Forecasting of Time Series Telemetry for Satellite Operations using Deep Learning Techniques

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***Abstract*—The current expansion of CubeSats being utilized for business and in particular academic ventures has increased in the last decade. This has been positive because businesses can now expand into and offer different services that are only possible within the space sector. CubeSat development requires specialized skills, fiscal commitment, and facilities, which are far less expensive in comparison to vastly larger satellites. However, CubeSats need to be monitored and various parameters need to be adjusted accordingly to fulfil their respective mission requirements. Depending on the available infrastructure and personnel, the analysis of the generated telemetry may often not be addressed until the mission has been completed, and various risks present during the mission would have been mitigated. The purpose of this research is to provide a platform which is a semi-automated deep learning (artificial intelligence) system that will provide an objective assessment of the operational performance of the CubeSat which can be compared against the various resource budgets and/or mission design specifications. In addition, this system will be capable of forecasting telemetry values that the operational team, post-handover, can leverage on as a tool to fine tune the CubeSat operations for their optimum performance. The balance of the study is to have a fully documented developed standalone deep learning system, which with minimal modification may be used in other facilities or systems, such as: where in-depth data analysis for multiple large data sets is needed.**

Keywords—CubeSats, Data Analysis, Deep Learning, Forecasted Values, Time Series, Machine Learning, Performance Optimization, Mission Analysis, Telemetry

I. INTRODUCTION

The South African government is committed to the transformation of the national economy into a digital economy in readiness for the fourth industrial revolution (4IR) [1]. Space research is a national prerogative to develop the space industry and entails capacity-building to train and develop expertise various aspects, including satellite communications, navigation, and positioning, through graduate studies and research in space science and communication, navigation/e-Navigation, and surveillance for economic development. This ethos has been demonstrated with the Cape Peninsula University of Technology (CPUT) satellite programme, hosted by the French South African Institute of Technology (F'SATI) and the African Space Innovation Centre (ASIC).

With funding from the South African Department of Science and Innovation (DSI), CPUT has launched and operated three CubeSats namely ZACube-1 (TshepisoSat), ZACube-2 and MDASat, a constellation consisting of three CubeSats aptly designated as 1a, 1b and 1c. These three satellites, in particular ZACube-2 serving as the genesis, aids in the prime objective of providing sovereign maritime domain awareness services in support of Operation Phakisa, which is an initiative in support of the National Development Plan (NDP) [2].

The plan is toward establishing a broader constellation of satellites as an immediate development, with the MDASat constellation laying the groundwork that seeks to be an accompaniment and further develop the overall maritime communications system. This endeavour is supported through the technology and mission roadmap of the CPUT satellite programme which aims to continually support national imperatives, such as the National Development Plan. Therefore, ongoing data analysis of the telemetry generated from the aforementioned satellites is imperative as the mission can be carried out optimally by continual adjustment of the various subsystem operating parameters. This leads to both the possibility of a further constellation expansion, and extension of the operational life and a more rapid commissioning phase.

Thus, it is highly advantageous that machine learning (ML) techniques, such as deep learning, and assisted data analytics is used, system dependent, due to the magnitude of data being generated owing to the various subsystems being employed and the temporal resolution at which the telemetry is recorded. Deep learning can be used to analyse historical missions which can be compared to the different resource budget whilst discovering operational trends. Continuous forecasting of the current mission's future telemetry is possible which can be leveraged for mitigating risk and/or optimizing the daily operational capacity.

II. ARTIFICAL INTELLIGENCE OVERVIEW

Artificial intelligence (AI) has become ubiquitous in the last decade in this era of the fourth industrial revolution. AI is the artificial creation of cognitive functions emulating the human problem-solving process [2], [3]. This is advantageous when dealing with substantial amounts of data that can be parsed in a matter of minutes. This is carried out through the application of logic and mathematical models, called machine learning. Therefore, machine learning is a function of AI which is meant to process vast amounts of data which the computer uses to teach itself to recognize trends or specifics pointers that identify objects with the use of neural networks.

Neural networks (NN) commonly known as artificial neural networks (ANN) are algorithms that are based on human reasoning and are the application of deep learning, a subset of machine learning [2], [3]. Deep learning is at the core of AI and used by the machine learning process to identify and solve composite problems such as image and voice recognition. There are several diverse types of machine learning methods with each network having a specific advantage over the other. There are currently four methods of machine learning, namely [2], [3].

(i.) Supervised

(ii.) Unsupervised

(iii.) Semi-supervised

(iv.) Reinforcement

Each methodology has various subsets with a particular usage. The same applies to various types of neural networks, the structure in which there is a specific network dependent on the needs of the user. For the case of time series related data either a recurrent neural network (RNN) or long short-term memory (LSTM) which is a special variant of a RNN can be employed. A neural network is a framework of multiple neurons or nodes interconnected with each node.

These nodes aim to emulate the way a human brain functions. This emulation is achieved through the usage of mathematical expressions that is comprised of [8], [9], [10].

a. The system inputs.

b. Weightings that influence how much a particular input stimulates the system.

c. A predetermined constant bias that shifts the outputs allowing a node or neuron to activate when the input(s) are zero.

d. The activation function that governs the transformation of the input(s) to a chosen range.

e. The output of the neuron.

III. LITERATURE REVIEW

This study builds upon the previous work [5], with an improvement of the methodology, the analysis of the various telemetry channels and by extension the resource budgets were all conducted with the aid of MATLAB.

The three budgets that were under scrutiny were the link, thermal and power budget in addition to various other factors that could play a role on system performance such as space weather, attitude determination control system, orbital decay, mission battery discharge. These three budgets' calculations surmised from the various telemetry channels took a substantial amount of time and effort. Whilst these sets of data were meticulously examined the analytics still had the possibility of human error which can cause some unintended biases with which with the aid deep learning can be circumnavigated thus leading to purely objective analyses.

A. Power Budget

The various power profile telemetry calculated values when compared to the respective counterpart profiles in the power budget were lower suggesting that the power budget was conservative and allowed for instances where generation of power would be either hindered due to either internal or external factors. In terms of metrics, the safe eclipse profile was only 1.7% lower than the budget stated value while the payload sun was significantly lower at 53.8%. A credible reason was that planned operation at which the power budget was built upon did not occur as frequently alternatively there was no pre-defined interval at which the data was sampled leading to discrepancies when analysing the telemetry.

The orbital period was well within the range of the values assumed in the power budget.

The largest difference was found to be 156 seconds. The minimum power generated when compared to the respective power budget profile was low. Two separate samples were calculated, each sample yielded a power value lower than the one determined in the power budget however the two samples did not output the same power value.

This dissimilarity was credited to the varying solar declination, which was experienced throughout the year, as the samples were calculated on 15 March 2019 UTC and 17 February 2020 UTC, respectively. In addition, the variance could be attributed to the solar cycle as the range of the data range at solar minimum during the transition phase of solar cycle 24 to 25.

Whilst the output of both telemetry sample calculations showed that not ample power was being generated in terms of the operational requirement there was no considerable battery discharge. The battery discharge calculated from the respective telemetry channel indicated that the maximum discharge was only 8.42% leading to either the power values being calculated incorrectly or a problem in the recording and/or sampling of the telemetry.

B. Link Budget

Due to the UHF transceiver (UTRXC) making successful elevations above 3°, thus it's a issue of verifying the link integrity . By utilising the cumulative probability function (CDF), the RSSI of ZACube-2 UHF transceiver was plotted and subsequently converted to a power level. The output of this calculation showed that the telemetry was within the stipulated values in the transceivers operating limitations. Therefore, concluding that signals were above the receive level threshold for entire overpasses.

An additional method of verifying the budget was comparing the ground station downlink UHF RSSI against the link margin as stipulated in the link budget. It was observed that the RSSI values were offset due to said being relative to the ADC's full scale. To rectify this in order to have an absolute zero, calibration of the ground station's UHF receiver with a signal generator would be required.

C. Thermal Budget

Analysis of ZACube-2's thermal performance was conducted by the analysing the available thermal telemetry from various subsystems and calculating the thermal range using two techniques. During the processing of telemetry, it was observed that the K-line imager experienced the greatest thermal range of 44.2°C. This tends with the fact that the imager is mounted externally where temperatures range from a maximum of 29.1°C and a minimum of -15.1°C, respectively.

Out of all subsystems the S-band transceiver had the highest maximum temperature of 37.2°C, much higher than the K-line imager however, all subsystems operated nominally and within the manufacturers specified thermal range with thermal headroom to spare. This is an implication of excellent passive thermal management techniques employed by the design team and allows for a different stack.

configuration and/or a verified stack configuration at which additional subsystems can be introduced with little to no concerns regarding thermal constraints being encountered.

The various thermal telemetry values were additionally compared to two thermal calculation methods described by Fortescue (2011) [7] and by Gilmore (2002) [5], respectively. The initial method by [7] had the largest thermal out of the two by 16.2 °C the directly translates as the calculated values when compared to maximum and minimum telemetry-based values of 11.981°C and 6.327°C, respectfully. Using the method described by [5] leads to consistent differences between the two sets of values, in terms of maximum and minimum temperature, of 6.098°C and 5.969°C, respectively.

These values give an indication of the expected temperature that the satellite should experience prior to an extensive computer simulation. The method described by Gilmore (2002) [5] should be used as a starting point prior to computer simulation due to employing values that are based telemetry. Using this methodology aligns the process to more real-world values than Fortescue (2011) [7] method, which is purely theoretically based.

D. *System Performance and he Effects of Space Weather on Subsystems*

During the period in which the telemetry was recorded, there were multiple instances where several telemetry channels recorded no data or had multiple outliers present in the data sets, or the data recording temporal resolution as irregular. These occurrences were cross-referenced with well recorded space weather events, such as geomagnetic or solar flare events. While there were several storms that occurred, they were classified as “minor storm” and as such have little to no effect on spacecraft operations. It was concluded that these events were not related. In turn this leads to the possibility that the cause of the aforementioned events are internal in nature.

There were no discernible space weather events that influenced subsystem performance in which a trend occurred. However, a point of interest is that abnormal behaviour was experienced during the post commissioning phase. A prime example is the attitude angle for the Y-axis varying from +180° to -180°, when a geomagnetic storm with a Kp index of 6.33 occurred. An investigation of the storm Kp index was conducted to see if any effects were experienced however, no evidence of the storm influencing either the orbital period or the average apsis.

A similar investigation was conducted with the earlier mentioned telemetry channels once again these two events are uncorrelated as the moderate geomagnetic storm occurred during the period in which the telemetry channels had already started displaying the aforementioned issues. It can be ruled that the effects of these space weather events played no major role in performance of the system.

E. *Attitude Determination Contril System*

The ADCS operated as expected however, problems were experienced such as the calibration of the sun sensors. These sun sensors interpreted the reflection from the antenna as a “second” sun and caused navigation inaccuracy.

By altering the threshold of the fine sun sensor exposure, the reflections were not detected as a secondary input and the output of the data from the fine sun sensors were included to the EKF estimator. This gave an accurate reading of ZACube- 2 attitude angles and angular in.

F. *Orbital Decay*

The orbital decay was analysed using three methodologies, using a combination of TLE and simulation data. The first method used the average apsis with the second approach using the orbital period. A STELA simulation was performed in which the orbital decay of both apsis were simulated. A mean constant for the solar activity gave an orbital lifetime of 3.08 years whilst the variable solar activity gave an orbital lifetime of 8.67 years.

The solar activity variant was then compared to the respective TLE’s to evaluate the discrepancy. This comparison showed that the simulation yielded a higher value with a range of 10km to 12km for both the apogee and perigee, respectively. The second simulation was carried out in AGI’s STK using the same period as the telemetry data where a delta of 3.6 seconds was found.

G. *Battery*

A brief investigation was done for the battery in terms of the maximum depth of discharge (DoD). In the power budget it was prescribed as 20%. During the investigation the maximum discharge was found to only be 8.4%. With only roughly a 50% depth of discharge some of the subsystems, which use power such as the HSTXC (S-band transceiver) can be utilized for extended periods.

IV. Research Objectives

To achieve this outcome of having a semi-automated machine learning operation in which current telemetry is analysed and future telemetry forecasted, the following list of deliverables is needed which are as follows:

- Training of a neural network that will provide forecasted values for a subsystem or a particular subsystem channel, respectively.
- Real time analysis of telemetry data where real time is defined as soon as the telemetry is downloaded from a CubeSat during a downlink, respectively.

- Creation of a separate environment where telemetry is initially ingested in real time from the ground station and is prepared to be fed to the machine learning algorithm.
- Creation of a separate environment where the post investigated data is stored and kept for historical purposes. It is also where users can access the parsed data.
- Creation of a separate environment which acts as the intermediary environment between the telemetry ingest environment and output environment. This environment will host the actual neural network.
- Demonstration of a deployable system prototype that with minimal integration and modification can be used in other applications.
- The majority of the tools used to construct and manage a working prototype will be open source to reduce cost and licensing issues.

V. Research Design and Mehodology

A structured approach needs to be implemented for the deep learning application. For deep learning, a large dataset is needed to train the neural network as working with smaller datasets introduces a possibility of overshooting in the forecasted values.

Hence, telemetry from ZACube-2, the second CubeSat developed by CPUT in partnership with F'SATI will be used to develop a deep learning neural network as there is ample telemetry available. The process to achieve merely the deep learning aspect will be broken down into several distinctive steps, namely:

(i.) Acquisition of raw data

(ii.) Data pre-processing

(iii.) Building of neural network(s)

(iv.) Training of neural network(s)

(v.) Tuning of neural network(s)

(vi.) Visualize and verify results against actual telemetry.

(vii.) Exporting and deploying of finalized neural network(s)

This is a basic overview of the deep learning environment which is one part of the entire system. The research aims to construct environments which host the raw as well as the analysed data. Fig 1 shows a basic system overview of the system.

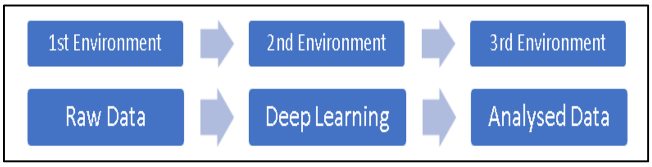

Fig. 1. Basic System Overview

It is proposed to create three separate environments with each environment having a specific purpose as shown in Fig. 2: basic system overview. The format for the first and third environment will use database management software such as PostgreSQL or Microsoft Access.

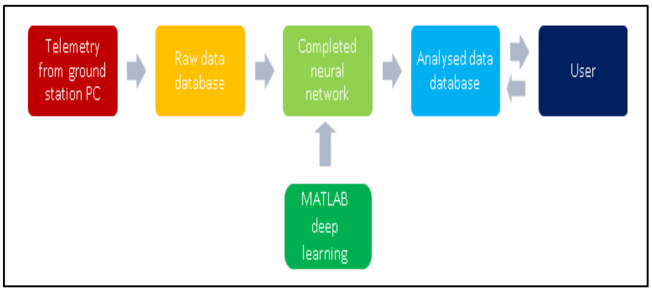

Fig. 2. Proposed Deep Learning Infrastructure.

However, if there are license restrictions prevalent or if an open-source solution is preferred the environments can be based on Structured Query Language (SQL) in particular MySQL or PostgreSQL which are open-source database management systems. This type of language is advantageous for the storing and handling of information in tabular forms.

The second environment contains the deep learning architecture which will initially be developed using MathWorks' MATLAB Deep Learning Toolbox after which will be exported to a TensorFlow model in the python language. Alternatively, the network can be exported to an open-source platform called the Open Neural Network Exchange or ONNX for short.

Telemetry is downloaded through overpasses onto the ground station PC, from there a copy of that telemetry is imported onto the database. The raw data is exported from the database to the neural network that is either being used in MATLAB TensorFlow or ONNX. Relevant changes, if any, are conducted using MATLAB which are then exported and imported into TensorFlow or ONNX, respectively.

Once the relevant analyses are completed, the now analysed data is exported to the relevant database where it is stored and can be viewed by the user. To achieve the exchanging of data, three dissimilar systems will need to be used. While combining the three is possible by having three different systems reduces the possibility that if one of the systems experiences an issue, the entire infrastructure is not at risk.

VI. Significance of Research

The application and utilization of machine learning and by extension deep learning has become abundant within various disciplines in industry, making operations efficient and minimizing errors incurred. From a system overview, with minimal influence from external factors, the operational life is extended, which from both an engineering and fiscal standpoint is a net positive. With satellites with special attention being focused on CubeSats, development is costly in terms of personnel, monetary and the duration that it takes from realizing the envisioned CubeSat into an actual product.

Whilst the launching and operating of CubeSats have been in practice for approximately 25 years, with the nature of space itself being a hostile environment, precautions are required with no guarantee that operations will be without any faults. One area in which a safety measure can be implemented is in maintaining and/or increasing the operating efficiency of the CubeSat. Evaluating operations using deep learning would yield valuable data that the operating team can use to increase operational efficiencies, investigate points of interests, and mitigate prospective errors. This will in turn increase the chances that the CubeSat survives the proposed period of operation if not longer without any significant errors concluding in a successful mission that yields validation for the design and/or operating team, provides confidence in future missions that there are tools available to help gain a deeper insight and showcases to shareholders both current and potential that the program is worth investing both in terms of fiscally and human capital.

VII. Conclusion and Contributions

The envisioned system, which is a work in progress where certified results will be subsequently published, can be employed as a tool that can assist the ground management team in improving CubeSat operations at an operating level. The system is entirely standalone or semi-automate and can operated with little to no human interaction required. Therefore, automating and providing highly accurate data analysis which can be consulted and if necessary, incorporated into future missions. The standalone deep learning network that can be deployed and integrated into any system with minimal effort with ample documentation such that the process can be duplicated and further be improved upon as mission criteria expands.

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