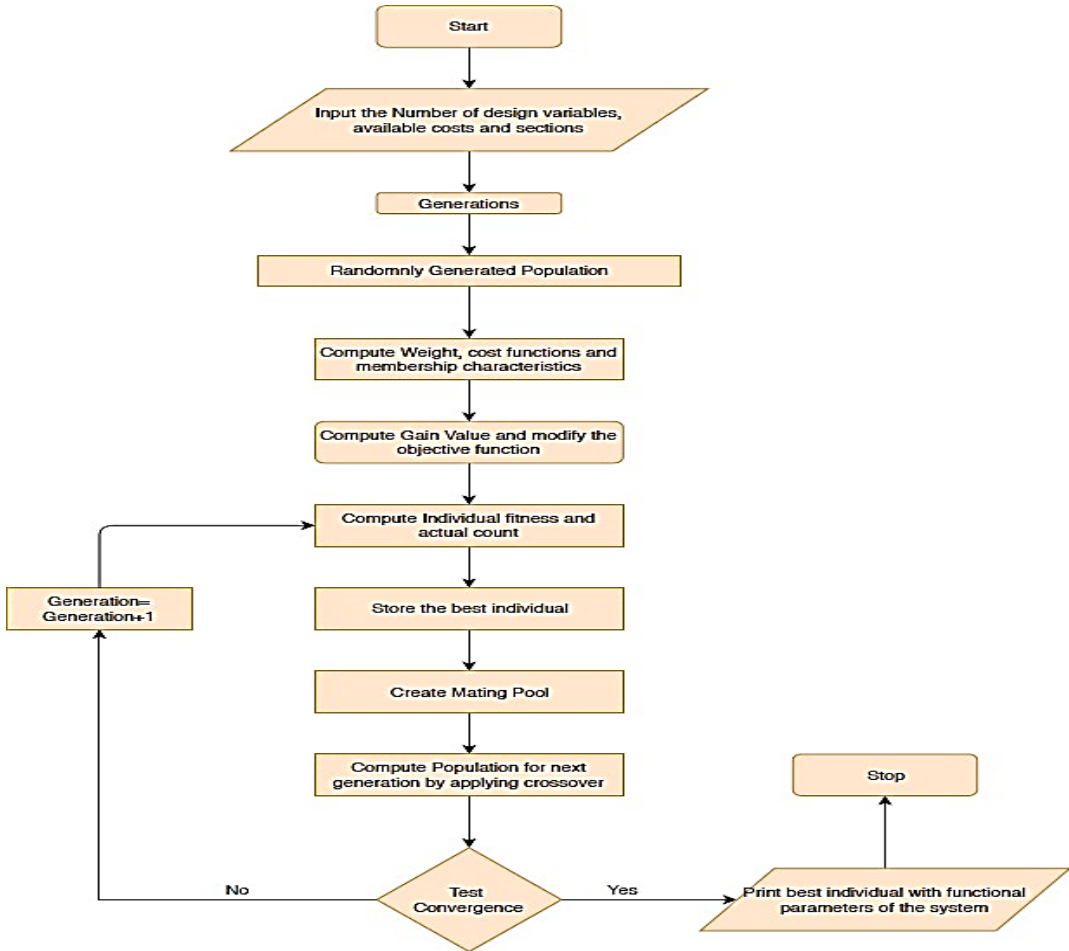


Fig. 1 Iterative Models to generate best-case individuals

In order to find the best individual amongst the multiple regression in the system, the above process is followed by convergence in each of the system. An initial constraint is considered in the blended and stacked model.

The data were sent to a different task pipeline, where the model can be implemented and tested as a whole.

The following algorithms were employed in the deployment of the final model, Vector Auto regression Models for comparison against LSTM models using multiple repressors library in order to generate the higher accuracy models.

Vector autoregressive models are fundamentally simple models. They are multivariate linear time series models designed to capture the joint dynamics of multiple time series [4]. VARs treat each endogenous variable in the system as a function of lagged values of all endogenous variables. To keep the model differentiable and with smooth curves in a range of zero to one, they constitute a sigmoid activation function. Other than the gates described above, there is one more vector called \bar{C} which is used to transform the cell state [5].

B. LSTM Model for regression analysis

The LSTM model is used to ensure that the VAR is kept in check in order to scale the system for higher data values and to avoid vanishing gradient problems.

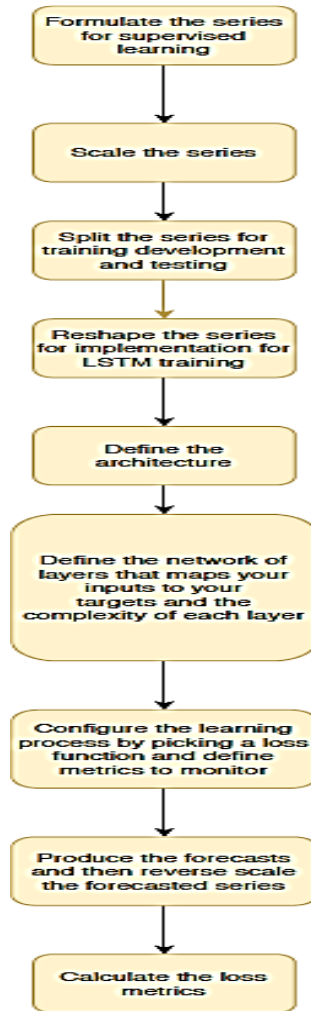


Fig. 2 LSTM Model for regression analysis

4. RESULTS AND DISCUSSIONS

Regression Model has compiled in MATLAB, this model plots the regression model and splits out data in terms of training data and the input data is used to categorize each step and compares the predicted model with the actual APM data. However, the data cannot be simulated in a multivariate system.

Thus each of the simulation is needed to be carried out for all of the six attitude data; yet this is a lengthy process since each of the variables is plotted and the MSE for each variable is plotted however the relevance between each of the data is not propagated. The rotation angles below are plotted with the target being the true attitude data values and the output being the data values achieved from the Neural Networks.

Table 1. Initial Details of the data set inputted to the Neural Network

Serial Number	Initial Condition Consideration	Response from Neural network
1	Transformation Target	FALSE
2	Transformation Target Response	None
3	Original Data	[6324x11]
4	Missing Values	FALSE
5	Numeric Values	6
6	Categorical Features	3
7	Sampled Data	[6324x11]
8	Transformed Train Set	(4886,20)
9	Transformed Test Set	(1438,20)

This gives us a brief idea as to which models to blend and stack in order to achieve better accuracy.

The following initial condition for the neural networks were used to configure the test conditions for the APM data achieved. The residual plot is a measure of the difference in the predicted values and actual values the graph looks jaggy however.

Thus, the regression achieved is accurate; the closeness in each component can be further increased with more data sent to the neural network [6].

The regression line tells us the error in the forecasted data; we can see a slight shift from the true value, which can be avoided with more data sent to the neural network.

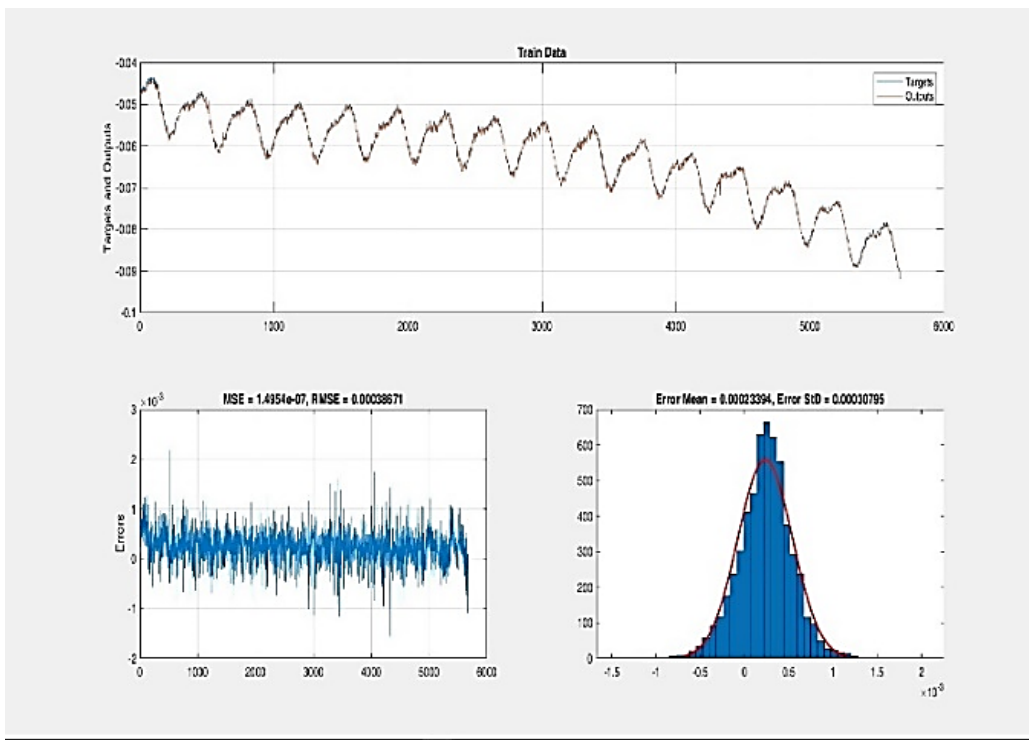


Fig. 3 Training data with the MSE and Standard Deviation

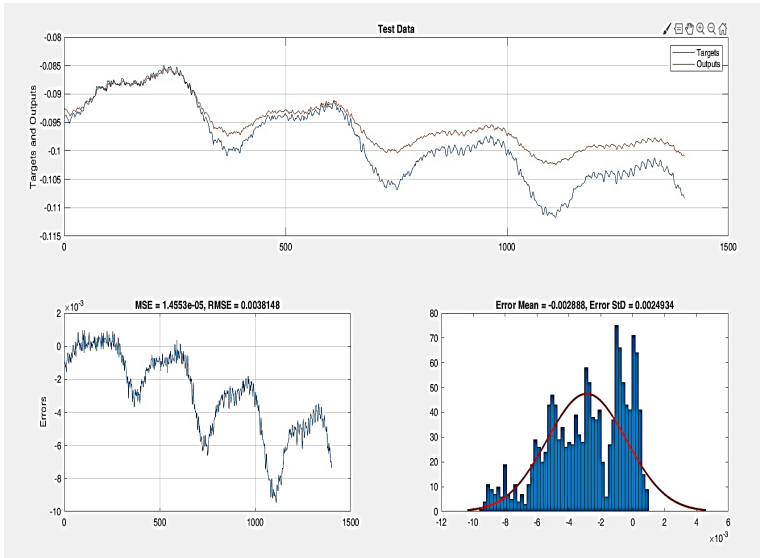


Fig. 4 Testing data with the MSE and Standard Deviation

Random test cases were sent to the system and deviation can be noticed in the first half where the system is able to retain the prediction true to the actual values and the number of epochs are increased [7].

The system is divided into the training and testing phase however, because of the lack of better regression processes it is tedious to calculate the errors for each of the system. It requires the better estimator models for system accuracy. Fig. 3 shows the Mean Absolute Error of each of the regresses available for the initial model generated.

Table 2 shows the comparative results of the error analyzed by the neural networks on average from 1000 iterations to 10 for the final model deployed.

Table 2. Comparative Results between the errors analyzed by the neural networks (Final model)

S.No	MAE	MSE	RMSE	R2	RMSLE	MAPE
0	5.3949	45.0522	6.4219	0.2781	0.6820	1.2135
1	5.1264	41.5191	6.1777	0.2732	0.6680	1.1722
2	5.5532	48.8503	6.6714	0.2702	0.6921	1.2455
3	5.5954	46.0245	6.6827	0.2731	0.6655	1.1362
4	5.4940	47.7901	6.6020	0.2701	0.6906	1.2908
5	5.5399	49.0248	6.6828	0.2652	0.7296	1.4427
6	5.0981	43.1708	6.2918	0.2850	0.6605	1.1418
7	5.2529	44.0053	6.3488	0.2788	0.6854	1.2351
8	6.3906	46.2476	6.4998	0.2798	0.6964	1.2753
9	6.4023	45.9019	6.4768	0.2817	0.6511	1.2126
Mean	6.3848	46.0620	6.4856	0.2755	0.6821	1.2356
SD	0.1660	2.5011	0.1477	0.0058	0.0213	0.0635

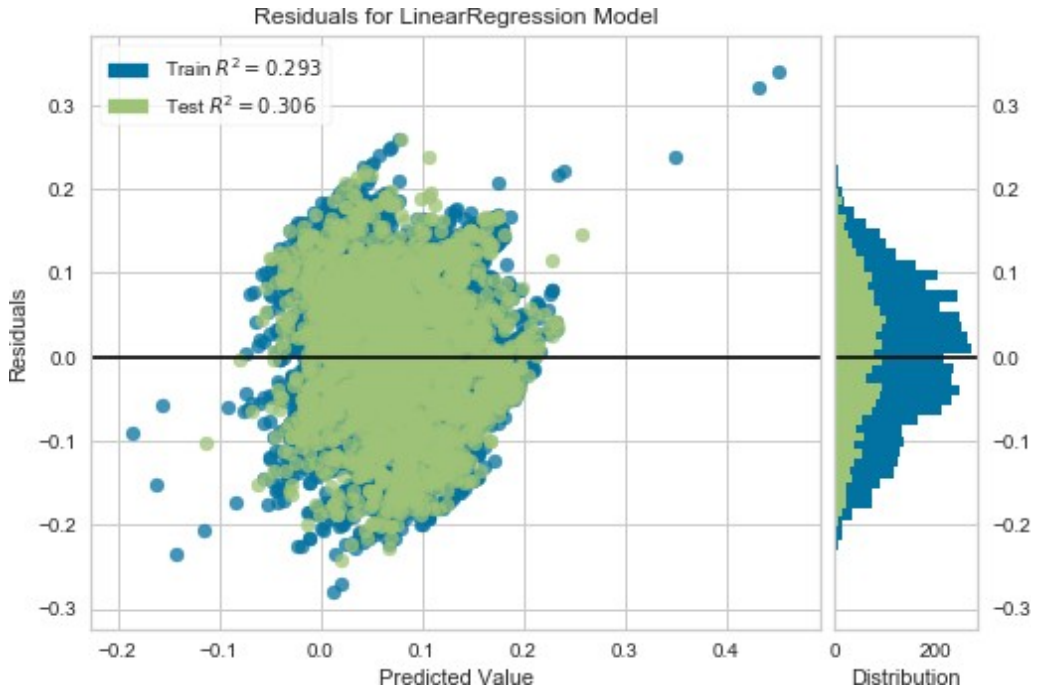


Fig. 5 Residual Plot for blended and stacked models

MSE= Mean Square Error

The number instances fed into the system.

MAE= Mean Absolute Error

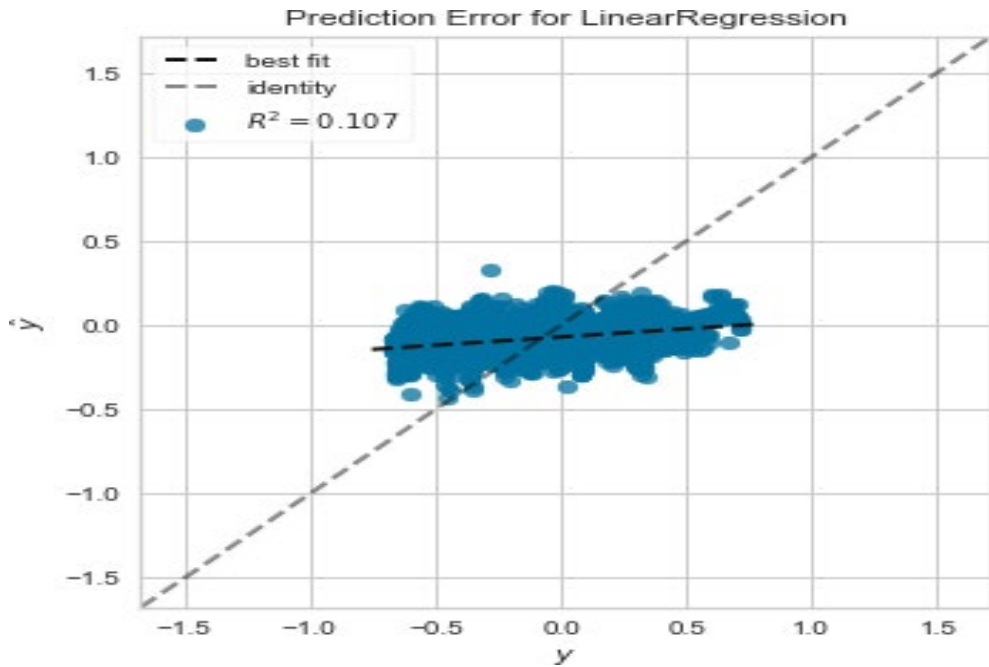


Fig. 6 Regression line generated using python

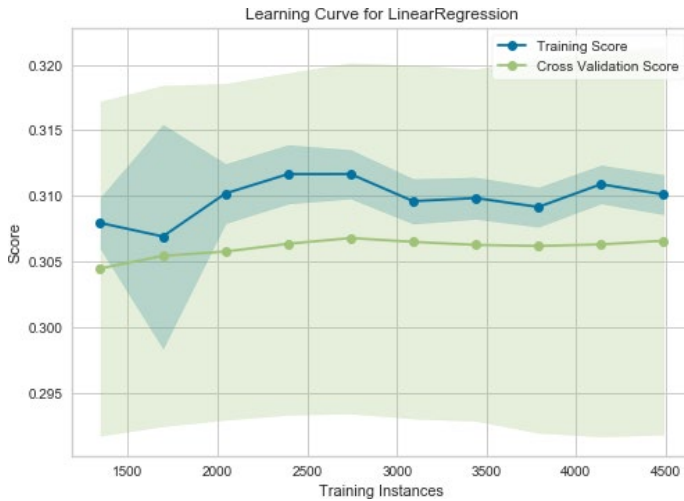


Fig. 7 Learning curve between the score and number of random training instances

As seen by the learning curve the estimator has a huge divergence between the training and cross validation scores. The Neural Networks will be more accurate with more data provided to the system to generalize the system more properly with comparing the calculated and generated values to find the Mean absolute percentage error over the 1000 iteration per data cycle that were, averaged over 10 for the final deployed model.

5. CONCLUSIONS

The Neural Networks are based on a regression analysis framework that determines the mean standard errors achieved. The neural networks iterative process models of approximately 12 percentage were analyzed. The NN fed to random state errors with satellite perturbation were considered. The comparative results of the error were analyzed by neural networks on average from 1000 iterations to 10 iterations for the final model deployed. The prediction of a complex perturbation model were considered with blended and stacked models. The neural networks will be able to increase their accuracy with more data and predict values to define setup parameters.

REFERENCES

- [1] A. Ismailova, K. Zhilishbayeva, Passive Magnetic Stabilisation of the Rotational Motion of satellite in its inclined orbit, *Applied Mathematical Sciences*, Vol. **9**, no. 16, 791- 802, 2015.
- [2] V. Carrara, A. R. Neto, *A Neural Network Satellite Attitude Controller with Error Based Reference Trajectory*, National Institute of space research, Brazil, 1999.
- [3] D. Izzo, M. Martens, B. Pan, A survey on Artificial Intelligence trends, in *Spacecraft Guidance Dynamics and Control, Astrodynamics*, Volume **3**, Issue 4, pp: 287–299, 2019.
- [4] K. He, X. Zhang, S. Ren, J. Sun, *Deep Residual Learning for Image Recognition*, The IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 770-778, 2016.
- [5] H. Y. Toda & P. C. B. Phillips, Vector auto regression and causality: a theoretical overview and simulation study, *Econometric Reviews*, **13**:2, 259-285, 1994, (https://www.scikit-yb.org/en/latest/api/model_selection/learning_curve.html)
- [6] J. L. Farrell, J. C. Stuelpnagel, R. H. Wessner, J. R. Velman, and J. E. Brook, A Least Squares Estimate of Satellite Attitude (Grace Wahba), *SIAM Review*, **8**:3, pp. 384-386, 1966.
- [7] F. L. Markley, Attitude Determination Using Vector Observations and the Singular Value Decomposition, *The journal of Astronautical sciences*, Vol. **38**, No. 3, pp. 245-258, 1988.