School of Computational and Data Sciences

Optimization Techniques for Data Science

[MATH301]

Optimized Power Management for Space Stations

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Abstract

The power management of space stations including the International Space Station (ISS) must achieve efficient usage of solar energy to sustain operations in space. with increasing operational demands. This paper examines existing power generation tools together with energy storage methods and distribution networks and recommends an advanced EMS system. The advanced energy management system (EMS) contains PV arrays together with Battery Energy Storage Systems (BESS) integrated for unified operation. Systems (BESS), and AI-driven optimization.

The system uses real-time modelling together with priority-based load control and fault-aware scheduling and mixed-integer linear programming. MILP serves as a mathematical optimization method together with linear programming to achieve optimal power allocation. MATLAB/Simulink conducts simulations to show how the approach operates under authentic orbital settings when fault conditions exist. The EMS proposal delivers between 10 and 15% conservation of energy while maintaining all critical operations at 100% uptime. The critical system durability reaches 100% by implementing new methods which overcome problems such as orbital eclipse cycles and battery degradation.

1. Introduction

These stations conduct operations in difficult conditions that need durable power management systems. Life support operations and scientific testing and communication systems find their power source in this system.

Energy production from the ISS takes place through eight solar arrays with a peak generating capacity of 120 kW which are then stored in lithium-ion batteries that reach a total capacity of 48 kWh. The system stores its power in batteries with 48 kWh capacity but faces problems from orbital changes that result in 90-minute cycles and 45-minute distinct periods.

The combination of ~45-minute-eclipses generates issues alongside battery deterioration and increasing power requirements in the range of 30-90 kW. (1; 7). Mission plans to explore the Moon and Mars need sustainable power systems which can also tolerate failures. This document evaluates existing ISS power systems through a detailed examination which then goes on to introduce an AI-enabled EMS.

We develop an optimization problem to achieve maximum efficiency and reliability by integrating hybrid power systems with AI, in this research. The system enhances reliability by integrating predictive modelling together with the data science techniques and optimized by MILP for better efficiency.

2. Literature Review

This study benefits from new developments in space power management systems.

Solar Power Utilization is the ISS achieves its range of power output from 84 to 120 kW using the eight solar arrays which orient toward the Sun to boost efficiency. Power availability fluctuates due to eclipse periods, The output efficiency drops by approximately 60 kW on average according to the report (p. 12).

Energy Storage Technologies is the ISS made a technology upgrade from nickel-hydrogen batteries to lithium-ion batteries in 2017. Lithium-ion batteries introduced their capacity to 48 kWh with a 95% round-trip efficiency and 80% depth of discharge in 2017 and 80% depth of discharge. The development of new battery technology includes solid-state batteries alongside flywheels. Flywheels promise higher efficiency (3; 10, p. 25).

Microgrid and Load Management is the ISS maintains operational status through its microgrid system along with distributed management capabilities. Smart load distribution within the ISS network follows procedures for critical life support system management. Redundancy ensures fault tolerance (2, p. 8).

Automation and AI is the AI-based algorithms that NASA employs for predictive load. It acquired 5–10% power savings when demonstrated through simulated operations by management systems (8; 11, p. 15). Real-time adaptability gets its improvements from combination of anomaly detection methods with reinforcement learning capabilities.

Hybrid Energy Solutions is the Radioisotope Thermoelectric Generators (RTGs) and Satellite operations in deep space use nuclear fission technology through Kilo power (1–10 kW) to back up solar power during eclipses (4, p. 30).

This foundation will help establish the proposed EMS by combining AI with hybrid systems for its implementation.

3. Literature Survey

The recent research produces the following main discoveries that Microgrid Technology is the ISS implements microgrid technology which unites PV arrays with BESS alongside load controllers to reach 99.9% reliability through redundancy (2; 9, pp. 10, 45). The implementation of redundant technologies including load controllers brings about 99.9% reliability in the ISS infrastructure (2; 9 pp. 10 45).

Load Control Strategies is an Artificial Intelligence-driven management system that implements a load shedding procedure that determines essential operational systems. The simulation results demonstrate that load outages could be reduced by 20% through this approach (5, p. 112). Dynamic algorithms adapted the system, this shows an ability to handle sudden power demand increases (for example 10 kW from experimental tests).

Hybrid Power Systems that include RTGs function nonstop at power ranges between 100 to 300W to strengthen solar power generation during periods when the Earth blocks the sunlight. The capability for adjustable power outputs exists in nuclear systems although they have regulatory barriers to overcome regulatory hurdles (4; 12, pp. 32).

The AI Optimization articles based on Reinforcement Learning help EMSs achieve 95% precision in predicting system loads and irradiance levels optimizing SoC management (11, p. 18).

4. Methodology

We propose an EMS which carries out real-time power distribution optimization by applying AI-driven load control together with fault-aware scheduling along with real-time modelling. Control systems and fault-aware scheduling generate simulation results using MATLAB/Simulink.

4.1 Real-Time Solar PV and BESS Modelling

The input layer models solar irradiance (0–1366 W/m2). Detailed modelling of ISS orbital parameters generates the system input through 90-minute orbital cycles and 45-minute periods of space station eclipse. Uses LSTM for time-series forecasting (95% accuracy) (11).

The PV output simulation through the Energy Generation Module undergoes adjustments to produce results between 84 kW and 120 kW. solar incidence angles and gimbal efficiency (90%) (1). While BESS Subsystem models like lithium-ion batteries (48 kWh, 95% efficiency) with the storage system exhibit 0.1% capacity degradation during each cycle while operating between 0 and 40 degrees Celsius (3).

$$SoC(t+1) = SoC(t) + \eta_{ch} \cdot P_{ch}(t) - \frac{P_{dis}(t)}{\eta_{dis}}$$

Fig: SoC dynamics

4.2 Priority-Based Load Distribution Engine

Dynamic SoC Control replaces static thresholds (¿80%, 40–80%, ¡40%) with RL-optimized thresholds (Q-learning, 10% efficiency gain) (5). Policies adapt to mission priorities and battery health. Later the system organizes load types into critical and noncritical categories with life support ranked at 20 kW and experiments requiring 10–70 kW power consumption. RL ensures critical loads maintain 100% uptime. Then binary-encoded signals enable the control logic to automatically switch loads through a system that reduces delays to less than one millisecond. (1 Ms).

4.3 Fault-Aware Energy Scheduling

The Recognition Layer that Employs Isolation Forest for anomaly detection (e.g., PV degradation, battery faults), achieves 98% precision (11). The Diagnosis Engine detects root causes through a system of rule-based logic structures which enables identification of problems such as 20% PV output loss. Next, the Action Scheduler allocates power through MILP to cut critical loads during faults such as reducing them by 50% (6).

4.4 MATLAB/Simulink Implementation

This simulation inputs solar irradiance from 0–1366 W/m2, 90-minute cycle. The simulation requires two load profiles from 30 to 90 kilowatts but with moments of ten-kilowatt spikes. The battery system features 48 kWh capacity and a 20kW charge/discharge capacity with capacity that reduces by 0.1% every cycle.

Scenarios maintenance Parameters like the system performs orbital cycles that use multiple levels of electrical loads. Faults are 20% PV degradation, 10% battery capacity loss.

Validation Metrics, SoC stability: ±5% deviation. The system provides complete efficiency in maintaining critical load uptime during load shedding events. It saves energy nearly 10–15% vs. static thresholds. Fault recovery time is 5 seconds.

5. Optimization Problem Formulation

5.1 Problem Description

This energy management system (EMS) determines how solar photovoltaic (PV) arrays and Battery Energy Storage Systems (BESS) would distribute power based on time-dependence. The energy management system functions to distribute power between solar photovoltaic arrays as well as Battery Energy Storage Systems to fulfill time-dependent load requirements of a space station. The system aims to maximize power efficiency through its operations. No power interruptions are tolerated for critical systems (such as life support) throughout orbital eclipse periods (45-minute sunlight, 45-minute eclipse), battery dynamics, load priorities, and fault scenarios (e.g., PV degradation). The optimization process depends on mixed-integer linear programming models (MILP) for optimization and long short-term memory (LSTM) models for forecasting. The system has been designed to adjust power generation capabilities with load demands in order to offer flexible operation.

5.2 Notation

The sequential timeline consists of distinct time points t which take values in {1, 2, . . . , T}. The time span T equals 90 minutes for one orbit around the ISS. , T}, where T = 90 minutes (one ISS orbit).

Power Generation: Solar PV power output named PP V (t) at time t (kW) receives forecast values through an LSTM network while its range falls between 0 kW (eclipse) and 120 kW (sunlight) (11), from 0 kW (eclipse) to 120 kW (sunlight) (11).

Battery Parameters:

– SoC(t) Battery state of charge at time t (kWh).

– Cmax: Battery capacity, 48 kWh (1).

– Pch(t): Battery charge power at time t (kW).

– Pdis(t): Battery discharge power at time t (kW).

– ηch: Charge efficiency, 0.95 (3).

– ηdis: Discharge efficiency, 0.95 (3).

– SoCmin: Minimum SoC, 9.6 kWh (20% of capacity) (3).

– SoCmax: Maximum SoC, 48 kWh (100% of capacity) (3).

– Pch,max: Maximum charge rate, 20 kW (1).

– Pdis,max: Maximum discharge rate, 20 kW (1).

Load Demands: The power demand value of load i during time t equals kW through microscopic index i belonging to the set {1, 2, . . . , N} (3). , N} (e.g., Life support requires 20 kW power along with experiments demanding power between 10 and 70 kW while both are modeled through LSTM (11). Where πi : Priority of load i, where πi = 1 for critical loads and πi = 0.5 for noncritical loads (5). The binary decision variable xi(t) has a value of 1 when load i receives power during time t and xi(t) = 0 otherwise.

Fault Parameters: The fault indicator F(t) takes a value of one when a fault occurs such as PV degradation and F(t) = 0 otherwise. Here α(t): PV efficiency reduction due to fault, where α(t) ∈ [0, 1] (e.g., α(t) = 0.2 for 20% output loss) (6).

5.3 Objective Function:

The optimization seeks to eliminate wasted energy which represents power both not used and not stored prioritize critical loads

Formula

$$J = \sum_{t=1}^{T} \left[w_1 \left(P_{PV}(t) + P_{dis}(t) - \sum_{i=1}^{N} x_i(t) L_i(t) - P_{ch}(t) \right)^2 + w_2 \sum_{i=1}^{N} (1 - x_i(t)) \, \pi_i L_i(t) \right]$$

First term, the first component function minimizes the squared deviations between PV power and system loads. The operational difference between power availability from PV alongside discharge battery capacity and active power usage for loads and battery charging operates at reduced levels.

Second term, the penalty system during the second term increases proportionally to the importance of critical unpowered loads. The values of πi set to 1 guarantee the highest priority for critical loads. The weights have been adjusted to w1 = 0.6 and w2 = 0.4 for balancing power efficiency and system reliability according to ISS operational research (5), on ISS operational studies (5).

5.4 Constraints

Power Balance, $P_{PV}(t)(1 - F(t)\alpha(t)) + P_{dis}(t) = \sum_{i=1}^{N} x_i(t)L_i(t) + P_{ch}(t), \ \forall t \in \{1,2,...,T\}$ ensures that power from PV (adjusted for faults) and battery discharge equals the power consumed by loads and used for charging.

Battery Dynamics, $SoC(t+1) = SoC(t)+\eta_{ch}P_{ch}(t) - \frac{P_{dis}(t)}{\eta_{dis}}, \ \forall t \in \{1,2,...,T-1\}$ Models the evolution of battery state of charge, accounting for charge and discharge efficiencies.

Battery Limits, $9.6 \leq SoC(t) \leq 48, \ \forall t \in \{1,2,...,T\}$ $0 \leq P_{ch}(t) \leq 20, \ \forall t \in \{1,2,...,T\}$ $0 \leq P_{dis}(t) \leq 20, \ \forall t \in \{1,2,...,T\}$ Ensures SoC stays within safe limits (20%–100%) and charge/discharge rates do not exceed battery specifications.

Load Constraints, $x_i(t) \in \{0,1\}, \ \forall i \in \{1,2,...,N\}, \ \forall t \in \{1,2,...,T\}$

$x_i(t) = 1, \ \forall t \in \{1,2,...,T\}, \ \forall i$ where $\pi_i = 1$ Ensures load decisions are binary and critical loads are always powered (if feasible).

Fault Response,

$$\sum_{i:\pi_i<1} x_i(t)L_i(t) \leq 0.5 \sum_{i:\pi_i<1} L_i(t), \quad \forall t \in \{1,2,\ldots,T\} \text{ where } F(t) = 1$$

Limits non-critical load power to 50% of their total demand during fault conditions, preserving energy for critical systems (5).

5.5 Implementation

The predictive model utilizes an LSTM model to forecast $P_{PV}(t)$ (0–120 kW) along with $L_i(t)$ (30–90 kW). The model achieves 95% accuracy when predicting $P_{PV}(t)$ (0–120 kW) and $L_i(t)$ (30– 90 kW) using ISS power data such as solar irradiance and load profiles, (11).

Optimization Solver, the MILP solver uses intlinprog from MATLAB and Gurobi from Python for its operation with the inputs $P_{PV}(t)$: LSTM-predicted PV output, 0–120 kW. The LSTM model predicts load demands within the $L_i(t)$ range from 30 to 90 kW total and the total predicted load demands sum to 120 kW. $SoC(1)$: Initial SoC, e.g., 38.4 kWh (80%).

Battery parameters, $C_{max} = 48$ kWh, $\eta_{ch} = \eta_{dis} = 0.95$, $P_{ch,max} = P_{dis,max} = 20$ kW. MATLAB/Simulink simulates orbital cycles involving 45-minute sunlight (1366 W/m2), 45-minute eclipse (0 W/m2). And fault scenarios have 20% PV degradation ($\alpha(t) = 0.2$), 10% battery capacity loss. Load profiles: The simulation model incorporates experimenting-induced 10 kW spikes inside 30 to 90 kW load profiles.

Validation, Monte Carlo simulations (1000 runs) assess the validation confirms SoC accuracy through 1000 Monte Carlo simulations. The system maintains a power state of charge stability which stays within a ±5% range of the specified target value. Critical load uptime to 100%. Energy savings implementation yields energy savings between 10 and 15 percent compared to traditional static SoC threshold strategies (5). Fault recovery time is less than 5 seconds

5.6. Expected Outcomes

Our system uses dynamic SoC which helps save energy between 10 to 15 percent than conventional constant SoC threshold strategies thresholds (¿80%, 40–80%, ¡40%) (5). Ensures 100% uptime for critical loads during nominal and fault conditions. Integrating LSTM enables the system to automatically handle orbital changes and system faults including forecasts and MILP optimization.

6. Discussion

The EMS leverages data science techniques (LSTM) to enhance forecasting accuracy for dynamic conditions.The application of RL demonstrates better SoC threshold performance compared to fixed techniques (5). MILP Balances efficiency and reliability, scalable to deep-space missions. Anomaly Detection ensures fault tolerance, critical for long-term operations.

The computational complexity of the system exists as one of its primary limitations through which MILP requires ~0.1 seconds to solve at each step. and reliance on accurate forecasts. Additional research needs to examine how to assimilate nuclear components with such systems. real-time hardware testing.

7. Conclusion

The proposed EMS increases space station power management efficiency through a system which delivers major improvements in energy conservation and operational reliability. energy savings and reliability. The system incorporates AI along with predictive modeling and MILP to achieve its operations. The system addresses present ISS demands as it establishes essential components required for upcoming mission needs.

8. References:

[1] NASA ™., et al-ISS Power System Overview, 220087. 2018, p. 12.

[2] Jones, R., et al. Intelligent Load Management for Space Applications. AIAA Journal, 2019, pp. 8–10.

[3] Smith, L., et al. Emerging Energy Storage Technologies for Space Exploration. IEEE Transactions on Aerospace, 2020, pp. 25–30.

[4] Brown, T., et al. Hybrid Power Systems for Space Missions. NASA TM-2020-221234, 2020, pp. 30–32.

[5] Herwald, E., et al. Development of a Load Control Algorithm to Enhance Energy Sustainability for the ISS. Old Dominion University, 2021, pp. 112–115.

[6] Dolce, J. L., et al. Automated Electric Power Management for Space Station Freedom. NASA TM-1990-102345, 1990, p. 10.

[7] Savoy, M., Miller, T., et al. ISS Electrical Power System: Operational Lessons Learned. NASA TM-2002-211678, 2002, p. 15.

[8] NASA ™.,et al. Space Electric Power System Automation,-103151 1989, p. 15.

[9] Kuzlu, M., et al. Modeling and Simulation of the ISS Electrical Power System. Wiley, 2021, pp. 45–50.

[10] Lee, S., et al. Solid-State Batteries for Space Applications. Journal of Power Sources, 2023, pp. 20–25.

[11] Zhang, Y., et al. AI-Driven Power Optimization for Space Missions. IEEE Aerospace Conference, 2024, pp. 18–22.

[12] NASA., et al. Kilopower Project Report, 2022, pp. 10–15.