

Original Article

Energy-Aware Navigation Strategies for Autonomous Service Robots

Dr. Pooja Agarwal

Professor, Aligarh Muslim University, India.

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ABSTRACT

Autonomous Service Robots (ASRs) operating in large-scale facilities like hospitals, warehouses, and airports face strict operational challenges related to battery longevity, continuous task availability, and efficient path planning. Standard navigation algorithms typically optimize paths solely for geometric distance or transit duration, often ignoring the complex thermodynamic and mechanical energy trade-offs caused by frequent velocity changes, irregular floor surfaces, and variable cargo payloads. This paper introduces an energy-aware navigation framework that incorporates a comprehensive physical power model directly into a dynamic path-planning algorithm. By fusing environmental costmaps with real-time payload tracking and kinetic energy estimation, the proposed framework allows service platforms to minimize overall energy depletion without sacrificing time-to-target performance. Multi-scenario experimental evaluations conducted using physical mobile platforms demonstrate that this energy-conscious architecture yields substantial power savings compared to standard distance-optimal baselines. The results show that combining electrical loss metrics with structural costmaps provides the operational reliability required for true, unassisted long-term robot autonomy.

KEYWORDS

Intelligent Automation, Service Robotics, Energy-Aware Navigation, Path Optimization, Costmap Fusion, Power Modeling.

1. INTRODUCTION

The widespread deployment of autonomous service robots across public and commercial settings has transformed material logistics, facilities maintenance, and healthcare support systems. Modern service robots are expected to execute extended multi-hour operational shifts, navigating complex indoor environments to transport payloads, conduct cleanings, or assist users. Because these platforms run on onboard battery packs, their operational capacity is directly constrained by the efficiency of their locomotion algorithms. When a robot runs out of energy prematurely, it can stall in active public pathways, requiring manual recovery and disrupting facility operations. Consequently, developing energy-aware navigation strategies has become a high priority within the field of intelligent automation and robotics engineering.

Traditional robotic path planning architectures, such as classical Dijkstra, A*, or standard Timed-Elastic-Band (TEB) local planners, treat the workspace as a purely geometric canvas. These frameworks generate trajectories aimed almost exclusively at discovering the shortest geometric distance or achieving the fastest traversal speed. While this perspective is effective for simple navigation tasks, it completely overlooks the underlying energy costs of mobile robotic systems. For instance, a path that is short but contains steep inclines, uneven flooring, or requires frequent stops and sharp turns can draw significantly more current from a lithium-ion battery than a longer path that maintains a uniform velocity over a flat surface.

To build truly sustainable service systems, motion planners must transform their primary objective from simple geometric optimization to a comprehensive approach centered on energy conservation. This transformation requires a deep understanding of the active sources of power depletion within a mobile platform, which can be broadly divided into kinetic locomotion losses and static overhead consumption. Kinetic energy consumption depends on the vehicle's structural weight, acceleration rate, mechanical friction, and changes in the surface incline. Static consumption, on the other hand, comprises the steady energy draw required to run computational processors, internal cooling fans, wireless radios, and active exteroceptive sensors like 3D LiDAR and depth cameras.

This research addresses the challenge of integrating complex power models into real-time path-planning pipelines without overloading onboard microcontrollers. The primary objectives of this investigation are defined below:

- To derive and validate a comprehensive, real-time power consumption model that accounts for changes in cargo payload, rotational friction, and localized surface textures.
- To design an energy-principled costmap layer that infuses expected power-draw values into global and local path planners.
- To quantitatively evaluate the energy savings and tracking accuracy of the developed framework against conventional geometric navigation pipelines under realistic working loads.

By fulfilling these objectives, this study establishes a direct link between low-level electrochemical energy conservation and high-level autonomous spatial navigation.

2. LITERATURE REVIEW

The mobile robot navigation algorithm has developed from geometric connectivity analysis to multi-objective optimization models. The foundational research for path planning was predominantly early work which either utilized grids map or graph search signaling approaches that successfully find roads that would clear obstacles while simultaneously minimizing the Euclidean distance traveled along said road. Also, researchers discovered that short and jerky movements of the algorithms can cause a lot of mechanical wear and tear on actuators in real world industrial settings. This was the basis for the development of kinodynamic trajectory planners that directly included the physical constraints of the robot – velocity caps, maximum torque limits and acceleration profiles – as part of the path generation loop.

Kinodynamic planning improved smoothness of trajectories, but it did not explicitly optimize for battery longevity to the best of our knowledge. This gap led to a new round of investigations that focused on creating model-driven power loss equations for the wheel-ground system. Realization of characteristic analytical relations between motor armature currents and mechanical resistance, wheel slip or surface slopesは禁止字元 Both these evaluations validated that batteries are mostly drained by the acceleration maneuvers and since friction on the road surfaces Nevertheless, original work to integrate these principles into path planning was computationally expensive, regularly needing off-line calculations that were not able to react and recalculate in real-time when macabre obstacles forced the rerouting of a robot.

As next generation robotic middleware implemented sophisticated multi-layered costmaps, they also started to directly encode environmental costs into the navigation space. In this method, modern costmaps utilize separate grid layers to signify different spatial hazards (e.g. density of pedestrian traffic or delivery vehicles and distance from fragile walls). However, a well-known limitation of the current literature is regarding how to dynamically scale these costmap weights in accordance with various internal states (e.g., battery state-of-charge reduction or carried payload increase). Current frameworks are still trained on a fixed traction assumption, resulting in the path planner being unable to exploit energy saving opportunities when the robot's internal payload or battery health changes throughout a shift.

Recently, there have been attempts to use machine learning-based methods such as deep reinforcement learning to learn the optimal velocity control policies preserving energy on complex surfaces. In spite of their promising performance on simulated tests, these data-driven models will be arduous to implement onto physical service platforms with unpredictable different behaviors when faced novel indoor floors or unexpected foot traffic. This clearly indicates the need for a pragmatic

power framework, grounded in physics principles and integrated into standard navigation stacks – actively reducing battery consumption to promote predictable and safety-compliant behavior.

3. RESEARCH METHODOLOGY

The developed energy-aware navigation methodology incorporates a physical power consumption model directly into a multi-layered costmap framework. The complete system architecture consists of a localized perception layer, an energy management module, and an updated path planner.

3.1. Total Power Consumption Estimation Framework

To accurately estimate traversal costs, the system evaluates the instantaneous power consumption of the mobile platform by combining independent operational factors. The total power draw is calculated by summing the steady baseline consumption from sensors and computing boards with the dynamic mechanical power consumed during active movement.

The baseline consumption accounts for the predictable energy required to run the computing hardware, depth sensors, and navigation telemetry. The dynamic locomotion power, conversely, is modeled by continuously calculating the forces acting against the robot's progress. This tracking includes the aggregate mass of the vehicle chassis added to the variable cargo weight measured by onboard suspension load cells.

As the robot moves, the system monitors acceleration changes, structural friction coefficients determined by the ground material, and gravitational resistance caused by changes in the floor incline, which are captured instantly via the pitch readings of an internal Inertial Measurement Unit (IMU). Finally, electrical heat losses within the internal motor winding circuits are tracked and added to the total calculation, providing the system with a complete electrical and mechanical awareness of real-time power drainage.

3.2. Computational Implementation Steps

To demonstrate the useful incorporation of the energy model into a robot's navigation stack we follow a sequence:

Payload and surface identifier: Task initialized, onboard load cells measure the current payload weight. At the same time, the exteroceptive sensor suite also detects upcoming floor types (like smooth tile or low-pile carpet) in order to come up with suitable rolling friction assumptions.

Energy Costmap Generation: The global path planner transforms the flat spatial map into the tailored energy costmap, in which each grid cell is assigned weights determined by the estimated achievable mechanical power to enter through with consideration for local slope angles and surface textures directly.

Trajectory optimization: The local path planner uses a modified version of the Timed-Elastic-Band algorithm to evaluate candidate velocity paths aiming at minimizing sudden accelerations and high-current turning maneuvers.

Dynamic Monitoring and Adjustment: When the battery state-of-charge drops below a set point value, the system automatically lowers the global top speed to drive the vehicle in ultra-low energy expenditure locomotion mode and its successful arrival at charging stations.

4. RESULTS AND DISCUSSION

The energy-aware navigation framework was evaluated through comparative trials using a differential-drive service robot equipped with a 20 Ampere-hour lithium-iron-phosphate battery pack. The proposed framework was benchmarked against a conventional geometric navigation architecture across three test locations: Track 1 (Flat, smooth linoleum tile floors), Track 2 (A continuous carpeted corridor with high surface friction), and Track 3 (A multi-floor access ramp with a uniform 6-degree incline).

4.1. Component-Level Energy Distribution Analysis

The initial tests were focused on mapping the changes in power consumption as a function of operational speed. Figure 2 shows a visual decomposition of energy as a proportionally at different speeds for various core subsystems of the platform.

At low velocities, as in shown Figure 2a, the energy profile is dominated by a static sensor and computing overhead with running close to 100% of the draw when the platform is not moving. But on linear speed reaching 1.0 m/s, the motion system power consumption skyrockets and forms 94.7% of total energy economy within continuing- maneuver at high-speed (Figure 2b). This behavioral shift reinforces the framework's approach of dynamically limiting peak velocities on high-friction or incline surfaces to avert substantial parasitic current spikes in the motors.

4.2. Comparative Energy and Navigational Performance Metrics

To confirm the practical benefits of the system, both controllers were tested under two distinct payload states: an empty configuration and a fully loaded configuration carrying a 25 kilogram payload. Table 1 details the quantitative metrics recorded during these test runs.

Table 1: Performance Comparison and Energy Savings across Test Settings

Physical Test Track	Internal Payload Condition	Navigation Controller Type	Total Traversal Time (seconds)	Total Energy Consumed (Watt-hours)	Mean Current Draw (Amperes)	Net Energy Saved (%)
Track 1: Linoleum	Unloaded (0 kg)	Distance-Optimal	45.2	3.12	2.48	—
		Proposed Energy-Aware	47.1	2.84	2.17	8.97

	Loaded (25 kg)	Distance-Optimal	46.8	4.85	3.73	—
		Proposed Energy-Aware	49.3	4.12	3.01	15.05
Track 2: Carpet	Unloaded (0 kg)	Distance-Optimal	52.4	5.62	3.85	—
		Proposed Energy-Aware	55.8	4.71	3.03	16.19
	Loaded (25 kg)	Distance-Optimal	55.1	8.94	5.84	—
		Proposed Energy-Aware	60.2	7.15	4.27	20.02
Track 3: Ramps	Loaded (25 kg)	Distance-Optimal	62.7	14.21	8.16	—
		Proposed Energy-Aware	71.4	10.82	5.45	23.86

The experimental data demonstrates that the energy-aware framework consistently yields substantial energy savings, with efficiency gains increasing alongside environmental difficulty and payload weight. On Track 1 (Linoleum) with an empty platform, the energy savings were relatively modest at 8.97%, as the low friction profile minimized motor stress. However, when navigating the high-friction carpeted surface (Track 2) with a 25 kilogram cargo load, the proposed architecture achieved a 20.02% reduction in total energy consumption. The most pronounced saving occurred on the inclined ramps of Track 3, where the energy-aware system yielded a 23.86% reduction in watt-hours consumed.

This significant efficiency gain is explained by analyzing the trajectory differences between the two planners. While the distance-optimal baseline pushed the robot straight up the incline at maximum acceleration—causing the motors to draw high currents and experience significant heat losses—the energy-aware system executed a smooth, controlled ascent. It slightly reduced forward velocity and avoided sharp steering adjustments, keeping the motor current within its highly efficient operating range. Although this approach extended the traversal time by approximately 8.7 seconds, the substantial reduction in battery drain proves it is a highly favorable trade-off for non-emergency service missions.

4.3. Long-Term Fleet Longevity Analysis

To understand how these savings compound over time, a longitudinal simulation was structured to model a full 12-hour facility shift. Table 2 contrasts the operational readiness metrics of a service robot fleet running both navigation models.

Table 2: Simulated Longitudinal Metrics for a 12-Hour Operational Shift

Monitored Fleet Attribute	Distance-Optimal Navigation	Proposed Energy-Aware Navigation	Net Operational Variance
Total Successful Tasks Completed	42	48	+14.28%
Total Charging Cycles Required	3.0	2.0	-33.33%
Mean Battery Temperature (°C)	42.6	36.4	-14.55%
Accumulated Daily Downtime (minutes)	180.0	120.0	-33.33%

The long-term analysis indicates that the energy-aware system improves overall productivity, enabling the robot to complete 48 tasks per shift compared to 42 for the baseline. This improvement occurs because the energy-efficient paths allowed the platform to operate on two charging cycles instead of three, saving a full hour of daily charging downtime. Furthermore, keeping the motor currents steady reduced the average battery temperature by 6.2°C, which helps prevent thermal degradation and extends the long-term operational lifespan of the battery assets.

5. CONCLUSION

This paper presents an energy-aware navigation framework that successfully connects physical power modeling with real-time autonomous path planning for service robots. By embedding structural variables—such as cargo payload, floor material friction, and slope angles—directly into a multi-layered costmap, the proposed system prevents the high-current spikes that rapidly drain mobile platform batteries. Physical experiments confirmed that the energy-aware architecture consistently reduces power draw, achieving up to 23.86% energy savings on inclined tracks and high-friction surfaces. Ultimately, moving beyond pure geometric path planning toward energy-principled navigation is vital for extending operational runtimes, reducing charging downtime, and maximizing asset lifespans in large-scale commercial facilities.

6. FUTURE SCOPE

Although the existing navigation approach yields consistent energy savings on diffuse indoor surfaces, many of these technical aspects are open to exploration in future work. Improving the behavior of people has been an important but challenging priority, and the goal has been to incorporate real-time tracking of pedestrians into the energy model so that the robot can anticipate and avoid stop-and-go actions since stopping and going back again will cost much more energy. Moreover, online updates of rolling friction coefficients using machine learning algorithms will allow the system to automatically adapt to worn or damp flooring conditions. Finally, generalizing this single-agent architecture to a full decentralized multi-robot system will allow for coordinated fleet routing such that task assignment is performed online using both individual battery level states and the energy cost from one path to another throughout the facility.

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