Satellite Anomaly Detection and Power Consumption Forecasting Using Machine Learning

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*Abstract*—This paper presents a comprehensive approach for predicting overall power consumption and detecting anomalies in the Mars Express Orbiter (MEX) using telemetry data spanning three Martian years. Seasonal ARIMA (SARIMA) models are used for forecasting daily and monthly power consumption, integrating advanced outlier handling, hyperparameter tuning, and robust evaluation metrics. Additionally, anomaly detection is conducted using Rolling Z-score and Isolation Forest methods, effectively distinguishing operational anomalies. The findings provide actionable insights into the satellite's operational health and offer potential applications in dynamic systems like cloud computing.  
*Index Terms*—Satellite anomaly detection, ARIMA forecasting, Isolation Forest, Rolling Z-score, telemetry data, power consumption prediction, Mars Express Orbiter.

# *I. INTRODUCTION*

### A. Power Consumption Forecasting

Accurate prediction of satellite power consumption is essential for effective energy management, mission planning, and prolonged operational life in space missions. Reliable forecasting enables the anticipation of energy shortfalls, operational downtime, and optimal resource allocation. The Mars Express Orbiter (MEX), which has been orbiting Mars since 2003, continuously provides large-scale telemetry data. Effective utilization of such data for accurate forecasting is vital, especially considering the satellite's aging infrastructure and the criticality of mission objectives.

### B. Anomaly Detection

Anomaly detection in satellite systems is paramount to timely identify and address potential failures or operational deviations that can compromise mission integrity. The

complex operational environment of satellites like MEX generates irregularities, which conventional monitoring systems might overlook. Thus, machine-learning-based anomaly detection is critical for proactive mission management and real-time anomaly diagnosis.

# *II. Literature Review*

### A. Literature Review on Power Consumption Forecasting

Satellite telemetry data forecasting has traditionally employed time series models such as ARIMA and SARIMA. Previous research (Breskvar et al., 2017) demonstrated the efficacy of ARIMA models in accurately predicting power consumption by capturing seasonality and autocorrelation inherent in satellite telemetry data. Stevanoski et al. (2023) further indicated the superiority of SARIMA models, particularly emphasizing their robustness in managing seasonal periodicities common to satellites' power systems. Recent studies also explored advanced machine learning models such as Long Short-Term Memory (LSTM) networks, highlighting their potential in capturing nonlinear relationships within telemetry data (Jin et al., 2023).

### B. Literature Review on Anomaly Detection

Anomaly detection approaches in satellite data analysis range from statistical methods such as rolling Z-score, Isolation Forest, and DBSCAN, to sophisticated deep learning techniques. Isolation Forest, introduced by Liu et al. (2008), has gained significant traction due to its efficiency in isolating anomalies by recursively partitioning data points. Rolling Z-score methods are extensively adopted due to their simplicity and effectiveness in detecting point anomalies over time (Aggarwal, 2015). Jin et al. (2023) highlight the use of clustering-based approaches to anomaly detection, showing improved anomaly classification accuracy in telemetry datasets.

# *III. Methodology*

A. Power Consumption Forecasting

1) Dataset Description and Preprocessing

The dataset consists of telemetry from ESA’s Mars Express Orbiter over three Martian years (2008–2014). Key variables include power line measurements (NPWD2372), timestamps, event logs, and operational commands. Data preprocessing involved:

Converting time-stamps into datetime objects.

Aggregation of hourly telemetry data into daily and monthly intervals.

Outlier detection and handling using median replacement based on Z-score analysis.

Ensuring data stationarity via Augmented Dickey-Fuller tests (ADF) and transformations like logarithmic scaling and differencing.

2) Seasonal ARIMA Model (SARIMA)

The SARIMA model was selected due to its strength in capturing seasonality, trends, and periodicities typical of satellite telemetry data:

**Daily forecasting** employed a weekly seasonal pattern (m=7).

**Monthly forecasting** utilized annual seasonal patterns (m=12).

*Hyperparameter Optimization:*

**Stepwise ARIMA:** Faster, heuristic-driven model selection.

**Grid Search ARIMA:** Comprehensive parameter search (p, d, q) and seasonal (P, D, Q) components for optimized accuracy.

*Evaluation Metrics:*

Root Mean Square Error (RMSE)

Mean Absolute Error (MAE)

Mean Absolute Percentage Error (MAPE)

B. Anomaly Detection

1) Dataset Description and Preprocessing

The same telemetry dataset (MEX, 2008–2014) was utilized. Hourly downsampling was performed to improve computational efficiency. The preprocessing included:

Hourly resampling and missing-value imputation.

Z-score normalization to highlight deviations clearly.

2) Anomaly Detection Models:

Two distinct methods were employed:

**Rolling Z-Score Method:** Calculated on a moving 24-hour window, anomalies detected when the absolute Z-score exceeded 3.5.

**Isolation Forest:** Selected due to its capacity for high-dimensional data, set to a 1% contamination rate.

## Pre-processing and Feature Engineering

This section outlines the detailed methodology adopted to preprocess and engineer meaningful features from the Mars Express Orbiter (MEX) satellite telemetry data, crucial for accurate power consumption forecasting and anomaly detection. The raw telemetry dataset comprises context files—**Detailed Mission Operations Plan (DMOP)**, **Event Timeline (EVTF)**, **Flight Dynamics Timeline (FTL)**, **Solar Aspect Angles File (SAAF)**, and **Long-Term Data (LTDATA)**—as well as direct observation files, primarily power consumption data. These datasets, each capturing unique operational aspects, were methodically processed to derive predictive features reflecting the spacecraft’s behavioral patterns.

1) Data Source and Initial Structure

Telemetry data from the Mars Express Orbiter, provided by the European Space Agency (ESA), spanned approximately three Martian years (2008–2014). Data were initially fragmented into multiple files capturing various telemetry aspects. Each file was meticulously aligned on standardized 15-minute intervals, providing temporal synchronization essential for subsequent analyses and predictive modeling.

2) DMOP (Detailed Mission Operations Plan) Preprocessing

The DMOP file documents operational commands executed aboard the spacecraft. Initially, timestamps recorded as UTC values underwent conversion into Python-compatible datetime objects. Command labels were simplified by truncating the initial four-character subsystem identifiers, enabling effective aggregation into meaningful categories. Data points were subsequently resampled into discrete 15-minute intervals to quantify operational command frequency clearly. Furthermore, co-occurrence metrics between critical subsystem pairs were computed to detect synchronous operational patterns, facilitating insights into interactions influencing power fluctuations.

**Key steps:**

Conversion to standardized datetime.

Aggregation of commands by subsystem category.

Co-occurrence counts to assess subsystem interactions.

3) EVTF (Event Timeline) Preprocessing

EVTF logs discrete event occurrences impacting spacecraft operations, such as eclipses or communication anomalies. Initially, event indicators like "loss of signal (LOS)" and "acquisition of signal (AOS)" were transformed into binary flags representing event occurrences within each 15-minute segment. Events were then synchronized with the standard timeline intervals, with event counts aggregated to reflect the frequency and distribution over time.

**Key steps:**

Extraction of critical event keywords (LOS, AOS).

Conversion to binary presence indicators.

Aggregation into standardized intervals.

4) FTL (Flight Dynamics Timeline) Preprocessing

The FTL files chronicle pointing events altering spacecraft orientation. Raw data with original timestamps (utb\_ms) were converted into datetime objects. Subsequently, spacecraft pointing events such as EARTH (communication), SLEW (transition), and NADIR (science observation) were represented via one-hot encoding to reflect binary occurrences. Each pointing event's occurrence was then aggregated into 15-minute intervals to effectively model spacecraft attitude dynamics over time, critical for correlating attitude shifts with power variations.

**Key steps:**

Conversion of timestamps to datetime.

One-hot encoding for EARTH, SLEW, NADIR events.

Frequency aggregation in standardized intervals.

5) SAAF (Solar Aspect Angles) Preprocessing

SAAF files include angular measurements between spacecraft orientation and solar direction, directly influencing solar energy acquisition. Initially, these angular measurements underwent cosine transformations to reflect more physically meaningful correlations with solar energy availability. Subsequently, data points were resampled to 15-minute intervals, where mean angle values were computed. This facilitated consistent temporal alignment with other telemetry variables, essential for accurate correlation analysis and feature creation.

**Key steps:**

Cosine transformation of solar angles.

Aggregation and resampling into 15-minute intervals.

Computation of mean solar aspect angles per interval.

6) LTDATA (Long Term Data) Preprocessing

LTDATA provides information about the relative positions of celestial bodies (e.g., spacecraft-to-Mars and spacecraft-to-Sun distances), impacting communication latency and solar power availability. These data points were resampled into uniform 15-minute intervals and forward-filled to address missing entries, ensuring continuous temporal alignment across telemetry datasets.

**Key steps:**

Temporal resampling at uniform intervals.

Forward-filling for temporal consistency.

7) Power Data Preprocessing

Power telemetry data, capturing electrical current through thermal power lines (specifically NPWD2372), was converted from raw timestamp measurements into standardized datetime format. Data points were resampled at 15-minute intervals with linear interpolation utilized to address gaps and ensure smooth temporal data continuity. The resulting clean power dataset served as the foundational target variable for power forecasting and anomaly detection models.

**Key steps:**

Timestamp standardization.

Resampling at uniform intervals (15-minute).

Linear interpolation for missing value handling.

8) Feature Engineering

To enhance predictive modeling and anomaly detection effectiveness, multiple domain-driven features were engineered:

*a) Solar Energy Intake Calculation:*

A critical derived feature, **Energy Received**, was calculated to estimate spacecraft solar energy intake. The solar energy flux was modeled by leveraging cosine-transformed solar aspect angles and spacecraft-to-Sun distances from the LTDATA files, using the following formula:

Energy Received=Pmax×cos⁡(θ)(Sun-Mars Distance (km))2\text{Energy Received} = \frac{P\_{\text{max}} \times \cos(\theta)}{(\text{Sun-Mars Distance (km)})^2}Energy Received=(Sun-Mars Distance (km))2Pmax​×cos(θ)​

Where:

PmaxP\_{\text{max}}Pmax​: Maximum theoretical solar power flux available.

θ\thetaθ: Solar aspect angle (spacecraft-Sun orientation angle).

This physically motivated feature directly correlated spacecraft positioning and orientation with observed power consumption fluctuations, enhancing model interpretability and accuracy.

*b) Subsystem Interaction Features:*

Additional interaction-based features quantified concurrent subsystem operations, providing insights into correlated activities impacting power consumption dynamics. For example, simultaneous communication (EARTH pointing) and scientific observations (NADIR pointing) indicated increased energy demands, enabling more precise modeling of power consumption spikes.

*c) Event-Driven Features:*

Event-derived features, such as binary indicators of LOS/AOS occurrences, enabled models to capture transient operational disruptions and their associated power consumption variations. Such events often correlate with sudden power changes due to spacecraft entering eclipses or losing ground station connectivity.

Summary of Feature Engineering:

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| **Feature Type** | **Example** | **Impact on Power Consumption** |
| Solar Angles | Cosine transformed angles | Solar energy availability |
| Solar Energy | Energy Received | Directly affects solar-based power intake |
| Subsystem Events | EARTH, NADIR, SLEW co-occurrences | Energy demands from concurrent subsystem usage |
| Operational Events | LOS/AOS occurrences | Power fluctuations during communication outages or eclipses |

Through meticulous preprocessing and comprehensive feature engineering, a robust and insightful dataset was generated, significantly enhancing the forecasting accuracy of satellite power consumption models and the sensitivity of anomaly detection methodologies.

# *IV. Results*

1. Power Consumption Forecasting

We compared multiple models including Linear Regression, Random Forest, XGBoost, and SARIMA:

**Linear Regression:** Baseline performance was unsatisfactory (low R² scores).

**Random Forest & XGBoost:** Provided better performance but lacked in consistently capturing seasonality.

**SARIMA (Chosen Model):** Achieved optimal performance, effectively capturing daily and monthly seasonalities, as demonstrated by minimal forecasting errors:

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| **Model** | **RMSE** | **MAE** | **MAPE (%)** |
| Daily SARIMA | 0.0375 | 0.0251 | 3.56% |
| Monthly SARIMA | 0.0448 | 0.0312 | 4.22% |

Residual diagnostics indicated minimal autocorrelation, validating the model's effectiveness.

2. Anomaly Detection

Two approaches were employed:

**Rolling Z-score Method:** A statistical approach identifying anomalies based on deviations from rolling averages (detected 250 anomalies aligned with known historical operational anomalies).

**Isolation Forest (Selected Method):** Machine learning method employing tree-based isolation techniques, sensitive to subtle anomalies (detected 310 anomalies). Isolation Forest notably outperformed rolling Z-score, providing early detection capabilities and uncovering previously unidentified operational deviations.

*V. Challenges Faced*

During the project, several significant challenges were encountered, primarily stemming from the inherent complexity and scale of telemetry data from the Mars Express Orbiter (MEX). The main challenges include:

1. Data Integration and Alignment

Integrating multiple telemetry datasets, including DMOP, EVTF, FTL, SAAF, and LTDATA files, presented substantial difficulties due to varying time resolutions, missing timestamps, and inconsistent data formats. Ensuring accurate temporal alignment across these datasets required extensive preprocessing. Any misalignment could potentially lead to misleading patterns, affecting the overall accuracy of power consumption predictions and anomaly detection.

2. Feature Engineering Complexity

Extracting meaningful features to accurately represent operational behavior and energy consumption patterns required in-depth domain knowledge. Crafting suitable transformations such as cosine transformations for solar aspect angles and deriving the spacecraft’s energy intake feature involved extensive experimentation. Identifying effective features and their transformations was iterative and computationally expensive.

3. Stationarity and Seasonality Detection

Determining and ensuring the stationarity of time-series data was critical for the SARIMA model's performance. The Augmented Dickey-Fuller test indicated non-stationarity in raw data, necessitating multiple transformations and differencing steps. Furthermore, accurately identifying and modeling seasonal patterns required rigorous testing to confirm that daily and monthly seasonalities were correctly captured by the SARIMA model.

4. Model Selection and Hyperparameter Tuning

Selecting the optimal models and tuning their hyperparameters involved substantial computational resources and time due to the complexity and scale of the dataset. Grid search and stepwise methods employed for SARIMA model selection proved computationally intensive, especially for the daily dataset, which required balancing between computational efficiency and forecast accuracy.

5. Anomaly Detection Sensitivity

Distinguishing between genuine anomalies and normal operational variations proved challenging. While Isolation Forest demonstrated superior sensitivity compared to rolling Z-score, setting appropriate contamination levels and thresholds was challenging, as excessively sensitive models generated false positives, while overly conservative settings risked missing critical anomalies.

6. Computational Resource Constraints

The computational demand of real-time anomaly detection and comprehensive forecasting was substantial, requiring careful optimization of algorithms and deployment strategies. Dockerization and database orchestration with PostgreSQL partially alleviated these constraints, but scaling for larger data volumes or real-time analytics remains a significant future challenge.

*VI. Future Scope*

This project has laid a strong foundation for further enhancements and expansions. Several promising directions include:

1. Real-Time Data Analytics and Forecasting

Integrating real-time telemetry data streams to enable immediate anomaly detection and dynamic forecasting presents a compelling direction. Real-time analytics can significantly improve operational responsiveness, allowing ESA operators to proactively manage spacecraft operations, extending the orbiter’s operational lifespan.

2. Deep Learning Approaches

Future research can investigate deep learning methodologies such as Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), or Transformer architectures for forecasting and anomaly detection. These methods potentially offer higher predictive accuracy by capturing complex temporal relationships beyond the capabilities of SARIMA or Isolation Forest.

3. Improved Anomaly Detection Techniques

Enhancing anomaly detection methods by employing hybrid or ensemble models—combining Isolation Forest with deep anomaly detection frameworks such as Autoencoders—can provide more robust detection capabilities. Leveraging Extreme Value Theory (EVT) combined with deep learning models, such as GRUs, can dynamically adapt anomaly thresholds and improve sensitivity.

4. Extended Feature Engineering

Exploring additional external factors affecting power consumption—such as detailed subsystem-level command interactions, operational command sequences, and additional astronomical positioning parameters—could yield even greater predictive accuracy. Such enhanced feature engineering can enrich model inputs and improve understanding of spacecraft dynamics.

5. Transfer Learning for Similar Missions

Applying transfer learning methodologies to adapt trained models and analytical frameworks to other space missions could significantly reduce development time and computational resources. Insights and modeling approaches from this study could be generalized and adapted to other ESA missions or comparable telemetry data, accelerating model deployment and efficiency across diverse aerospace projects.

6. Interactive Visualization and Operational Dashboard

Enhancing the developed Streamlit dashboard into a fully interactive decision-support tool for ESA operational engineers is a significant future opportunity. Integrating additional features—such as real-time anomaly alerts, adaptive forecasting intervals, and automated model retraining capabilities—can vastly improve the operational management and decision-making process for mission control teams.

*VII. Conclusion*

This study successfully demonstrated the effective integration of advanced time-series forecasting and anomaly detection methodologies applied to the Mars Express Orbiter telemetry dataset. By employing SARIMA modeling, we accurately predicted spacecraft power consumption with low forecasting errors (daily RMSE: 0.0375, monthly RMSE: 0.0448). Residual analyses verified that seasonal patterns and operational trends were comprehensively captured, indicating robust model performance.

In anomaly detection, the Isolation Forest method notably outperformed the rolling Z-score technique, identifying subtle and critical anomalies, including previously undetected operational deviations. This capability significantly enhances the spacecraft’s operational reliability and reduces potential risks, enabling proactive rather than reactive operational management.

The developed analytical pipeline—comprising extensive feature engineering, rigorous preprocessing, predictive modeling, anomaly detection, and visualization—provides a comprehensive, replicable framework beneficial not only for current Mars Express operations but also adaptable to future space missions.

Although substantial progress has been achieved, challenges such as computational complexity, sensitivity calibration, and real-time integration remain. The identified future research opportunities, including advanced deep learning models, real-time analytics, and transfer learning approaches, promise further enhancements in operational efficiency, anomaly detection accuracy, and overall spacecraft management.

In conclusion, this project significantly contributes to telemetry data analysis methodologies in aerospace engineering, providing practical tools and insights crucial for the continued success and longevity

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