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Machine Learning Methods for Spacecraft Telemetry Mining

Sara K. Ibrahim, Ayman Ahmed, M. Amal Eldin Zeidan, and Ibrahim E. Ziedan

Abstract— **Spacecrafts are critical systems that have to survive space environment effects. Due to its complexity, these types of systems are designed in a way to mitigate errors and maneuver the critical situations. Spacecraft delivers to the ground operator an abundance data related to system status telemetry; the telemetry parameters are monitored to indicate spacecraft performance. Recently, researchers proposed using Machine Learning (ML) / Telemetry Mining (TM) techniques for telemetry parameters forecasting. Telemetry processing facilitates the data visualization to enable operators understanding the behavior of the satellite in order to reduce failure risks.**

In this paper, we introduce a comparison between the different machine learning techniques that can be applied for low earth orbit satellite telemetry mining. The techniques are evaluated on the bases of calculating the prediction accuracy using mean error and correlation estimation. We used telemetry data received from Egyptsat-1 satellite including parameters such as battery temperature, power bus voltage and load current. The research summarizes the performance of processing telemetry data using autoregressive integrated moving average (ARIMA), Multi-Layer Perceptron (MLP), Recurrent Neural Network (RNN), Long Short-Term Memory Recurrent Neural Network (LSTM RNN), Deep Long Short-Term Memory Recurrent Neural Networks (DLSTM RNNs), Gated Recurrent Unit Recurrent Neural Network (GRU RNN), and Deep Gated Recurrent Unit Recurrent Neural Networks (DGRU RNNs).

Index Terms— **data mining, deep learning, machine learning, neural networks, satellite performance analysis, telemetry mining.**

I. Introduction

The tremendous number of spacecraft launched in the past decades, enabled national dependence on space based services; such as earth observation, communication and satellite navigation. The recent advances in technology and corresponding spin off enabled satellite developers to use state of the art electronics and software to either operate the spacecraft or control its onboard equipment. Recent trend announced in the field of building satellites, is the dependency on low cost commercially available components. However, despite of using fault mitigation techniques and additional shielding onboard spacecraft, may reduce space environment effects on satellite components and subsystems, this harsh environment has many effects starting from thermal and vacuum conditions ending with radiation effects. Spacecraft failure has many reasons, such as the significant effects of radiation environment on one of the critical components of satellite, for example the onboard computer, communication system, or power supply[1].

Nowadays machine learning(ML) / Data Mining(DM) techniques are used widely in various fields such as spacecraft operations support - the MARS express power challenge[2] spacecraft ground systems[3], failure prognostic of avionics[4], and communication networks control which is an important aspect for both the service provider and end user. Data mining methods have been successfully used to address and optimized solutions to this issue where learning algorithms for data mining allow following and understanding the network behavior so that control functions and parameters can be updated during network operation to achieve optimal performance in real condition[5]. For the next-generation wireless networks, Machine learning is able to overcome the challenge of assisting the radio in intelligent adaptive learning and decision making, so that the diverse requirements of next-generation wireless networks can be satisfied [6]. The Age of Digital Astronomy is such an extremely data-rich environment beyond the capabilities of traditional methodologies and approaches for analyzing and extracting new knowledge from the data. Way et al.[7] have applied some state-of-the-art machine learning and data mining techniques in astronomy; where the scientific discovery process is increasingly dependent on the ability to analyze massive amounts of complex data generated by scientific instruments and simulations. JIAO et al.[8] presented a machine learning algorithm to detect automatic equatorial GPS amplitude ionospheric scintillation and classify scintillation events based on training data in the frequency domain. ML / DM techniques are also applied on real-time system traces[9], Cyclic Time Series classification[10], stock price forecasting[11] and fall detection ML approach for Range-Doppler Radars [12].

In this research, we investigate the machine learning / data mining (ML/DM) techniques that can be utilized to analyze the performance of the spacecraft. We used Data mining to explore the performance presented by telemetry parameter(s) that reflect the health of certain onboard unit. This enables satellite operator to monitor the overall satellite health to

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reduce the risk of failure with accurate and automated manner. One of the possible ways to monitor the satellite health is to use its online telemetry to allow assessment of its status. The prediction of telemetry parameters helps the operator to determine potential/ upcoming satellite operating mode, which can help support decision making for urgent situations. this is important issue, as an urgent situation may cause satellite complete loss. The numerical nature of satellite telemetry parameter is usually formatted/presented as a time series due to nature of satellite operation. The time series regression of the satellite telemetry parameters can point to trend in telemetry parameter value change, which may cause satellite subsystem failure. Monitoring of such trends will alarm for possible failure. One simple method is to predict the next value(s) of one parameter and apply limit check, so that potential failure can be foreseen. When the predicted value probability exceeds the percentage of error probability defined by satellite operators/designer, it indicates that the related subsystem may go into a faulty behavior and thus the satellite system will be affected; operator, then, should take precautions to avoid this situation.

This paper is organized as follow; we first give an introduction about monitoring the performance of spacecraft. Then, we described the satellite subsystems. The third section introduces a literature review about machine learning techniques used for diverse application; followed by section four, we described the detailed algorithms to be evaluated. Section five explains the format of the telemetry data received from the EGYPTSAT-1 satellite and its associated correlation theme. The evaluation methodology is then introduced followed by the results of applying the selected algorithms on telemetry data. Finally, we conclude the research and illustrate our future work.

II. Satellite Subsystems

Spacecraft has a set of subsystems, such as Attitude Determination and Control Subsystem (ADCS), Telemetry, Tracking and Command (TT&C), Command and Data Handling (CDH), Electrical Power Subsystem (EPS), Structures and Mechanisms, Guidance and Navigation and Thermal Control Subsystem (TCS). The ADCS stabilizes the vehicle and orients it in a desired direction during the mission despite the external disturbance torques acting on it. The structure and mechanism subsystem mechanically support all other spacecraft subsystems, attaches the spacecraft to the launch vehicle, and provides for ordnance-activated separation[13].

The telemetry measurements onboard the spacecraft ensure obtaining of adequate information about the onboard subsystems functioning during the flight operation as well as ensure controlled counteracting the off-nominal situations onboard the satellite. The satellite telemetry data enables the operators in the ground station to monitor the satellite in different situations such as separation after orbital injection from the launcher, satellite orientation and its dynamics, onboard subsystems status and mal-functioning, control program and commands execution, revealing of malfunctions in the onboard subsystems operation and monitoring of satellite instruments and structural elements temperature[14].

In our case, to guarantee the full confidence of interpreting the input telemetry data set, and to compare the real scenario of operation with the corresponding telemetry data set, authors used the telemetry data of EGYPTSAT-1, the first Egyptian remote sensing satellite, with support from satellite operation and design team members[15].

III. Satellite Performance Analysis Using Machine Learning- Literature Review

Recently, researchers suggested using approaches to monitor and evaluate the performance of satellite subsystems; furthermore, advanced techniques may be used to predict the performance of satellite devices and prepare for early stage decision-making. In this context, many algorithms have been developed to forecast the failure before it happens based on telemetry data received from satellite.

Yairi et al.[16] proposed a data-driven health monitoring method based on probabilistic clustering and dimensionality reduction for artificial satellites housekeeping data. Nassar and Hussein[17] presented a novel supervised learning algorithm based on projection to latent structure discriminant analysis technique (PLS-DA) applied to spacecraft telemetry data in order to manage the nominal and off-nominal status of the spacecraft operations and overcome faulty states in the space mission operation. Yang et al.[18] proposed data mining methods for in-orbit satellite fault detection and prediction which is one of the key technologies for health monitoring of in-orbit satellites.

In this research, we carried out a comparative study between some state-of-the-art data mining techniques applied on the Egyptsat-1 telemetry. These algorithms are, autoregressive integrated moving average (ARIMA), Multi-Layer Perceptron (MLP), Recurrent Neural Network (RNN), Long Short-Term Memory Recurrent Neural Network (LSTM RNN), Deep Long Short-Term Memory Recurrent Neural Networks (DLSTM RNNs), Gated Recurrent Unit Recurrent Neural Network (GRU RNN), and Deep Gated Recurrent Unit Recurrent Neural Networks (DGRU RNNs). We selected these techniques as surveyed by many previous researches [19-25]. Despite many researchers have built their outcomes on satellite telemetry available through internet, with low level of confidence[26, 27]. Our research used telemetry data with very high-level of confidence due to the availability of both design documentations of each satellite modules and telemetry format corresponding to data ranges of each sensor.

A. Limit Checking

Limit checking is the simplest algorithm, which is applied earlier and widely used. The technique is based on setting a proper range for the applied parameter such as (temperature, voltage, and current). By monitoring the variance of each parameter, out of that range events can be easily detected.

The only advantage of this algorithm is its simplicity where limits can be set and modified to monitor spacecraft operation. Limit checking can be applied for one sensor value.

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Practically, there is a set of sensors need to be simultaneously monitored to assess spacecraft performance. Hence, Limit checking is, still, not proper methodology for telemetry deep analysis[28, 29].

B. Expert System (ES)

Recently, the Artificial Intelligence is becoming an interested field of application for automated systems; one of its important developed algorithms is Expert System (ES). ES can be applied by establishing knowledge database and knowledge-based reasoning engine; using the reasoning engine, the ES can predict faults according to the telemetry data. Its disadvantage is that a predefined knowledge rules should be set first which requires an accurate knowledge of the system overall possible cases since it does not implement the self-learning concept. Consequently, the ES cannot produce new knowledge[28, 29].

C. Clustering Techniques

There are several data driven software tools, such as Orca and the Inductive Monitoring System (IMS), have been successfully applied to mission operations for both the Space Shuttle and the International Space Station. The IMS tool[30] uses K-Means clustering data mining technique to analyze archived spacecraft data and characterize nominal interactions between selected parameters. The Orca tool[31] uses a nearest neighbor approach to search for outliers data points in multivariate data sets by calculating the distance of each data point from neighboring points. Iverson[32] described how such data driven techniques have been applied to NASA mission control operations where these “data driven” applications are able to characterize and monitor interactions between multiple parameters and can complement existing practice to provide valuable decision support for mission controllers.

K-Means clustering is an approach of machine learning techniques. The algorithm is based on partitioning of an (n) observation into k clusters in which, each observation belongs to the cluster with the nearest mean; it depends on minimizing the sum of within-cluster distances. The clustering algorithm may converge to different final solutions based on the start point of search. These solutions may be local minima if the initial partition is not properly chosen; that is why the convergence to local minima is the main disadvantage of the K-means clustering algorithm[33].

K-nearest neighbors(KNN) clustering technique depends on the distance to neighboring members of a class; KNN splits the dataset into clusters based on a simple majority vote of the nearest neighbors of each point[34]. KNN is simple, straight and effective however it cannot identify the effect of attributes in dataset; For some cases like non-Gaussian distribution or non- Elliptical distribution, KNN cannot solve these two kinds of problem effectively[35].

D. Other approaches

One of the well-known statistical algorithms is the autoregressive integrated moving average (ARIMA), which is used for time series forecasting such as prediction of traffic noise time series[36]. ARIMA usually produces low forecasting accuracy in case of nonlinear long-term time series. Therefore, it is usually combined with support vector machine (SVM), which is also a statistical algorithm, or with artificial neural network (ANN). The SVM and ANN support the ARIMA to produce better results. Zhang[19] presented a hybrid of ANN with ARIMA to predict the Canadian lynx time series. Pai and Lin[20] developed a hybrid forecasting model consists of SVM and ARIMA for stock price forecasting. The SVM is widely used to minimize the generalized error bound in order to enhance the performance for not only time series forecasting but also classification tasks. Yu et al.[21] made a real-time flood stooge forecasting using SVM. Tay and Cao[37] proposed a financial time series forecasting using SVM. The ANN is a popular technique as well, that is used in recognition or regression problems. Park et al.[38] presented electric load forecasting using ANN by learning the relationship between past, current and future temperature readings and the corresponding loads. Khashei and Bijari[39] proved that ANN gives better performance than ARIMA in time series forecasting. Recently long-short term memory (LSTM) has been introduced as recurrent neural network (RNN) architecture applied to various real-world problems, such as protein secondary structure prediction[40, 41], reinforcement learning[42], speech recognition[43] and handwriting recognition[25]. It has solved several artificial problems that remain impossible with any other RNN architecture[44]. Ballas et al.[45] presented video representations using Gated recurrent units (GRU) RNN and stacked layers of GRU RNNs. Another technique known as Gaussian Process technique is used for time series evolution prediction of complex systems across various engineering and business domains, such as the prediction of exchange rate in finance, weather and demand for energy using mixture of experts. Chandorkar et al.[46] presented a methodology for generating probabilistic predictions for the Disturbance Storm Time geomagnetic activity index based on Gaussian Process Regression models. Mattos et al.[47] performed nonlinear system identification in the presence of outliers using Deep recurrent Gaussian processes which comprise a powerful kernel-based machine learning paradigm that has recently attracted the attention of the nonlinear system identification community, especially due to its inherent Bayesian-style treatment of the uncertainty. A Recently discussed technique used for machine learning is State-Space Model, which is used for Identification of the nonlinear dynamical systems. Noël et al.[48] selected state-space models with polynomial nonlinear terms to identify hysteresis in dynamic systems. The researchers fitted the data to the model using a rigorous two-step methodology involving weighted least-squares minimization. Jacob et al.[49] proposed a Bayesian approach to identify the battery parameters of generic fractional-order systems using state-space models where the latent process is not Markovian. Stathopoulos and Karlaftis [50] proved that the multivariate state space modeling of urban areas parameters is complex and tedious, compared with ARIMA model, which gives high accuracy in the field of relatively

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short-term prediction of traffic characteristics.

As for applying machine learning data mining technique in the field of spacecraft performance analysis (named telemetry mining), Li et al.[28] and Yairi et al.[29] introduced a comparison between most common machine learning techniques applied in spacecraft telemetry mining. Yairi et al.[29] has surveyed wide range of algorithms and techniques used in space systems data mining; the research concluded that "*a significant issue is how we can guarantee the reliability and generality of the acquired information from data. Effective and intuitive ways of presenting outputs from the detection / diagnosis systems must be also considered, because a ML/DM technique is often used as a "black-box"* ". In this research, we overcome this issue by using high reliability information from confident telemetry data source.

IV. MACHINE LEARNING TECHNIQUES

This section introduces the usage of telemetry data from the satellite in form of Time Series. We represent the data vector: $X=\{x^{(1)}; x^{(2)};\ldots; x^{(n)}\}$, where each element $x^{(t)} \in R^m$ pertaining to X is an array of m values such that $\{x_1^{(t)} ; x_2^{(t)}; \ldots ; x_m^{(t)}\}$. Each value of m corresponds to input variables measured in the time series telemetry data.

A. Auto-Regressive Integrated Moving-Average

The autoregressive integrated moving average (ARIMA) model is a generalized form of an autoregressive moving average (ARMA) model[51]. Both of them are used to forecast time series data. ARIMA algorithm consists of three parts; the first one is the Auto Regressive part where the model uses a dependent relationship between an observation and number of lagged observations. The second part is the integration, where it uses difference between raw observations to make a stationary time series. The last part is the Moving Average where the model uses the dependency between an observation and a residual error from a moving average model applied to lag observations. The ARIMA model standard uses notation (p,d,q), where p is The number of lag observations, d is the degree of differencing, and q is The size of the moving average window[52, 53].

B. Multi-Layer Perceptron

Multi-Layer Perceptron (MLP) is the simplest form of Artificial Neural Network (ANN). It consists of input layer, one or more hidden layers which is used to transform the input vectors into something that the output layer can use or if there are more than one hidden layer; the one's output is an input to the next one, and output layer. MLP is free of cycling so it is called Feed-forward neural network (FNN) where the output is derived from current input and do not depend on input history[22, 54].

C. Recurrent Neural Network

Recurrent Neural Network (RNN) is an advanced form of MLP, its output depends not only on current input but also on previous neurons, because of cycling between neurons of hidden and output layers, which give better results than MLP network[55]. The hidden layer extracts a set of features from the input vectors then they are translated into the target context by the output layer. The hidden and output layer outputs depend on the nature of the presented problem (regression, classification) and the applied cost function such as cross entropy, least square errors.

Due to its recurrent nature, the network can maintain a value inside, which enables the RNN to be used as a memory. However, it cannot keep a value for more than 5 to 10 time steps; this is known as vanishing gradient descent[56]. RNN cannot control the timing of reset, forget and store of the data. Gating RNN algorithms such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) are used to overcome the problems stated above by using additional gates dedicated for these purposes.

D. Long Short-Term Memory Recurrent Neural Network

Hochreiter and Schmidhuber[57] have developed the basic Long Short-Term Memory (LSTM) architecture with less gates (without forget gate) and connections. Gers et al.[56] proposed the first modification for the LSTM architecture by adding the forget gate that allow LSTM to reset its memory cell. LSTM is one of the most effective way to carry out learning process for the RNN, such that it can remember values for longer time. LSTM is developed from RNN by replacing the RNN hidden layer neurons with LSTM blocks. Each block has a memory cell that help to overcome the RNN vanishing gradient problem. LSTM block consists of memory cell to store information for longer time periods; and three multiplication units called as gates, where each gate use the sigmoid activation function to act as a switch with values 0 (gate off) and 1(gate on) [44, 55]. Srivastava and Lessmann [58] demonstrated that a properly configured LSTM model outperforms other techniques used in global horizontal irradiance with satellite data.

E. Deep Long Short-Term Memory Recurrent Neural Network

Deep Long Short-Term Memory Recurrent Neural Networks (DLSTM RNNs) are consisted of stacked multiple layers of LSTM blocks, where each block output is an input to the next block in next layer. It is used to maximize the memory size in case of forecasting next values or classification problems[26]. Using more stacked layers usually enhances the prediction accuracy. This technique achieves higher learning capacity but needs large dataset for model training[59]. The key aspect of deep learning is that these layers of features are not designed by human engineers; they are learned from the dataset using a general-purpose learning procedure[60]. Fischer and Krauss[61] applied DLSTM to a large scale financial market prediction task on the S&P 500, from December 1992 until October 2015; they found that DLSTM is more suitable for the forecasting domain rather than standard deep neural network and the logistic regression by a very clear margin.

F. Gated Recurrent Unit Recurrent Neural Network

Gated Recurrent Unit (GRU) is an alternative form of LSTM with more simplicity. The GRU combines the input

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and forget gate together in one gate called update gate; and the peephole connections is removed in-order to decrease the number of parameters used in calculations, this helps to improve the training performance and accelerate the algorithm speed[23]. The GRU does not have a separate memory cell that is why it uses the gates to modulate information flow in the unit. The update gate controls the importance degree of the previous memory content, to either keep it or update its content. The reset gate allows the GRU to forget unnecessary memory content[62]. Zhao et al.[63] applied GRU recurrent neural networks on machine health monitoring systems for modern industries.

G. *Deep Gated recurrent unit Recurrent Neural Network*

Deep Gated Recurrent Unit Recurrent Neural Networks (DGRU RNNs) are built by stacking multi layers of GRU units, such that each lower unit output feeds the next unit in next layer. It is used as storage for regression or classification tasks[24]. Deep learning neural network is making major advances in solving problems that have resisted the best attempts of the artificial intelligence community for many years. It has turned out to be very good at discovering complicated structures in high-dimensional data and is therefore applicable to many domains of science, business and government[64]. Tan et al.[65] used a hierarchical gated recurrent neural network to model the context information. They used gate mechanism at both word level and sentence level to select words and sentences closely related to the question. Mou et al.[66] proposed a novel deep RNN model that can effectively analyze hyperspectral pixels as sequential data and then determine information categories via network reasoning.

V. FORMATION OF TELEMETRY PARAMETERS

In a complicated system, such as satellite, telemetry parameters are the only indictors for satellite performance and subsystems health. Total number of telemetry parameters may be over few thousand. In this research, we select (based on system designers' recommendation) the most essential parameters that indicate the satellite status/health, most of these parameters are much correlated to each other; as shown by performing pattern matching. This enabled us to find the most related parameters and subsystems behavior. Fig. 1 shows the correlation between parameters in following subsystems: communication subsystem, Command and Data Handling (CDH), Electrical Power Subsystem (EPS).

The correlation is estimated using the parameters readings from five successive telemetry files. These subsystems are the most critical ones in the satellite. CDH failure means complete loss of the satellite, EPS failure means no power will be supplied to any subsystem, and communication system failure means satellite may be working by itself while no communication with ground station (no inter-satellite communication exists).

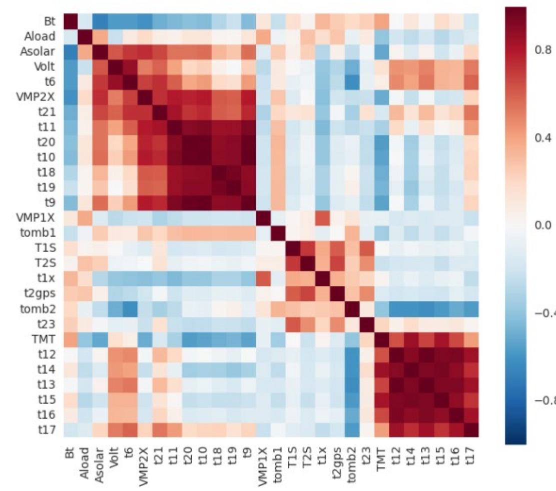

Fig. 1. The correlation between the satellite telemetry parameters in different subsystems.

The proposed parameters are ***Bt***: represents battery temperature, ***Asolar:*** is the solar array current, ***Aload*** is the load current, ***volt*** is the power bus voltage. ***VMP1X*** and ***VMP2X*** are the output power of main and reserve set of communication system transmitter. The ***tomb1*** and ***tomb2*** are the camera lens temperature. The ***t2gps*** parameter represents the casing temperature of the GPS. The ***TMT*** parameter is the telemetry secondary power subsystem temperature. Thermal subsystem parameters are represented by the temperature sensors reading t_x mounted at external heat shield of satellite body. In general, Satellite telemetry parameters are high dimensional and highly correlated in the manner as shown in Fig. 1. Principle component analysis is usually used for dimensionality reduction; However, this method cause loss in physical representation of resulted dimensions, and since domain expert knowledge will be more useful in our study, we decided to select system parameters that reflects critical health of satellite. The correlation between these parameters allows us to select those who are highly correlated to each other's, and consequently express their behavior. The selected parameters can be treated separately (univariate with respect to other selected parameters, but covariate with respect to its correlated -not selected- parameters); in the same time, they are more expressing overall satellite performance and possible failures.

In our case (Egyptsat-1), we based our study on the domain expert knowledge in conjunction with correlation matrix to select critical parameters. Similar study has been carried out on x-11 Chinese satellite, where autoregressive model, back propagation neural network and non-parametric regression techniques have been compared and applied to satellite power systems in order to predict the selected parameters with high accuracy (measured by mean percentage error 1%) [67].

VI. EVALUATION METHODOLOGY

In this section, an evaluation of the above-mentioned algorithms is introduced. We formatted the telemetry parameters extracted from the raw telemetry data received from the Egyptsat-1 satellite, so that it can be used as an input to each algorithm; based on this we selected the following

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telemetry parameters: power bus voltage, load current and battery temperature. These parameters are recommended by satellite designers that can indicate potential failure of satellite critical subsystems including power, communication and onboard computer (these parameters have high correlation with other parameters). The telemetry parameters are time tagged counting for number of ticks (in seconds), so we used the first 67% of the telemetry values for learning each algorithm while the other 33% of the total period is used for evaluation; as a result, about 7000 to 8000 value from each parameter have been used in the evaluation process. we then estimate the root mean square error (RMSE), mean absolute error (MAE), Pearson coefficient, and r^2 – correlation [68] to assess prediction accuracy.

We started by using telemetry files from different periods of satellite lifetime; five successive raw data files have been used from each period. The data are extracted and formatted to allow easy interpretation of values. As a result, we constructed a comparison table to illustrate the accuracy of each algorithm. All techniques are implemented based on Python3 programming language. The neural network techniques are implemented using Keras deep learning library on top of Google TensorFlow; figures are obtained using matplotlib library for Python 2D plotting; we run algorithms on a computing platform with processor speed Intel® core™ i5 - 2410M CPU@ 2.30 GHZ 2.30GHZ, RAM 6 GB, and 64-bit operating system windows 7. Unifying the platform of implementation allowed us to calculate the execution time of the tasks per telemetry file. We concluded the comparison between algorithms based on accuracy of prediction and time of execution.

VII. Results

This section introduces the results of running the seven selected algorithms (ARIMA, MLP, RNN, LSTM, GRU, DLSTM, and DGRU) for three telemetry datasets; each set is composed of five successive telemetry files from years 2008, 2009, and 2010.

The time series regression of telemetry parameters has been used to demonstrate the ability of this method to detect possible failures; we used a simple approach to predict the next value(s) of one parameter and apply Shewhart control [69] to check the limits of the predicted values, as shown in Fig. 2.

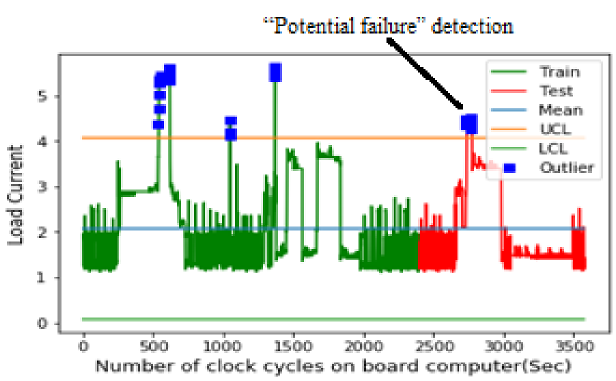

Fig. 2. Shewhart Control Chart for detecting abnormal values.

LSTM was able to predict the satellite load current values (which is defined by expert as main indication of power subsystem health). When the LSTM predicted value exceeds the upper control limit (UCL) or the lower control limit (LCL), it alerts for possible failure.

For each parameter, a time series is constructed and used as an input to the algorithm under evaluation. About 5000 values/readings have been used for training for each algorithm, followed by about 2700 reading used for test. The predicted values are compared with the actual values to measure prediction accuracy. High prediction accuracy means that the technique can inform about the future values (either normal or abnormal state) with high probability. Figures from Fig. 3 to Fig. 9 represent the results of evaluation for the seven algorithms for "voltage sensor for power bus" for year 2008.

The blue lines, always behind the green and red data lines- usually will not be in clear view, represent the original/ real data values; while green lines represent the predicted values of data used for training; in this research we re-predicted the values of the data used for training to get more accurate results for overall prediction performance of the algorithm under evaluation; the prediction accuracy of the training data is not always 100%; the red lines represent the prediction values of the test data. As for ARIMA and LSTM, predicted values are almost identical to original ones, so that blue lines are totally covered by both green and red lines; on the other hand, for the other algorithms an observable difference occurs, so that visible parts of blue lines can be distinguished.

A. *ARIMA Algorithm:*

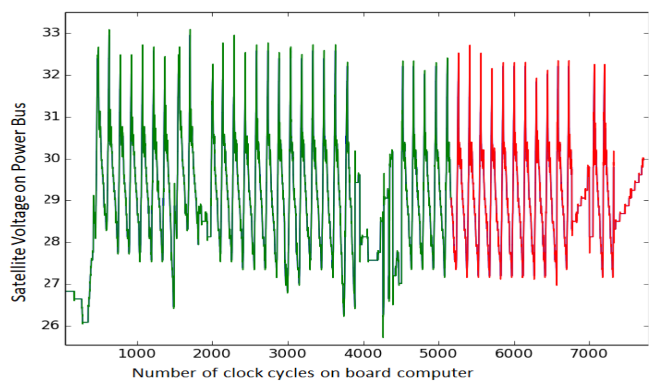

Fig. 3. ARIMA prediction result for 2008 telemetry data files.

B. *MLP Algorithm:*

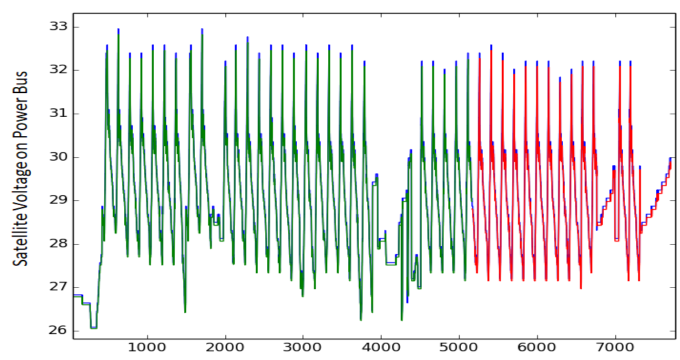

Fig. 4. MLP prediction result for 2008 data files.

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C. *RNN Algorithm:*

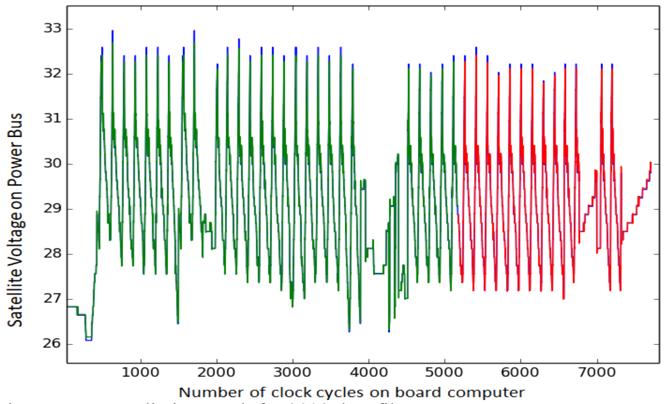

Fig. 5. RNN prediction result for 2008 data files.

D. *LSTM Algorithm:*

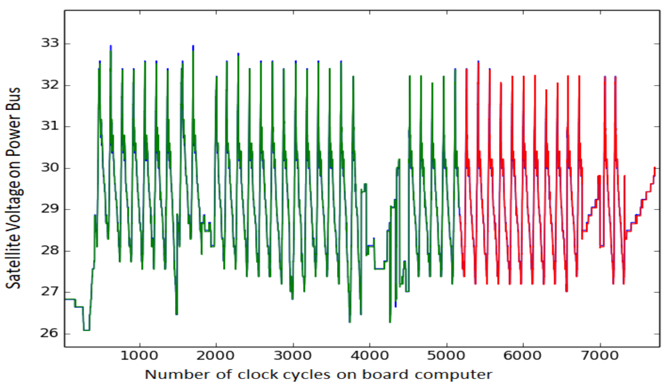

Fig. 6. LSTM prediction result for 2008 data files.

E. *GRU Algorithm:*

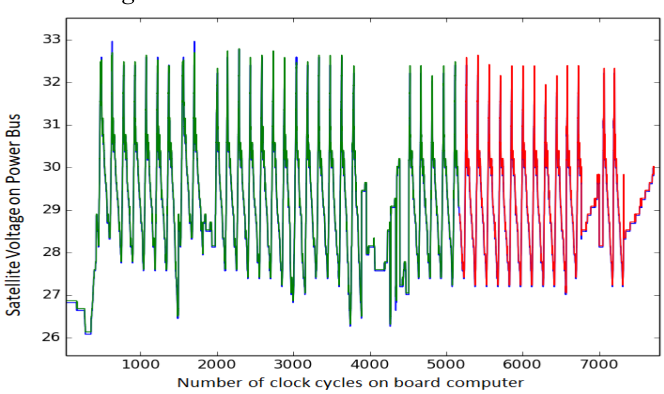

Fig. 7. GRU prediction result for 2008 data files.

F. *DLSTM Algorithm:*

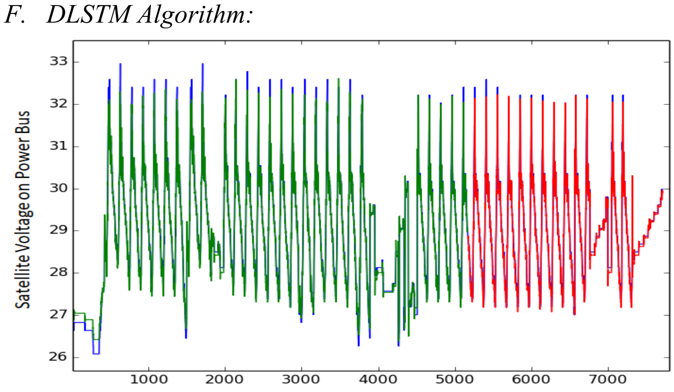

Fig. 8. DLSTM prediction result for 2008 data files.

G. *DGRU Algorithm:*

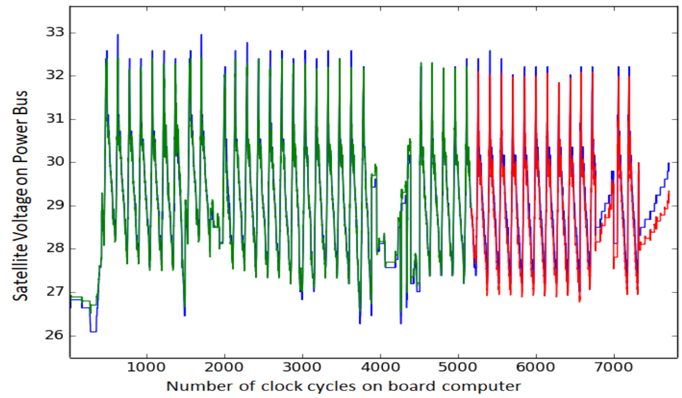

Fig. 9. DGRU prediction result for 2008 data files.

VIII. Discussion

A comparison between the proposed techniques is presented in Table I. The techniques (ARIMA, MLP, RNN, LSTM, GRU, DLSTM, and DGRU) are applied on three different datasets from 2008, 2009, and 2010 of Egyptsat-1 lifetime.

TABLE I
TECHNIQUES COMPARISON

Algorithm	year	RMSE	MAE	Pearson Coe.	r^2 Coe.	Execution time (S)
	2008	0.2021	0.0695	0.9861	0.9724	20016
ARIMA	2009	0.2104	0.0675	0.9866	0.9734	12665
	2010	0.1889	0.0682	0.9903	0.9808	24516
	2008	0.2214	0.0945	0.9855	0.9712	11531
MLP	2009	0.2651	0.2354	0.9860	0.9721	10200
	2010	0.2210	0.1260	0.9890	0.9781	13494
	2008	0.2037	0.0896	0.9859	0.9720	34757
RNN	2009	0.2141	0.1098	0.9864	0.9729	30915
	2010	0.2051	0.0901	0.9893	0.9787	37084
	2008	0.2047	0.0758	0.9864	0.9730	66090
LSTM	2009	0.2016	0.0958	0.9877	0.9756	51526
	2010	0.1985	0.0824	0.9901	0.9802	71267
	2008	0.2037	0.1214	0.9863	0.9728	48000
GRU	2009	0.2117	0.0783	0.9874	0.9749	44713
	2010	0.1956	0.0882	0.9900	0.9801	55143
	2008	0.2074	0.1048	0.9878	0.9758	79832
DLSTM	2009	0.2134	0.1680	0.9857	0.9715	67888
	2010	0.2017	0.1285	0.9906	0.9812	88174
	2008	0.3012	0.1216	0.9859	0.9720	68359
DGRU	2009	0.2042	0.1397	0.9829	0.9661	60863
	2010	0.2139	0.2168	0.9892	0.9785	67672

We calculated the root mean square error (RMSE), Mean Absolute Error (MAE), Pearson coefficient and r^2 correlation coefficient for each technique as an accuracy measure. The

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average accuracy is then computed for each year, as shown in Table I, and the overall accuracy of each technique is calculated in Fig. 10 to Fig. 13. The execution time is calculated in seconds for each process.

From the results Table I, we can see that Autoregressive integrated moving average (ARIMA), has the best prediction accuracy all over the whole datasets regarding to RMSE and MAE. This statistical approach runs in a time series prediction behavior faster than all other neural network techniques; moreover, ARIMA is relatively simple algorithm and cost-effective approach to carry on the required function.

On the other hand, for the neural network algorithms, long short-term memory recurrent neural network (LSTM-RNN) achieved the highest performance accuracy regarding Pearson coefficient and r^2 correlation coefficient, but timely consumed; multilayer perceptron (MLP) is the fastest neural network algorithm but with less accuracy. The dataset for 2010 is relatively larger than dataset for 2008 and 2009 which makes the accuracy of 2010 dataset relatively better than the others as shown in Table I.

The figures from Fig. 10 to Fig. 13 present a comparison between different techniques from point of view of each accuracy measure RMSE, MAE, Pearson and r^2 Coefficient. As for root mean square error (RMSE) accuracy measure, shown in Fig. 10, ARIMA gives better accuracy followed by LSTM then GRU; the same behavior is found in mean absolute error (MAE) as shown in Fig. 11. The correlation accuracy measure techniques: Pearson and r^2 correlation, shows that the LSTM followed by GRU and DLSTM gives higher accuracy as shown in Fig. 12 and Fig. 13.

As we can see from these figures; for artificial low earth orbit satellites, that have relatively short life time (3-5 years) relative to communication and navigation satellites (15-20 years), both regression techniques and neural network technique (used for prediction) have very closed accuracy measures values (especially ARIMA and LSTM). This can be explained due to the smaller datasets introduced to the neural network as learning period; terrestrial systems and artificial communication satellites may last for longer time (15-20 years life time) which means more data can be provided for training. Fischer and Krauss [61] used LSTM for large data set (1992-2015) with very good prediction performance.

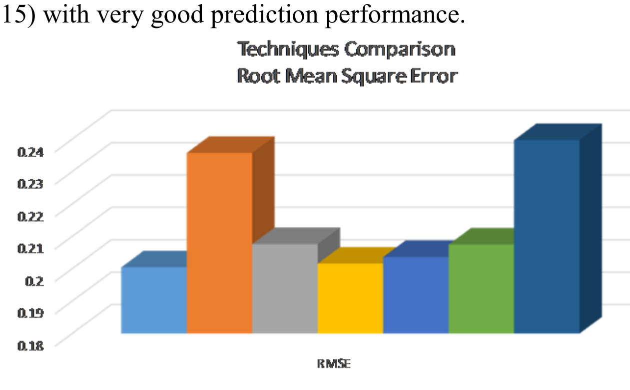

Fig. 10. Techniques Comparison according to RMSE.

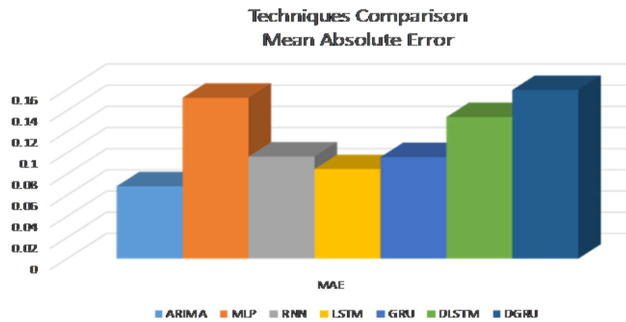

Fig. 11. Techniques Comparison according to MAE.

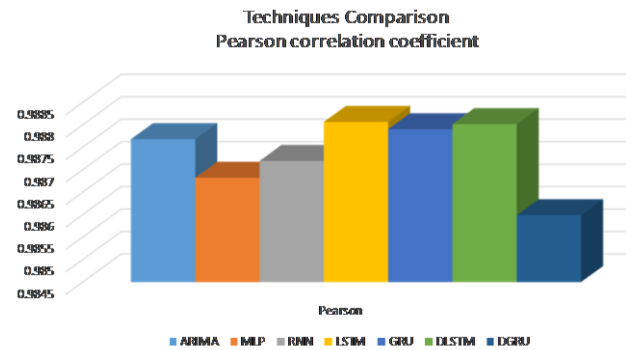

Fig. 12. Techniques Comparison according to Pearson.

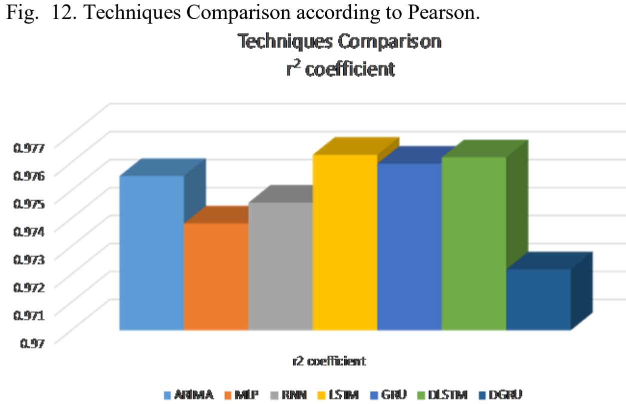

Fig. 13. Techniques Comparison according to r^2.

IX. CONCLUSION

This paper introduces comparison between machine-learning algorithms (ARIMA, MLP, RNN, LSTM, DLSTM, GRU, and DGRU) used for prediction of spacecraft telemetry data. Spacecraft parameters value are predicted using real telemetry data of Egyptsat-1 satellite. From the results, LSTM and GRU algorithms give a high prediction accuracy (from correlation accuracy measure point of view); while ARIMA and LSTM have highest prediction accuracy (from mean error accuracy measure point of view). By applying these algorithms on presented parameters, we found that ARIMA and MLP models run with highest speed. While RNN takes relatively more time due to its recurrent nature. GRU is faster than LSTM due to its lower number of gates; however, LSTM gives better performance. DGRU and DLSTM take more time in processing between staked layers used in each algorithm; these algorithms give less accurate results because it requires large size of dataset for deep learning process.

The results show that, at least in Egyptsat-1 case, for short lifetime satellites (3-5 years) it would be more efficient to use simple linear regression (such as ARIMA) for predicting critical parameters of satellite. Using neural network may be

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more efficient in long-term prediction as the case of communication satellites (15-20 years).

We recommend simpler regression techniques such as ARIMA for implementation “for low earth orbit satellite telemetry mining” that will give comparable results with complex neural network. However, for building an integrated system for both telemetry mining and classification, the LSTM will be best candidate for this purpose, as it can be used for prediction, fault diagnoses and classification.

Planned Future work is the implementation of LSTM using wither Graphical Processing Unit or Field Programmable Gate Array for fast and real time data processing, toward an integrated system for telemetry prediction, fault diagnoses and classification. The system will be used in operation of satellite Ground control station at Cairo, Egypt for next satellite 2019.

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