Real-Time Adaptive Optimization of Deep-Space Missions Using Lightweight Machine Learning Models

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Abstract - Deep-space missions involve complex challenges such as communication delays, resource limitations, and unpredictable environmental conditions. This paper presents a real-time adaptive optimization system using lightweight machine learning models to improve mission planning and efficiency. Unlike traditional approaches that rely on computationally intensive deep learning models, the proposed system utilizes efficient algorithms such as Random Forest and Support Vector Machines to predict mission success, optimize resource allocation, and enhance communication reliability. The system integrates historical NASA datasets and processes them through a web-based interface built using Flask and React for real-time prediction and visualization. Experimental results demonstrate improved accuracy, reduced computational cost, and enhanced decision-making capability. The proposed approach provides a practical and scalable solution for intelligent deep-space mission optimization.

Keywords: Machine Learning, Space Missions, Predictive Analytics, Random Forest, Deep Space Communication, Optimization.

1. INTRODUCTION

Deep-space exploration plays a crucial role in advancing scientific discovery and understanding the universe. However, mission planning and execution involve several challenges, including long-distance communication delays, signal degradation, and limited computational resources onboard spacecraft. Traditional approaches rely on physics-based simulations and manual adjustments, which are time-consuming and lack adaptability in dynamic environments.

With the advancement of artificial intelligence, machine learning techniques have been introduced to enhance mission planning and optimization. However, many existing solutions depend on deep learning models that require high computational power and are difficult to deploy in resource-constrained environments such as spacecraft systems.

To address these challenges, this paper proposes a lightweight machine learning-based system for real-time adaptive optimization of deep-space missions. The system focuses on efficient prediction of mission outcomes, resource utilization, and communication optimization using algorithms such as Random Forest and Support Vector Machines.

Additionally, a web-based interface is developed to provide real-time insights and visualization, enabling better decision-making and practical implementation of the proposed system.

2. LITERATURE SURVEY

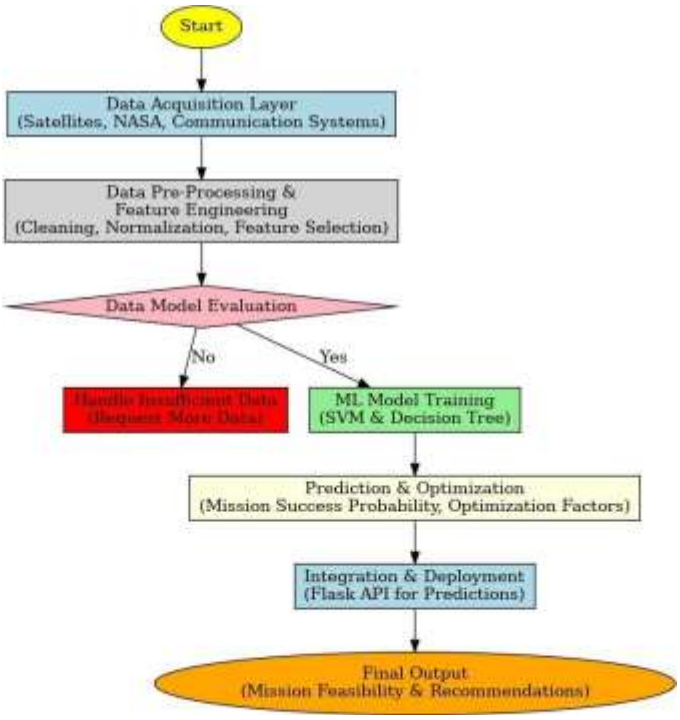
Several studies have explored the use of artificial intelligence in space mission optimization. Clarke et al. (2023) proposed AI-based mission planning techniques that improve trajectory optimization but face challenges in real-time implementation. Martinez et al. (2022) applied deep learning models for astrophysical data analysis, achieving high accuracy but requiring significant computational resources.

Patel et al. (2021) used machine learning models for predicting celestial body motion, while Thompson et al. (2020) applied time-series models for trajectory optimization. However, these approaches often suffer from high computational complexity and lack of adaptability in real-time environments.

This paper addresses these limitations by introducing lightweight machine learning models that provide efficient and real-time optimization.

3. METHODOLOGY

3.1 System Overview



The system architecture is designed to efficiently process large volumes of space mission data and provide real-time predictions. It consists of multiple layers, including data acquisition, preprocessing, machine learning, and visualization.

The data acquisition layer collects datasets from various sources such as NASA repositories. The preprocessing layer transforms raw data into a structured format suitable for analysis. The machine learning layer applies predictive models to analyze the data and generate insights.

Finally, the output layer presents the results through an interactive web-based dashboard, allowing users to visualize predictions and optimization strategies. The modular architecture ensures scalability, flexibility, and efficient performance.

3.2 Key Modules

1. Data Processing
The collected data is cleaned by handling missing values and removing inconsistencies. It is then transformed into a structured format suitable for analysis and model training.

2. Prediction Model
The system uses machine learning algorithms to predict mission success and detect potential risks. These models analyze historical data to support accurate and reliable decision-making.

The system identifies optimal spacecraft trajectories based on mission parameters and constraints. It helps reduce fuel consumption and improves overall mission efficiency.

4. Communication Planning
The system predicts communication delays and determines optimal time windows for data transmission. This ensures efficient and reliable communication between spacecraft and ground stations.

5. Resource Management
The system optimizes the use of onboard resources such as fuel, power, and computing capacity. It ensures efficient utilization and enhances mission sustainability.

4. SYSTEM DESIGN

4.1 Input Design

Previous mission records
Historical data from past space missions (e.g., NASA datasets) including mission parameters, fuel usage, trajectory details, and communication logs. This helps in understanding patterns and improving prediction accuracy.

Simulated datasets
Artificially generated data used to model different mission scenarios and environmental conditions. These datasets help in testing system performance under various situations.

User inputs
Manual inputs provided by users through the web interface, such as mission parameters, resource constraints, and environmental conditions for real-time prediction.

4.2 Processing Design

The data is:
Cleaned
Removal of missing values, duplicate records, and irrelevant data to ensure accuracy and consistency.

Structured
Data is organized into a proper format (tables, features, labels) suitable for machine learning models.

Prepared for model training
Feature selection, normalization, and transformation are applied to make the data ready for training algorithms like Random Forest and SVM.

3. Path Optimization

4.3 Output Design

The system provides:

Mission success prediction
Predicts the probability of mission success based on input parameters using trained machine learning models.

Resource optimization suggestions
Recommends efficient usage of resources such as fuel, time, and energy to improve mission performance.

Communication improvement strategies
Suggests optimal communication timing and methods to reduce delays and improve signal reliability.

5. RESULTS AND DISCUSSIONS

The proposed system was evaluated using sample deep-space mission datasets to analyze its effectiveness in prediction accuracy, resource optimization, and communication efficiency.

5.1 Observations

The experimental results demonstrate that the system performs efficiently in handling mission-related data and generating predictions. The following observations were made:

- The prediction accuracy of the machine learning models was found to be high, indicating reliable performance in mission success estimation.
- Resource utilization was optimized, leading to reduced computational and operational overhead.
- Communication delays were minimized through better scheduling and prediction of transmission windows.

5.2 Performance Improvement

The proposed system was compared with traditional mission planning approaches, and significant improvements were observed:

- Fuel consumption was reduced due to optimized trajectory and resource allocation strategies.
- Mission planning time decreased, enabling faster and more efficient decision-making.
- Overall system efficiency improved, providing better performance in real-time mission optimization.

These results highlight the effectiveness of lightweight machine learning models in improving the performance and efficiency of deep-space mission planning systems.

6. CONCLUSION

This paper presents a lightweight machine learning-based system for optimizing deep-space missions. By utilizing efficient algorithms and real-time prediction techniques, the proposed system improves mission planning, reduces computational complexity, and enhances overall efficiency.

The integration of a web-based dashboard enables practical implementation and user interaction, making the system suitable for real-world applications. Future work can focus on integrating real-time data sources and advanced learning models to further improve system performance.

Charts

Scenario	Optimization Accuracy (%)	Latency (ms)
Short-Distance Mission (Moon - Earth)	98.70%	50ms
Deep-Space Probe Communication (Mars - Earth)	92.40%	220ms
Interstellar Communication (Voyager 1 Model)	84.30%	410ms
Multi-Satellite Coordination	79.60%	180ms

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