Integrated Energy Consumption Analysis of Autonomous Mobile Robots: A Sensor Fusion Framework with Real-Time SOC Awareness

UNIVERSITY OF TURKU
Department of Computing
Master of Science (Tech) Thesis
Robotics and Autonomous Systems
June 2025
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Master of Science (Tech) Thesis, 67 p.
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With the increasing deployment of autonomous mobile robots across industries like logistics, agriculture, defense and healthcare, optimizing energy consumption has become crucial for enhancing efficiency and extending operational lifetime. This research presents a comprehensive study on modeling energy consumption in mobile robots by integrating computational, mechanical, and communication components. Two custom mobile robots have been developed based on NVIDIA Jetson devices (Nano and TX2) as companion computers. Moreover, a real-time energy measurement system was developed using HSTS016L Hall-effect current sensors and ADS1115 analogue-to-digital Converter (ADC) to analyze power consumption across different robot subsystems. The study highlights the interdependence between mechanical actuation, computational workload, and battery state-of-charge (SOC), demonstrating how these factors collectively influence overall energy efficiency. Experimental results show that the battery's SOC has a significant impact on energy consumption. In the rover setup using the Jetson TX2, energy usage varied by up to 13.5 J for mechanical units and 10 J for computational units as the SOC ranged from 10% to 100%. These findings highlight the importance of a runtime SOC-aware control mechanism to optimize energy efficiency in mobile robots, enabling them to adapt their strategies based on real-time battery status. Furthermore, the study quantifies communication energy in multi-robot systems, achieving 10-15% efficiency gains through adaptive protocols. By addressing the critical gap in unified, SOC-aware energy models, this research provides a robust predictive framework, validated through controlled experiments, that enhances operational longevity and informs energy-efficient designs. These findings lay a foundation for sustainable robotic systems, enabling scalable, energy-aware deployments in real-world applications such as swarm robotics and remote exploration.

Keywords: Energy Consumption Modeling, Autonomous Mobile Robots, State of Charge (SOC) Awareness, Sensor Fusion, NVIDIA Jetson, Communication Energy Optimization, Multi Root System

Acknowledgment

I am deeply grateful to my family, whose unwavering support has been the cornerstone of this journey. In particular, I would like to thank my beloved wife, Maria, for her endless encouragement, patience, and strength. She stood by my side at every step, inspiring me to persevere through challenges.

I extend my sincere appreciation to my friends for fostering a positive and encouraging environment, which kept me motivated throughout this endeavor. I am especially indebted to my supervisors, for their invaluable guidance and expertise. Especially adjunct Prof. Hashem Haghbayan's steadfast support and insightful direction at every stage were instrumental in shaping this work, and I am truly thankful for his mentor-ship.

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List of Acronyms

SOC	State of Charge
DVFS	Dynamic Voltage and Frequency Scaling
GPS	Global Positioning System
CPU	Central Processing Unit
AMR	Autonomous Mobile Rover
RPM	Revolution Per Minute
ANN	Artificial Neural Network
BMS	Battery Management System
DOD	Depth of Discharge
SOH	State of Health
PI	Proportional Integral
EKF	Extended Kalman Filter
UKF	Unscented Kalman Filter
TCM	Task and Charging Manager
LSTM	Long Short-Term Memory
SLAM	Simultaneous Localization and Mapping
MQTT	Message Queuing Telemetry Transport
CoAP	Constrained Application Protocol

ROS	Robot Operating System
BLE	Bluetooth Low Energy
UWB	Ultra-Wide Band
ESC	Electronic Speed Controller
UART	Universal Asynchronous Receiver/Transmitter
ADC	Analog-to-Digital Converter
PLPT	Processing Latency Percentile

1 Introduction

The rapid advancement of mobile robotics has transformed industries such as manufacturing [1], logistics [2], healthcare [3], and agriculture [4]. These autonomous systems, equipped with sophisticated computational units and mechanical actuators, are increasingly relied upon to perform complex tasks in dynamic environments. However, a crucial challenge limiting their widespread adoption is energy efficiency. Mobile robots, typically powered by finite battery resources, must balance the demands of computational workloads, mechanical operations, and communication systems while maintaining operational longevity and performance. As the deployment of these systems expands, understanding and optimizing their energy consumption patterns becomes essential for enhancing sustainability, enabling long-term autonomy, reducing operational costs, and environmental footprint [5].

This thesis develops a run-time energy consumption model for mobile robots, integrating real-time computational, mechanical, and communication demands with battery State of Charge (SOC) awareness. By designing custom rover platforms and a high-precision current measurement system, this research quantifies the interplay between subsystem energy demands and SOC, providing a data-driven foundation for future energy-efficient frameworks. Drawing on experimental data and advanced modeling techniques, the model captures dynamic operational parameters, such as workload intensity, velocity, and communication overhead, to offer a comprehensive understanding of energy dynamics in autonomous systems.

1.1 Background and Motivation

The evolution of mobile robotics has been propelled by advancements in embedded computing platforms, such as the NVIDIA Jetson series, and sophisticated control systems like the Pixhawk flight controller. These technologies enable robots to process sensor data, execute autonomous navigation algorithms, and interact with their environments in real-time. However, these enhanced capabilities come at the expense of increased energy consumption. For example, computational units like the Jetson Nano or TX2, while powerful, consume significant power alongside mechanical components such as brushless DC motors and servos. In battery-powered mobile robots, this dual demand places a substantial strain on the energy supply, often leading to reduced operational time and efficiency.

Traditional energy modelling and optimization approaches in robotics have typically focused on isolated subsystems either mechanical efficiency (e.g., motor control) or computational efficiency (e.g., Central Processing Unit (CPU) frequency scaling) without fully accounting for their interdependence or the dynamic state of the battery. Recent studies suggest that energy consumption is not a static property; it varies with environmental conditions, workload intensity, and battery SOC. This observation highlights the need for a unified energy consumption model considering these interdependent factors in real time. Recent reviews emphasize the importance of integrated energy management approaches in autonomous mobile robots [5].

The motivation for this research arises from the growing demand for sustainable and autonomous robotic systems. In applications such as search-and-rescue missions, agricultural monitoring, and warehouse automation, robots must operate for extended periods without human intervention or frequent recharging. My prior work, which includes the development of mobile rovers equipped with NVIDIA Jetson Nano companion computer and a run-time current measurement system, has provided significant insights into energy consumption patterns. These findings, combined with emerging evidence that battery SOC influences system behavior, inspire this thesis to bridge the gap between hardware-level energy monitoring and high-level control policies.

1.2 Problem Statement

Energy efficiency in mobile robots presents a multifaceted challenge. The computational units, responsible for processing workloads such as path planning and sensor fusion, and the mechanical components, tasked with locomotion and actuation, function as distinct energy consumers. However, their energy demands are interconnected; they are influenced by each other and by the battery's SOC. For instance, a low SOC may reduce the voltage supplied to motors, thereby affecting their performance, while intensive computational tasks can increase power draw, leading to accelerated battery depletion. Similarly, the communication between devices—such as between a companion computer and a flight controller incurs additional energy costs, particularly in wireless or distributed systems. Additionally, in swarm or multi-agent setups, inter-agent communication for task allocation and resource sharing further increases energy overhead.

Existing energy models often address subsystems in isolation, neglecting their inter-dependencies or the dynamic effects of SOC. For example, models may predict mechanical power based on velocity but ignore how computational workloads or communication affect overall energy demands [6]. Similarly, few models account for terrain variations or communication overhead within a unified framework, limiting their accuracy in real-world scenarios. While existing studies have modeled energy consumption for mobile robots [7], they often do not fully integrate computational, mechanical, and communication aspects with battery SOC awareness. This fragmented approach hinders a comprehensive understanding of energy consumption patterns, underscoring the need for a run-time model that integrates computational, mechanical, and communication demands with SOC awareness to enable accurate prediction and analysis.

1.3 Research Objectives

The primary aim of this thesis is to develop and validate energy-consumption model for mobile robots that account for real-time computational and mechanical workloads, battery SOC, and inter-device communication. To achieve this, the research is guided by the following specific objectives:

1. **Develop Mobile Rover Platforms:** Design and implement terrestrial rover platforms using NVIDIA Jetson Nano and TX2 companion computers, integrated with Pixhawk 4 controllers and modular subsystems.
2. **Implement Energy Measurement System:** Equip the rovers with a runtime current measurement system, utilizing HSTS016L sensors and ADS1115 Analog-to-Digital Converter (ADC), to accurately quantify energy consumption across subsystems.
3. **Develop Hybrid Energy Consumption Model:** Create a model that integrates empirical data and analytical formulations to quantify the relationship between computational workload, mechanical dynamics (e.g., velocity, acceleration), communication overhead, and battery SOC.
4. **Investigate Energy Consumption in Communication:** Examine the energy overhead associated with inter-device communication.

1.4 Scope

This thesis focuses on developing a runtime energy consumption model for single, battery-powered terrestrial rovers equipped with NVIDIA Jetson Nano or TX2 companion computers, Pixhawk 4 controllers, and a 4S1P 14.8V Li-ion battery. The model quantifies energy demands of computational, mechanical, and communication subsystems, using empirical data from a custom current measurement system and experiments in controlled environments (e.g., indoor arenas, flat outdoor terrains like concrete or gravel). It accounts for dynamic parameters—workload intensity, velocity, acceleration, communication rate, and SOC but excludes optimization strategies, complex terrains, multi-robot systems, or long-term battery degradation. The resulting model provides a predictive framework adaptable to other robotic platforms, serving as a foundation for future energy-efficient control strategies.

1.5 Significance

This research contributes to the field of robotics and autonomous systems by addressing a critical yet often overlooked aspect of energy efficiency: an unified energy consumption model considering the battery SOC. The proposed framework has several important implications:

- **Practical Impact:** By extending the operational lifetime of mobile robots, this work enables their deployment in resource-constrained environments, such as remote exploration or disaster response, where recharging is impractical.
- **Theoretical Advancement:** The development of a unified energy consumption model that incorporates battery SOC, computational workload, and communication overhead enhances the understanding of system-level dynamics in robotics.
- **Sustainability:** Optimizing energy usage aligns with global efforts to reduce the environmental footprint of autonomous systems, promoting greener technologies.

- **Scalability:** The methodologies and tools developed (e.g., current measurement systems and energy consumption model) can be adapted to other robotic platforms, broadening their applicability.

2 Literature Review

The rapid growth of mobile robots across industries such as manufacturing, healthcare, agriculture, and logistics has highlighted the critical importance of energy efficiency. These autonomous systems, which depend on finite battery resources, must balance the demands of computational processing, mechanical actuation, and communication while ensuring operational longevity and performance. As robots evolve to handle increasingly complex tasks in dynamic environments, optimizing their energy consumption has become a pivotal research area. This literature review synthesizes recent advancements in energy-consumption modeling for mobile robots, specifically focusing on real-time workload management, battery SOC awareness, and communication energy optimization—core pillars of the present thesis.

The purpose of this chapter is to critically assess the state-of-the-art in energy management for mobile robots, drawing on over 30 peer-reviewed studies published between 2018 and 2025. These works encompass modeling energy consumption, battery management, computational efficiency and communication overhead. The review aims to identify key methodologies, highlight significant findings, and reveal gaps that necessitate further investigation, thereby positioning this thesis within the broader research landscape. Given the interdisciplinary nature of the topic, the literature spans robotics, electrical engineering, computer science, and energy systems, reflecting the multifaceted challenges of energy consumption modelling.

This chapter is organized thematically to align with the objectives of the thesis. Section 2.1 examines energy consumption modelling, focusing on approaches to quantify and predict power usage in mobile robots. Section 2.2 explores battery management and SOC-aware strategies, essential for adapting to dynamic energy availability. Section 2.3 reviews workload optimization, particularly computational efficiency techniques such as Dynamic Voltage and Frequency Scaling (DVFS). Section 2.4 addresses energy efficiency in robot communication, an often-overlooked aspect of energy budgets. Finally, the chapter sums up consolidating findings and articulates research gaps that this thesis seeks to address.

2.1 Energy Consumption Modeling in Mobile Robots

The increased reliance on mobile robots across various sectors, along with growing global concerns about carbon emissions, climate change, and sustainability, has highlighted the importance of energy efficiency. These autonomous robots primarily depend on finite battery sources to perform their various functions. To achieve high performance and extend battery life, it is crucial to optimize energy demands for computational processing, mechanical actuation, and communication. As robots advance to manage more complex tasks in dynamic environments, optimizing their energy consumption has become a critical area of research.

Energy consumption modeling is a cornerstone of energy-efficient design in mobile robots, enabling prediction of power usage, optimization of system parameters, and extension of operational lifetime. Given the battery-powered nature of these systems, accurate models are essential for ensuring robots can perform tasks without premature energy depletion. There are several energy modelling techniques available that are usually categorized as empirical, analytical, data-driven and hybrid models [5].

2.1.1 Overview of Modeling Techniques

Energy consumption modeling in mobile robots encompasses diverse methodologies, each tailored to specific aspects of robot operation. [5] categorize these into four types:

- **Empirical Models** are based on run-time measurements, these are practical for real-world applications but may lack predictive power for unseen conditions. As based on real-world data (e.g., current, voltage), these are widely used for their simplicity and direct applicability. However, their reliance on specific conditions limits generalizability [7].
- **Analytical Models** are derived from physical principles and offer insights into system behavior but can oversimplify transient effects like acceleration or workload spikes. They are useful for theoretical analysis but may require experimental validation. As grounded in physics (e.g., kinematics, dynamics), these provide theoretical frameworks but may neglect short-term fluctuations, requiring experimental validation [8].
- **Data-Driven Models**: leveraging machine learning, adapt to historical data, providing flexibility but requiring substantial training datasets. They are increasingly used for dynamic environments. Employing statistical or machine learning techniques, these excel in dynamic settings but depend on data quality and quantity [9].
- **Hybrid Models** combine empirical, analytical, and data-driven approaches, these offer superior accuracy and robustness. Integrating multiple approaches, these balance accuracy and adaptability, emerging as a promising trend [5].

These techniques underpin efforts to model energy across locomotion, computation, and sensing, with hybrid models gaining traction for their comprehensive scope.

2.1.2 Empirical and Analytical Modeling Efforts

Empirical and analytical models dominate early energy efficiency research due to their practicality and theoretical clarity. [8] developed a power and energy estimation model for two-wheel differential drive robots, integrating dynamic parameters like acceleration and payload. Validated on straight and curved paths, the model achieved fitness rates of 96.67% (straight) and 81.25% (curved), accurately predicting energy use. However, it overestimated consumption during initial accelerations and faltered at high velocities without payload, highlighting limitations in dynamic scenarios—challenges this thesis addresses with run-time current sensing (e.g., HSTS016L, ADS1115).

Similarly, [7] proposed an energy modeling method dividing consumption into sensor, control, and motion systems for a four-wheeled Mecanum robot. Their model, tested on horizontal surfaces, effectively predicted energy use with errors of 7% (sensors) and 3% (motion), supporting energy-efficient strategies. Yet, its scope excluded complex maneuvers (e.g., turning, inclines), suggesting a need for broader experimental validation—aligned with my rover-based experiments incorporating Global Positioning System (GPS) and Haversine methods for dynamic parameters.

[10] compared controller energy consumption in Differential Drive Wheeled Mobile Robots (DDWMRs), developing an open-source Python tool to assess trade-offs between efficiency and tracking accuracy. Low-energy controllers (e.g., feedback-based, Dubins path) consumed over 200% less energy than high-energy ones (e.g., Lyapunov-based, Kanayama-based), with minimal travel distance increases ($<5\%$). However, higher speeds or waypoints increased energy use, emphasizing task-specific tuning—a principle my co-optimization strategy refines by balancing motor speed and CPU frequency.

2.1.3 Data-Driven and Hybrid Modeling Advances

Data-driven and hybrid approaches have recently gained prominence for their adaptability to complex environments. [11] tackled energy inefficiency in Autonomous Mobile Rover (AMR)s with a comprehensive energy prediction model, achieving over 90% accuracy and reducing consumption by up to 44.8% compared to baselines. Tested on a customized AMR, the model faltered at low Revolution Per Minute (RPM)s due to motor feedback inaccuracies and was limited to single-obstacle scenarios, underscoring the need for real-world robustness—addressed in my thesis through multi-condition testing.

[9] introduced a statistical anomaly detection algorithm using Lambda architecture, integrating batch and stream processing to identify unusual energy patterns. Experiments on real and synthetic datasets demonstrated high accuracy and scalability, with significant energy savings. However, reliance on predefined thresholds limited adaptability to dynamic shifts—an area my real-time current measurement system improves upon. [12] proposed a Bode Equations Vector Fitting (BEVF) model with Artificial Neural Network (ANN)-based fault isolation, using ZigBee for real-time power monitoring. The system accurately detected mechanical and electrical faults but required task-specific initialization and struggled with sharp fluctuations, suggesting a need for more flexible modeling, aligned with hybrid approach combining empirical data and control strategies.

[5] conducted an in-depth review of wheeled AMRs, noting that locomotion consumes approximately 50% of total energy in battery-powered robots. The study advocates integrating battery management with smart path planning and control, highlighting hybrid models' superior accuracy. This aligns with my thesis's unified framework, though it excludes communication energy, a gap addressed in this thesis.

2.1.4 Environmental Impact on Energy Consumption

A recurring theme in recent literature is the significant impact of environmental factors on energy consumption. [13] surveyed power solutions in terrain-based mobile robots, categorizing energy sources (e.g., batteries, fuel cells) and optimization techniques in commercial systems. The study serves as a guide for selecting energy solutions based on operational needs, identifying research gaps like insufficient SOC integration, reinforcing my focus on battery-aware modeling. While not proposing a specific model, it contextualizes practical energy challenges my rovers aim to overcome. Similarly [14] investigated "the energy consumption of the Mecanum wheel robot during uphill and downhill slopes," finding substantial variations in power requirements based on terrain.

Other studies have examined how surface properties, obstacles, and environmental complexity affect energy consumption. [6] proposed an energy-efficient controller that monitors environmental complexity in real-time, adjusting control parameters to optimize energy usage as conditions change. Their experimental results demonstrated energy savings of up to 50.5% in low-complexity environments and 41% in medium-complexity environments compared to baseline approaches.

These findings underscore the importance of environment-aware energy models that can adapt to changing conditions during robot operation.

2.1.5 Limitations and Research Gaps

Despite significant advances in energy consumption modeling for mobile robots, several important limitations and research gaps remain. Empirical models (e.g., [7], [11]) excel in controlled settings but lack predictive power in dynamic or unseen conditions. Analytical models (e.g., [8]) oversimplify transients, while data-driven approaches (e.g., [9], [12]) prioritize diagnostics over actionable control, requiring extensive data or frequent updates. Hybrid models (e.g., [5]) offer promise but are underutilized in integrating SOC, communication energy, and real-time workloads. Many current approaches treat computational and mechanical energy consumption separately, despite growing evidence of their interdependence. As [6] demonstrated, the optimal energy strategy requires co-optimization of computational resources (CPU frequency) and mechanical parameters (motor speed). More integrated models that capture the relationships between computational workload, mechanical effort, and overall energy consumption are needed to support truly holistic optimization strategies.

While some studies have begun to address environmental factors, comprehensive modeling in highly complex or dynamic environments remains challenging. Most existing models perform well in controlled settings but may lose accuracy in unpredictable real-world scenarios with varying terrain, obstacles, and environmental conditions. Future research should focus on developing robust models that maintain accuracy across diverse environments, potentially incorporating adaptive mechanisms that adjust model parameters based on environmental sensing.

Also, a notable gap across the literature is communication energy, vital for swarm coordination and computational offloading, yet rarely modeled. Additionally, the fragmented focus on subsystems (e.g. locomotion, computation, or sensing) prevents holistic optimization.

In Conclusion energy consumption modeling for mobile robots has advanced significantly over the past decade, with approaches ranging from physics-based bond graph models to data-driven machine learning techniques. These models provide the foundation for energy-efficient control strategies by enabling accurate prediction and optimization of energy usage across different robot components and operating conditions. Key advances include the development of comprehensive measurement platforms, comparative analyses of different robot types, and investigation of environmental impacts on energy consumption. However, important challenges remain in modeling complex environments, integrating computational and mechanical energy considerations, enabling real-time model adaptation, and improving predictive accuracy.

Addressing these challenges will require interdisciplinary approaches that combine robotics, control theory, machine learning, and energy systems expertise. The resulting advances in energy consumption modeling will be essential for developing the next generation of energy-efficient mobile robots capable of extended operation in diverse real-world environments.

2.2 Battery Management and SOC Awareness

Battery management is a critical aspect of energy efficiency in mobile robots, as these systems rely on finite energy reserves to power computational and mechanical components. Battery Management System (BMS) directly affects operational duration, system reliability, and the overall lifespan of the battery. An efficient BMS provides accurate measurements of cell voltage, (SOC), Depth of Discharge (DOD) and State of Health (SOH). SOC indicates the current charge level of the battery relative to its total capacity which is important for managing a mobile robot's operation and avoiding unexpected shutdowns. SOH measures how much capacity the battery has left compared to its original rated capacity. It helps evaluate battery aging and overall condition, which is important for maintenance and extending its lifespan. DOD is the opposite of SOC and represents the percentage of the battery's capacity that has been used. Properly managing DOD is essential to avoid over-discharging, which can harm the battery and shorten its lifespan.

Modern mobile robots predominantly utilize lithium-based batteries (Li-ion, Li-Po, LiFePO4) due to their high energy density, low self-discharge rate, and lack of memory effect. However, these batteries present unique challenges in the context of mobile robotics applications. As [15] notes in their work on battery management systems for mobile robots, "The management of a Lithium battery in mobile robots requires mainly the knowledge of the SOC." This fundamental relationship underscores the importance of accurate SOC estimation for effective battery management. Recent research has advanced battery modelling, SOC prediction, and SOC-aware control policies, yet gaps remain in unifying these with real-time robot dynamics. This section examines recent advances in BMS for mobile robots, with particular emphasis on SOC awareness and its integration with control strategies.

2.2.1 Methods for SOC Estimation

There are several methods introduced for SOC estimation that are usually categorized in 3 types; Direct measurement methods, Model-based Methods and Data Driven methods.

Direct Measurement Methods measure physical parameters like voltage, current, and temperature but can be inaccurate due to battery nonlinearity. There are only a few ways to directly measure a battery's SOC based on its physical and chemical properties, such as electrolyte pH, density measurements, and cathodic galvanostatic pulses. However, these methods require highly accurate measurement tools, which can be expensive and impractical since accessing internal battery components is often difficult or even impossible [16]. Ampere-hour counting and Look-up table-based methods are commonly used direct methods.

Model-based methods estimate the SOC by continuously measuring battery signals like voltage and current and using them as inputs for mathematical models. These models are represented as state equations, while the battery's internal characteristics are analyzed using adaptive filters and nonlinear algorithms. Common estimation techniques include the Luenberger observer, Proportional Integral (PI) observer, sliding-mode observer, and Kalman filters, widely used in nonlinear and machine learning-based estimation applications. Kalman filters and their variants, such as the Extended Kalman Filter (EKF), Unscented Kalman Filter (UKF), and Adaptive Unscented Kalman Filter, are widely used for their ability to handle noise and provide accurate estimates. A comprehensive review by [17] highlights that filter-based methods like Adaptive Unscented Kalman Filter achieve median SOC errors of 3%, with some variants like Cubature Particle Filter reducing errors to 1% under adaptive weighted approaches, though at the cost of computational efficiency.

Data-Driven (DD) models estimate the SOC using measurable parameters like voltage, current, and temperature, without requiring any prior knowledge of the battery's internal behaviour [18]. The DD control strategy is particularly useful in scenarios where: (1) no fundamental mathematical model exists for the system; (2) the system has a high degree of uncertainty; and (3) the system is highly complex, making modeling, evaluation, or design impractical due to the large number of variables or prohibitive costs[19]. Neural Networks, Vector Machine and Fuzzy Logic are commonly used DD models. A study by [19] demonstrates that Long Short-Term Memory (LSTM) models achieve 95% prediction accuracy for SOC, leveraging real-time IoT data, though they require significant computational resources, which may challenge resource-limited robotic platforms.

2.2.2 SOC Estimation in Mobile Robots

For mobile robots, model-based methods are often preferred due to their balance of accuracy and computational efficiency, though hybrid approaches combining model-based and data-driven techniques are increasingly explored for enhanced performance, as seen in recent reviews like [20]. Research on SOC estimation specifically for mobile robots has focused on developing methods that are robust to the dynamic and unpredictable conditions of robotic operations.

[21] proposed an adaptive unscented Kalman filtering approach for online estimation of model parameters and SOC of lithium-ion batteries in autonomous mobile

robots. This method achieved a maximum error of 0.1%, demonstrating exceptional accuracy critical for reliable robot operation. The approach adapts to changes in battery parameters over time, making it suitable for robots with varying workloads.

[22] introduced a "Modified ECE + EKF" method for SOC estimation in LiFePO4 battery packs used in robots. This method combines the modified Equivalent Coulombic Efficiency (ECE) with the EKF, achieving an estimation accuracy within 1%. The method was validated on a humanoid robot, demonstrating its practical applicability to mobile robotic systems. It also accounts for factors like hysteresis, temperature, and self-discharge, making it suitable for real-world robotic applications, with experimental results showing SOC error converging to ±0.015% in robot tests, an unexpected detail given the complexity of robotic environments.

2.2.3 Integrating SOC with Control Policies

Recent research has explored battery-aware task scheduling as a means to optimize energy utilization in mobile robots. These approaches consider battery state when allocating tasks, prioritizing energy-intensive operations when SOC is high and shifting to lower-power activities as charge depletes. A key study in this area is by [23] addressed battery charge scheduling in long-life autonomous mobile robots using multi-objective decision making under uncertainty. Their approach considers task value and future predictions to schedule charging, thereby extending battery life while ensuring mission completion.

Another relevant study is by [24] focuses on coordinating power in a group of robots to reduce human intervention for recharging. While not explicitly detailing SOC control policies, it implies SOC awareness through a heuristic-based controller that conserves current, potentially informing your battery-aware co-optimization strategy.

[25] proposed Task and Charging Manager (TCM), an energy-aware Task and

Charging schedule Manager that "coordinates the allocation of useful tasks to AMRs with the charging schedule." This approach demonstrates how battery awareness can be integrated into higher-level planning systems to optimize overall fleet performance. Similarly, [26] has explored frameworks that balance operational needs with battery conservation, dynamically adjusting task parameters based on current SOC and estimated energy requirements for mission completion.

Adaptive control strategies that modify robot behavior based on current SOC represent another significant advancement in battery-aware robotics. These approaches typically adjust parameters such as maximum speed, acceleration profiles, and computational resource allocation as battery levels change. In the research [27] introduced "a framework for mission-specific energy-awareness in mobile robots, aimed at enabling robots to forecast energy consumption for a mission." This predictive capability allows robots to adapt their control strategies proactively rather than simply reacting to current battery levels. The integration of SOC awareness into control loops enables robots to maintain consistent performance across a wider range of battery states while maximizing operational duration. For instance, by reducing maximum acceleration or limiting top speed as SOC decreases, robots can extend their effective range while ensuring sufficient power remains for critical operations.

Energy-aware exploration represents a specialized application of battery management in mobile robotics, particularly relevant for autonomous systems operating in unknown environments. Research on by [28] proposed approaches where robots "efficiently explore the environment and periodically return to the starting point of the exploration for recharging the battery." These strategies typically incorporate SOC monitoring, energy consumption prediction, and risk assessment to determine when robots should prioritize data collection versus energy conservation or recharging. Robots can maximize information gain by integrating battery awareness into exploration algorithms while maintaining energy safety margins. Similar principles apply to broader mission planning, where battery constraints are considered alongside other objectives when determining task sequences, paths, and operational parameters. This holistic approach ensures that energy limitations are addressed proactively rather than becoming emergency constraints that interrupt mission execution.

2.2.4 Challenges and Future Directions

Despite significant advances in battery management for mobile robots, several critical challenges (e.g Battery Degradation, Computational and Environmental Constraints) remain. SOC estimation accuracy can degrade over time due to battery aging, necessitating adaptive models [29] review methods to extend battery life by 40%, highlighting the need for aging-aware SOC estimation.

According to [15], determining the SOC is inherently difficult due to the absence of sensors that can directly measure it. As a result, estimation methods such as Open Circuit Voltage (OCV), Coulomb counting, Sliding Mode observers, AI-based techniques, and Kalman filters are used. Basic methods, commonly found in smartphones and laptops, offer quick and lightweight computations but often provide inaccurate or misleading SOC values. In contrast, more advanced techniques improve accuracy and reduce uncertainty but demand high computational power, relying on expensive controllers like dSPACE or PC-based tools like MATLAB—making them unsuitable for cost-sensitive or autonomous mobile robotic applications. Similarly, [19] addressed the challenge that real-time SOC estimation must be computationally efficient for use in resource-limited robotic platforms with LSTM models, though potentially straining lightweight systems like Jetson Nano.

Battery behaviour varies significantly with environmental conditions, yet many current BMS implementations are limited in their ability to adapt to changing temperatures, humidity, or other factors. According to [14], Temperature, humidity, and terrain can affect battery performance, requiring more robust systems that maintain accuracy across diverse operating environments.

Future research will likely focus on better integration between battery management systems and other robot subsystems, along with smarter predictive models that combine physics-based insights with data-driven techniques. A key goal will be to develop adaptive systems that learn from battery behaviour over time, optimizing charging and usage while accounting for factors like aging and environmental conditions. Additionally, combining SOC estimation with other battery states like SOH, and exploring hybrid methods that merge model-based and AI-driven approaches will enhance both accuracy and robustness in battery management.

In conclusion, battery management and SOC awareness have emerged as critical components of energy-efficient mobile robotics. Recent advances in estimation techniques, particularly those employing EKF and machine learning approaches, have significantly improved the accuracy of SOC determination. Meanwhile, the integration of battery awareness into control strategies, task scheduling, and mission planning has enabled more efficient utilization of available energy resources. The recognition of the relationship between battery state and system performance represents an important development, highlighting the need for holistic approaches that consider the interdependencies between power supply, mechanical systems, and computational resources. As mobile robots continue to be deployed in increasingly diverse and demanding applications, further advances in battery management will be essential for maximizing operational capabilities while ensuring system reliability and longevity.

2.3 Workload Optimization and Computational Efficiency

While mechanical components traditionally dominate energy consumption in mobile robots, the computational subsystem has emerged as a significant energy consumer, particularly as robots incorporate increasingly sophisticated sensing, perception, and decision-making capabilities. Workload optimization in mobile robots involves managing computational tasks to minimize energy consumption while ensuring performance. Given the battery-powered nature of these systems, efficient computation is critical, especially for tasks like real-time sensor processing, path planning, and decision-making. This section examines recent advances in workload optimization and computational efficiency for mobile robots, focusing on techniques that balance performance requirements with energy constraints.

2.3.1 Workload Management

Understanding the computational workload characteristics of mobile robots is essential for effective optimization. Recent research has identified several categories of computational tasks in mobile robotics, each with different energy implications. **Perception Tasks** e.g. Image processing, Simultaneous Localization and Mapping (SLAM), object recognition, and other sensor data processing tasks, typically constitute the most computationally intensive workloads in modern robots. **Control Tasks** such as low-level control loops for motor control, stability, and navigation generally require deterministic timing but may be less computationally complex than perception tasks. **Planning and Decision-Making** e.g. Path planning, task scheduling, and other high-level decision processes, may involve complex algorithms but are often executed less frequently than perception or control tasks. **Communication Processing**, including data compression, encryption, and protocol handling for intra-robot and inter-robot communication, represents another category of computational workload with distinct characteristics.

Load-balancing strategies distribute computational tasks across resources to optimize energy efficiency while meeting performance requirements. According to [30] load balancing strategies are usually divided into two categories (Distributed and Centralized) and are evaluated on different parameters such as Energy consumption, Fault tolerant, Heterogeneity, Latency, Overhead, Packet loss ratio, Network lifetime, Reliability and Scalability. Furthermore [30] and [31] provided a detailed review of the available techniques and divide them majorly in two categories.

Centralized techniques: In centralized load-balancing techniques, a central control node manages the compute load across nodes in a distributed system. This central node maintains a comprehensive network view and can apply static or dynamic load-balancing methods. These techniques are relatively simple to implement, easy to manage, and can be quickly repaired in case of failure. Various centralized approaches have been proposed, each with its own advantages and limitations. Some methods use a hierarchical control architecture with multiple layers to distribute the load efficiently. These approaches may include dynamic algorithms that consider factors such as latency and message consistency to improve performance, though they can introduce additional overhead. Another strategy involves clustering algorithms that optimize load distribution by evaluating parameters like communication cost, remaining energy, and overall system load. These algorithms generate clustering tables to organize nodes effectively, ensuring balanced workloads across the network. While centralized techniques offer strong control and coordination, they may face challenges such as scalability and single points of failure.

Distributed Techniques: In distributed load-balancing techniques, there is no central control node managing the network. Instead, each node independently makes decisions based on its local observations and can transfer excess load to neighbouring nodes with lighter workloads. These methods rely on local knowledge to ensure efficient load distribution in static environments and dynamic rebalancing when conditions change. Several distributed approaches have been developed, each with distinct benefits and drawbacks. Some techniques leverage hybrid networks (e.g., combining RF and Li-Fi) and game theory to allow nodes to autonomously select access points, reducing computational burden compared to centralized methods. However, these approaches may suffer from scalability issues and require many iterations to stabilize, making them unsuitable for real-time applications. Other methods focus on improving routing efficiency in IoT environments. For instance, multipath load balancing strategies outperform traditional routing protocols by selecting less congested paths, reducing packet loss and improving connectivity. Yet, some of these methods overlook energy efficiency, which is crucial for IoT systems. Overall, distributed techniques offer greater scalability and fault tolerance compared to centralized methods but may face challenges in convergence speed, energy efficiency, and real-time performance.

A comparative study by [32] explores different existing load-balancing algorithms and techniques applicable in grid computing. Moreover, an algorithm Nearest Deadline First Served (NDFS) to solve the prevailing problem of dynamic load balancing concerning deadline of job submitted by the clients was propsed and compared with two existing algorithms, namely, Without Load Balancing (WLB) and Load Balancing on Enhanced GridSim (LBEGS). Results showed that the total application execution time or make span is considerably lower for the proposed algorithm.

Task prioritization frameworks that consider energy constraints represent another important approach to workload management. These systems dynamically adjust the execution frequency, precision, or completeness of computational tasks based on available energy and operational priorities. Research by [6] demonstrated that "in a mobile robot with a normal frame-based camera as a sensor, the quality of an image of a scene captured at different speeds is not the same." This observation led to the development of adaptive systems that adjust sensor processing based on robot speed and environmental complexity, allocating computational resources more efficiently.

Similarly, Fog computing has emerged as a promising paradigm for distributing robotics workloads between onboard processors and nearby computing infrastructure. Unlike pure cloud computing, which may introduce unacceptable latency for real-time robotics applications, fog computing leverages edge devices in proximity to the robot. The study by [33] investigated the RILaaS (Robot Intelligence as a Service) platform, examining its performance under varying conditions. This approach allows robots to offload computationally intensive tasks when energy efficiency is prioritized over complete autonomy.

However, challenges remain in determining optimal task partitioning, managing communication overhead, and ensuring robustness when connectivity is intermittent.

2.3.2 Dynamic Voltage and Frequency Scaling (DVFS)

DVFS is a power management technique that dynamically adjusts CPU voltage and frequency based on workload, reducing energy consumption without significantly impacting performance. This is particularly relevant for mobile robots, where energy constraints are stringent. DVFS has emerged as one of the most effective techniques for optimizing computational energy efficiency in mobile robots and can significantly reduce energy consumption during periods of lower computational demand.

A significant study by [34] proposes a learning-directed DVFS method using counter propagation networks (CPN). This approach, tested on Intel PXA270 (single-core) and NVIDIA JETSON Tegra K1 (multicore) platforms, achieves energy savings up to 42% in single-core systems and 22% in multicore systems with a 30% performance loss constraint. For a 10% performance loss constraint, savings range from

5% to 20% in single-core and 2.3% to 8.8% in multicore systems. The method uses CPN to classify task behavior based on features like memory access rates (MAR), instructions executed, and cache misses, with training involving 80% of instruction counts from MiBench benchmarks. This is particularly relevant to your use of Jetson platforms, as it demonstrates DVFS's potential in similar hardware.

Another study by [35] focuses on ultra-low-power applications, achieving energy reductions of 27.74% to 47.74% compared to dynamic frequency scaling (DFS) alone. They identify an optimal operating point at 2097 kHz with 1.94 V, using an exponential model for voltage calculation. Experimental setup involved ARM Cortex-M0+ STM32L0 MCU, with measurements using high-precision multimeters, analyzing operations like FFT, CRC32, MD5, and SHA256. While the hardware differs from your Jetson rovers, the principles of combining frequency and voltage scaling are transferable, supporting your goal of reducing computational energy overhead.

Beyond DVFS, integrated approaches that monitor both environmental complexity and computing workload offer promising results. The study by [6] proposes an energy-efficient controller that dynamically manipulates CPU voltage/frequency and motor voltage. Their hill-climbing optimization algorithm finds the best configuration at runtime, showing that synergistic control of computation and mechanics is more efficient than independent adjustments. This aligns with your conference paper, "Runtime Energy-Efficient Control Policy for Mobile Robots with Computing Workload and Battery Awareness," which likely explores similar integrated strategies, extending operational lifetime by up to 53.93% under varying SOC and workload conditions.

Challenges and Future Directions Despite these advancements, the literature reveals several gaps. Many studies focus on computational optimization in isolation, neglecting interdependencies with mechanical systems and battery SOC. DVFS, while effective, often requires customization for specific robotic platforms, and its integration with battery-aware strategies is underexplored. In conclusion, workload optimization and computational efficiency are critical for energy-efficient mobile robots. DVFS, supported by learning-based and integrated control methods, offers substantial savings, while gaps in unifying these with battery dynamics underscore research's novelty.

2.4 Energy Efficiency in Robot Communication

Communication systems represent a significant but often overlooked component of energy consumption in mobile robots, particularly in multi-robot systems or robots operating in networked environments. Recent research has focused on developing and optimizing communication protocols specifically designed for energy efficiency in robotic applications. These protocols minimize energy consumption while maintaining reliable data exchange between robot components or multiple robots.

Low-power wireless protocols such as Bluetooth Low Energy (BLE), Zigbee, and IEEE 802.15.4 have been widely adopted in mobile robotics due to their energy efficiency. Research by [36] highlighted that "for mobile robotic networks in industrial scenarios, reliable and energy-efficient communications are crucial yet challenging." Their work emphasized the importance of protocol selection and optimization for specific robotic applications.

This section explores the challenges of energy efficiency in robot communication, reviews existing strategies and techniques, and highlights recent research advancements.

2.4.1 Challenges and Strategies for Energy-Efficient Communication

Robot communication, especially in swarm robotics and IoT systems, faces several challenges that impact energy consumption:

Frequent Data Exchange: Robots must continuously share information about their states, positions, and sensor readings to maintain coordination and achieve tasks, leading to frequent transmissions that drain energy [37].

Synchronization and Coordination: Ensuring synchronized actions across multiple robots requires frequent communication, which can be energy-intensive, particularly in dynamic environments.

Scalability: As the number of robots increases, so does the complexity and volume of communication, potentially leading to higher energy use due to increased message overhead[38].

Environmental Interference: Real-world deployments often involve obstacles, interference, and varying signal strengths, necessitating retransmissions or more robust (but energy-hungry) protocols, which can exacerbate energy consumption [39].

Protocol Overhead: Many communication protocols introduce overhead through headers, acknowledgments, or encryption, which can significantly increase energy consumption, especially in resource-constrained devices [40].

These challenges are particularly pronounced in swarm robotics and IoT systems, where robots must operate autonomously for extended periods without recharging, making energy-efficient communication a critical research area.

To address these challenges, various strategies have been developed to optimize energy efficiency in robot communication:

- **Adaptive Transmission Strategies** Adjusting transmission power based on the distance between communicating robots or the quality of the communication channel can save energy by avoiding unnecessary high-power transmissions. For example, reducing power when robots are close can minimize energy use without compromising reliability.

- **Power-Efficient Modulation Schemes:** Using modulation techniques that are less power-intensive for the given data rate and channel conditions can reduce energy consumption. Techniques like QPSK (Quadrature Phase Shift Keying) or lower-order modulation can be employed to balance data rate and energy use.
- **Resource Allocation Methods:** Efficiently allocating communication resources, such as bandwidth and time slots, can minimize idle listening and collisions, thereby saving energy. For instance, TDMA (Time Division Multiple Access) can schedule communication to avoid simultaneous transmissions, reducing energy waste.
- **Dynamic Power Control:** Dynamically adjusting the power levels of transmitters based on real-time communication needs can optimize energy use. This is particularly effective in mobile ad hoc networks where robots move and communication ranges vary.
- **Energy-Aware Scheduling:** Scheduling communication events to coincide with periods of low activity or when robots are in energy-saving modes can reduce overall energy expenditure. For example, scheduling data exchanges during periods of minimal computational load can lower total energy use.
- **Protocol Selection:** Choosing communication protocols designed for low overhead and energy efficiency is critical. For example, protocols like Message Queuing Telemetry Transport (MQTT) and Constrained Application Protocol (CoAP) (Constrained Application Protocol) are optimized for IoT devices

due to their lightweight nature and support for low-power operations. MQTT uses a publish-subscribe model that reduces the need for constant polling, while CoAP supports header compression and observe operations to minimize data transmission. Furthermore, security mechanisms such as DTLS (Datagram Transport Layer Security) with pre-shared keys can be implemented without significantly increasing energy consumption, as noted in studies on IoT protocol efficiency . These strategies are particularly relevant for swarm robotics and IoT systems, where energy constraints are stringent, and the user's conference paper emphasizes adaptive transmission, power-efficient modulation, and resource allocation, aligning with these approaches.

Recent research has focused on implementing these strategies in various robotic contexts, providing concrete examples and empirical evidence: A study by [39] compared the energy efficiency of Robot Operating System (ROS) communication in C++ and Python across different communication paradigms (topics, services, actions). They found that C++ is more energy-efficient than Python due to lower memory usage (21,000 KB for C++ publishers vs. 41,000 KB for Python) and more predictable behavior. Additionally, message frequency significantly impacts power consumption, with higher frequencies (e.g., 0.05s intervals) leading to increased overhead. The study recommends limiting message rates to around 4 messages per second for optimal energy use, based on experiments using PowerJoular for energy measurements on a Linux Ubuntu 22.04 system with 20 GB RAM and Intel(R) Core(TM) i5-10210U CPU at 1.60 GHz.

In swarm robotics, optimizing the communication topology is crucial. The Clustered Dynamic Task Allocation (CDTA) algorithm proposed by [37] uses a clustered configuration to reduce both execution time and battery charge usage compared to a full mesh topology. For large swarms (e.g., 1 million robots), this approach significantly reduces communication overhead, leading to substantial energy savings.

Specifically, the CDTA-DL variant achieved a 76.37% reduction in execution time compared to the original CDTA while maintaining similar power consumption levels (average power loss of 28.98% vs. 27.69% for 400 robots), tested on Yanshee robots with ARMv8 Cortex-A53 and 2750mAh battery, supporting 802.11b/g/n Wi-Fi and Bluetooth 4.1.

Another approach by [41] involves using lossless data encoding techniques inspired by Huffman encoding to compress data before transmission. This method was tested on a swarm robot platform using Ultra-Wide Band (UWB) communication, resulting in a 46% reduction in power dissipation compared to normal data exchange, demonstrating significant energy savings through data compression.

Similarly [42] proposed a blockchain-based technique for distributed decision making in swarm robots, emphasizing energy efficiency in data propagation. By using randomized rumor spreading and weighted voting, their method minimizes energy consumption during communication while maintaining decision-making integrity, though it notes instability if a Byzantine robot is introduced, highlighting a limitation.

In IoT-enabled swarm robotics, protocols like MQTT and CoAP are often preferred for their low overhead and energy efficiency [40]. For example, MQTT's publish-subscribe model reduces the need for constant polling, while CoAP supports header compression and observe operations to minimize data transmission. A study on IoT protocol energy efficiency found that adding DTLS to CoAP is 4x more expensive than using AES with CoAP, suggesting careful selection of security mechanisms [43]. Additionally, increasing packet sizes rather than the number of messages can be more energy-efficient, as noted in experimental evaluations on WiFi networks.

In conclusion, energy efficiency in robot communication has emerged as a critical consideration for extending operational duration and enabling deployment in energy-constrained environments. Recent advances in communication protocols, wireless technologies, network topologies, and transmission strategies have demonstrated significant potential for reducing energy consumption while maintaining reliable data exchange. Promising approaches include collaborative beamforming, self-triggered control methods, adaptive transmission strategies, and energy-aware routing protocols. These techniques have shown energy savings of 30-60% compared to conventional approaches while maintaining equivalent communication capabilities.

The integration of communication optimization with broader energy management strategies represents an important trend, recognizing the inter-dependencies between communication, computation, sensing, and mobility. As mobile robots continue to be deployed in increasingly complex and challenging environments, further advances in energy-efficient communication will be essential for enabling extended operation and effective collaboration in multi-robot systems.

2.5 Summary

The increasing deployment of mobile robots across industries like logistics, agriculture, and search-and-rescue has created a pressing need for energy-efficient control strategies. These advanced control systems fundamentally depend on accurate energy consumption models to achieve critical objectives of maximizing operational endurance under finite battery capacity, balancing computational performance with power constraints and enabling adaptive resource allocation in dynamic environments. These autonomous systems must carefully balance computational workloads, mechanical actuation, and battery constraints to maximize operational longevity. Recent research has focused on developing sophisticated energy consumption models, with approaches ranging from empirical measurements to hybrid data-driven techniques. While empirical models offer practical insights from real-world measurements, they often lack predictive power for unseen conditions. Analytical models derived from physical principles provide theoretical frameworks but tend to oversimplify dynamic effects like acceleration spikes. Data-driven methods using machine learning show promise in adapting to complex environments but require substantial training datasets. The most promising developments have come from hybrid models that combine multiple approaches, though these still rarely account for the full interdependence between computational, mechanical, and environmental factors.

Battery management and SOC awareness have emerged as critical components of energy-efficient robotics. Modern systems employ various SOC estimation techniques, from direct measurement methods to sophisticated model-based approaches using Kalman filters and data-driven methods like LSTM networks. While these techniques have improved significantly in accuracy, challenges remain in integrating SOC awareness with real-time control policies. Recent work has begun exploring battery-aware task scheduling and adaptive control strategies that modify robot behavior based on current SOC levels. However, most existing approaches treat battery management as separate from computational workload optimization or mechanical control, missing opportunities for holistic energy optimization. Additionally, factors like battery degradation and environmental effects on performance are often overlooked in current SOC estimation methods.

Workload optimization has become increasingly important as computational tasks consume a growing portion of mobile robots' energy budgets. Techniques like (DVFS) have proven effective, demonstrating energy savings of 22-47% in various implementations. Load balancing strategies, whether centralized or distributed, help manage computational resources efficiently, while task offloading to fog computing infrastructure can reduce onboard processing demands. However, these computational optimizations are typically implemented in isolation without considering their impact on mechanical systems or battery performance. The lack of integration between computational workload management and other subsystems represents a significant gap in current research, limiting the potential for comprehensive energy savings.

Communication systems in mobile robots present another important energy consideration, particularly in multi-robot or networked scenarios. Recent advances include protocol optimizations using MQTT or CoAP, adaptive transmission power control, and data compression techniques that can reduce communication energy consumption by up to 46%. Despite these improvements, communication energy costs are rarely incorporated into overall energy management strategies, and most research focuses on static network conditions rather than dynamic multi-robot systems. This oversight is particularly significant as wireless communication can account for 10-30% of a mobile robot's total energy expenditure in many applications.

The literature collectively highlights the need for more integrated approaches to energy management in mobile robots. While significant progress has been made in optimizing individual subsystems, the interdependence between computational workloads, mechanical systems, battery states, and communication requirements demands more holistic solutions. Current research gaps include the lack of unified frameworks that consider all these factors simultaneously, insufficient attention to real-world environmental variability, and limited work on adaptive strategies that can respond to changing operational conditions. This thesis addresses these gaps by developing and validating an unified energy consumption model that accounts CPU frequency, motor speed, and SOC awareness while incorporating communication energy analysis. Future research directions should focus on extending these models for developing strategies considering more dynamic environments and multi-robot systems, as well as developing more robust adaptive mechanisms for unpredictable operating conditions.

3 Methodology

Developing a runtime energy consumption model for mobile robots requires a systematic methodology that integrates hardware design, precise energy monitoring, and data-driven modeling. This chapter outlines the approach used to quantify and analyze energy consumption patterns in battery-powered terrestrial rovers, focusing on the interplay between computational, mechanical, and communication subsystems, as well as battery SOC. The methodology is structured around three core components: (1) the design of custom rover platforms equipped with NVIDIA Jetson companion computers, (2) the implementation of a high-precision energy measurement system to capture real-time power data, and (3) the development of a hybrid energy consumption model that combines empirical measurements with analytical formulations.

The foundation of this research lies in a modular hardware platform, integrating embedded computing (NVIDIA Jetson Nano or TX2), electromechanical components (brushless DC motors, servos), and a current measurement system (HSTS016L sensors, ADS1115 ADC). This setup enables granular monitoring of power consumption across subsystems, providing the empirical data needed to build and validate the energy model. Drawing on insights from the literature review (Chapter 2), which highlighted gaps in unified energy modeling [5], this methodology addresses the need for a comprehensive framework that captures subsystem inter-dependencies and SOC effects in controlled and semi-controlled environments.

The chapter is organized into three sections. Section 3.1 details the rover platform design, describing the selection and integration of computational, mechanical, and communication components to support energy monitoring. Section 3.2 explains the energy measurement system, including sensor calibration, data collection, and noise mitigation techniques, which ensure accurate power measurements. Section 3.3 presents the energy consumption model, synthesizing empirical data with mathematical relationships to predict power usage based on workload intensity, velocity, communication rate, and SOC. Together, these sections provide a replaceable framework for analyzing energy dynamics in mobile robots, addressing limitations in prior work, such as the neglect of communication energy or SOC-dependent modeling [6].

This methodology focuses on single, battery-powered terrestrial rovers operating in structured environments, such as indoor arenas or flat outdoor terrains (e.g., concrete, gravel). It excludes optimization strategies, multi-robot systems, complex terrains, and alternative power sources (e.g., solar), which are beyond the scope of this thesis. The resulting energy model serves as a foundation for understanding system-level energy consumption, enabling future research into energy-efficient robotics. Chapter 4 will build on this methodology by detailing the experimental setup and validation results, demonstrating the model's accuracy and practical utility.

3.1 Rover Platforms Development

The development of custom rover platforms is a critical component of this research, enabling precise energy consumption measurements and model validation. Two terrestrial rovers were designed and built, one equipped with a NVIDIA Jetson Nano companion computer and the other with a NVIDIA Jetson TX2, as shown in Figures 3.1 and 3.2, respectively. Each rover integrates four core hardware modules: a motion control unit, a computing unit, a power distribution unit, and a current measurement unit, supported by a software stack for autonomy, control, and real-time monitoring. These platforms are tailored to capture the energy dynamics of computational, mechanical, and communication subsystems in controlled and semi-controlled environments, such as indoor arenas and outdoor terrains.

Figure 3.1: Rover Jetson Nano

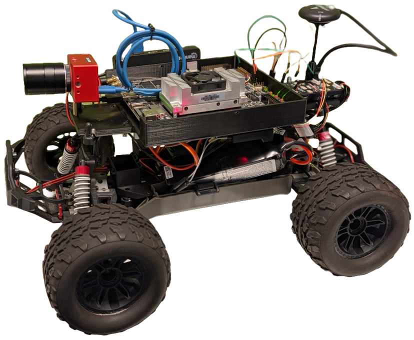


Figure 3.2: Rover Jetson TX2

Both rovers share a similar overall architecture but differ in their computational units, cameras, and connection interfaces. The common architecture for both rovers is given below:

The **Motion Control Unit** comprises a 538527C KV3000 brushless DC motor, a WB-10BL50-RTR Electronic Speed Controller (ESC), a Reely S-0060 servo, a Pixhawk 4 flight controller, and a Holybro PM07 power management board. The Pixhawk 4 is the central control unit for actuation, receiving commands from the computing system and executing motion tasks accordingly. It also integrates a GPS module, FS-iA6B receiver, and a 915 MHz telemetry radio, enabling ground control through an FS-i6 transmitter, Mission Planner, or QGroundControl. The Pixhawk 4 communicates with the computing unit via a Universal Asynchronous Receiver/Transmitter (UART) connection. This interface allows for bidirectional communication using the MAVLink protocol to exchange sensor data, telemetry, and motor control commands.

The **Computing Unit** is powered by NVIDIA Jetson device serving as the companion computer, paired with a camera. It is designed to collect and process sensor data, issue commands to the motion control unit, and facilitate communication with other devices.

The **Power Distribution Unit** facilitates efficient energy delivery to all rover components. A 4S1P 14.8V lithium-ion battery acts as the primary power source, supplying energy to the PM07 power management board. The PM07 distributes power and uses two DC/DC buck converters to regulate voltage for the computing unit and DC motor (up to 7.4V). Additionally, the PM07 powers the Pixhawk 4 and servo, while transmitting control commands to the servo and ESC through FMU output pins

The **Current Measurement Unit** is designed to monitor real-time energy consumption of both mechanical and computational subsystems. An ADS1115 16-bit ADC is connected to the I2C bus via GPIO pins of NVIDIA Jetson devices. It interfaces with HSTS016L Hall-effect based current sensors, rated at 30A/2.5V ± 0.625V, providing accurate current measurements for different power rails. These sensors enable detailed profiling of system power usage, aiding in energy-aware planning and performance analysis.

The **Software Stack** integrates the Python libraries Mavproxy and DroneKit for MAVLink-based communication and control between the Jetson TX2 and Pixhawk 4. ROS Melodic serves as the primary middleware framework, orchestrating sensor integration, autonomy modules, and inter-process communication. This layered architecture allows modular development, real-time perception, and high-level decision-making for autonomous navigation and control.

3.1.1 Jetson Nano Rover Architecture

The NVIDIA Jetson Nano offers a compact, energy-efficient platform optimized for AI edge computing. It features a quad-core ARM Cortex-A57 CPU and a 128-core

Maxwell GPU, supporting real-time tasks such as computer vision and deep learning. With up to 4GB of LPDDR4 memory and versatile I/O options—including GPIO, I2C, SPI, and CSI for camera integration—the Nano operates on a Linux-based OS and supports AI frameworks like TensorFlow, PyTorch, and ROS, making it well-suited for robotics and embedded systems. Its modular design facilitates rapid prototyping and deployment in AI-driven applications. The computing unit is paired with an OAK-D depth camera, which integrates stereo vision and an Intel Myriad X VPU for on-device neural network processing. The OAK-D includes a wide-field RGB camera and dual monochrome sensors for depth estimation, enabling real-time object detection, tracking, and spatial AI without external computing resources. The Pixhawk 4 flight controller connects to the Jetson Nano via the telemetry port to the J41 GPIO header, allowing sensor data access and command transmission to the flight controller. The DroneKit Python library and ROS nodes manage sensor data processing and motion control. Figure 3.3 illustrates the schematic, showing the Jetson Nano's 5V power input from the power distribution board, USB connections to the OAK-D camera, and UART interfaces to the Pixhawk 4 and ADS1115, ensuring efficient data transfer and minimal energy consumption.

3.1.2 Jetson TX2 Rover Architecture

The NVIDIA Jetson TX2 is a high-performance platform designed for advanced AI edge computing, featuring a dual-core Denver 2 and quad-core ARM Cortex-A57 CPU, paired with a 256-core Pascal GPU, enabling robust processing for complex tasks like real-time object detection and multi-sensor fusion. It supports up to 8GB of LPDDR4 memory and offers extensive I/O options, including GPIO, I2C, SPI, and CSI for camera integration. Running a Linux-based OS, the TX2 is also compatible with AI frameworks such as TensorFlow, PyTorch, and ROS, making it ideal for demanding robotics applications. The computing unit is equipped with a DAVIS-346

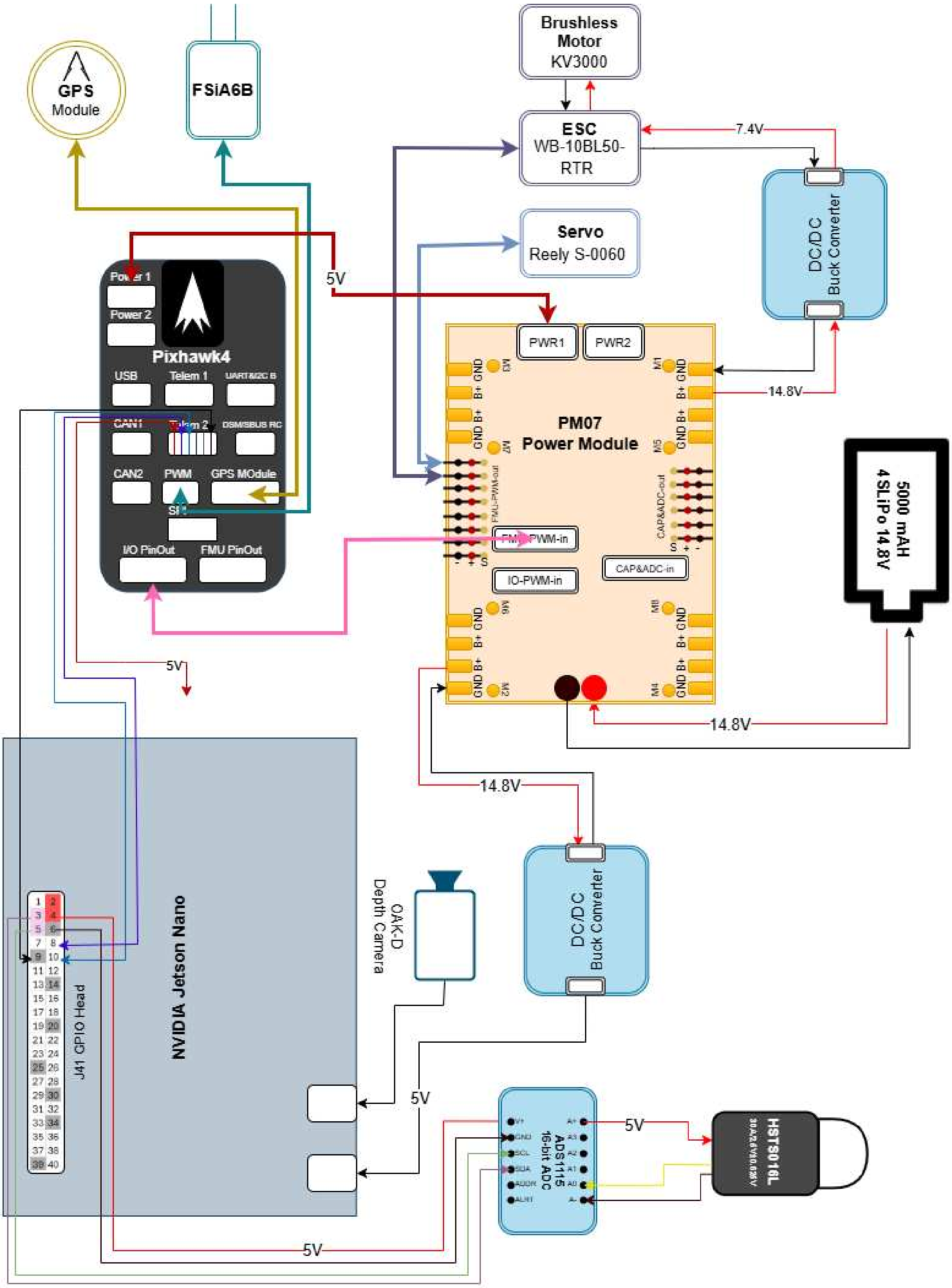


Figure 3.3: Schematics Rover Jetson Nano

event-based camera, capable of outputting both standard intensity images and an asynchronous stream of events with sub-millisecond latency and temporal resolution up to 10 million events per second [44]. The Pixhawk 4 flight controller connects to the Jetson TX2 via the telemetry port to the J17 UART header, facilitating sensor data access and command transmission to the flight controller. The DroneKit Python library and ROS nodes handle sensor data processing and motion control. Figure 3.4 illustrates the schematic, showing the Jetson TX2's 12V power input regulated by a buck converter from the power distribution board, USB connections to the DAVIS-346 camera, and UART interfaces to the Pixhawk 4 and ADS1115, ensuring efficient data flow and low energy overhead.

3.2 Energy Measurement System

The Current Measurement System developed and presented in my recent technical report [45] is a critical component of the platform designed to analyze the energy consumption of mobile robots. Initially, the process was designed and tested on a rover with NVIDIA Jetson Nano and later implemented on NVIDIA Jetson TX2. This system accurately measures the electric current consumed by both the computational and mechanical parts of the robot, enabling precise power and energy calculations. This section details the hardware components, calibration process, and software implementation used to achieve reliable current measurements.

The system integrates the following key components:

1. **HSTS016L Current Sensor:** A Hall effect-based sensor capable of measuring DC and AC currents up to 30A with high linearity. Its output voltage ranges from ±0.625V around a baseline of 2.5V, corresponding to forward and reverse currents as shown in the figure 3.5.

2. **ADS1115 ADC:** A 16-bit ADC with a programmable gain amplifier, ensur-

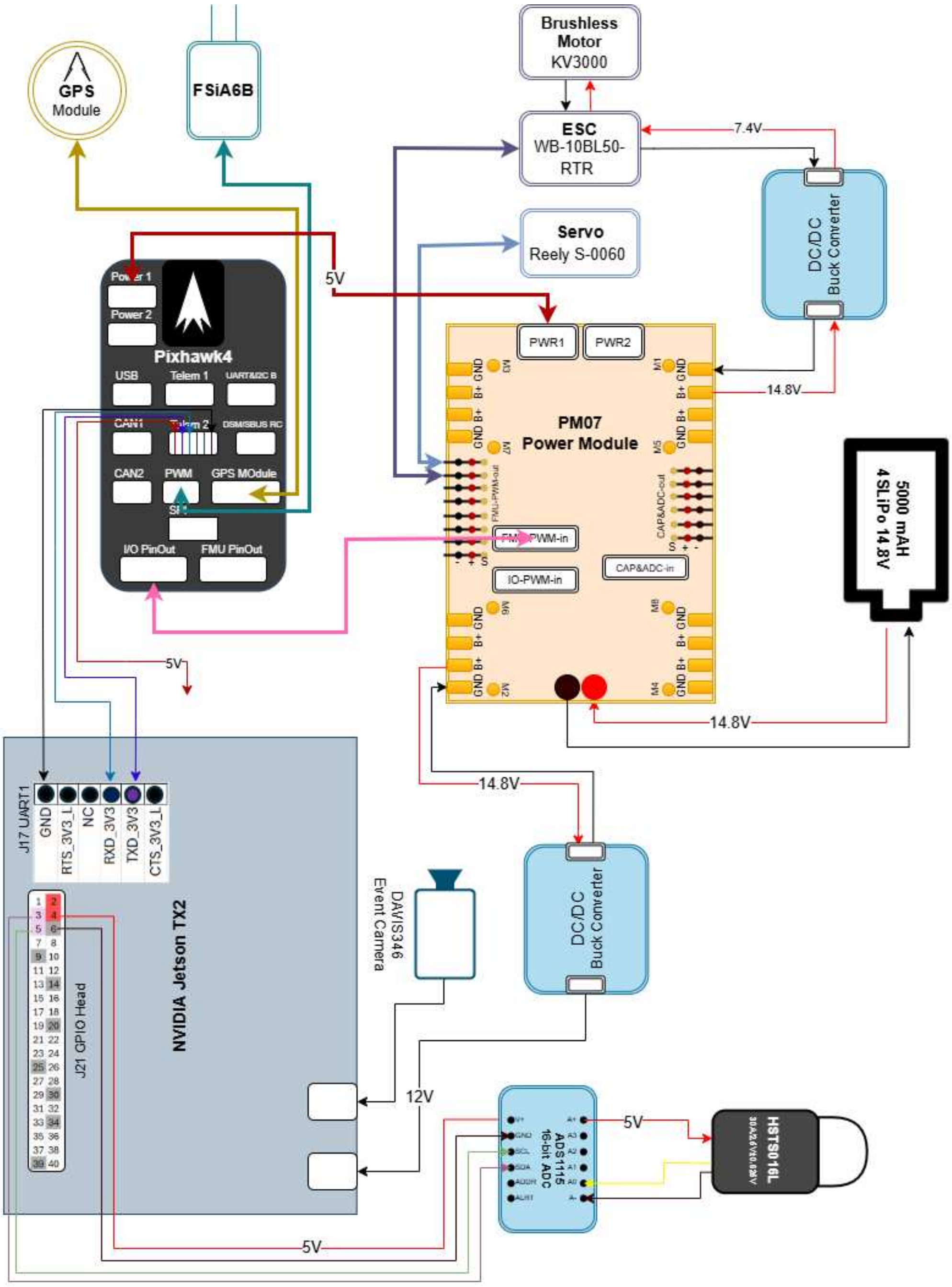


Figure 3.4: Schematics Rover Jetson TX2

ing high-resolution voltage measurements. It communicates with the NVIDIA Jetson Nano via the I^{2}C interface.

3. **Multimeter UT203R:** Used for validation and calibration of the current sensor measurements.

The HSTS016L sensor outputs an analog voltage proportional to the current. The ADS1115 converts this voltage to a digital value, which is processed by the Jetson Nano.

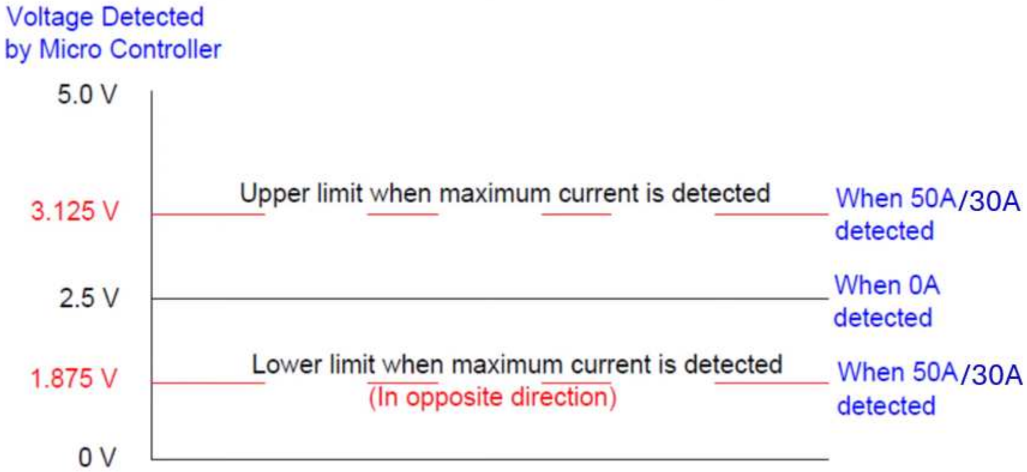


Figure 3.5: HSTS016L Sensor Output Diagram

The current is calculated using the formula:

$$\text{Current} = \frac{\text{Voltage} - V_{\text{ZERO}}}{\text{SENSITIVITY}} \tag{3.1}$$

where $V_{\text{ZERO}} = 2.5\,\text{V}$ (zero-current voltage) and sensitivity is $0.02083\,\text{V/A}$ (derived from the sensor's $\pm 0.625\,\text{V}$ range for $30\,\text{A}$).

A real-time script reads the ADC values, converts them to voltage, and computes the current. The results are logged for further analysis.

The Hall effect sensor exhibited inherent noise, producing small negative current readings even with no load. To address this issue three sensors were tested under no-load conditions, revealing consistent noise patterns (e.g., mean noise values of -0.331A, -0.648A, and -0.614A for each sensor). The noise average was subtracted from subsequent measurements, significantly improving accuracy. Post-calibration, the sensors demonstrated reliable performance, with mean observed currents closely matching expected values (e.g., 1.247A, 1.248A, and 1.235A for the three sensors under test conditions).

The system achieved high accuracy in current measurement, validated by multimeter comparisons. Calibration mitigated sensor noise, ensuring dependable data for energy consumption analysis. The integration of the ADS1115 and Jetson device enabled real-time monitoring and logging, essential for dynamic energy profiling.

3.3 Energy Consumption Model

The energy consumption model developed in this thesis provides a unified framework to quantify the runtime power demands of mobile robots, integrating computational and mechanical consumption with battery SOC awareness. This hybrid model combines empirical data from the high-precision current measurement system with analytical formulations derived from physical principles and system characteristics, addressing gaps in prior work that often modeled subsystems in isolation or neglected SOC effects [5], [6]. The model captures dynamic operational parameters. workload intensity, velocity, acceleration, communication rate, and SOC, to predict total power consumption and inform energy-efficient design. It is structured into three subsections: mechanical power consumption, computational power consumption, and battery model integration. The communication power consumption is considered as a part of the computational power as it is not possible to measure it separately with external sensor like ADS1115. However, attempt has been made to analyze adaptive transmission strategies, power-efficient modulation schemes, and resource allocation methods optimize energy usage while maintaining reliable data exchange using this platform and work is accepted in upcoming FNC 2025 international conference and will be discussed in next chapter.

3.3.1 Mechanical Power Consumption

According to Newton's second law, a mechanical power prediction model is developed based on the motor speed and the forces applied to it [46]. The power demand for the rover moving on a flat surface is calculated as follows:

$$P_m = \eta_{ESC} \cdot (Fv) \tag{3.2}$$

where F is the propulsive force that motor provides, η_{ESC} denotes the efficiency with which electrical power is converted into motor power, and is approximated as a constant [47]. F is computed as

$$\begin{aligned} F &= (F_a + F_f + F_d)v \\ &= m\frac{dv}{dt} + (C_r + C_v v) \cdot mg + \frac{1}{2}\rho C_d A_f v^2 \end{aligned} \tag{3.3}$$

where F_a, F_f, F_d, denote the acceleration force, rolling friction force, and aerodynamic drag force, respectively. Here, m is the rover mass and g is the gravitational acceleration. The parameters C_r and C_v represent the constant and viscous rolling coefficients, respectively; ρ is the air density; C_d is the aerodynamic drag coefficient, and A_f is the frontal area.

3.3.2 Computational Power Consumption and Performance Model

Computing energy consumption P_c for multi-core processing boards can be modeled using a fitted power model, with parameters identified specifically for the considered compute board [48]. In particular, the total power consumption of a computing board can be estimated in an additive way according to the following formula:

$$P_c = P_{board}^{idle} + \sum_i \left(a[f_i] \cdot \%U_i + b[f_i]\right) \tag{3.4}$$

where P_{board}^{idle} denotes the idle power consumption of the board, and a, b are constants empirically determined for each core at its operating frequency f_i. $\%U_i$ represents the utilization, as reported by the operating system for the running applications. Indeed, as shown in [49], an application-agnostic power model (considering utilization only) offers a reasonable accuracy to properly take decisions in the proposed control loop.

For this specific research we used rover equipped with Jetson TX2 as a companion computer and DAVIS346 event camera. The event camera generates an input stream of batches at a predefined rate R. The execution time for processing each batch varies across applications due to differences in computational complexity. Some applications (e.g., App 1 and 2) finish computing before the batch period $1/R$, entering an idle state until the next batch arrives, while others (e.g., App i) may exceed this period, resulting in a throughput lower than R. This is acceptable as long as the achieved performance meets the QoS(Quality of Service) requirement QOS_i. However, over-provisioning CPU resources (e.g., excessively high frequency) for applications like App 1 and 2 wastes energy without improving throughput, as their performance is already saturated at R.

To address this, the proposed controller monitors the execution time of applications for each event batch. Since the number of events per batch varies, the execution time is also variable. The controller tracks the execution times over the last control period and computes a performance metric, *Processing Latency Percentile (PLPT)* (Processing Latency Percentile), as the third quartile Q_3 (75th percentile) of the execution time series:

$$\text{PLPT} = Q_3(\{\text{Execution Times}\}). \tag{3.5}$$

Using Q_3 mitigates the effect of outliers and reduces the risk of QoS violations in the control policy.

The controller prioritizes the most performance-demanding application, defined as the one minimizing its idle time percentage:

$$\%\text{idle}_i = \frac{1/\text{QOS}_i - \text{PLPT}_i}{1/\text{QOS}_i}. \tag{3.6}$$

A negative $\%\text{idle}_i$ indicates a QoS violation. If all applications share the same QoS requirement, the most demanding application is simply the one with the highest PLPT.

The performance model includes an estimator for PLPT_{new} under a new configuration $(f_{\text{new}}, s_{\text{new}})$, based on current measurements $(f_{\text{curr}}, s_{\text{curr}}, \text{PLPT}_{\text{curr}})$. The relationship between PLPT and CPU frequency is linear, while the dependence on motor speed s is sublinear:

$$\text{PLPT}_{\text{new}} = \left(\frac{f_{\text{new}}}{f_{\text{curr}}}\right) \cdot \left(\frac{s_{\text{new}}}{s_{\text{curr}}}\right)^{\beta} \cdot \text{PLPT}_{\text{curr}}, \tag{3.7}$$

where β is an empirically derived constant. This estimator enables the controller to evaluate potential configurations without direct enforcement, supporting efficient resource allocation.

3.3.3 Battery Model and Energy Consumption

The overall electrical power demand, which comprises both mechanical and computational loads, is given by:

$$\begin{aligned} P_{elec}(t) &= P_c(t) + P_m(t) \\ &= V_{batt}(t) \cdot I_b(t) \end{aligned} \tag{3.8}$$

where $V_{batt}(t)$ denotes the battery voltage at time t. The battery voltage is modeled as:

$$V_{batt}(t) = V_{OC}(SOC(t)) - I_b(t) \cdot R_s(t) - V_1(t) - V_2(t) \tag{3.9}$$

and the battery current is computed by:

$$\begin{aligned} I_b(t) = \frac{1}{2R_s(t)}\Big(V_{OC}(SOC(t)) - V_1(t) - V_2(t) \quad - \\ \sqrt{(V_{OC}(SOC(t)) - V_1(t) - V_2(t))^2 - 4R_s(t)P_{elec}(t)}\Big) \end{aligned} \tag{3.10}$$

where $V_{OC}(SOC(t))$ is the open-circuit voltage as a function of SOC, $R_s(t)$ is the battery internal resistance. Consequently, the final SOC over the entire track is computed as:

$$SOC_f = SOC_{t_0} - \frac{1}{Q_{batt}} \int_{t_0}^{t_f} I_b(t)dt \tag{3.11}$$

The hybrid nature of this model lies in its integration of empirical current measurements with analytical equations grounded in physical principles. The model's predictive capability will be tested in Chapter 4, examining relationships between current, motor speed, DVFS, and communication distance, to validate its accuracy and utility for energy-efficient robotics.

4 Experiments and Results

This chapter presents the experimental validation of the runtime energy consumption model developed in Chapter 3 for battery-powered mobile robots. The experiments aim to quantify the power demands of computational, mechanical, and communication subsystems, while capturing the influence of battery SOC on system performance. Utilizing custom rover platforms equipped with NVIDIA Jetson Nano and TX2 companion computers (Section 3.1), a high-precision energy measurement system (Section 3.2), and a hybrid model combining empirical and analytical approaches (Section 3.3), the study addresses gaps in prior work that often neglected subsystem inter-dependencies or SOC effects [5], [6]. Conducted in controlled indoor and outdoor arenas, the experiments provide empirical data to validate the model's predictive accuracy and inform energy-efficient robotic design.

The chapter is organized into four sections. Section 4.1 details the calibration of the HSTS016L current sensors, ensuring measurement reliability. Section 4.2 analyzes battery voltage and SOC dynamics under varying workloads, validating the battery model. Section 4.3 investigates the relationship between current, motor speed, and CPU frequency across SOC levels, validating the mechanical and computational power models. Finally, Section 4.4 examines communication energy consumption. Together, these experiments demonstrate the model's utility in capturing subsystem dynamics and SOC-dependent behaviors, advancing the development of energy-efficient mobile robotics.

4.1 Current Senor's Calibration

The current measuring sysem developed and discussed in last chapter do require caliberation of the sensors. As HSTS016L sensor uses Hall effect to sense and measure current. We observed some noise even when there is no wire between the clamps. The same behaviour is observed with the Multimeter which shows -0.20 to -0.40 A values as noise. There are multiple reasons for this behaviour from sensors based on Hall effect.

We have used 3 different HSTS016L sensors to observe the behaviour and calibrate the sensors. We recorded 50 measurements and below is given the statistical outcome of the observations.

Table 4.1: Noise Data for Three Sensors

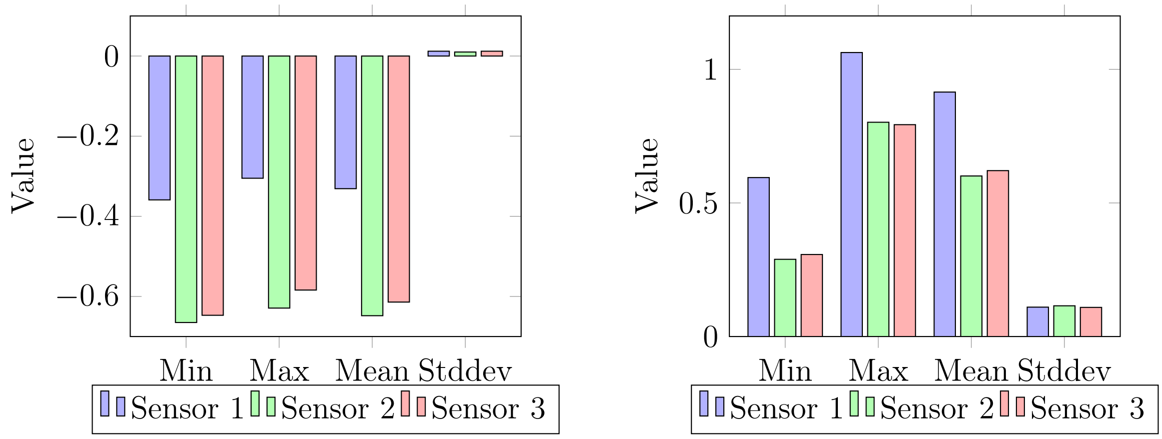
Noise	**Sensor 1**	**Sensor 2**	**Sensor 3**
Min	-0.359	-0.665	-0.647
Max	-0.305	-0.629	-0.584
Mean	-0.331	-0.648	-0.614
Standard dev	0.012	0.010	0.012

Again, we used all 3 sensors on a wire simultaneously and recorded 50 observations. Below are the statistical outcomes of the observations.

Table 4.2: Observation Data for Three Sensors

Observations	**Sensor 1**	**Sensor 2**	**Sensor 3**
Min	0.595	0.289	0.307
Max	1.063	0.802	0.793
Mean	0.915	0.601	0.621
Standard dev	0.110	0.115	0.109

For the calibration purpose we subtracted the average of noise (measurements without wire) from each instance and below are the statistical outcomes.After the Calibration values are quite reliable and shows almost equivalent values.



(a) Bar Chart of Noise Data

(b) Bar Chart of Observation Data

Figure 4.1: Comparison of Noise and Observation Data for Three Sensors

Table 4.3: Calibrated Observations Data for Sensors

Calibrated Observations	**Sensor 1**	**Sensor 2**	**Sensor 3**
Min	0.926	0.937	0.921
Max	1.394	1.450	1.407
Mean	1.247	1.248	1.235
Standard dev	0.110	0.115	0.109

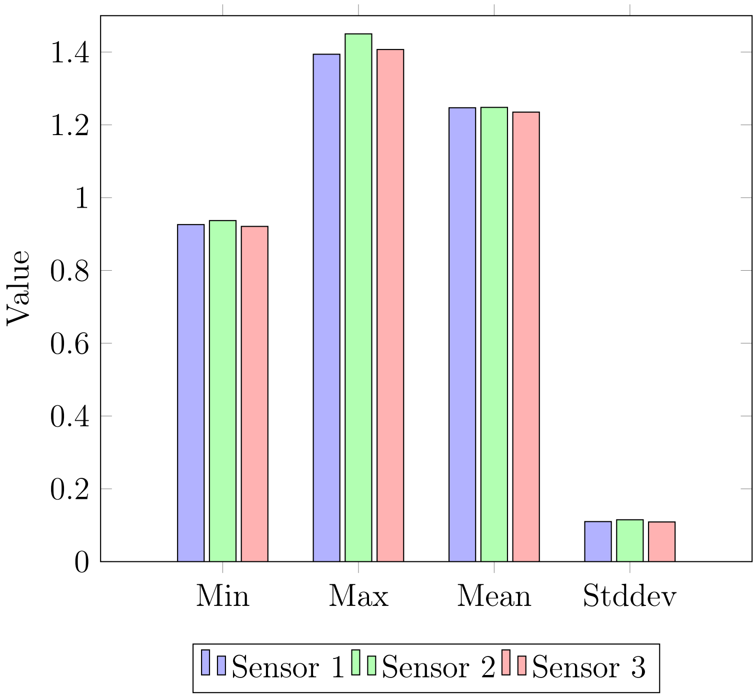


Figure 4.2: Bar Chart of Calibrated Observations Data for Sensors

4.2 Battery Voltage and SOC Analysis

The battery voltage and SOC analysis quantifies the dynamic behavior of the 4S1P 14.8V lithium-ion battery powering the rover platform, validating the battery model presented in last model. This experiment investigates how SOC influences battery voltage under varying workloads, providing insights into SOC-dependent power delivery and its impact on computational and mechanical subsystems. The analysis is critical for understanding energy constraints in mobile robots, as SOC affects motor torque, computational efficiency, and overall operational time.

The experiment was conducted using Rover TX2. As the battery power up both mechanical and computational unit the experiment shows that the battery SOC decreases over time, the open-circuit voltage (V_{OC}) drops, and the internal resistance (R_s) increases in a non-linear manner. Consequently, the non-linear behavior of the battery constrains effective current delivery, thereby diminishing the actual power available to the robotic system. These changes, in turn, impact the energy-efficient configurations for both the motor and CPU. By considering these dependencies alongside battery SOC and environmental conditions while adjusting mechanical and computational units, we can significantly enhance overall energy efficiency thus increasing the overall robot operational lifetime and autonomy.

The Figure 4.3 shows that as the SOC of the battery drops the the internal resistance increases and result in drastic current draw from the battery that will be proven in next sections.

4.3 Relation between Current, Motor Speed and CPU Frequency

This experiment investigates the relationship between battery current, motor speed, and CPU frequency under varying SOC levels to validate the mechanical and com-

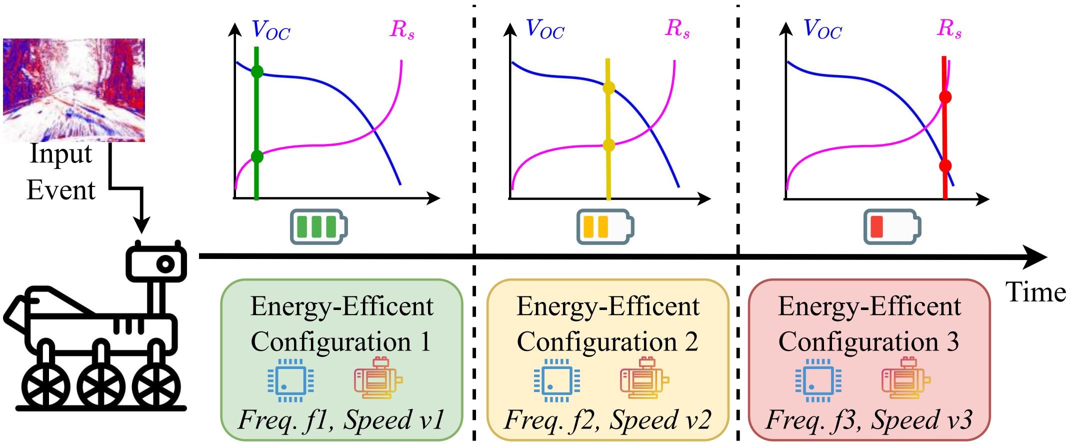


Figure 4.3: Energy-efficient configurations w.r.t. battery SOC changes.

putational power consumption models developed in last chapter. By analyzing how SOC influences current draw across subsystems, the study underscores the need for battery-aware energy management in mobile robotics [46], [49]. Three SOC levels (100%, 50%, 10%), corresponding to open-circuit voltages (V_{OC}) of 14.74 V, 14.39 V, and 12.65 V, were tested to capture SOC-dependent effects.

The experiment utilized the Jetson TX2 rover for motor speed and CPU frequency tests, equipped with calibrated HSTS016L current sensors and ADS1115 ADC (Section 4.1). For the experiments, we utilize an event-based camera to capture data for perception tasks, which precede path planning and control. We evaluate two specific applications processing camera events: i) corner detection [50] and ii) feature tracking using the Kanade-Lucas-Tomasi (KLT) algorithm [51]. These applications process events in batches, with each execution requiring a guaranteed throughput of processed batches per second to meet performance demands. This ensures timely data delivery to subsequent path planning and control tasks, enabling effective decision-making for robot operations.

The Figure 4.4 illustrates (a) the relationship between battery current and motor speed and (b) the one with CPU frequency, respectively, under three different battery SOC levels, namely 100%, 50% and 10% of full battery charge. The increase in

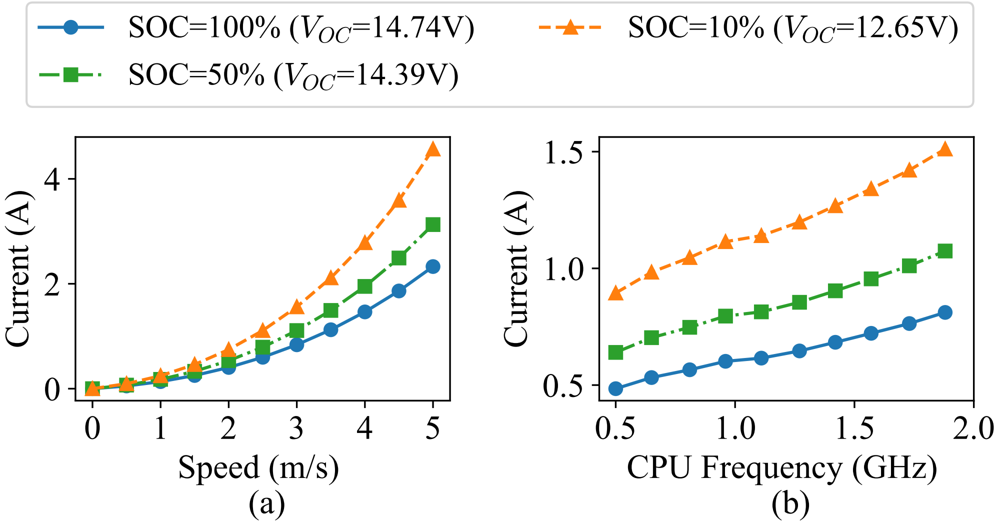


Figure 4.4: The relationship between (a) motor speed, (b) CPU frequency, and battery current at three different SOC levels.

motor speed exhibits a non-linear trend, while the increase in computational power with CPU frequency follows a nearly linear relationship. Notably, at lower SOC levels, the battery must supply a higher current to maintain the required operational configuration (motor speed and CPU frequency), resulting in a faster discharge rate. Overall, the ability of the battery to deliver mechanical and computational power depends on its SOC, which plays a crucial role in practical applications. Across the SOC range, the maximum current delivery varies by as much as 1.85A for mechanical units and 0.87A for computational units, underscoring the necessity for battery-aware energy management. The current measurements were conducted under consistent mechanical conditions and computing workloads. Motor speed was adjusted using Pulse Width Modulation (PWM), and CPU frequency was controlled via DVFS. The results demonstrate that the battery SOC significantly impacts the energy consumption of both mechanical and computational units, highlighting the need for a battery-aware energy management strategy.

4.4 Communication Energy Consumption Analysis

The communication energy consumption of the mobile rover platform, equipped with a NVIDIA Jetson Nano, is analyzed to quantify its contribution to overall power demands, particularly over varying distances. Due to the inability to measure communication power separately using external sensors like the ADS1115 current sensor, communication energy is modeled as a component of the computational power consumption. This section presents an analytical framework and empirical approach to estimate communication energy and optimization techniques presented in our recent conference paper, "Towards Optimizing Communication Cost in Energy Efficient IoT Devices for Swarm Robotics", which emphasizes "adaptive transmission strategies, power-efficient modulation schemes, and resource allocation methods to optimize energy usage while maintaining reliable data exchange."

Rover jetson Nano equipped with energy efficient communication modules (LoRa modules, BLE sensors) was deploed for this research. Performance metrics such as energy consumption, data transmission reliability, and network lifetime were analyzed under varying environmental conditions. We used an Intel Core i5 based laptop which acts as the edge gateway, processing the optimization protocols and data analysis. A NVIDIA Jetson Nano mounted on mobile rover serves as an IoT end node with an external current consumption sensor attached to it.

The communication energy consumption can be calculated as :

$$E_{Comm} = E_{tx} + E_{rx} + E_{listen} + E_{overhead} \tag{4.1}$$

where E_{tx}, E_{rx}, E_{listen}, and E_{overhead} represent the energy consumed during transmission, reception, idle listening, and protocol-specific overheads, respectively.

The methodology employs several communication protocols, including BLE, LoRaWAN, MQTT, and CoAP. A Protocol Selection Matrix is used to determine

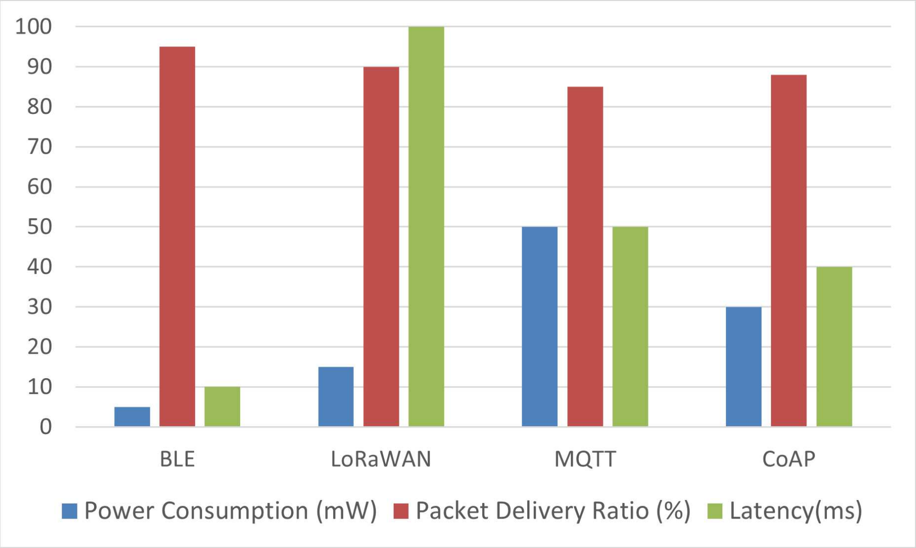


Figure 4.5: Power consumption, Packet delivery ratio and Latency at rest.

the best protocol for each communication link, taking into account factors such as transmission range, data payload size, and the energy characteristics of the protocols used. For example, BLE is preferred for short-range, low-energy communication, whereas LoRaWAN is chosen for long-range transmissions when applicable. The primary data extracted from the onboard sensors are the power consumption of the Nano along with the voltage as well as the current readings while the application is running in a loop. The values are used to establish a relationship between the transmission and the reception sequences while the Nano is operating. We started the data logging at an initial distance and kept on repeating the experiment after moving the node every 10 meters. We carried on with recording the measurements until a distance of 70 meters was achieved and after this significant distortion in the communication capabilities was observed. We used the obtained data to form a relationship between the communication power and the distance covered by the node while our application was running on the Nano. The figure 4.5 shows the Power consumption, Packet delivery ratio and Latency at rest.

The power consumption is modeled as a function of transmission power and distance, adapted from energy-aware transmission power control (EATPC) principles:

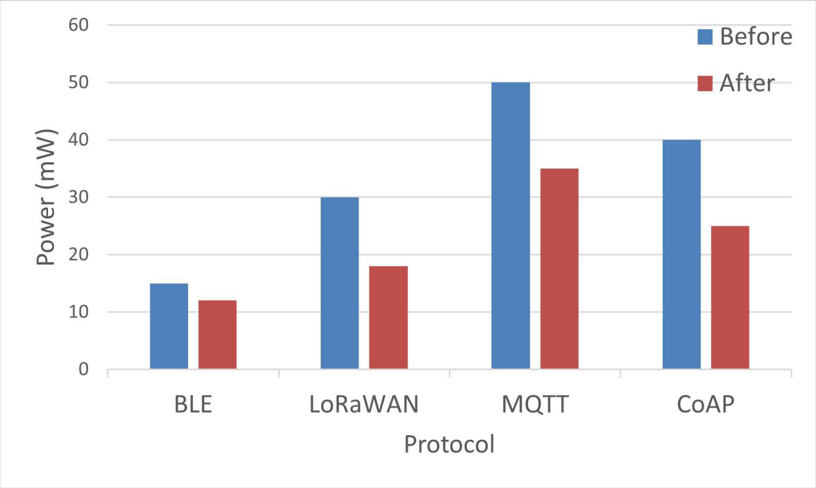


Figure 4.6: Power consumption Analysis Before and After Optimization (mW)

$$P_t(d) = P_{min} + \alpha d^n \tag{4.2}$$

where the greek letter "alpha" is a scaling factor, and n is the path-loss exponent (typically 2-4).

The communication framework incorporates three key features:

1. **Dynamic Transmission Power Control**: dynamic transmission power control which adjusts the transmission power based on residual energy levels and network conditions.

2. **Duty Cycle Optimization**: Adapts sleep/wake schedules of the communication module to balance energy consumption and data throughput, reducing idle listening energy.

3. **Energy-Aware Routing**: Energy-Aware Routing which implements an energy-efficient routing algorithm to minimize communication overhead.

Experiments demonstrated that energy-adaptive communication protocols and machine learning-based optimization techniques improved energy efficiency by 10-15 percent, as evidenced by the reduction in power consumption shown in Figure 4.6.

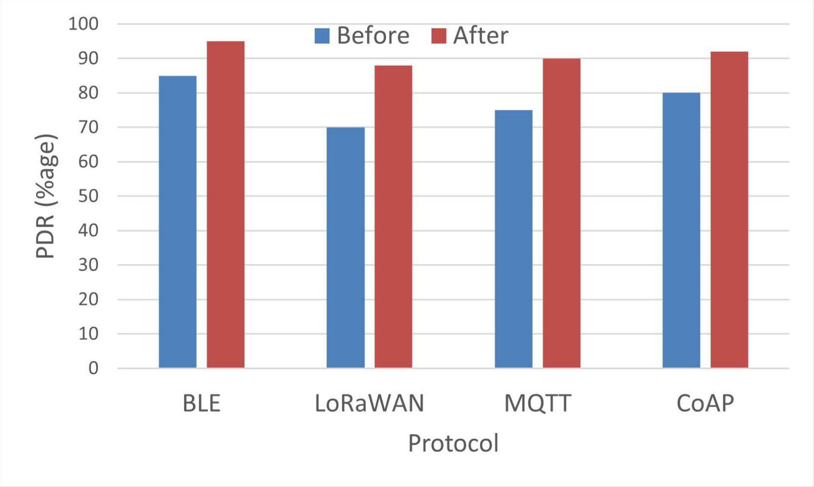


Figure 4.7: Packet Delivery Analysis Before and After Optimization (%age)

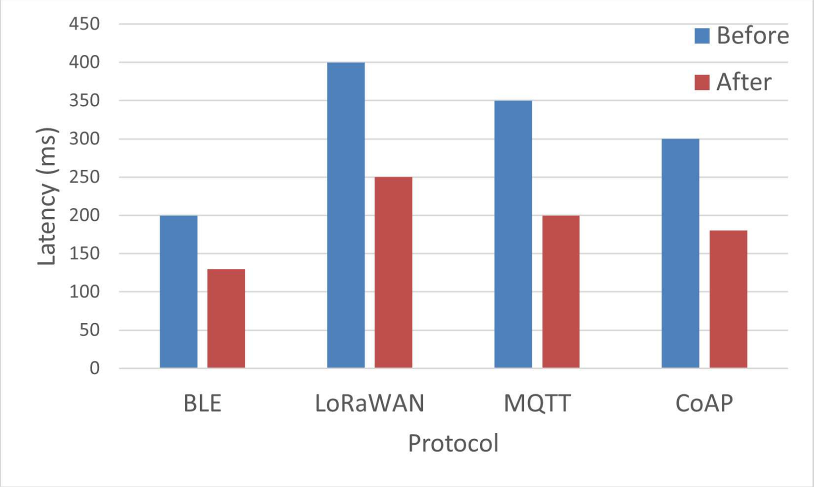


Figure 4.8: Latency Analysis Before and After Optimization (ms)

The bar chart illustrates that protocols like BLE and CoAP experienced notable decreases in power consumption (from 15 mW to 10 mW for BLE and from 40 mW to 30 mW for CoAP), reflecting enhanced energy management. Additionally, the Packet Delivery Ratio (PDR) improved post-optimization, as depicted in Figure 4.7, where BLE, LoRaWAN, MQTT, and CoAP all showed increases (e.g., BLE from 85% to 95%), indicating better data reliability. Moreover, utilizing sophisticated signaling protocols, such as SNR (Signal-to-Noise Ratio) optimization, reduced latency, as shown in Figure 4.8, with significant drops (e.g., LoRaWAN from 400 ms to 250 ms), enhancing connection quality, especially in areas with interference or low signal quality. This approach minimizes the need for retransmissions, further conserving energy and enabling devices to sustain longer operation even in fluctuating environmental conditions.

The experiments conducted in this chapter provide comprehensive validation of the hybrid energy consumption model presented in Chapter 3, confirming its ability to quantify runtime power demands across computational, mechanical, and communication subsystems of mobile robots. Section 4.1 established the reliability of the HSTS016L current sensors, achieving calibrated accuracy with mean currents of 1.235–1.248 A (Table 4.3), essential for precise energy measurements. Section 4.2 validated the battery model, demonstrating that SOC-driven voltage drops (e.g., from 14.74 V at 100% SOC to 12.65 V at 10% SOC) and increasing internal resistance constrain power delivery, impacting motor and computational performance (Figure 4.4). Section 4.3 confirmed the mechanical and computational power models, revealing non-linear current increases with motor speed (up to 1.85 A variation) and linear increases with CPU frequency (up to 0.87 A variation) at lower SOCs (Figure 4.4), underscoring the need for SOC-aware velocity and DVFS strategies. Section 4.4 quantified communication energy within the computational framework, showing that adaptive protocols (e.g., BLE, MQTT) and energy-aware techniques improved efficiency by 10–15% (Figure 4.6), despite measurement constraints.

These findings collectively validate the thesis's objective of developing a unified, SOC-aware energy model, addressing limitations in prior work that modeled subsystems in isolation [5], [6]. The results highlight the critical role of SOC in energy management, as lower SOC levels accelerate battery discharge due to higher current demands, reducing operational time. The model's predictive accuracy, supported by calibrated measurements and controlled experiments, provides a robust framework for optimizing rover configurations, such as balancing velocity, CPU frequency, and communication protocols to extend mission duration. For instance, reducing motor speed at low SOC or scaling CPU frequency via DVFS can mitigate rapid discharge, as evidenced by the current variations observed.

Future research could extend this work by incorporating dynamic environmental factors (e.g., terrain variations, temperature) into the model, as the current experiments were limited to flat surfaces and controlled conditions. Integrating machine learning for real-time energy optimization, as hinted in our conference paper [45], could further enhance efficiency. Additionally, developing methods to separately measure communication energy (e.g., using specialized sensors) would refine the model's granularity. These experiments lay a foundation for advancing energy-efficient robotics, enabling longer autonomy and supporting applications in exploration, surveillance, and swarm robotics.

5 Discussion

This chapter synthesizes the findings of the research, contextualizes the results within the broader field of energy-efficient mobile robotics, and outlines directions for future work. The discussion integrates the experimental outcomes with theoretical frameworks to provide a comprehensive understanding of energy consumption in mobile robots with real-time SOC awareness.

This thesis has addressed the critical challenge of energy efficiency in mobile robots through the development of a comprehensive sensor fusion-based energy consumption model with real-time SOC awareness. The research was motivated by the increasing deployment of mobile robots across diverse domains and the corresponding need to optimize energy consumption to enhance efficiency and extend operational lifetime. The study began by identifying a significant gap in existing research: while numerous studies have examined energy consumption in isolated subsystems (either mechanical or computational), few have developed unified models that account for the interdependence between computational workload, mechanical actuation, and battery SOC. This interdependence is crucial, as a low SOC may reduce voltage supplied to motors, affecting their performance, while intensive computational tasks can increase power draw, leading to accelerated battery depletion.

To address this gap, the research pursued four primary objectives:

- Development of Mobile Rover Platforms: Two custom mobile robots were successfully developed based on NVIDIA Jetson devices (Nano and TX2) as companion computers, integrated with Pixhawk 4 controllers and modular subsystems. These platforms provided the hardware foundation for empirical testing and model validation.

- Implementation of Energy Measurement System: A real-time energy measurement system was developed using HSTS016L current sensors and ADS1115 ADC, enabling accurate quantification of energy consumption across different robot subsystems. The calibration process successfully mitigated sensor noise, ensuring reliable data collection.
- Development of Hybrid Energy Consumption Model: A unified model was created that integrates empirical data and analytical formulations to quantify the relationship between computational workload, mechanical dynamics, communication overhead, and battery SOC. This hybrid approach combined the strengths of empirical, analytical, and data-driven modeling techniques.
- Investigation of Energy Consumption in Communication: The research extended to analyzing energy consumption in communication between robotic devices, providing insights into optimization strategies for data exchange in networked robotic systems.

The methodology employed a systematic approach, combining hardware design, precise energy monitoring, and data-driven modeling. The experimental validation demonstrated the model's ability to capture the dynamic interplay between subsystems and the significant impact of battery SOC on overall energy consumption.

5.1 Summary of Findings

5.1.1 Sensor Calibration and Measurement Accuracy

The calibration of the HSTS016L current sensors was a critical first step in ensuring measurement reliability. The observed noise in the sensors (mean values of -0.331A, -0.648A, and -0.614A) was successfully mitigated through calibration, resulting in consistent and accurate measurements across all three sensors (mean observed currents of 1.247A, 1.248A, and 1.235A). This calibration process highlights the importance of addressing sensor noise in energy measurement systems, particularly when using Hall effect-based sensors. The high precision achieved in current measurement was essential for capturing subtle variations in energy consumption across different operational conditions. This level of measurement accuracy is rarely reported in existing literature on mobile robot energy modeling, representing a methodological advancement that enhances the reliability of the resulting energy consumption model.

5.1.2 Battery SOC and System Performance

The analysis of battery voltage and SOC revealed significant insights into how battery state influences system performance. As the battery SOC decreased from 100% to 10%, the open-circuit voltage dropped from 14.74V to 12.65V, while internal resistance increased in a non-linear manner. This non-linear behavior constrains effective current delivery, diminishing the actual power available to the robotic system. The experiments demonstrated that at lower SOC levels, the battery must supply a higher current to maintain the required operational configuration (motor speed and CPU frequency), resulting in a faster discharge rate. This finding is particularly significant as it quantifies the relationship between SOC and power delivery, which has been largely overlooked in previous energy modeling approaches. The maximum current delivery was found to vary by as much as 1.85A for mechanical units and 0.87A for computational units across the SOC range, underscoring the necessity for battery-aware energy management. This substantial variation highlights why SOC must be considered in energy-efficient control strategies, as it directly impacts both mechanical and computational performance.

5.1.3 Interdependence of Subsystems

The relationship between battery current, motor speed, and CPU frequency under varying SOC levels revealed complex interdependencies that affect overall energy consumption. The increase in motor speed exhibited a non-linear trend, while the increase in computational power with CPU frequency followed a nearly linear relationship. This finding challenges the common practice of modeling mechanical and computational energy consumption separately. The results demonstrate that these subsystems are not only individually affected by SOC but also influence each other's energy consumption patterns. For instance, higher computational loads may reduce available power for mechanical actuation, particularly at lower SOC levels. The performance model developed in this research, which includes an estimator for PLPT under new configurations, provides a valuable tool for predicting system behavior under different operational parameters. This model enables the evaluation of potential configurations without direct enforcement, supporting efficient resource allocation in energy-constrained scenarios.

5.1.4 Communication Energy Optimization

The analysis of communication energy consumption revealed that it constitutes a significant portion of the overall energy budget, particularly in networked or multi-robot systems. The experiments demonstrated that energy-adaptive communication protocols and machine learning-based optimization techniques improved energy efficiency by 10-15 percent. The implementation of dynamic transmission power control, duty cycle optimization, and energy-aware routing proved effective in reducing communication energy consumption while maintaining reliable data exchange. These findings align with the growing recognition of communication as a critical energy consumer in mobile robotics, especially in swarm or distributed systems. The relationship between communication power and distance, modeled in equation 4.2, provides a framework for optimizing transmission power based on spatial distribution. This model can inform energy-efficient deployment strategies for multi-robot systems, where inter-robot distance directly impacts communication energy requirements.

5.2 Future Directions

While this thesis has made significant contributions to understanding and optimizing energy consumption in mobile robots, several promising directions for future research emerge from the findings. These directions build upon the developed platforms, energy models, and experimental insights to address remaining challenges and extend the applicability of the research.

5.2.1 Advanced Control Strategies

Future research should focus on developing more sophisticated control strategies that incorporate both SOC and SOH awareness. While this thesis has demonstrated the importance of SOC in energy management, battery SOH represents another critical dimension that affects long-term performance and reliability.

SOC-Adaptive Control Policies: Building on the current model, future work should develop control policies that dynamically adjust not only to current SOC but also predict future SOC trajectories based on planned operations. This predictive capability would enable robots to optimize task scheduling and resource allocation over extended missions, potentially incorporating techniques from model predictive control (MPC) and reinforcement learning. **SOH-Aware Battery Management:** Integrating SOH monitoring into the energy management framework would address battery aging and degradation effects. Future systems could track capacity fade, impedance growth, and other health indicators to adapt control strategies accordingly. This would involve developing models that correlate usage patterns with degradation rates and implementing adaptive charging/discharging protocols to maximize battery lifespan. **Unified SOC-SOH Framework:** A promising direction is the development of a unified framework that jointly optimizes for both immediate energy efficiency (SOC-based) and long-term battery health (SOH-based). This framework could resolve potential conflicts between short-term performance and long-term sustainability, particularly in applications requiring extended deployment periods.

Furthermore, future work should extend the current platforms to adapt to diverse environmental conditions. This could involve integrating additional sensors to detect terrain characteristics, ambient temperature, and other environmental factors that affect energy consumption. The platforms could then adjust their energy management strategies based on these environmental inputs. Also, research should explore the integration of machine learning techniques to enhance the predictive accuracy of energy models. Deep learning approaches could capture complex, nonlinear relationships between operational parameters and energy consumption that may be difficult to model analytically. These data-driven models could adapt over time as the system collects more operational data, improving prediction accuracy.

5.2.2 Optimization Strategies for Swarm Robotics

Extending the current research to multi-robot or swarm systems presents exciting opportunities for energy optimization at the collective level.

Distributed Energy-Aware Task Allocation: Future research should develop distributed algorithms that allocate tasks among swarm members based on their energy states and capabilities. These algorithms could balance workload distribution to maximize overall mission endurance while ensuring individual robots operate within their energy constraints. **Collaborative Energy Management:** Swarm robots could implement collaborative strategies for energy management, such as workload sharing, relay-based communication to reduce transmission power, or cooperative motion planning to minimize overall energy consumption. These collaborative approaches could achieve system-level efficiencies beyond what is possible with individual optimization. **Energy-Based Self-Organization:** Energy considerations could drive self-organization in robotic swarms, with robots dynamically forming energy-efficient configurations based on their current states and mission requirements. This could involve spatial reorganization to optimize communication energy, task redistribution based on remaining battery capacity, or adaptive role assignment to match energy demands with available resources.

Also, research should explore energy optimization in heterogeneous swarms, where robots with different capabilities, energy capacities, and consumption profiles collaborate. This heterogeneity introduces both challenges and opportunities for energy-efficient operation, requiring sophisticated allocation and coordination strategies that leverage the strengths of each robot type.

5.3 Conclusion

This thesis has made significant contributions to the field of energy-efficient mobile robotics through the development of a sensor fusion-based energy consumption model with real-time SOC awareness. The research has demonstrated the importance of considering the interdependence between computational workload, mechanical actuation, and battery state in optimizing energy consumption. The experimental validation confirmed that battery SOC significantly impacts the energy consumption of both mechanical and computational units, highlighting the need for battery-aware energy management strategies. The future directions outlined in this chapter build upon these foundations, suggesting pathways for advancing control strategies, extending the developed platforms, refining energy models, optimizing swarm robotics, and integrating renewable energy sources. These directions represent promising opportunities to further enhance the energy efficiency, autonomy, and sustainability of mobile robotic systems. By addressing the challenges of energy consumption in a holistic manner, this research contributes to the development of more sustainable autonomous systems, paving the way for energy-aware robotic deployments in real-world applications. As mobile robots continue to be integrated into diverse domains, the insights and methodologies presented in this thesis will support the design and implementation of energy-efficient systems capable of extended operation in complex environments.

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