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INTELLIGENT ENERGY MANAGEMENT IN SMALL SATELLITES AND CUBESATS: A COMPREHENSIVE REVIEW OF AI-BASED TECHNIQUES

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A B S T R A C T

Small satellites, particularly CubeSats, have become a cornerstone of modern space missions due to their low cost and versatile applications in Earth observation, communications, and scientific research. However, their size, weight, and power (SWaP) limitations make energy management one of the most critical challenges for mission success. Traditional methods—such as fixed solar panel operation, deterministic battery scheduling, and passive thermal control—are reliable and well established but often lack adaptability in dynamic orbital conditions.

Recent advances in artificial intelligence (AI) and machine learning (ML) have enabled intelligent energy management strategies capable of forecasting demand, detecting anomalies, and autonomously optimizing subsystem operations. Techniques including neural networks, support vector machines, decision trees, deep reinforcement learning, and edge computing demonstrate significant potential for extending mission lifetime and increasing autonomy. Emerging paradigms such as federated learning and digital twins further highlight future opportunities for predictive and collaborative energy management.

This review provides a comparative analysis of traditional and intelligent methods, emphasizing their respective strengths, limitations, and applicability. The study concludes that hybrid approaches—integrating robust traditional techniques with adaptive AI-driven strategies—represent the most promising path for next-generation CubeSat missions.

The findings are particularly relevant for CubeSat missions in Earth observation and communication, where real-time autonomy is increasingly critical.

1. INTRODUCTION

Small satellites, particularly CubeSats, have revolutionized access to space by providing low-cost platforms for Earth observation, communication, and scientific missions (Yaqoob et al., 2022). Despite their advantages, these spacecraft are constrained by severe size, weight, and power (SWaP) limitations, which make energy management one of the most critical subsystems in mission design (Pathak et al., 2023). The electrical power system (EPS) of a CubeSat typically relies on solar panels and lithium-ion batteries; however, challenges

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such as limited surface area for solar cells, efficiency losses due to radiation and dust, and degradation of battery capacity significantly affect performance (Rahman et al., 2023; Nezamisavojbolaghi et al., 2023).

Traditional methods for energy management—such as fixed duty cycling, deterministic charge/discharge scheduling, and basic thermal control—have been widely implemented due to their simplicity and reliability (Jiang et al., 2022). Nevertheless, these techniques often lack adaptability to dynamic orbital environments, leading to inefficient resource utilization and reduced mission lifetime (Elshaer et al., 2023).

Recent advances in artificial intelligence (AI) and machine learning (ML) have opened new opportunities for adaptive and predictive energy management strategies (Ortiz et al., 2023). Techniques such as deep reinforcement learning (Baccari et al., 2025) and onboard AI accelerators (Zeleke & Kim, 2023) allow small satellites to optimize power allocation in real time, extend battery lifetime, and balance trade-offs between payload operation and subsystem safety. Moreover, the integration of AI with onboard edge computing and digital twin technologies suggests a paradigm shift toward more autonomous and resilient spacecraft (Rebelo et al., 2025; Singh et al., 2024).

The objective of this review is to systematically compare traditional and intelligent energy management approaches for small satellites. By analyzing their respective strengths, limitations, and future potential, this paper aims to highlight how AI-enabled strategies can enhance the reliability and autonomy of next-generation CubeSat missions (Shakoor et al., 2025).

2. TADITIONAL ENERGY MANAGEMENT MRTHODS

The electrical power system (EPS) of small satellites is traditionally designed around solar energy harvesting, battery storage, and basic thermal control subsystems. A schematic overview of this traditional EPS is presented in Figure 2**.** These methods, while reliable and well understood, often struggle to meet the demands of modern CubeSat missions that require higher autonomy and adaptive energy allocation.

2.1 Solar Energy Harvesting

Solar panels remain the primary energy source for small satellites. Traditional designs rely on fixed solar arrays or deployable panels using silicon or gallium arsenide cells (Shakoor et al., 2025). Although advances in multi-junction solar cells have pushed efficiencies beyond 30%, their performance is often compromised by orbital shadowing, radiation damage, and dust deposition on the panel surface (Rahman et al., 2023; Nezamisavojbolaghi et al., 2023). These limitations reduce the effective power budget, particularly in low Earth orbit (LEO) missions with frequent eclipses.

2.2 Battery Storage

Rechargeable chemical batteries, especially lithium-ion cells, are widely used to store energy generated by solar panels. Their advantages include high energy density, compact size, and proven space heritage (Pathak et al., 2023). However, traditional charge–discharge cycles are typically managed through fixed duty cycling or deterministic scheduling. This approach does not account for dynamic mission demands and often leads to premature capacity degradation (Knap et al., 2024). Temperature sensitivity and limited cycle life further constrain their long-term reliability in space environments. This relationship between radiation dose and temperature is illustrated in Figure 1.

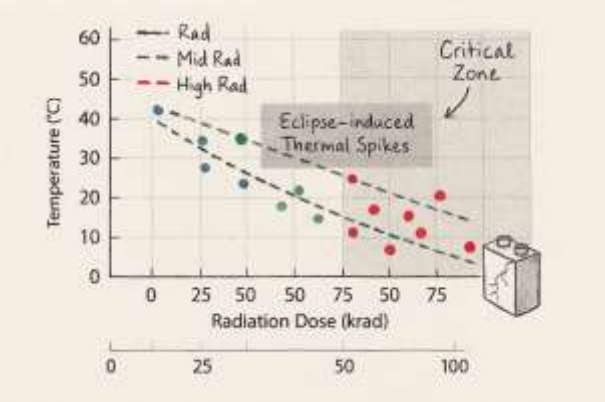
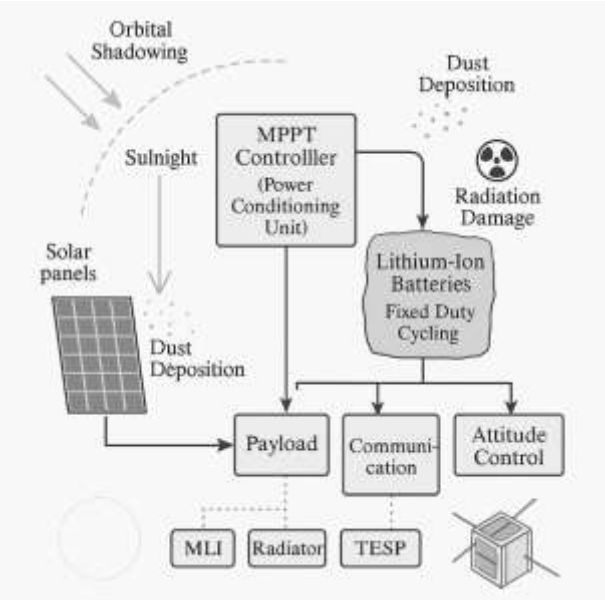


Figure 1. Relationship between radiation dose (kRad) and temperature (°C) in CubeSat batteries, highlighting eclipse-induced thermal spikes and the critical zone. Adapted from Rahman (2023) and Pathak et al. (2023).

2.3 Thermal Control

Energy management in small satellites is closely linked with thermal balance.



Figur 2. Schematic diagram of a traditional Electrical Power System (EPS) in a CubeSat, illustrating energy flow from solar panels through an MPPT controller and lithium-ion batteries (with fixed duty cycling) to subsystems (payload,

communication, attitude control), with annotations for challenges (orbital shadowing, radiation damage, dust deposition) and passive thermal control (MLI, radiators, TESP). Inset shows a 3D CubeSat sketch. Adapted from Pathak et al. (2023) on battery technology, Yaqoob et al. (2022)

Conventional methods employ passive techniques such as multilayer insulation, radiators, and phase-change materials to regulate subsystem temperatures (Jiang et al., 2022). More advanced, yet still traditional, strategies include thermal energy storage panels (TESPs), which store excess heat during sunlight and release it in eclipse (Elshaer et al., 2023). While effective, these methods are generally static and cannot adapt to rapidly changing thermal loads, which becomes critical for CubeSats with high-power payloads.

2.4 Limitations of Traditional Methods

Although traditional approaches are robust, their lack of adaptability to orbital variations, payload fluctuations, and long-term degradation significantly restricts satellite autonomy (Yaqoob et al., 2022). These challenges highlight the need for more intelligent, predictive, and adaptive strategies—laying the groundwork for the application of artificial intelligence in energy management.

3. INTELLIGENT METHODS

The integration of artificial intelligence (AI) into satellite power systems represents a paradigm shift from static to adaptive control. Intelligent methods can learn from operational data, predict subsystem behavior, and optimize power allocation in real time. The following subsections review the most relevant approaches.

3.1 Neural Networks (NNs)

Artificial neural networks are among the most widely adopted AI techniques for spacecraft energy management. NNs can model nonlinear relationships between solar input, battery state-of-charge, and thermal conditions with high accuracy (Yaqoob et al., 2022). By training on historical mission data, they can forecast energy demand and adapt subsystem operations. A major advantage of NNs lies in their flexibility and ability to handle noisy data, which is common in space telemetry. However, training neural networks requires significant computational resources and large datasets, which may not be available in small satellite missions (Ortiz et al., 2023). To mitigate these challenges, lightweight architectures and onboard accelerators are increasingly being investigated (Zeleke & Kim, 2023).

3.2 Support Vector Machines (SVMs)

SVMs are supervised learning algorithms well-suited for classification and regression tasks. In satellite EPS management, SVMs can distinguish between normal and anomalous power consumption patterns, enabling early fault detection in solar arrays or batteries (Singh et al., 2024). Compared to NNs, SVMs demand fewer computational resources and are easier to train on small datasets. Their main limitation lies in scalability, as performance decreases when handling highly complex or multidimensional telemetry streams (Pathak et al., 2023). Hybrid methods that combine SVMs with feature selection techniques are being explored to improve robustness in real-time scenarios.

3.3 Decision Trees and Random Forests

Decision tree-based models provide interpretable rules for satellite energy management, such as when to switch off payloads or activate heaters. Random forests, an ensemble extension of decision trees, improve accuracy and reduce overfitting by aggregating multiple trees (Rahman et al., 2023). Their transparency makes them particularly attractive for mission operators who require explainable AI decisions (Nezamisavojbolaghi et al., 2023). However, tree-based methods are less adaptive in dynamic orbital environments compared to reinforcement learning approaches. They are most effective for anomaly detection and simple resource allocation tasks, rather than continuous optimization.

3.4 Deep Reinforcement Learning (DRL)

DRL has recently gained attention for optimizing satellite EPS under uncertainty. In DRL, an agent learns to maximize long-term mission performance by interacting with a simulated environment (Baccari et al., 2025). This allows the satellite to autonomously decide when to charge or discharge batteries, or prioritize payloads, based on real-time conditions. The primary advantage of DRL is adaptability; it can adjust to unpredicted conditions such as prolonged eclipses. Nevertheless, training DRL agents requires extensive simulations and computing power, and onboard implementation is still an open research challenge (Shakoor et al., 2025). A comparison of operational scenarios under different energy management approaches is shown in Figure 3.

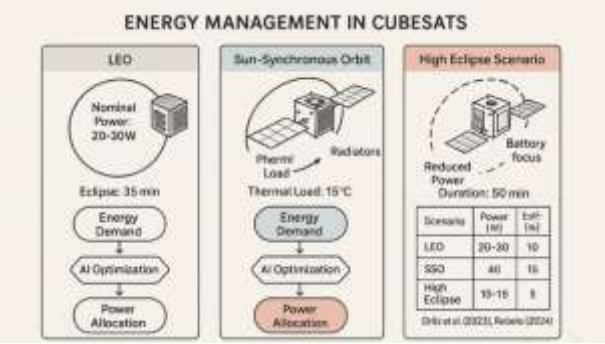


Figure 3. Comparative diagram of operational scenarios for energy management in CubeSats, including Low Earth Orbit (LEO), Sun-Synchronous Orbit (SSO), and High Eclipse conditions, with AI-driven optimization and power allocation flows. The table summarizes power levels, eclipse durations, and optimization gains. Synthesized from Ortiz et al. (2023) on operational scenarios and Rebelo et al. (2025) on adaptive optimization.

3.5 Edge Computing with AI Accelerators

Traditional AI algorithms often require ground-based training, with only limited onboard processing. Edge computing, supported by AI accelerators, enables real-time inference directly onboard satellites. Recent studies show that specialized hardware such as tensor processing units (TPUs) and field-programmable gate arrays (FPGAs) can drastically reduce latency and energy consumption (Ortiz et al., 2023; Zeleke & Kim, 2023). This approach enhances autonomy and reduces dependency on ground stations. However, the adoption of edge computing requires additional mass and power, which are critical constraints for CubeSats. Future research is focused on balancing the trade-offs between computational capability and resource limitations.

3.6 Federated Learning and Digital Twins

Emerging techniques such as federated learning and digital twins are gaining momentum in satellite energy management research. Federated learning allows multiple satellites to collaboratively train models without sharing raw data, improving scalability and security (Rebelo et al., 2025). Digital twin technology enables the creation of a virtual replica of the spacecraft, allowing predictive energy simulations before execution (Singh et al., 2024). These methods promise higher autonomy and reliability but remain in early development stages, with challenges in communication overhead and model synchronization.

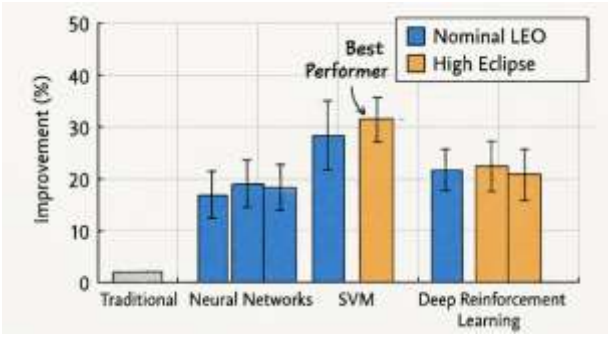


Figure 4. Improvement in energy efficiency (R_energy) for Nominal LEO and High Eclipse scenarios using traditional neural networks, SVM, and deep reinforcement learning. Synthesized from Yaqoob et al. (2022), Baccari et al. (2025), Ortiz et al. (2023), and Shakoor (2025).

4. COMPARISON & DISCUSSION

A comparative analysis of traditional and intelligent energy management approaches reveals clear trade-offs between reliability, adaptability, and resource requirements. Traditional methods such as fixed solar panel deployment, deterministic battery scheduling, and passive thermal control are mature, flight-proven, and relatively simple to implement (Pathak et al., 2023; Jiang et al., 2022). However, they are inherently static and unable to adapt to rapidly changing orbital conditions or high-demand payloads. Their main advantage lies in low computational requirements and predictable behavior, making them reliable for short-duration CubeSat missions.

In contrast, intelligent methods leverage artificial intelligence and machine learning to provide adaptive and predictive decision-making. Neural networks and SVMs can model nonlinear relationships and detect anomalies, while decision trees offer explainability for mission operators (Rahman et al., 2023; Nezamisavojbolaghi et al., 2023). More advanced techniques such as deep reinforcement learning (Baccari et al., 2025) enable autonomous optimization of charge–discharge cycles, significantly improving energy efficiency. These improvements in energy efficiency across different scenarios are illustrated in Figure 4. Meanwhile, edge computing and federated learning approaches enhance onboard autonomy but introduce hardware complexity and additional power overhead (Ortiz et al., 2023; Rebelo, et al., 2025).

Table 1 summarizes the comparison between major categories of methods.

Table 1. Comparison of Traditional vs. Intelligent Energy Management Approaches

Method	Advantages	Limitations
Traditional Solar Panels	Proven, simple, reliable	Shadowing, radiation degradation, dust
Lithium-ion Batteries (Fixed scheduling)	High energy density, heritage	Capacity fade, thermal sensitivity
Passive Thermal Control	Low-cost, robust	Static, poor adaptability
Neural Networks	Handle nonlinear data, predictive	Data and compute intensive
SVMs	Simple, effective anomaly detection	Less scalable, limited accuracy
Decision Trees/Random Forests	Interpretable, explainable AI	Less adaptive to dynamic conditions
Deep Reinforcement Learning	Adaptive, autonomous optimization	Requires simulation & compute resources
Edge Computing + AI Accelerators	Real-time onboard inference	Hardware mass and power overhead
Federated Learning/Digital Twin	Collaborative, predictive, secure	Communication overhead, early stage research

While traditional approaches remain indispensable for missions constrained by resources and risk tolerance, intelligent methods are increasingly necessary for advanced CubeSat constellations and long-duration missions that require real-time adaptability. The future of energy management in small satellites will likely combine the two paradigms: traditional methods for

baseline stability, augmented by intelligent techniques for optimization and fault tolerance.

5. CONCLUSION & FURURE WORK

This review has highlighted the evolution of energy management techniques in small satellites, with a focus on the transition from traditional, deterministic approaches to intelligent, adaptive strategies. Traditional methods—such as fixed solar panel deployment, scheduled battery cycling, and passive thermal control—remain reliable and well-proven in space missions. However, their static nature limits their effectiveness in dynamic orbital environments and long-duration CubeSat missions (Jiang et al., 2022; Pathak et al., 2023). Intelligent methods offer significant improvements by integrating artificial intelligence and machine learning into power system management. Neural networks and SVMs enhance anomaly detection and forecasting, decision trees provide interpretability, and deep reinforcement learning enables real-time optimization of charging and discharging cycles (Baccari et al., 2025; Singh et al., 2024). Furthermore, emerging paradigms such as edge computing, federated learning, and digital twins suggest a shift toward more autonomous and resilient spacecraft (Rebelo et al., 2025; Ortiz et al., 2023).

Despite their promise, AI-driven approaches face challenges in terms of data requirements, onboard computational constraints, and the need for explainability to mission operators. Therefore, the most effective path forward may lie in hybrid systems that combine the robustness of traditional techniques with the adaptability of intelligent methods (Shakoor et al., 2025).

6. FUTURE WORK

Several research directions are expected to shape the next decade of satellite energy management:

1. **Federated Learning in Constellations:** Multiple satellites collaborating on shared models without transferring raw data, improving scalability and security (Rebelo et al., 2025).
2. **Digital Twin Integration:** Virtual replicas of spacecraft to simulate and optimize EPS operations before execution (Singh et al., 2024).
3. **Lightweight AI Models:** Development of resource-efficient algorithms tailored for CubeSat-class hardware (Ortiz et al., 2023; Zeleke & Kim, 2023).
4. **Hybrid Architectures:** Combining traditional hardware scheduling with AI-driven prediction to balance reliability and adaptability.
5. **Space Qualification of AI Systems:** Establishing standards and validation protocols for deploying machine learning algorithms in space.

By systematically addressing these challenges, future CubeSat missions will achieve higher autonomy, longer lifetimes, and more efficient use of limited power resources

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