Simulation of Mechanical and Computational Power Consumption in Mobile Robots

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KEYWORDS

Mobile Robot, Computational Power, Mechanical Power, Multi-Fidelity Power Estimation.

ABSTRACT

This paper presents a simulation model to estimate the instantaneous power consumption of a mobile robot by taking into account both its mechanical and computational components. The simulation model is adaptable to be tuned based on the level of accuracy needed for estimating the power consumption for the robot and the simulation time penalty. This makes a multi-fidelity power estimation tool for the robot with the capability to run-time changing the fidelity according to environmental conditions and internal computational capabilities. Such multi-fidelity energy prediction is suitable for run-time predictive decision making in a wide range of usages such as training process in model-based Reinforcement Learning (RL) as well as decision making in Model Predictive Control (MPC). The experimental results show that the simulation accurately estimates energy consumption at different fidelity levels. Higher-fidelity models closely match real-world measurements, while lower-fidelity models trade some accuracy for faster predictions. Therefore, higher estimation precision comes at the cost of increased computation.

1 INTRODUCTION

Energy efficiency plays a crucial role in the control of battery-powered mobile robots. These robots consist of multiple components, including sensors, computing units, and mechanical systems, each consuming a considerable portion of the overall energy consumption of the robot (Liu et al., 2023). An important consideration is that while various units individually draw energy from the battery, there is significant interdependence among their energy consumption. This interrelation must be taken into account when estimating the overall energy usage. A key aspect of such interdependence is the mutual reliance of mechanical and computational energy consumption. For instance, previous studies have demonstrated how a robot's mechanical and computational energy requirements are linked, especially when a certain accuracy level in perception is essential (Shahsavari et al., 2024). Although this codependence has been a driving factor behind efforts to co-optimize mechanical and computational units, there remains a gap in the development of a simulation model that explicitly incorporates this interdependence for real-time power consumption estimation of the robot.

In this paper, we introduce a structured simulation framework designed to estimate the power consumption of a mobile robot at run-time. The proposed framework accounts for both the power usage of mechanical and computational units, along with their interdependence. Additionally, the accuracy of the power estimation can be adjusted based on the computational cost required for the estimation process. This flexibility makes the framework well-suited for both real-time and offline power estimation. This adaptability makes the framework suitable for a variety of applications, including MPC and model-based RL, where the underlying system dynamic is needed for cost optimization and model training. Notably, the framework can adjust its fidelity during run-time to align with environmental conditions and internal computational capabilities, enabling adaptive and proactive energy optimization.

The main contributions of this paper can be summarized as follows:

- Proposing a simulation framework for real-time power estimation of a mobile robot, incorporating both mechanical and computational energy consumption.
- Implementing a dynamic tuning mechanism to balance energy estimation accuracy and computational efficiency based on environmental conditions and computational constraints.
- Conducting system identification and experimental validation on a wheeled ground robot equipped with an event camera for perception, a brushless DC motor for the mechanical system, and a microprocessor for computational tasks.

The rest of this paper is structured as follows: Section 2 presents an overview of related research in the area of power consumption in robotics. In section 3, we detail the methodology employed to model the system. This is followed by the presentation of result and system configuration in the fourth section. Lastly, the final section wraps up the paper with concluding remarks.

Communications of the ECMS, Volume 39, Issue 1,
Proceedings, ©ECMS Marco Scarpa, Salvatore Cavalieri,
Salvatore Serrano, Fabrizio De Vita (Editors) 2025
ISBN: 978-3-937 436-86-9/978-3-937 436-85-2
(CD) ISSN 2522-2414

2 RELATED WORKS

The related works in this research can be examined from three points of view: mechanical, computational, and joint modeling of mechanical and computational energy consumption.

Mechanical: There has been extensive research on estimating mechanical energy in various types of robots. Most proposed techniques rely on modeling the robots' mechanical components using different formal and data driven techniques. For instance Petrichenko et al. (2024) presents a simplified modeling approach to estimate the energy consumption of robotic systems. The authors propose mechanical and motor electrical power models, which are then extended to calculate the total energy along specified trajectories. By adjusting motion interpolator parameters such as acceleration and velocity, the model aids in optimizing energy usage. Similarly, Liu et al. (2018) addresses the significant energy consumption of industrial robots in manufacturing by focusing on mechanical energy consumption and developing a detailed consumption model. They identify inertial and friction parameters—essential for accurate modeling—using software-simulated power data instead of direct torque measurements, which are often inaccessible. The authors in Tokekar et al. (2014) developed a mathematical model of a brushed DC motor focused on its angular velocity to predict mechanical power. In Othman et al. (2015) and Shivam and Hsiao (2023), researchers model mechanical energy consumption in articulated robotic systems. The former uses a physics-based approach to analyze joint movements, while the latter integrates robot dynamics with machine learning to enhance energy estimation and trajectory planning.

Although the proposed techniques provide a good approximation of the robot's mechanical components, they only account for a fraction of the various power-consuming elements within the system. Furthermore, the functionalities of separate components—such as sensors, computing units, and mechanical parts—interact with one another, resulting in a dependency on power consumption among different parts. Another crucial aspect that these models often overlook is the impact of environmental characteristics on the robot's power consumption. Different environmental conditions can significantly influence the performance and power consumption of the robot's various components.

Computational: Parallel to advancements in mechanical energy modeling, computational energy management has also seen progress. For example, in the following works, researchers have explored various methods to model and optimize computational energy consumption. Haghbayan et al. (2017) models computational energy by integrating run-time thermal and power models to optimize energy allocation in many-core architectures. The framework dynamically adjusts resource management to balance energy efficiency and reliability, addressing dark silicon challenges while mitigating overheating and aging effects. Similarly, Haghbayan et al. (2023) focuses on modeling computational energy within Chip Multiprocessors (CMPs) by integrating energy-aware workload allocation and run-time management techniques. The authors propose a framework that estimates/monitors energy consumption alongside other computing characteristics, such as chip reliability, to dynamically adjust resource allocation while reducing energy usage. Moreover, in Zhai et al. (2021), McPAT-Calib, a framework designed to enhance the accuracy of power modeling in contemporary CPU architectures, has been introduced. By calibrating existing models with empirical data, McPAT-Calib provides more precise estimations of power consumption across various microarchitectural components.

In this paper, we address these factors by presenting a comprehensive power estimation framework. Our approach integrates mechanical power consumption into the overall power budget of the robot, considering its dependence on environmental characteristics and the computing unit's ability to process perceptual data. For example, consider a rover that can adjust its speed based on its computational capabilities, which are influenced by the required accuracy of sensory data processing. Enhanced computational capabilities allow for faster data processing, enabling the rover to operate at higher speeds. Conversely, lower computational capabilities result in slower data processing and, consequently, a reduction in speed. This relationship is analogous to human driving behavior; for example, a more agitated or impaired mindset often prefers slower speeds, while driving at higher speeds requires greater focus and consideration. The dependencies between computational and mechanical components are not adequately captured in current state-of-the-art power modeling. The only works that have specifically considered the cost of computation are Mohamed et al. (2021) and Shahsavari et al. (2024). These studies tackled the challenge of optimizing both mechanical and computational energy. Hill Climbing (HC) based approach in Mohamed et al. (2021), explored co-optimization of mechanical and computational energy in robotics but incurred long execution times due to the inefficient trial-and-error process for identifying optimal configurations. A more advanced method in Shahsavari et al. (2024) improved this by using trained internal models to predict power consumption, reducing unnecessary trials and energy usage.

This paper presents an adaptive simulation framework based on Shahsavari et al. (2024) that allows for the tuning of computational features and robot speed to achieve the necessary accuracy across various optimization models. Specifically, it emphasizes the importance of balancing high-speed computation with accuracy, as the performance can vary among different approaches.

3 METHODOLOGY

The overall structure framework of the simulation system proposed in this paper is shown in Figure 1. The model takes three key input parameters, i.e., CPU frequency, robot speed, and fidelity level, which influence the power

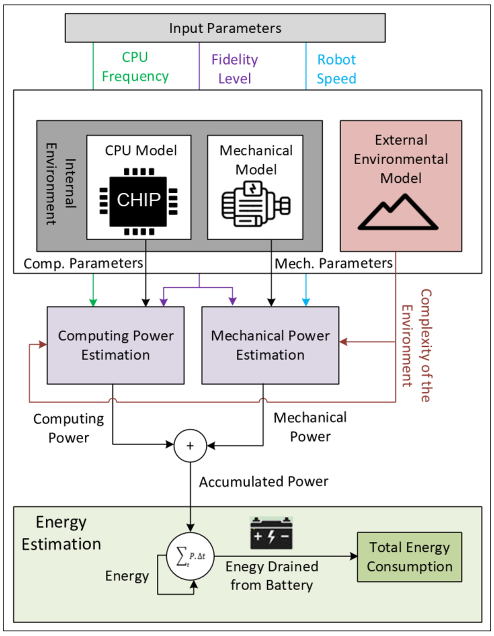

Figure 1: Schematic of Simulation System

demands of computing and mechanical components. The external environmental model accounts for the complexity of the surroundings, impacting both computing and mechanical power needs. The internal environment consists of the mechanical and computational models of the robot, which includes the electric DC motor and steering system, and a CPU model, which consists of the onboard embedded computing chip. The running applications on the computing chip consist of vision algorithms to perform environment perception and enable autonomous operation. These applications receive event batches as input by a fixed rate R and need to process them in real-time to ensure safe operation and avoid information loss.

The Quality of Service (QoS) (or equivalently throughput) of these applications, defined as the number of processed batches per second, must then be equal to R for all applications. The QoS relies on the required precision of the obstacle detection and path planning algorithms, which must increase as the robot's speed rises. This indicates that the computational workload is influenced by both the robot's mechanical velocity and the complexity of the visual data, which is tied to the robot's surroundings. Additionally, QoS is determined by the availability of computational resources and the capacity of the individual processing units. Consequently, when computational resources are constrained, the robot must adjust its speed to maintain QoS requirements at a manageable level. This interdependence between the mechanical and computational components highlights the necessity of managing both aspects cohesively rather than optimizing each independently without considering their mutual impact. Moreover, application performance is monitored by utilizing the execution times of each running application for processing a single event batch to compute the Per Loop Processing Time (PLPT). It serves as an application-level metric designed to track the performance of applications in real-time. It provides a clear indication of how efficiently each application handles its workload under varying operational conditions. By integrating PLPT into the system, it becomes possible to dynamically assess the computational performance and adjust operational parameters to maintain the desired QoS while balancing resource constraints and environmental complexities.

Building on this interdependence, the energy consumption of the robotic system is estimated by considering both computational and mechanical power demands. The CPU model estimates the computing power required by utilizing CPU frequency, fidelity level, and environmental complexity, while the mechanical model calculates the mechanical power demand based on motor speed, fidelity level, and environmental complexity. These estimations of power consumption are then summed over time to compute the overall energy consumption of the system, providing a precise evaluation of the robot's energy requirements based on its operational parameters and environmental conditions.

We have employed two mathematical models to estimate the power usage of the mechanical and computational components under a specific configuration. Here are the models for estimation:

Estimation of Mechanical Power

In a similar manner to previous studies (Shahidinejad et al., 2010) and (Yan et al., 2014), we have developed a model to forecast the mechanical power consumption of the robot based on its velocity and the applied forces, according to Newton's second law. The power required to move the robot on a flat surface is computed by the following formula:

$$P_m = Fv \tag{1}$$

The velocity of the robot is represented by v, and the propulsive force provided by the motor is denoted as F. The value of F is determined by the following calculation:

$$F = F_a + F_f + F_d \tag{2}$$

$$F_a = m\frac{dv}{dt} \tag{3}$$

$$F_f = (C_r + C_v v) \cdot mg \tag{4}$$

$$F_d = \frac{1}{2}\rho C_d A_f v^2 \tag{5}$$

where F_a is the acceleration force, F_f is the rolling friction force, and F_d is the aerodynamic drag. Then, m is mass and g the gravitational constant, C_r and C_v are constant and viscous rolling coefficients respectively, ρ is the air density, C_d is the aerodynamic drag coefficient, and A_f is the robot's frontal area. The power model's parameters (C_r,C_v, and C_d) can be determined empirically by fitting equations (1–5) to the robot's measurements. It should be mentioned that parameter fitting is done using the regularized least squares method.

Estimation of Computing Power

In order to determine the computing power, we use a model that has been commonly utilized in the literature for multi-core processing boards (Angioletti et al., 2019) and (Pathania et al., 2014), and we determine the parameters for the compute board under consideration. Specifically, the total power consumption of a computing board can be calculated by using the following formula:

$$P_c = P_{\text{board}}^{idle} + \sum_i \left[P_{\text{i}}^{idle}(f_i) + P_{\text{i}}^{work}(f_i) \cdot \%U_i \right] \quad (6)$$

The power of the board in idle conditions, which also encompasses the camera power consumption, is denoted as P_{board}^{idle}. The dynamic power consumption arises from the CPU activity, which depends on the frequency level f_i and the utilization U_i of each core i. Within this part of the equation, P_{i}^{idle} and P_{i}^{work} represent the experimentally determined power consumption of an individual core i at a specific frequency level fi when the core is inactive ($Ui = 0\%$) and when it is fully utilized for computations ($U_i = 100\%$), respectively. Based on the operating system's report of each core's current usage, the power consumption of a core can be estimated using a linear scaling function.

Energy Estimation

The robot's energy usage during a certain time frame is determined by calculating the integral of its power usage over that time period. Because the suggested method operates in real-time, we use energy per distance as the optimization cost function. We calculate the energy per distance $E_d(v, f)$ of a specific setup with motor speed s and CPU frequency f by dividing the total computing and mechanical power by the motor speed:

$$E^d(v, f) = \frac{P_m(v) + P_c(f)}{v} \quad (7)$$

Multi-Fidelity Energy Estimation

To enable the run-time fidelity adjustment, we provide an input for the simulation environment, i.e., the fidelity level, to adjust the level of granularity, of the simulation parameters including speed and CPU voltage/frequency level. This process allows energy consumption to be estimated at different levels of energy estimation fatalities. For example, by selecting a finer speed granularity, i.e., resulting in increasing the fidelity of the analysis, the model enhances the precision of energy consumption estimation. However, this comes at the cost of increased computational overhead. Conversely, coarser granularity reduces computational time but may introduce higher estimation errors. This adaptive mechanism allows the robot to estimate energy consumption in real time. The accuracy of the energy consumption model is traded off against computational overhead, adjusting dynamically based on available resources.

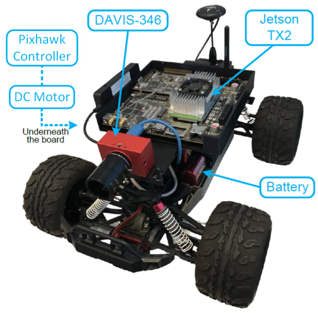

Figure 2: Demonstrator Setup

4 RESULTS

For experimental purposes, we utilized the demonstrator shown in Figure 2. A 3000Kv brushless DC motor generates the propulsive force for the robot. The motor is regulated by an Electronic Speed Controller (ESC) linked to a Pixhawk (Pix32) controller. Additionally, an NVIDIA Jetson TX2 is installed on the robot as a power-efficient high-performance embedded board which provides computing resources to run the necessary applications for intelligent and autonomous operation. The installed event camera is a DAVIS-346 which can capture both intensity images and a stream of asynchronous events with a high temporal resolution. We have run the proposed model for three different environments, i.e., i) low, ii) moderate and iii) high complexities. The number of generated events increases according to the increase in complexity.

The parameters listed in Table 1 are crucial for understanding the mechanical power modeling. The values represent typical settings used in the analysis and are essential for accurate modeling and simulation. Each parameter affects different aspects of the model, and adjusting these values can lead to changes in the results.

Table 1: Parameters used in Mechanical Power Modeling

Parameter	m	Cr	Cv	Cd	Af	ρ
Value	3.7	0.031	0.023	0.68	0.1	1.2

Figure 3 illustrates the relation between computational and mechanical energy consumption and speed across various environmental complexities. Notably, energy consumption peaks at the lowest speed, then declines as speed increases, reaching optimal points. However, after surpassing these optimal points, energy consumption starts to rise again with further increases in speed. In the high-complexity environment shown in the second row of Figure 3, increasing the speed beyond 7.5 (m/s) prevents the system from meeting the QoS standards. Conversely, in the low-complexity environment depicted in the first row of Figure 3, exceeding the optimal speed increases energy consumption; however, the system still meets the QoS requirements. Additionally, as the speed intervals de-

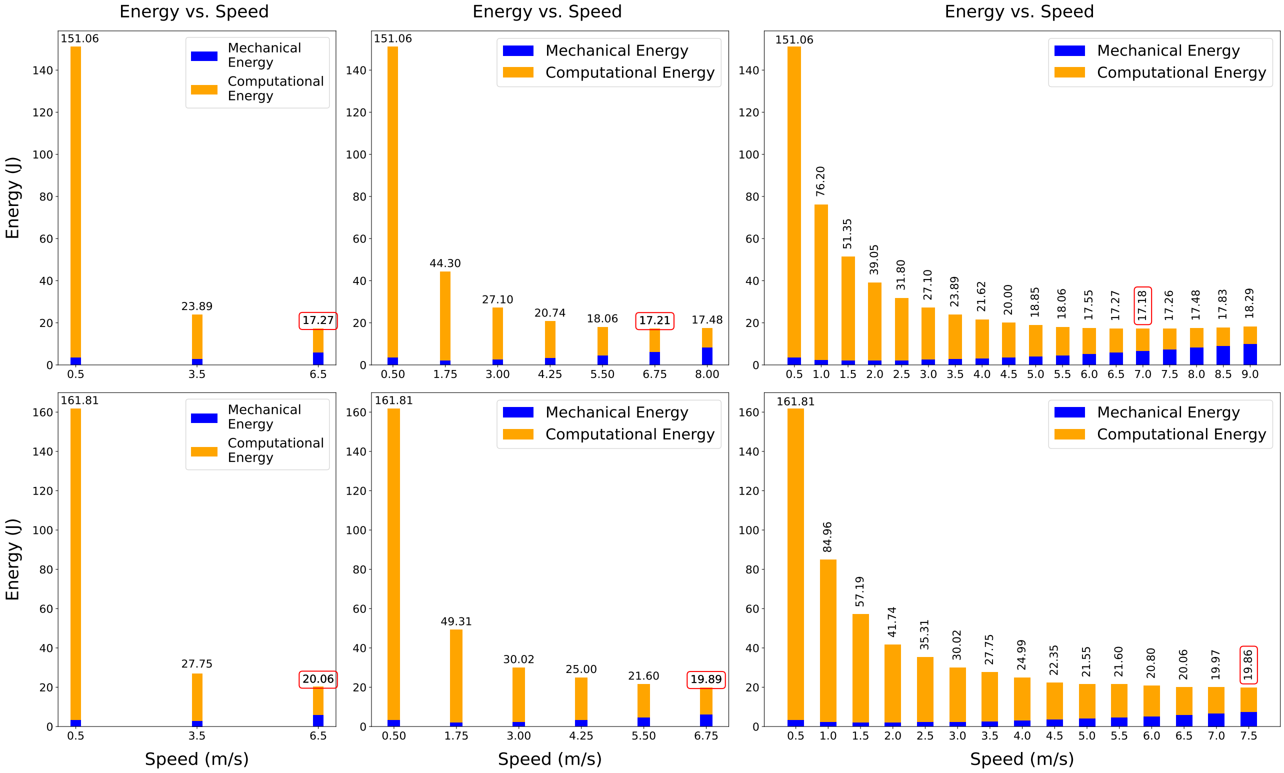

Figure 3: Energy Consumption for Different Speed Granularity Configurations in Low and High Complexities

crease—resulting in a finer-grained speed spectrum in the right-side graphs—the accuracy of the results improves, allowing for a more precise identification of the optimal energy point. The increased granularity in speed intervals allows for a finer resolution in capturing energy dynamics, ultimately leading to more informed decisions regarding energy efficiency. The enhanced accuracy in the plots highlights the significance of carefully selecting speed ranges when analyzing energy performance, as it facilitates a more detailed examination of how varying speeds influence energy consumption in the given system.

Building on this energy analysis, Figure 4 examines the trade-off between energy estimation error and computational time across different speed granularity intervals. As the speed granularity interval decreases (increasing the granularity of the analysis), the error in energy consumption reduces. Additionally, the computational time increases significantly with smaller granularity, reflecting the trade-off between accuracy and computational cost. The observed trends emphasize the balance required to achieve accurate energy estimations while managing computational resources effectively.

Since the mechanical energy consumption in Figure 3 is relatively small compared to computational energy, we present Figure 5 to show the trend of mechanical energy variation across different speed settings. It is observed that when the robot operates at its minimum speed, the energy consumption is elevated. This occurs because integration of power is performed over a longer period of time, and despite low electric power requirements, the in-

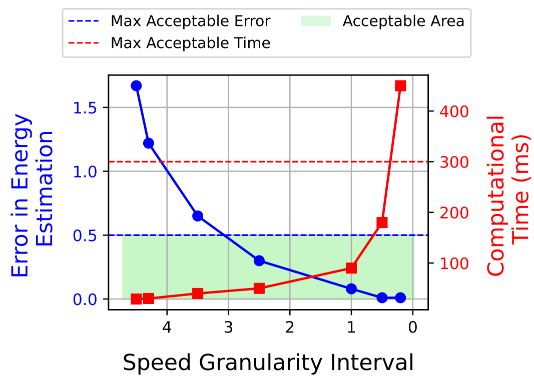

Figure 4: Error in Energy Estimation and Computational Time vs. Speed Granularity Interval

tegral interval governs the amount of energy consumption. In contrast, when the robot moves at a higher speed, the motor demands a substantial amount of electric power, resulting in increased energy consumption due to the larger integrand. As shown in Figure 5, when considering only mechanical energy, the optimal speed for minimizing mechanical energy consumption is 2 (m/s). However, this differs from the optimal speed when both mechanical and computational power consumption are taken into account.

To illustrate the impact of changes in robot speed and CPU voltage/frequency on application QoS, we conducted experiments at various speeds, gradually increasing the CPU voltage/frequency at each speed and measuring throughput in batches per second. This analysis is cru-

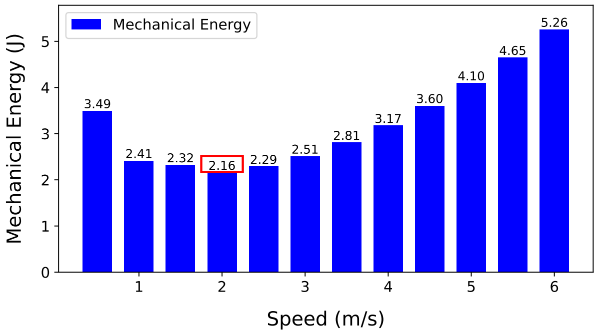

Figure 5: Mechanical Energy for Different Speed Configurations

cial because, as discussed in the methodology section, maintaining an acceptable QoS is a strict constraint when adjusting mechanical and computational parameters and must be carefully monitored at runtime. Figure 6 shows the plot of energy versus application throughput (batches per second) for a high-complexity environment. It shows the effect of changing the speed and frequency on both energy and throughput criteria. The frequency is increased from 0.4992 (GHz) to 2.0352 (GHz) while keeping the speed constant at 6- 9 (m/s). In the red curve, which goes from P1 to P3, the frequency is kept constant and the speed is increased. P* shows the energy-optimal configuration. It means that when the speed is 7.5 (m/s) and the frequency is 2.03 (GHz), the energy consumption will be at its minimum while meeting the throughput requirements.

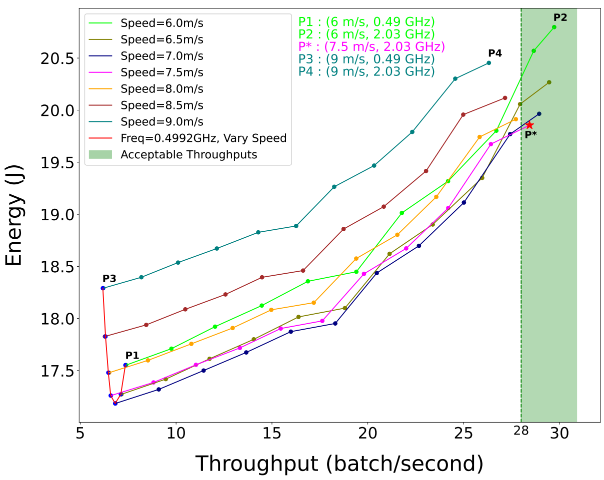

Figure 6: Energy Consumption vs. Application Throughput for High Complexity Environment

Figure 7 presents a comparison of the average value of batch per second and PLPT across various frequency and speed levels. As anticipated, it shows that PLPT decreases as frequency increases, while the batch per second reaches a saturation point of R = 30 with rising frequency. This logical trend in PLPT allows for effective management of computing resources in real-time applications that involve online data streams.

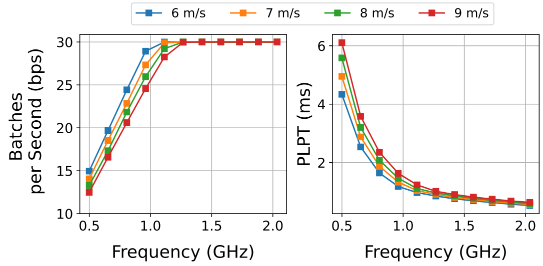

Figure 7: Average Batch per Second and PLPT vs. Frequency Level for Different Speeds

5 CONCLUSION

In this paper, we presented a simulation framework for estimating the instantaneous power consumption of a mobile robot by incorporating both mechanical and computational energy usage along with their interdependence. The proposed model introduces a multi-fidelity power estimation approach, allowing dynamic adjustments in accuracy and computational cost based on environmental conditions and available computational resources. This adaptability makes the framework highly suitable for real-time predictive decision-making in applications such as model-based reinforcement learning and model predictive control. Experimental validation demonstrated the effectiveness of the proposed framework in accurately estimating energy consumption at different fidelity levels. The results further highlighted a trade-off between estimation accuracy and computational cost, emphasizing the importance of balancing these factors for practical deployment in robotic systems. Overall, this work contributes to energy-efficient robotic operation by providing a flexible tool for adaptive energy estimation.

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