A Review on Energy Efficiency in Autonomous Mobile Robots

Abstract

Purpose: This paper aims to provide a comprehensive analysis of the state of the art in energy efficiency for Autonomous Mobile Robots (AMRs), focusing on energy sources, consumption models, energy-efficient locomotion, hardware energy consumption, optimization in path planning and scheduling methods, and to suggest future research directions.

Design/methodology/approach: The systematic literature review identified 244 papers for analysis. Research articles published from 2010 onwards were searched in databases including Google Scholar, ScienceDirect, and Scopus using keywords and search criteria related to energy and power management in various robotic systems.

Findings: The review highlights the following key findings: 1) batteries are the primary energy source for AMRs, with advances in Battery Management Systems enhancing efficiency; 2) hybrid models offer superior accuracy and robustness; 3) locomotion contributes over 50% of a mobile robot's total energy consumption, emphasizing the need for optimized control methods; 4) factors like the center of mass impact AMR energy consumption; 5) path planning algorithms and scheduling methods are essential for energy optimization, with algorithm choice depending on specific requirements and constraints.

Research limitations: The review concentrates on wheeled robots, excluding walking ones. Future work should improve consumption models, explore optimization methods, examine AI/ML roles, and assess energy efficiency trade-offs.

Originality/value: This paper provides a comprehensive analysis of energy efficiency in AMRs, highlighting the key findings from the systematic literature review and suggests future research directions for further advancements in this field.

Keywords: Autonomous Mobile Robots, Energy Efficiency, Systematic Literature Review, Optimization, Energy Consumption Models, Path Planning

Article Type: Review

1. Introduction

Global concerns regarding CO2 emissions and climate change have intensified in recent years. Among the various sectors, manufacturing has emerged as a significant contributor to these pressing environmental challenges. Often, stakeholders in this industry concentrate on functional aspects and solutions, overlooking the critical role of energy efficiency in mitigating the adverse impacts of manufacturing processes. This oversight extends to utilizing AMRs and Automated Guided Vehicles (AGVs), which have become increasingly prevalent in manufacturing settings.

Considering these concerns, this review paper will specifically focus on the energy efficiency of wheeled mobile robots within the realm of AMRs, analyzing their application in manufacturing environments. The objective of this study is to contribute to the ongoing discourse on sustainable manufacturing and climate change mitigation by exploring the diverse aspects of energy efficiency within this framework.

The increasing adoption of AMRs has revolutionized various industries, including manufacturing, logistics, agriculture, and healthcare (Alexovič et al. 2021).

According to a report by the International Federation of Robots (IFR), the global installation of industrial robots has experienced a significant increase, from 166,000 units in 2011 to 571,000 units in 2021 (Zhang and Zhu 2023). As industries continue to rely heavily on robots to improve efficiency and productivity, the energy consumption of the robotics sector is projected to grow considerably in the coming years. This rapid growth in energy consumption emphasizes the urgent need to address energy efficiency in AMR, as they play a critical role in reducing greenhouse gas emissions and mitigating the impacts of climate change.

Designed to navigate and execute tasks in complex, dynamic environments with minimal human intervention, AMRs can perceive their surroundings, make decisions, and act based on their internal algorithms and sensor data. This review paper encompasses AGVs, mobile robots, and wheeled robots under the umbrella term of AMRs. These versatile robotic systems hold the potential to significantly enhance efficiency, productivity, and safety across a wide array of applications. Fig. 1 shows a common AMR.

Fig. 1 AMR is used for logistics

Considering the environmental impact of the increasing energy consumption of AMRs, this review aims to provide a comprehensive analysis of the state-of-the-art in energy efficiency for AMRs, including energy sources, consumption models, energy-efficient locomotion, hardware energy consumption, optimization in path planning, and scheduling methods. By addressing these issues, researchers and practitioners can develop more sustainable and energy-efficient AMR technologies, contributing to a greener future.

2. Review Methods

In this Systematic Literature Review (SLR), a thorough search was carried out to pinpoint studies that concentrate on energy and power optimization across diverse mobile robotic platforms. The search terms employed in this study consisted of combinations such as "Energy" or "Power" or "Solar panels" or "Fuel Cells" or "Green" or "Battery," along with phrases like "Automated Guided Vehicle (AGV)", "Autonomous Mobile Robot (AMR)", "Mobile Robot", "Wheeled Robot", "Automated Intelligent Vehicle (AIV)", "Self-guided vehicle", and "Robotic vehicle". To ensure a comprehensive examination of the existing literature in this field, databases including Google Scholar, ScienceDirect, and Scopus were utilized, with a focus on research articles published from 2010 onwards. By employing these keywords and search criteria, the aim was to encompass a wide range of energy and power management research within various robotic systems. The systematic literature review centered on document type, excluding dissertations, books, and review articles.

This process identified a total of 384 papers for further analysis. The 140 documents retrieved are unrelated to the topics covered in this literature review or are book type. This literature review focuses on wheeled mobile robots and does not discuss walking robots like quadruped ones. A total of 244 papers were finally selected for the systematic review, focusing on robot/vehicle energy optimization.

After analyzing the 244 papers, several insightful statistical conclusions have been derived:

- Energy optimization
- Battery management system (BMS) and charging technology
- Energy consumption model
- Energy source
- Battery swap
- Energy recovery system

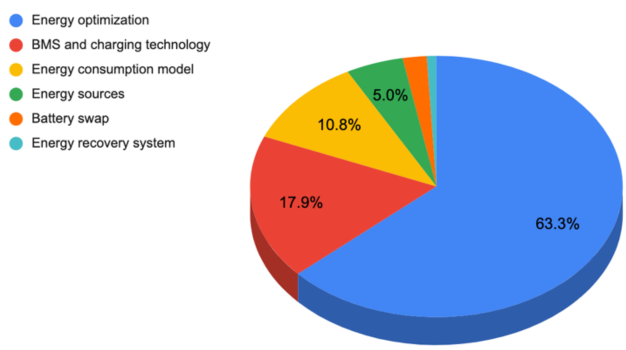


Fig. 2 Statistics About Topic Type

As shown in Fig. 2, the research interest in these topics has evolved over the past decade. The classification of studies reveals diverse topics being explored within the field. Specifically, 63.3% of research is concentrated on optimization, while 17.9% is dedicated to battery management systems (BMS) and charging technology. Additionally, 10.8% focus on energy consumption measurement methods and 5 % delve into energy sources.

Through the analysis of the results shown in Fig. 2, it can be found that current research about energy efficiency can be mainly divided into three aspects, which refers to the energy sources and its managements, energy consumption model research, and energy efficient optimization research. Therefore, the review paper is organized as follows:

Section 3 introduces the brief hardware structure and energy consumption in hardware of the AMRs. Section 4 focuses on the current research on energy source and management technologies, which includes the state-of-art research of energy sources, and BMS and charging technology in AMRs. Section 5 analyses and summarizes the research status of energy consumption model, which includes the energy consumption model, and the factors influencing AMR energy consumption. Section 6 focuses on the analysis and summary of the current energy optimization research methods. The last part summarizes the energy efficiency review and gives the main findings of the review and our judgment on the future research trends in this field.

3. System Overview

An AMR is a mobile robot capable of autonomously navigating from one location to another while carrying loads (Illah Nourbakhsh 2004).

AMRs have applications in various industries, such as in logistics, support services in healthcare, food and beverage or household cleaning and security checks. Although AMR and AGV are sometimes used interchangeably, they have subtle differences. AMRs are often considered more intelligent because they use technologies like LIDAR, cameras, and SLAM (Simultaneous Localization and Mapping) for navigation. On the other hand, AGVs typically rely on guidance mechanisms such as magnetic tape, induction, or colored tape on the floor for navigation.

Despite these differences, some individuals regard AMRs and AGVs as synonymous, given that both robots perform tasks autonomously. Various terms refer to AMRs, including AIV (Automatic Intelligent Vehicle), AGV (Automatic Guided Vehicle), self-guided vehicle, mobile robot, guided robot, and wheeled robot. Understanding these distinctions and similarities is essential for comprehensively evaluating the energy efficiency of AMRs and their applications in different industries.

3.1. Overview of Hardware Structure in AMRs

The standard hardware structure of an AMR comprises sensor, control, driver, motor and power modules. Control modules typically utilize embedded systems, programmable logic controllers (PLCs), or industrial PCs. Holonomic robots can move in any direction without altering their orientation, whereas nonholonomic robots need to turn or change direction for movement.

Various locomotion configurations are employed by AMRs, such as differential-driven systems or four-wheel drives. Some AMRs also incorporate mecanum wheels to achieve holonomic motion capabilities. In general, AMRs with a higher number of motors consume more energy, making it essential to understand hardware design aspects for assessing energy efficiency.

Figure 3 shows the hardware architecture of AMRs, which consists of four primary components: sensor, control, driver and power modules. These components work together to ensure the efficient operation and seamless integration of the robot's subsystems.

The sensor module gathers data from the environment, while the control module processes this information and decides on suitable actions.

The driver module manages actuators, and the power module provides power like electrical to the entire robot. Effectively integrating these components is crucial for successfully developing a well-functioning AMR system.

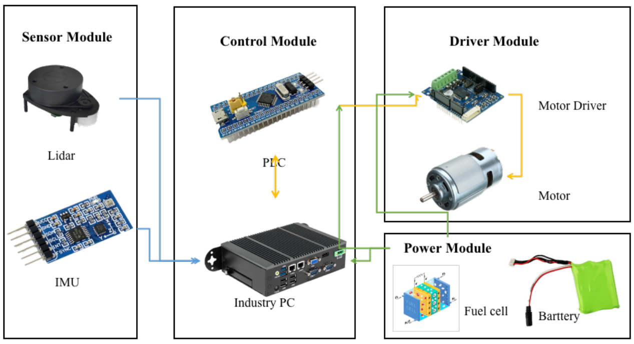


Fig. 3 Hardware structure diagram of a mobile robot

3.2. Energy Consumption in Hardware

The energy consumption of robots is primarily concentrated in hardware and motion control. The central control factors of hardware energy consumption lie in energy management and its control techniques. This is achieved by studying theoretical energy consumption models and methods of optimizing motion energy.

Liangkai Liu et al. conducted a study (Liangkai Liu et al. 2019) where they first described the experimental setup using an indoor AMR called HydraOne, a multi-purpose platform for various computer vision applications. HydraOne uses the Robot Operating System (ROS) to manage resources and has multiple concurrent computer vision applications running on it. The power analysis of HydraOne reveals that locomotion accounts for over 50% of total power dissipation, while computation and sensors make up 33% and 11%, respectively. Fig. 4 from the study shows the percentage of power consumption by different modules. The main reason locomotion accounts for a high proportion of energy consumption in AMR is that motors require significant power to operate.

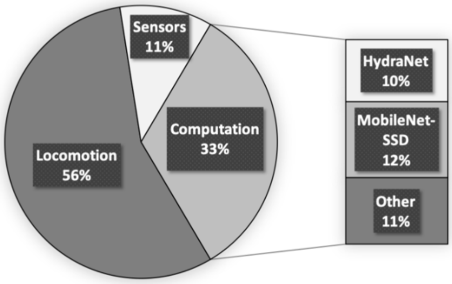


Fig. 4 Power dissipation breakdown of an AMR (Liangkai Liu et al. 2019).

Although this study may not represent the energy consumption model of all AMRs, it raises awareness among researchers that computation and sensors contribute significantly to energy consumption.

4. Energy Sources and Management Technologies in AMRs

4.1. Energy Sources for AMRs

AMRs rely on various energy sources to function effectively. Batteries are the most common and account for 98.5% of the research found in the systematic literature review. These energy storage devices are composed of electrochemical cells that transform stored chemical energy into electrical energy. Different battery types, such as lead-acid, nickel, and lithium batteries, have unique advantages and drawbacks, offering diverse options for specific AMR requirements (McNulty et al. 2022).

Despite the dominance of batteries, other energy sources show promise for AMR applications. Solar energy, for instance, has been studied by A. Sulaiman et al. in 2013, who explored solar hydrogen energy systems for mobile robots (A. Sulaiman et al. 2013). Although solar energy faces challenges like photovoltaic efficiency, hydrogen storage technology, and cost, further research could improve its viability as a renewable energy source for AMRs.

Fuel cells have also been investigated as potential energy sources for AMRs, comprising approximately 1% of related studies (J. S. Artal et al. 2012; J.S. Artal-Sevil et al. 2017). J.S. Artal-Sevil's research in 2012 and 2017 focused on active hybrid power systems, suggesting that combining PEM fuel cells with ultracapacitors or lithium batteries could offer significant advantages. However, economic factors and practical applications require more in-depth exploration.

Supercapacitors, another alternative energy source, exhibit high energy density and perform between electrolytic capacitors and batteries. In 2020, Lukasz Wieckowski et al. demonstrated that combining batteries and supercapacitors could improve robot power system performance (Lukasz Wieckowski and Klimek 2020). Similarly, Marvin Sperling et al. developed a dual-energy storage system (DESS) in 2022 (Marvin Sperling and Kivelä 2022), which effectively reduced the required battery capacity but faced challenges in development and integration into AGVs.

By investigating and refining these alternative energy sources, AMRs can become more efficient and versatile, expanding their applicability across various industries and environments.

Table. 1 Advantages and Disadvantages of Each Energy Source

Energy Source	Advantages	Disadvantages	Proportion
Batteries	● Widely studied and mature technology ● Simple to implement and maintain ● Variety of battery types for specific applications	● Limited energy storage capacity ● Long charging times ● Performance degradation over time ● Environmental concerns	98.5%
Solar Panels	● Renewable and eco-friendly energy source ● Continuous energy supply (in optimal conditions) ● No direct emissions or pollution	● Limited applicability in indoor/low sunlight areas ● Relatively low photovoltaic efficiency ● High initial cost and complexity	0.2%
Fuel Cells	● High energy efficiency and low operational noise ● Zero emissions during energy conversion ● Faster refueling and longer operating times	● Limited research and development ● High initial cost and complexity ● Uncertain economic feasibility and practicality	0.9%
Supercapacitor	● High power density and rapid charging capabilities ● Longer cycle life and minimal degradation over time ● Less sensitive to temperature fluctuations	● Limited energy storage capacity ● Lower energy density compared to batteries ● Higher initial cost and complexity ● Requires additional energy management systems for optimal performance	0.4%

Table 1 summarizes the advantages and disadvantages of three commonly used energy sources and their relative representation in the literature searched for this review (Rosenbaum and Schröder 2010; Gröger et al. 2015). Proportion represents the number of papers on the topic over the total papers reviewed.

This part covers AMR energy sources, discussing their pros and cons. Batteries, are widely studied and versatile but have limitations in energy storage, charging times, and environmental impact. Solar panels offer renewable, eco-friendly energy but face indoor applicability, efficiency, and cost challenges. Fuel cells boast high energy efficiency and low noise but have limited research, high costs, and uncertain feasibility. Exploring solar panels and fuel cells can lead to diverse, efficient, sustainable mobile robot energy solutions.

4.2. Battery Management Systems (BMS)

Battery Management Systems (BMS) are crucial systems that monitor and manage various battery parameters in mobile robots, particularly AGVs. BMS optimizes the charging and discharging processes by monitoring parameters such as voltage, current, and temperature to ensure efficient battery operation and extend their lifespan.

BMS plays a vital role in the efficient performance and longevity of batteries in mobile robots, including AGVs (Hanschek et al. 2021). It is responsible for monitoring and managing various battery parameters, such as voltage, current, and temperature, for optimizing the charging and discharging processes. By doing so, the BMS ensures the efficient operation of batteries and prolongs their life, thereby contributing to the overall performance and reliability of the mobile robots that rely on these energy sources.

Due to the numerous studies and recent literature reviews available in the field of BMS, this paper will not go into detailed discussions regarding BMS.

4.3. Charging Technology for Energy Storages in AMRs

Efficient charging technologies for AMRs are essential for seamless operation and widespread adoption. Inductive coupling and conductive coupling are two primary charging methods. Inductive coupling uses magnetic fields for wireless power transfer, offering benefits like simplified alignment, reduced wear and tear, and increased safety, but with lower efficiency than conductive coupling (Kojima et al. 2015; Huang et al. 2017, 2019; Anyapo 2019; Chen et al. 2019; Dewi et al. 2019; Zhang et al. 2019; Yi et al. 2020; Ying-Chun Chuang et al. 2020; Pamungkas et al. 2022; Pan et al. 2022; Lee et al. 2023). Conductive coupling transfers power through a physical connection, providing higher efficiency and quicker charging times, but requires more accurate alignment and is prone to wear and tear. Customized AMR charging infrastructures can be implemented for different application requirements and environments, combining inductive and conductive methods as needed for flexibility and convenience.

5. Energy Consumption for AMRs

The energy consumption model of AMRs and the key factors affecting energy consumption are prerequisites for optimizing AMR energy consumption. This section focuses on the study of theoretical energy consumption models and key factors that impact the energy consumption of AMRs.

5.1. Models for Estimating Energy Consumption

Numerous models have been devised to accurately estimate energy consumption by accounting for factors like robot motion, power losses, and energy storage capacities. Such models play a crucial role in pinpointing areas for enhancement and devising more energy-efficient robotic systems. In the subsequent subsections, an overview of various energy consumption models is provided, encompassing physics-based models, data-driven models, hybrid models, as well as approaches for model validation and comparison.

Physics-based models are founded on fundamental principles such as forces, torques, and energy loss. They offer an in-depth understanding of a robot's motion dynamics, providing critical insights for designing energy-efficient systems.

Data-driven models utilize machine learning techniques and historical data to estimate a robot's energy consumption. These models are adaptable and can deliver high accuracy in various scenarios.

Hybrid models combine the benefits of both physics-based and data-driven models. They integrate the fundamental principles from physics with machine learning techniques to create robust and highly accurate energy consumption estimations in robotic systems.

As shown in Fig. 5, there were 11 studies (44%) that focused on physics-based models, 10 studies (40%) on data-driven models, and 4 studies (16%) on hybrid models. In addition, one study compared two different types of models.

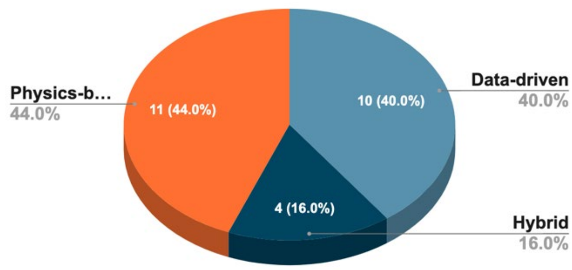


Fig. 5 Energy consumption model research classification

5.1.1. Physics-based Models

Physics-based models primarily concentrate on the fundamental principles governing a robot's motion, such as forces, torques, and power losses. By incorporating these factors, these models provide a deeper understanding of energy consumption patterns and allow for developing more energy-efficient robotic systems.

In 2015, Merlin Stampa et al. proposed a physics-based model, a polynomial function model based on physical principles and experimental data to estimate the energy consumption of a four-wheel mecanum omnidirectional autonomous navigation vehicle on any trajectory (Merlin Stampa et al. 2015). In the paper, the authors demonstrated a comparison between the proposed energy consumption estimation method and actual measurement data but did not provide specific error ranges or accuracy percentages. Equation (1) represents the calculation method for total energy consumption. Equation (3) is the calculation method for mechanical power, and Equation (4) is the calculation method for electrical power.

$$E = \int_{t=t_{\mathrm{start}}}^{t_{\mathrm{end}}} P_{\mathrm{loss}}\, \mathrm{d}t \tag{1}$$

$$P_{\mathrm{loss}} = \sum_i \left(P_{\mathrm{m},i} + P_{\mathrm{e},i}\right) \tag{2}$$

$$P_{\mathrm{m},i} = M_{\mathrm{fric},i} \dot{\varphi}_i \tag{3}$$

$$P_{\mathrm{e},i} = R_{\mathrm{a}} I_{\mathrm{a},i}^2 \tag{4}$$

In a 2017 study by Vaibhav Deshmukh et al. (Vaibhav Deshmukh et al. 2017)., the primary focus was on an energy consumption estimation method based on kinetic energy transformation and traction resistance. This approach originates from physical principles, considering the changes in kinetic energy and motion resistance of the robot during the interception of a moving target. The authors conducted simulation experiments to analyze the energy consumption under nonholonomic and holonomic constraints in various scenarios. They discussed various influencing factors, such as path curvature and velocity constraints. This paper still holds significant reference value for understanding the energy consumption patterns of robots under dynamic trajectory planning. However, the article does not provide a specific accuracy metric to evaluate the proposed method. Equation (5) represents the sum of motor energy, including kinetic energy and resistance energy. In this model, motor energy is assumed to be the combined energy of kinetic and resistance energy. In other words, the energy provided by the motor is used to overcome resistance and provide kinetic energy for the robot. Equations (6) and (7) respectively demonstrate the calculation methods for kinetic energy and resistance energy.

$$E_{\mathrm{motor}}(t) = E_{\mathrm{kinetic}} + E_{\mathrm{res}} \tag{5}$$

$$E_{\mathrm{kinetic}} = \frac{1}{2} m v_c(t)^2 + \frac{1}{2} I \omega_c(t)^2 \tag{6}$$

$$E_{\mathrm{res}}(t) = \int_t (P_l + P_r) dt \tag{7}$$

In 2020, Said Fadlo et al. established an energy model for a differential drive mobile robot using Simscape software (Said Fadlo et al. 2020). They conducted a multi-domain dynamic simulation using the Simscape tool developed by Mathworks. They proposed a complete physics-based energy model that considers DC motors, gear heads, kinetic losses, and friction losses. As the paper did not furnish specific accuracy data, it is not possible to directly quantify the accuracy of the proposed model. However, from the experimental results, the model proposed in the paper is superior to the hybrid energy model in predicting energy consumption. In the motor model, the total energy is 80 joules; in the hybrid energy model, the total energy is 105 joules, while in the model proposed by Said Fadlo et al., the total energy is 120 joules. This suggests that the model proposed in the paper considers more energy consumption. Equations (8) to (12) illustrate the calculation relationships whereE_{DC} term symbolizes the energy losses in dc motors, E_G the energy losses in gearhead, E_K the kinetic losses, and $E_f$the energy losses due to friction.

$$E_{Tot} = E_{DC} + E_G + E_K + E_f \tag{8}$$

$$E_{DC} = \int R(i_L^2 + i_R^2) dt \tag{9}$$

$$E_G = (1-\eta) K_t \int \left(i_L \dot{\theta}_L + i_R \dot{\theta}_R\right) dt \tag{10}$$

$$E_k = \frac{1}{2}\left(m v(t)^2 + I \omega(t)^2\right) \tag{11}$$

$$E_f = \mu m g \int v dt \tag{12}$$

5.1.2. Data-driven Models

Data-driven models employ machine learning techniques and historical data to estimate energy consumption in robotic systems, offering adaptability and accuracy across various scenarios. In a 2022 study, Pawel Benecki et al. thoroughly investigated various Recurrent Neural Network (RNN) architectures, such as LSTM and

BiLSTM (Pawel Benecki et al. 2022). Their findings showed that the IEEE Battery BiLSTM 1-layer 70 model performed best with all features, achieving a μMSE value of 0.0102 and a μMAE value of 0.3348, indicating high accuracy. However, it is essential to recognize that the appropriate model depends on the specific task, dataset, and performance requirements. Fig. 6 illustrates the basic structure of an RNN (Pawel Benecki et al. 2022). In Fig. 7, an algorithm flowchart is depicted, which demonstrates the process of training a recurrent neural network on a single sequence. This flowchart provides a visual representation of the critical steps involved in the training procedure, helping the reader better understand the algorithm's underlying logic. Similarly, Fig. 8 showcases an algorithm flowchart detailing the process of applying a model to a dataset. This flowchart highlights the essential steps in processing the model on a dataset, offering a clear and concise overview of the algorithm's implementation.

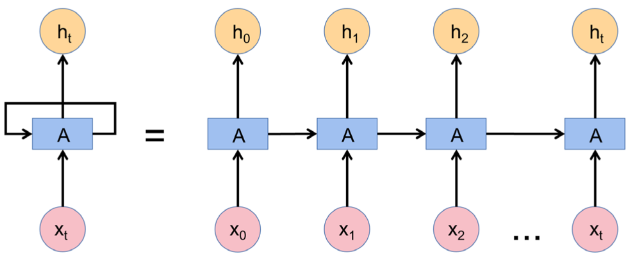


Fig. 6 Recurrent Neural Network Architecture

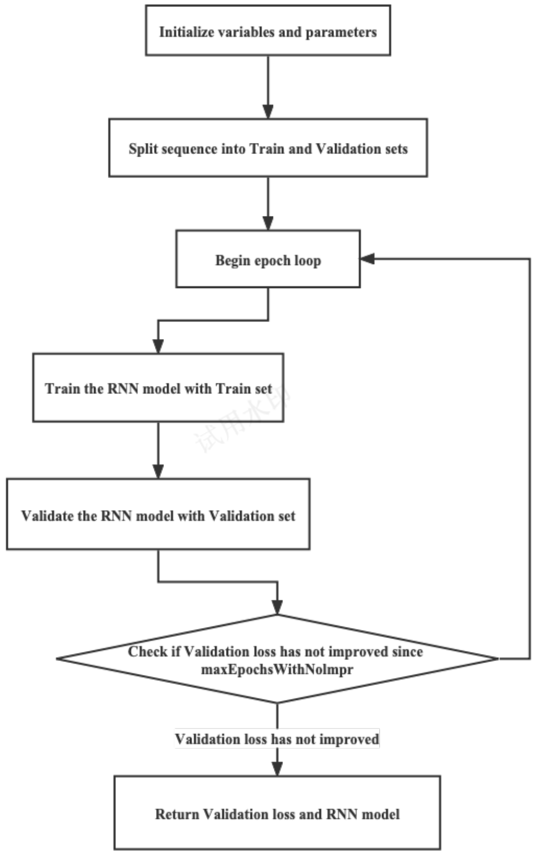


Fig. 7 Algorithm flowchart for training recurrent neural network on a single sequence.

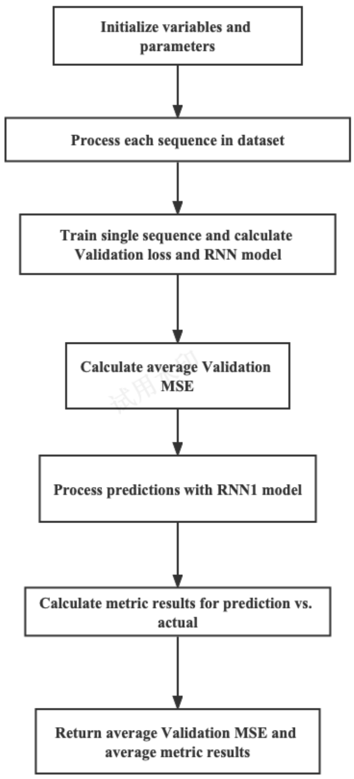


Fig. 8 Algorithm flowchart for processing a model on a dataset.

In a 2022 study by Marco Visca et al. , the authors proposed a probabilistic deep meta-learning approach for predicting driving energy consumption of AMRs navigating in complex, unstructured environments (Marco Visca et al. 2022). Figure 9 visually demonstrates the difference between meta-learning and multi-task learning. Through five different train-validation splits, the study found that as the number of meta-training samples increased, the accuracy of the most likely predictions improved for all methods that decreasing root mean square error (RMSE) and increasing R2. At the same time, the uncertainty associated with the probabilistic approaches also reduced that decreasing Negative Log-Likelihood (NLL). This feature was particularly pronounced in the highly unstructured subsets. For example, in the case of only three meta-training samples, the R2 scores decreased by 3.59%, 5.55%, 2.79%, and 4.61% for Meta-Conv1D-Gamma, Meta-Conv1D-Lognorm, Meta-Conv1D-Gaussian, and Meta-Conv1D-GMM models, respectively. In simpler subsets, the reductions were smaller, at 1.55%, 0.54%, -0.03%, and 1.37%, respectively.

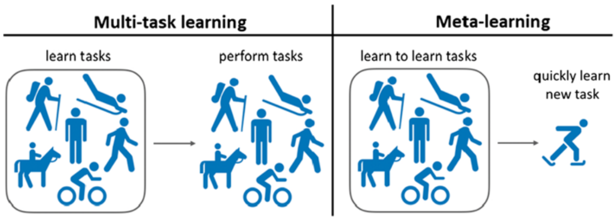


Fig. 9 The difference between multi-task learning and meta-learning(Huisman et al. 2021).

5.1.3. Hybrid Models

Hybrid models merge physics-based and data-driven models to estimate energy consumption in robotic systems, capitalizing on both approaches' strengths for accurate and robust predictions(S. D. Lee and Jung 2015; Sedat Dogru and Marques 2016; Morales and Mendoza 2018; Pushpendra Kumar et al. 2018). Mauricio F. Jaramillo Morales et al. proposed a hybrid energy model for differentially steered mobile robots, combining dynamic robot and motor models and providing more accurate energy consumption estimates in some aspects (Morales and Mendoza 2018). Equation (12) describes the calculation of electrical energy, E(t). It is the integral of voltage, V(t), multiplied by current, i(t), over time, t. Equations (13) and (14) provide the methods for calculating voltage and current, respectively.

V and i = is the armature voltage and current.
R and L = is the armature resistance and inductance.
ν = is the viscous friction coefficient.
τ = is the dynamic load applied to the motor.
K_t = is the motor torque constant.
K_w = is the voltage constant.
I_s = is the motor shaft inertia.
$\theta = [\theta_1 \quad \theta_2]$ = are the angular positions of the wheels.

$$E(t) = \int V(t)i(t)dt \tag{12}$$

$$i = \frac{V - K_w\dot{\theta}}{R} \tag{13}$$

$$V = (S^T T)^{-1}(S^T M S\dot{\eta} + S^T M \dot{S}\eta + S^T F S\eta + S^T C) \tag{14}$$

In another study, they proposed a power model for a two-wheel differential drive mobile robot with prediction accuracies of 96.67% for linear trajectories and 81.25% for curved trajectories, making it an excellent hybrid model (Mauricio F Jaramillo-Morales et al. 2020).

5.1.4. Model Validation and Comparison

Understanding various models and approaches for estimating energy consumption in autonomous mobile robots is vital for optimizing performance and efficiency. Each of the physics-based, data-driven, and hybrid models possesses its own advantages. Drawing on previous research, the strengths and weaknesses of these various models have been summarized and are presented in Table 2. Proportion refers to the percentage of studies in the SLR that belong to this subcategory.

Table. 2 Advantages and Disadvantages of Each Model for Estimating Energy Consumption

Models for Estimating Energy Consumption	Advantages	Disadvantages	Proportion
Physics-based Models	● Based on fundamental principles and physics ● Deeper understanding of energy consumption ● Allows for more energy-efficient design	● Limited adaptability to diverse scenarios ● May require complex calculations and assumptions ● May not account for all factors in real-world systems	44%
Data-driven Models	● Adaptable to various scenarios ● High accuracy ● Can automatically improve with more data	● Dependent on historical data and its quality ● May require large amount of data ● May not provide insights into underlying principles	40%

Hybrid Models	● Combine the strengths of both approaches ● Accurate and robust predictions ● Can account for a wide range of factors	● Can be more complex to develop and implement ● May still require large amount of data ● Limited interpretability of the underlying principles	16%

In 2022, Tomas Petr and colleagues conducted a comparative study, showing that mathematical models and artificial neural networks could be used interchangeably for predicting energy consumption, with AI methods being more versatile and not dependent on the robot's motion structure (Krystian Góra et al. 2021). Model validation and comparison are essential for identifying areas for improvement and developing more energy-efficient robotic systems. Hybrid models perform better but require relevant physics knowledge and strong mathematical skills. Comparing models helps guide future research in the field.

5.2. Factors Influencing AMR Energy Consumption

Understanding the factors influencing energy consumption in mobile robots is essential for designing energy-efficient systems and optimizing their performance. Factors including rolling friction, cornering, passage dimensions, and payload weight can have a significant effect on a robot's energy consumption.

This part covers a discussion of the primary factors that influence energy consumption, along with a review of relevant studies that explore these elements.

5.2.1. Impact of Rolling Friction

Rolling friction is a crucial factor affecting a robot's energy consumption as it moves on various surfaces. In 2011, Shuang Liu et al. conducted a study comparing a single algorithm's performance in different path environments (Shuang Liu and Dong Sun 2011). They employed the A* path planning algorithm to generate three distinct paths. The path traversing gravel was 8% faster but consumed 123% more energy than the path traversing a regular road surface. Notably, the fastest and most energy-efficient paths were not the shortest. This study introduced one of the earlier methods in the field of mobile robots that took both path planning and trajectory planning into consideration. In 2014, Piotr Jaroszek et al. conducted a related study where they experimentally examined friction on different types of surfaces and modeled it (Piotr Jaroszek and Trojnacki 2014). The surfaces included concrete/asphalt, unpaved, crushed stone, and ice. They quantitatively analyzed the energy consumption of robot motion on each surface and found that energy consumption varied depending on the surface type. Among them, the friction on the ice surface is the smallest. However, the influence of surface friction on energy consumption differed on inclined surfaces at various angles.

Fig. 10 illustrates this relationship. After reaching 2 degrees, the coefficient of friction on the contact surface is no longer a factor affecting energy consumption.

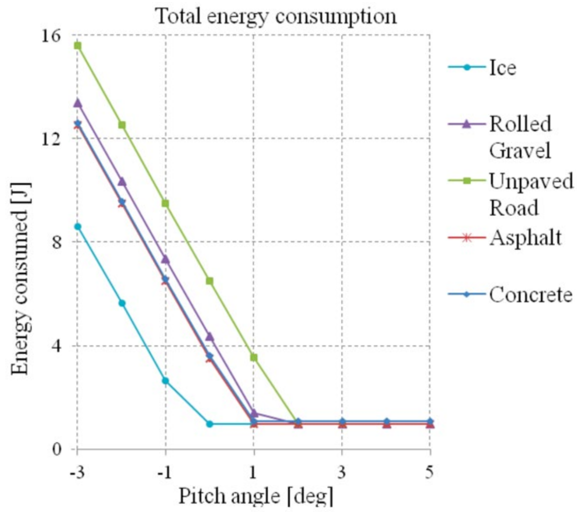


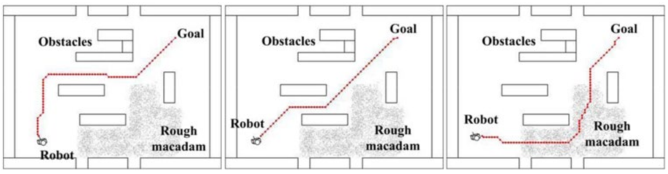
Fig. 10 energy consumption for different pitch angles and surface (Piotr Jaroszek and Trojnacki 2014)

5.2.2. Impact of Cornering

Cornering is another critical factor influencing energy consumption in mobile robots. In optimal control theory, "cornering" refers to the that-planning strategy adopted by a robot when making turns. The chosen path-planning method significantly impacts the robot's energy consumption during cornering. Research has shown that using energy-minimizing path planning methods can reduce the energy consumption of robots during cornering, thus extending battery life and enhancing work efficiency. In a 2017 study by Hongjun Kim and colleagues (Kim and Kim 2017), they found that the curvature of turns in a virtual simulation environment affected the energy consumption of path planning algorithms. Their research revealed varying performance levels for loss-minimization, Minimum Energy, and TRAPE methods in acute, right, and obtuse angle scenarios. For angles close to 90°, the energy consumption of loss-minimization and TRAPE methods increased by 1.49% to 5.47% compared to Minimum Energy, indicating a decrease in energy efficiency. When dealing with obtuse angles, the energy consumption of these methods increased by 1.12% to 2.81%, suggesting relatively better energy efficiency. However, for acute angles, the energy consumption increased by 3.34% to 15.20%, indicating poorer energy efficiency.

5.2.3. Impact of Passages Dimension

The dimensions of passages through which mobile robots navigate can also play a significant role in their energy consumption. A study conducted by Dong Sun et al. in 2011 experimentally found that mobile robots consume more energy when passing through narrow passages (Shuang Liu and Dong Sun 2011). Although the path through narrow passages is shorter, mobile robots require more time and an additional 20% energy consumption than those without narrow passages. Fig. 11 (a) and (b) illustrate these two paths. They discovered that mobile robots require more time and energy to avoid collisions (like PID) when passing through narrow passages.



(a) (b) (c)

Fig. 11 Optimal path generation: (a) minimum energy; (b) minimum travel distance; (c) minimum travel time (Shuang Liu and Dong Sun 2011).

5.2.4. Impact of Payload Weight

Payload weight significantly impacts mobile robot energy consumption, as heavier payloads require more moving energy. This is crucial for robots involved in material handling or delivery tasks. Optimizing robot design and movement strategies can minimize energy consumption with different payload weights, but further research is needed for comprehensive models and strategies addressing energy management in such scenarios.

5.2.5. Impact of Terrain

The terrain is an essential factor to consider when assessing the energy consumption of AMRs. It refers to the surface characteristics and topography of the robot's environment. Different terrains include smooth surfaces like concrete or asphalt, uneven surfaces like grass or gravel, and more complex terrains like sandy or rocky areas. In a study conducted by Qingdan Yuan and others in 2017 (Yuan et al. 2017), researchers calculated the power ratio factors of the same algorithm on different terrains. On concrete roads, the power ratio factor is 1, which represents the baseline energy consumption. On grass and sandy terrains, the power ratio factors are higher than 1, indicating that the energy consumption of the robot on these terrains is higher than concrete roads. On grassy terrain, the energy consumption of the robot is slightly higher than on concrete roads, while on sandy terrain, the energy consumption is even higher.

5.2.6. Impact of the Center of Mass

The center of mass is fundamental in physics and engineering, significantly affecting robotic systems' energy consumption. In 2022, Mohammad pour et al. proposed a path-planning algorithm considering the center of mass (Mohammad pour et al. 2022). Their research emphasizes the impact of centroid displacement on self-guided vehicles' (SGVs) energy consumption, showing that payload placement alters the SGV's dynamic inertial parameters and shifts the center of mass, affecting energy consumption during rotational motion. In this study, it was found that when the center of mass is placed on the right side of the SGV, allowing the SGV to perform obstacle avoidance rotation with the right side as the outer edge, it consumes less energy compared to the scenario where the center of mass is in the middle. However, when the center of mass is on the right side and the SGV performs a curved right-angle turn with the right side as the outer edge, it consumes more energy than the scenario with the center of mass in the middle. Researchers utilized data-driven methods to find more energy-efficient paths under different center of mass distributions.

5.2.7. Impact of Hardware Design

Liangkai Liu et al. discovered in their study that power analysis of HydraOne revealed computational power and sensor power accounted for 33% and 11% respectively (Liangkai Liu et al. 2019). This indicates that hardware does have an impact on AMR energy consumption. Jaiem and colleagues proposed an energy consumption model that divides energy expenditure into dynamic and static components (Jaiem et al. 2016). In this model, the energy consumption of sensors in AMR (Autonomous Mobile Robot) differs between stationary and motion states.

The research demonstrates that the design of hardware significantly affects the energy consumption of Autonomous Mobile Robots (AMRs), with computational power and sensor power being major contributors.

6. Energy Optimization for AMRs

Energy optimization is crucial in reducing the energy consumption of AMRs. It can be achieved through various approaches, including hardware and software modifications. By employing these strategies, designers can improve the overall energy efficiency of AMRs, which is a critical aspect of research in the field of energy-related topics for AMRs.

Various methods can be employed for energy optimization, such as optimizing the control method, enhancing sensor and computing systems, implementing efficient power management systems, improving path planning, and refining scheduling methods. These strategies target different aspects of AMR's operation and can be employed individually or in combination to achieve significant energy savings.

6.1. Energy Optimization for AMR in Control Method

Control methods refer to various algorithms and techniques used to regulate the behavior of systems, such as AMRs, to achieve desired performance characteristics. Several control methods have been proposed to optimize energy consumption in AMRs, including PID (Proportional-Integral-Derivative) Control, Model Predictive Control (MPC), PID (Proportional-Integral-Derivative), Fuzzy Logic Controller and Minimum-energy Trajectory Tracking Controller.

PID is a widely used control algorithm in engineering and industrial processes that achieves stable and precise control by adjusting proportional, integral, and derivative gains. Kim et al. proposed the Intelligent Slip-Optimization Control (ISOC) algorithm in 2014 for balancing traction force and energy consumption in wheeled robots on different terrains (Jayoung Kim and Lee 2014). In 2018, they introduced the Traction Energy Balance (TEB) adaptive control to optimize sliding and traction energy balance on rough terrain (Jayoung Kim and Lee 2018).

MPC is another control method to address energy optimization challenges. In 2013, Yacoub tackled torque saturation in robot climbing with an energy optimization algorithm using MPC (Yacoub et al. 2013). MPC using voltage and current control reduced energy consumption by 63% and 53%, respectively, compared to PID control, while providing more robust speed control performance.

The methods are considered classic control optimization approaches. However, there are newer control optimization methods specifically targeted at AMR energy optimization that are worth considering and exploring.

Deep Reinforcement Learning (DRL) combines deep learning and reinforcement learning to enable adaptive control strategies through learning from environmental feedback. Drungilas et al. applied DRL in 2022 to control AGV speed and optimize energy consumption in container terminals, achieving a 4.6% reduction in energy consumption (Darius Drungilas et al. 2023). However, their method focused solely on AGV speed control and did not consider other factors, such as scheduling and path planning.

Said Fadlo et al. introduced a method based on a fuzzy logic controller that optimizes energy consumption by adjusting the input voltage according to the motor's angular velocity (Said Fadlo et al. 2021). This approach results in a reduction of 2.51% in energy consumption for each actuator. However, this method requires a detailed understanding of the robot's parameters, as well as intricate computational and programming skills for its design and implementation.

Jianbin Wang et al. introduced the Minimum-energy Trajectory Tracking Controller, which achieves up to 79% reduction in motor power consumption (Jianbin Wang et al.

2018). It utilizes Lyapunov stability theory and backstepping control methods. However, precomputation is necessary for all optimization results, limiting its real-time control applicability. For practical use, a pre-established database can be created using the minimum-energy trajectory tracking algorithm, considering robots' common linear path tasks.

Various control methods have been developed to optimize energy consumption in AMRs, enhancing their efficiency and performance in diverse applications. Table 3 summarizes the pros and cons of different optimization methods based on the reviewed studies. However, it should be noted that these advantages and disadvantages are generalized and may vary depending on specific models, applications, and implementation details.

Table. 3 Advantages and Disadvantages of Different Energy Optimization Methods for AMRs in Control Methods

Optimization Method	Advantages	Disadvantages
PID Control	● Simple and widely used control algorithm. ● Stable and precise control ● Easy to implement and tune	● May not handle complex dynamics efficiently. ● Limited optimization capabilities ● Less adaptive to changing conditions
Model Predictive Control (MPC)	● Can handle complex dynamics and constraints. ● It offers more robust and efficient control. ● Can achieve significant energy savings compared to other methods	● Computationally intensive ● Requires accurate models for effective performance. ● May be more challenging to implement and tune
Deep Reinforcement Learning (DRL)	● Adaptable to various scenarios ● Can learn from environmental feedback. ● Potential for significant energy savings	● Requires large amounts of data for training. ● Computationally intensive ● May not consider all factors, such as scheduling and path planning
Fuzzy Logic Controller	● Handles uncertainty and imprecision well. ● Does not require precise mathematical models. ● Adaptable to changing conditions	● Requires expert knowledge to design and tune. ● Can be computationally intensive. ● May not provide optimal control in all scenarios
Minimum-energy Trajectory Tracking Controller	● Effective for path tracking problems ● Can save up to 79% of motor power consumption. ● Considers wheel speed redundancy for optimization	● All optimization results need to be computed in advance, not suitable for real-time control. ● Requires pre-built database for most daily tasks

6.2. Energy Optimization for AMR in Sensors and Computing Systems

Energy optimization in AMRs can also be achieved through sensors and computing systems enhancements. Approaches include energy efficiency middleware and sensor network design optimization.

Liangkai Liu et al. investigated the energy efficiency of AMRs during computer vision tasks in 2019 (Liangkai Liu et al. 2019). They identified three major energy efficiency issues and proposed an energy-efficient middleware called E2M to address them. E2M improved the energy efficiency of the computing platform by 24% and increased battery usage time and robot running time by 11.5% and 14 minutes, respectively.

Sensor network design optimization is another approach to energy conservation. In 2011, Myounggyu Won et al. proposed an innovative mobile sensor design to reduce energy consumption and processing time by controlling the movement of robots (Myounggyu Won et al. 2011). This design was demonstrated to be feasible through a sensor repositioning application, but further practical applications may be necessary to verify its feasibility and performance. In 2019, Paola Flocchini (Paola Flocchini et al. 2019) examined the effectiveness of mobile robots for distributed energy retrieval with a decentralized online strategy called Local Information and Communication (LIC). Theoretical and experimental analysis showed that LIC's effectiveness is on par with most networks' optimal centralized strategy, OPTIMAL. However, its effectiveness is lower than the OPTIMAL strategy in smaller networks.

A type of robot, named Brain-inspired Intelligent Robotics, merits our attention (Qiao et al. 2023). This robot emulates human brain processes for decision-making and control. This represents an interdisciplinary endeavor that could offer novel insights into optimizing energy consumption for AMRs.

These approaches offer valuable insights into enhancing energy efficiency and performance, but further research and practical applications may be needed to understand and optimize these strategies in various network environments fully.

6.3. Energy Optimization for AMR in power management systems

The studies reviewed cover a wide range of topics, including the optimal design of energy sources for photovoltaic/fuel cell extended-range agricultural mobile robots (Ghobadpour et al. 2023), forecasting AMR battery discharging using machine learning methods (Pavliuk et al. 2022), and reviewing lithium-ion batteries for autonomous mobile robots (Partovibakhsh and Liu 2015). Other studies explore applying artificial intelligence techniques, such as reinforcement learning for energy-constrained coverage with mobile robots (Lee and Jae Jang 2022). Additionally, several studies propose different algorithms for battery management, including replacing the battery of an automated tool using serving mobile robots (Kozyr' et al. 2022) and designing an embedded energy management system for Li-Po batteries based on a DCC-EKF approach for use in mobile robots (Chellal, Gonçalves, et al. 2021).

Recent developments in power management systems for mobile robots emphasize the potential for more efficient energy consumption in the future. Researchers have not extensively focused on using BMS to reduce the energy consumption of AMRs, but rather on algorithms with lower hardware requirements to implement energy management systems.

Two notable studies have made significant contributions to power management systems in AMRs, focusing on battery management systems and innovative power source designs, respectively.

In 2021, Arezki Abderrahim Chellal and colleagues proposed a BMS based on the Extended Kalman Filter (EKF) and an Embedded Energy Management System for Li-Po batteries using a Dual Coulomb Counting Extended Kalman Filter (DCC-EKF) approach for energy management in mobile robots (Chellal, Gonçalves, et al. 2021; Chellal, Lima, et al. 2021). These algorithms achieved high energy efficiency and provided more accurate remaining battery capacity predictions for mobile robots without relying on external devices to process data. The Li-Po Embedded Energy Management System achieves a high energy efficiency of 94% and realizes a SOC accuracy error between 2% and 8% using low-cost components.

Amin Ghobadpour and colleagues proposed an energy optimization design for a photovoltaic/fuel cell extended-range agricultural mobile robot (Pavliuk et al. 2022). This innovative design combines photovoltaic and fuel cell technologies, enhancing the energy efficiency of the mobile robot. The proposed design reduces fuel consumption and total cost, contributing to lower operating costs, increased energy efficiency, and sustainability, making agricultural mobile robots more competitive in practical applications. The proposed design can reduce fuel consumption in the power transmission system by up to 12.21% compared to the particle swarm optimization (PSO) method by employing a rule-based component sizing adjustment method. Furthermore, utilizing PSO to optimize the powertrain reduces the total cost by 8.79% compared to traditional theoretical selection methods.

6.4. Energy Optimization for AMR in path planning

Path planning is an essential component of AMR energy optimization. The path planning algorithm aims to generate the shortest path for AMR navigation while considering various constraints such as obstacle avoidance, task requirements, and energy consumption. The path planning algorithm reduces AMR energy consumption by minimizing the distance traveled (Alajlan et al. 2017; Yuan et al. 2017; Dechao Chen et al. 2022; Satyendra Shukla and Kumar 2022) and avoiding unnecessary movements (Vinay Singh et al. 2015; Inderjeet Singh et al. 2020; Satyendra Shukla and Kumar 2022). In addition, some algorithms can consider the energy characteristics of different paths and choose the path with the lowest energy consumption (Piotr Jaroszek and Trojnacki 2014; Dogru and Marques 2015, 2015; Go Sakayori and Ishigami 2017; Yuan et al. 2017). Therefore, effective path planning algorithms can significantly reduce AMR energy consumption, extend AMR operating time, and improve AMR efficiency. This is particularly important for battery-powered AMRs, where energy consumption directly affects their operating time and efficiency.

6.4.1. Path planning algorithms about shortest-path planning (SPP)

Shortest-path planning involves finding the shortest path between two points in each environment while avoiding obstacles. The relationship between shortest-path planning algorithms and energy consumption lies in their potential to optimize the energy use of systems that rely on navigation, such as AMRs or transportation networks. By finding the shortest or least-cost path, these algorithms can reduce the distance traveled, decreasing energy expenditure. This is particularly relevant for battery-powered systems, where energy conservation and maximizing operational time are critical.

However, it is crucial to recognize that the shortest path may not always be synonymous with the most energy-efficient route. Terrain, environmental conditions, and system dynamics can influence energy consumption. Therefore, researchers often explore adaptations or enhancements to traditional shortest-path planning algorithms to consider energy-related factors better. These adaptations aim to balance the optimization of path planning to minimize energy consumption, ultimately leading to more sustainable and efficient systems.

For achieving path planning in AMRs, various path planning algorithms have been proposed in the literature. These algorithms can generally be divided into two main categories: algorithm types and optimization directions. Algorithm types include: (1) the Dijkstra algorithm (Zhongwei Zhang et al. 2021; Emna Mejri et al. 2022), (2) the A* algorithm (Shuang Liu and Dong Sun 2011; Piotr Jaroszek and Trojnacki 2014; Shuang Liu and Sun 2014; Go Sakayori and Ishigami 2017; Jing Liu et al. 2020; Cong Liu et al. 2021; Satyendra Shukla and Kumar 2022), (3) The optimal control theory (Kim and Kim 2012; Hongjun Kim and Kim 2014), (4) Tabu-search (Wei et al. 2012), (5) the Genetic algorithm, (6) Ant Colony Optimization algorithm (Wongwirat and Anuntachai 2011; Anuntapat Anuntachai et al. 2014), (7) Bee Swarm Optimization (BSO), (8) Particle Swarm Optimization (PSO), (9) Cuckoo–beetle swarm search (CBSS) algorithm (Dechao Chen et al. 2022), (10) Deep reinforcement learning algorithm (Nguyen et al. 2020). Optimization directions can be categorized based on factors such as: (1) Terrain (Wongwirat and Anuntachai 2011; Anuntachai and Wongwirat 2012; Anuntapat Anuntachai et al. 2014; Piotr Jaroszek and Trojnacki 2014; Xu Zhao et al. 2014; Satyendra Shukla and Kumar 2022), (2) velocity trajectory (Shuang Liu and Dong Sun 2011; Hongjun Kim and Kim 2014; Shuang Liu and Sun 2014), (3) path smoothing (Manas Chaudhari et al. 2014; Jing Liu et al. 2020; Cong Liu et al. 2021).

Fig. 12 provides an intuitive demonstration of path smoothing. By employing the Hamiltonian function formulation, the optimal velocity profile that guarantees minimal energy consumption can be obtained.

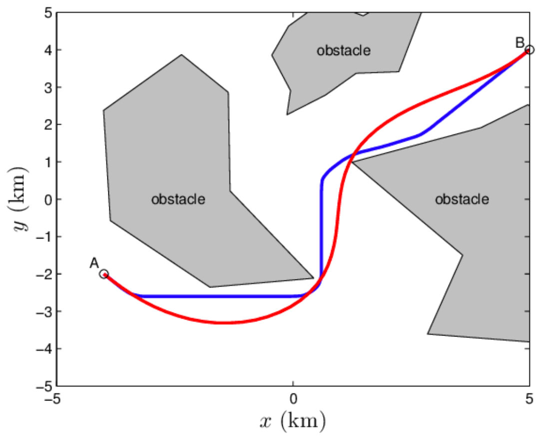


Fig. 12. Path Smoothing (Zhao and Tsiotras 2011)

A thorough review and synthesis of these algorithms have been carried out, examining the advantages, disadvantages, and key focus points of each method. This examination allows for a better understanding of their respective strengths and weaknesses in the context of mobile robot energy consumption optimization. Table 4 provides a specific comparison of the differences.

Table. 4 Comparison of common SPP algorithms

Algorithm	Advantage	Disadvantage	Primary Focus Points
Dijkstra	1. Guarantees finding the shortest path. 2. Simple algorithm, easy to implement. 3. Applicable to directed and undirected graphs.	1. Cannot handle edges with negative weights. 2. Lower computational efficiency for dense graphs.	1. Shortest path. 2. Applicable scenarios.
A* Algorithm	1. Improves search efficiency through heuristic search. 2. Finds the shortest path.	1. Heuristic function choice significantly impacts performance. 2. Higher memory requirements.	1. Heuristic search. 2. Heuristic function selection.

	3. Relatively general-purpose algorithm.		
The optimal control theory	1. Provides mathematically optimal solutions. 2. Applicable to both linear and nonlinear systems.	1. Computationally expensive for large systems. 2. Assumes perfect system model and knowledge.	1 . Minimization of energy consumption. 2 . Model-based design and control.
Tabu-search	1. Efficiently explores solution space. 2. Can escape local optima with tabu list.	1. Sensitive to parameter tuning. 2. It May require long computational times.	1. Exploration and exploitation balance. 2. Neighborhood search and trajectory guidance.
Genetic Algorithm (GA)	1. Strong global search capabilities. 2. Applicable to various optimization problems. 3. Easy to combine with other methods.	1. Slow convergence speed. 2. Requires significant computational resources.	1. Crossover, mutation, and selection operations. 2. Encoding and decoding.
Ant Colony Optimization algorithm	1. Population-based approach. 2. Robust to uncertainties and noise.	1. Computationally intensive due to large populations. 2. Requires parameter tuning.	1.Bio-inspired optimization. 2.Pheromone update and evaporation.
Bee Swarm Optimization (BSO)	1. Utilizes bee foraging behavior for global search. 2. High convergence speed. 3. Avoids local optima.	1. Parameter selection greatly affects performance. 2. The initial solution May influence it.	1. Bee foraging behavior. 2. Parameter selection.
Particle Swarm Optimization (PSO)	1. Simple and easy to implement. 2. Suitable for continuous and discrete optimization problems. 3. Possesses good global search capabilities.	1. Prone to local optima. 2. Parameter settings greatly affect performance.	1. Particle velocity and position updates. 2. Parameter selection.
Cuckoo-Beetle Swarm Search (CBSS)	1. Combines optimization strategies with global search, improving search efficiency. 2. High search precision. 3. Better at avoiding local optima.	1. Higher algorithm complexity. 2. Parameter settings greatly affect performance.	1. Stability and convergence. 2. Parameter selection. 3. Search strategies.
Deep reinforcement learning (DRL)	1. Adapts to complex and changing environments. 2. Learned from experience, improving over time. 3. Can handle high-dimensional spaces.	1. Requires large amounts of training data. 2. Computationally expensive. 3. High sensitivity to hyperparameters	1. Energy-efficient reward functions. 2. Policy optimization for energy minimization. 3. Integration with domain knowledge for energy-aware path planning.

In a 2022 study conducted by Dechao Chen et al., they compared the performance of various algorithms under specific conditions. Table 5 presents a summary of the experimental data collected. Regrettably, the research does not provide a direct comparison of the energy consumption for these algorithms. As a result, it is necessary to consult other data sources for reference.

Table. 5 The average planning and average execution time of the experiment (Dechao Chen et al. 2022).

Algorithm	Average Planning Time (s)	Average Execution Time (s)
CBSS	0.68	4.23
Dijkstra	1.56	4.94
A*	2.35	5.32
BSO	1.64	5.04
PSO	1.86	5.29
GA	2.93	5.98

This is a significant study; however, the authors did not directly compare the energy consumption between different algorithms, opting to use time as a proxy, raising questions for the readers.

6.4.2. Path planning algorithms about coverage path planning (CPP)

Coverage path planning, on the other hand, involves finding a path that covers all or a specified portion of a given area. This technique is commonly used in cleaning, surveillance, and agriculture tasks. Fig. 13 provides a simple demonstration of coverage path planning.

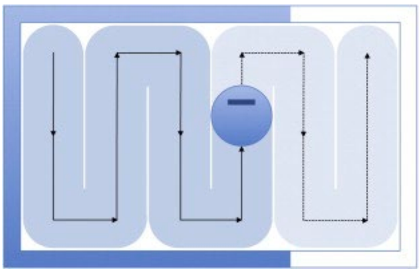


Fig. 13 Coverage path planning algorithm (Galceran and Carreras 2013)

The primary difference between SPP and CPP algorithms is that SPP focuses on finding the shortest or least-cost path between two points, while CPP aims to determine an optimal route that covers an entire area or region without unnecessary overlap or redundancy.

The relationship between coverage path planning algorithms and the energy consumption is centered around their ability to optimize energy use in systems that require complete coverage of a specified area. By finding a path that minimizes redundancy and overlap while ensuring full coverage, these algorithms can reduce the total distance traveled, decreasing energy expenditure. This is particularly important for battery-powered systems, where energy conservation and maximizing operational time are paramount.

A compilation of standard CPP algorithms has been assembled. Table 6 presents a comparison of these algorithms, emphasizing their focal points, advantages, and disadvantages.

Table. 6 Algorithm comparison.

Algorithm	Principle	Advantage	Disadvantage
CBD	Calculates the longest distance between two points in the environment.	1. Lower energy consumption in environments with fewer obstacles. 2. It reduced computational energy consumption due to simplicity.	1. Higher energy consumption in complex obstacle environments. 2. Limited adaptability, potentially leading to increased energy consumption.
TASP	Finds an optimal starting point by turning away from obstacles.	1. More efficient energy usage in complex obstacle environments. 2. Adaptability optimizes energy consumption across various environments.	1. Less energy-efficient in environments with fewer obstacles. 2. Higher computational resource requirements may increase energy consumption.
BSA	Utilizes a spiral pattern and backtracks when encountering obstacles.	1. Complete area coverage potentially reduces energy waste. 2. Lower computational energy consumption due to ease of implementation.	1. Potential energy inefficiency in specific environments. 2. Suboptimal paths may increase energy consumption.
DT	Divides the environment into cells and finds a path from the goal location back to the start location.	1. Adaptability optimizes energy consumption across different environments. 2. Generation of energy-efficient paths.	1. Higher computational resource requirements increase energy consumption. 2. Complexity may lead to increased energy consumption.

In a study by Marcel Mitschke et al. in 2018, an efficient coverage path planning algorithm was proposed for tasks such as outdoor cleaning and mowing (Mitschke et al. 2018). The proposed algorithm considers energy consumption a criterion, as mobile robots generally have limited battery capacity. Two coverage path planning algorithms were proposed, one based on prior knowledge of the environment and the other based on sensor data. Experimental results showed that even online algorithms could generate satisfactory paths, and the quality of the path depended on the environment and starting point. The online algorithm had only a 2.98% difference in energy consumption compared to a genetic algorithm, making it a good choice for coverage path planning in large environments.

In this noteworthy paper, the author conducted a comparative analysis and evaluation of four algorithms, namely the Turn-away Starting-point (TASP) algorithm, Calculate Longest Distance (CLD) algorithm, Distance Transform Methodology (DT), and Backtracking Spiral Algorithm (BSA). Table. 7. presents the data from this experiment.

Table. 7. Comparison of generated trajectories by different algorithms (Mitschke et al. 2018)

Metric	CBD	TASP	BSA	DT
Av. Energy	5158 J	5483 J	5609 J	7542 J
Min. Energy	4871 J	5003 J	5030 J	5952 J
Max. Energy	5403 J	6027 J	5948 J	8659 J
St.Dev. Energy	101.12 J	224.87 J	206.86 J	474.53 J
Av. Time	907.5 s	949.9 s	949.8 s	1115 s
Min. Time	876.2 s	894.8 s	885.2 s	957.3 s
Max. Time	951.9 s	1014.6 s	990.2 s	1432 s
St.Dev. Time	14.81 s	25.76 s	21.64 s	76.27 s
Av. Length	244.9	254.9	248	224.9
Min. Length	237	241	239	224
Max. Length	258	268	264	227
St.Dev. Length	4.42	4.46	5	0.72
Av. Comp.T.	227.49 s	0.95 s	0.14 s	282.18 s
Min. Comp.T.	6.61 s	0.47 s	0.11 s	1.46 s
Max. Comp.T.	750.42 s	1.33 s	0.41 s	8916.57 s
St.Dev. Comp.T	138.53 s	0.163 s	0.043 s	675.59 s

Following a quantitative analysis of the experimental data, it becomes evident that CLD outperforms the other algorithms in terms of energy efficiency, with energy consumption being 6.3% lower than TASP, 8.7% lower than BSA, and 46.2% lower than DT. Regarding time, CLD is faster, requiring 4.7% less time than both TASP and BSA and 22.8% less time than DT.

When comparing path lengths, DT generates the shortest paths, with a 13.3% reduction compared to TASP, a 10.3% reduction compared to BSA, and an 8.9% reduction compared to CLD. TASP and BSA demonstrate remarkable efficiency in the context of computational time, with BSA being 85.3% faster than TASP. However, TASP and BSA are significantly faster than CLD and DT, with TASP being 23894.7% faster than CLD and 29655.8% faster than DT. Table. 4 shows an algorithm comparison(Mitschke et al. 2018).

The performance of each path planning algorithm varies in terms of energy consumption, with CLD being the most energy-efficient and DT consuming the most energy. The shortest path is not necessarily the fastest, nor is it guaranteed to be the most energy efficient. The choice of the most appropriate algorithm for minimizing energy consumption depends on the application's and environment's specific requirements and constraints, considering factors such as the complexity of the environment, computational resources, and adaptability. It is essential to weigh these factors in selecting the most suitable path-planning algorithm for optimizing energy efficiency.

Collaborative Deep Neural Networks (DNNs) also represent a potential optimization method, particularly the edge-device collaborative inference paradigm, which is applicable to path planning and energy consumption forecasting for AMRs (Ren et al. 2023).

6.5. Energy optimization for AMRs in the scheduling method

Energy optimization for AMRs in scheduling methods is crucial in intelligent industrial systems to improve productivity and reduce energy consumption. This chapter discusses the impact of scheduling methods on robot energy consumption, covering both single and multiple robot scenarios.

For individual robots, optimizing scheduling algorithms enhances efficiency and lowers energy consumption, especially in complex environments or tasks with tight deadlines. Consequently, addressing single AMR scheduling problems while considering energy consumption is vital for future research and development.

In the context of multiple robots, various methods have been proposed to optimize energy consumption. The Artificial Bee Colony (ABC) (Ezzeddine Fatnassi et al. 2014) is one such method, achieving an Average Relative Percentage Deviation (ARPD) value that was only 5% of the GA's average ARPD value. The Improved Knee point-driven Evolutionary Algorithm (IKnEA) (Zhang, Zhang, et al. 2023) was developed, demonstrating better distribution and convergence rates than NSGA-II and KnEA.

The cycle strategy (Colling et al. 2019) was introduced to address charging issues, which uniformly distributes the starting times of charging processes. In addition, the battery charge scheduling method [31] significantly improved performance, nearly 20-fold compared to the CPLEX method. Researchers also developed a time-dependent Markov decision-process model (Dehnavi-Arani et al. 2019) that achieved high rewards with lower battery stress, such as RBC1-40, which obtained 62.4% of the reward with a battery life below 40% only 3.4% of the time(Tomy et al. 2019).

Finally, bi-level programming models with bi-objective optimization (Wang et al. 2019) were explored, resulting in an 11.65% reduction in overall energy consumption compared to efficiency-only models. This approach decreased low-speed no-load energy consumption by 22.29% and low-speed full-load energy consumption by 72.2%. Further research should focus on incorporating dynamic production scheduling and including AGVs in other frequent production scheduling problems, such as job-shop and flexible job-shop scheduling (He et al. 2022).

Bio-inspired Single-population Swarm Intelligence and Human-machine Hybrid Swarm Intelligence can serve as new avenues for exploration in the optimization of multi-robot systems (Wang et al. 2023). This includes algorithms such as GA (Cheng and Meng 2023) and Differential Evolution Algorithm (DE). Hybrid Particle Swarm Optimization algorithms also represent a method worth exploring (Zhang, Dou, et al. 2023).

7. Conclusion

7.1. Summary of Key Findings

In this systematic literature review, a comprehensive examination of research on energy efficiency in AMR was conducted. The findings are as follows:

1. Most studies within the SLR scope focus on energy consumption optimization, concentrating on specific aspects such as path planning, control, and scheduling methods. Although systemic energy optimization solutions have not been proposed yet, significant achievements have been made in research for single and multiple robot scenarios.
2. Locomotion accounts for over 50% of a mobile robot's total energy consumption, while computation and sensors contribute 33% and 11% respectively. This underscores the importance of optimizing control methods to enhance energy efficiency when designing and operating mobile robots. In addition, improving middleware and optimizing sensor network design can achieve energy consumption optimization.
3. Batteries serve as the primary energy source for AMRs, with electric drive being the dominant propulsion method. However, other energy sources warrant attention. Battery Management Systems (BMS) are crucial for AMRs, as they optimize the charging and discharging processes by monitoring voltage, current, and temperature. By focusing on BMS and innovative power design, researchers have made significant advancements in AMR energy management systems, improving energy efficiency and reducing operational costs.
4. Hybrid models, which combine the strengths of physics-based and data-driven models, demonstrate superior accuracy and robustness in various scenarios. Energy consumption optimization for AMRs can be achieved by employing control methods such as PID, Deep

Reinforcement Learning, and Model Predictive Control, with PID optimization being the most common method.

5. AMR energy consumption factors include rolling friction, turning, aisle dimensions, load weight, terrain, and center of gravity location. A thorough understanding of these factors helps design energy-saving systems and optimize mobile robot performance.
6. Path planning algorithms are crucial in optimizing AMR energy consumption by generating efficient paths that minimize travel distance and avoid unnecessary movements. Selecting the most suitable algorithm depends on the specific requirements and constraints of the application and environment. Dijkstra and A* algorithms are popular choices for SPP, while CBSS demonstrates faster planning capabilities in some tests. In CPP, the CBD algorithm exhibits higher energy efficiency in environments with fewer obstacles; however, the TASP algorithm may be more suitable in complex environments, offering higher energy efficiency.
7. Scheduling methods are vital for AMR energy optimization, as they coordinate the movements and tasks of single and multiple robots to maximize energy efficiency. Research in this area has significantly progressed, addressing various challenges in different applications and environments.

7.2. Future Research Directions

Based on the findings, the following directions can be considered for future research in the field of energy efficiency in Autonomous Mobile Robots (AMR):

1. Develop systemic energy optimization solutions: While current research focuses on specific aspects like path planning, control, and scheduling methods, there is a need for a comprehensive approach that holistically addresses energy optimization in AMRs.
2. Explore alternative energy sources and storage technologies: Investigate novel energy sources and storage methods to diversify and improve the energy efficiency of AMRs beyond batteries and electric drives.
3. Advance hybrid modeling techniques: Further research into hybrid models can help improve the accuracy and robustness of energy consumption predictions and optimizations in various scenarios.
4. Enhance middleware and sensor network design: Investigate innovative middleware architectures and sensor network designs to optimize energy consumption during data processing and communication.
5. Analyze environmental and operational factors: Conduct in-depth research into factors affecting AMR energy consumption, such as terrain, load weight, and center of gravity location, to design energy-saving systems that can adapt to different environments and tasks.
6. Develop adaptive and context-aware path planning algorithms: Design new algorithms that can dynamically adapt to complex and changing environments, allowing AMRs to optimize energy consumption based on real-time environmental data.
7. Advance scheduling methods for energy optimization: Continue to develop scheduling methods that optimize energy consumption for single and multiple AMRs, considering constraints such as time, space, and battery life.
8. Investigate energy-aware collaboration strategies: Study collaboration strategies among multiple AMRs that focus on energy optimization, considering factors such as load distribution, cooperative path planning, and task allocation.
9. Evaluate energy-efficient control methods in real-world scenarios: Conduct experimental studies to assess the performance of energy-efficient control methods in diverse real-world applications, identifying challenges and opportunities for further improvement.
10. Investigate the impact of emerging technologies: Assess the potential of emerging technologies, such as edge computing and 5G communication, to enhance the energy efficiency of AMRs in various

applications and environments.

8. Reference

Sulaiman, A., Inambao, F. and Bright, G. (2013), "Development of solar hydrogen energy for mobile robots", *In 2013 6th Robotics and Mechatronics Conference RobMech*, *30-31 October , IEEE,* pp. 14-19.

Alajlan, A., Elleithy, K., Almasri, M. and Sobh, T. (2017), "An optimal and energy efficient multi-sensor collision-free path planning algorithm for a mobile robot in dynamic environments", *Robotics*, Vol. 6, pp.7.

Alexovič, S., Lacko, M., Bačík, J. and Perduková,D. (2021), "Introduction into Autonomous Mobile Robot Research and Multi Cooperation", *Artificial Intelligence in Intelligent Systems*. Cham: Springer International Publishing, pp. 326–336.

Anuntachai, A. and Wongwirat, O. (2012), "Searching energy-efficient route in rough terrain for mobile robot with ant algorithm", *Intelligent Robotics and Applications: 5th International Conference Montreal, QC, Canada*, *3-5 October,* Proceedings, Part III 5. Springer Berlin Heidelberg, pp. 194-204.

Anuntachai, A., Wongwirat, O. and Thammano, A, (2014), "An application of ant algorithm for searching energy-efficient route a mobile robot takes using energy as a weighting factor", *Artificial Life and Robotics*, Vol. 19, pp.354-362.

Anyapo, C. (2019), "Development of Long Rail Dynamic Wireless Power Transfer for Battery-Free Mobile Robot", *In 2019 10th International Conference on Power Electronics and ECCE Asia Busan, South Korea, 27~31 May, IEEE*, pp. 1-6.

Chellal, A. A., Gonçalves, J., Lima, J., Pinto, V. and Megnafi, H. (2021), "Design of an Embedded Energy Management System for Li–Po Batteries Based on a DCC-EKF Approach for Use in Mobile Robots", *Machines*, Vol. 9, pp.313.

Chellal, A. A., Lima, J., Gonçalves, J. and Megnafi, H. (2021), "Battery Management System For Mobile Robots based on an Extended Kalman Filter Approch", *In 2021 29th Mediterranean Conference on Control and Automation Puglia, Italy, 22-25 June,IEEE,* pp. 1131-1136.

Chen, J., Liu, J., Sun, Z., Chen, W. and Zhang, L. (2019), "Research on Passive Control Strategy of AGV Wireless Power Transfer System", *In 2019 34rd Youth Academic Annual Conference of Chinese Association of Automation Liaoning, China*, *7-8 June, IEEE,* pp. 200-205.

Cheng, W. and Meng, W. (2023), "An efficient genetic algorithm for multi AGV scheduling problem about intelligent warehouse", *Robotic Intelligence and Automation*, Vol. 43, pp. 382–393.

Colling, D., Oehler, J. and Furmans, K. (2019), "Battery Charging Strategies for AGV Systems", *Logistics Journal: Proceedings,* Vol. 2019.

Liu, C., Xu, X., Li, X., Pan, Z., Hu, K. and Shu, Y. (2021), "Path Planning for an Omnidirectional Mobile Robot Based on Modified A* Algorithm with Energy Model", *In 2021 IEEE International Conference on Progress in Informatics and Computing Shanghai, China, 17-19 December ,IEEE,* pp. 462-468.

Drungilas, D., Kurmis, M., Senulis, A., Lukosius, Z., Andziulis, A., Januteniene, J., Bogdevicius, M., Jankunas, V. and Voznak, M. (2023), "Deep reinforcement learning based optimization of automated guided vehicle time and energy consumption in a container terminal", *Alexandria Engineering Journal*, Vol. 67, pp.397-407.

Dechao, C., Wang, Z., Zhou, G. and Li, S. (2022), "Path Planning and Energy Efficiency of Heterogeneous Mobile Robots Using Cuckoo–Beetle Swarm Search Algorithms with Applications in UGV Obstacle Avoidance", *Sustainability*, Vol. 14, pp.15137.

Dehnavi-Arani, S., Sabaghian, A. and Fazli, M. (2019), "A Job Shop Scheduling and Location of Battery Charging Storage for the Automated Guided Vehicles", *Journal of Optimization in Industrial Engineering,* Vol. 12, pp.121-129.

Dewi, T., Risma, P., Oktarina, Y., Taqwa, A., Prasetyani, L. and Astra, A. A. (2019), "Experimental Analysis on Wireless Power Transfer for Continuous Charging of a Mobile Robot", *In 2019 International Conference on Technologies and Policies in Electric Power & Energy Yogyakarta, Indonesia,* 21-22 *October, IEEE,* pp. 1-6.

Dogru, S. and Marques, L. (2015), "Towards fully autonomous energy efficient Coverage Path Planning for autonomous mobile robots on 3D terrain", *In 2015 European Conference on Mobile Robots Lincoln, UK, 02-04 September , IEEE,* pp. 1-6.

Emna M., Kelouwani, S., Dube, Y., Henao, N. and Agbossou, K. (2022), "Energy Efficient Order Picking Routing for a Pick Support Automated Guided Vehicle", *IEEE Access*, Vol. 10, pp.108832-108847.

Ezzeddine, F., Chebbi, O. and Siala, J. C.(2014), "Bee colony algorithm for the routing of guided automated battery-operated electric vehicles in personal rapid transit systems", *In 2014 IEEE Congress on Evolutionary Computation Beijing, China, 06-11 July, IEEE,* pp. 536-543.

Fatnassi, E. and Chaouachi , J. (2015), "Scheduling automated guided vehicle with battery constraints", *In 2015 20th International Conference on Methods and Models in Automation and Robotics Miedzyzdroje, Poland, 24-27 August , IEEE,* pp. 1010-1015.

Galceran, E. and Carreras, M. (2013), "A survey on coverage path planning for robotics", *Robotics and Autonomous Systems*, Vol. 61, pp.1258-1276.

Ghobadpour, A., Cardenas, A., Monsalve, G. and Mousazadeh, H. (2023), "Optimal Design of Energy Sources for a Photovoltaic/Fuel Cell Extended-Range Agricultural Mobile Robot", *Robotics*, Vol. 12, pp.13.

Sakayori, G. and Ishigami, G. (2017), "Energy efficient slope traversability planning for mobile robot in loose soil", *In Proceedings - 2017 IEEE International Conference on Mechatronics, ICM 2017 Churchill, VIC, Australia, 13-15 February , IEEE,* pp. 99-104.

Gröger, O., Gasteiger, H. A. and Suchsland, J.-P. (2015), "Review—Electromobility: Batteries or Fuel Cells?" *Journal of The Electrochemical Society*, Vol. 162, pp. A2605.

Hanschek, A. J., Bouvier, Y. E., Jesacher, E. and Grbović, P. J. (2021), Analysis of power distribution systems based on low-voltage DC/DC power supplies for automated guided vehicles . *In 2021 21st International Symposium on Power Electronics Novi Sad, Serbia, 27-30 October ,IEEE,* pp. 1-6.

He, L., Chiong, R. and Li, W. (2022), "Energy-efficient open-shop scheduling with multiple automated guided vehicles and deteriorating jobs", *Journal of Industrial Information Integration*, Vol. 30, pp.100387.

Hongjun, K. and Kim, B. K. (2014), "Minimum-Energy Trajectory Generation for Cornering with a Fixed Heading for Three-Wheeled Omni-Directional Mobile Robots", *Journal of Intelligent & Robotic Systems*, Vol. 75, pp.205-221.

Huang, S.-J., Dai, S.-H., Su, J.-L. and Lee, T.-S. (2017), "Design of a contactless power supply system with dual output capability for AGV applications", *In 2017 IEEE 6th Global Conference on Consumer Electronics Nagoya, Japan, 24-27 October , IEEE,* pp. 1-3.

Huang, S.-J., Lee, T.-S., Li, W.-H. and Chen, R.-Y. (2019), "Modular On-Road AGV Wireless Charging Systems Via Interoperable Power Adjustment", *IEEE Transactions on Industrial Electronics*, Vol. 66, pp.5918-5928.

Huisman, M., van Rijn, J. N. and Plaat, A. (2021), "A survey of deep meta-learning", *Artificial Intelligence Review*,Vol. 54, pp.4483-4541.

Nourbakhsh, I. (2004), *Introduction to Autonomous Mobile Robots*.

Inderjeet, S., Singh, M., Bensekrane, I., Lakhal, O. and Merzouki, R. (2020), "Curve-based Approach for Optimal Trajectory Planning with Optimal Energy Consumption: application to Wheeled Mobile Robots", *IFAC-PapersOnLine*, Vol. 53, pp.9670-9675.

Artal, J. S., Dominguez, J. A. and Caraballo, J. (2012), "Autonomous mobile robot with hybrid pem fuel-cell and ultracapacitors energy system. Dedalo 2.0", *Renewable Energy and Power Quality Journal*, Vol. 1, pp.1795-1800.

Jaiem, L., Druon, S., Lapierre, L. and Crestani, D. (2016), "A Step Toward Mobile Robots Autonomy: Energy Estimation Models", *In Towards Autonomous Robotic Systems: 17th Annual Conference Sheffield, UK, June 26--July 1, Springer International Publishing,* pp. 177-188.

Kim, J. and Lee, J. (2014), "Intelligent slip-optimization control with traction-energy trade-off for wheeled robots on rough terrainGini Coefficient", *In: 2014 IEEE/RSJ International Conference on Intelligent Robots and Systems Chicago, IL, USA, 14-18 September, IEEE,* pp. 1938-1943.

Kim, J. and Lee, J. (2018), "Traction-energy balancing adaptive control with slip optimization for wheeled robots on rough terrain ", *Cognitive Systems Research*, Vol. 49, pp.142-156.

Wang, J., Chen, J. and Xiao, Q. (2018), "A Minimum-energy Trajectory Tracking Controller for Four-wheeled Omni-directional Mobile Robot", *In*: *2018 15th International Conference on Control, Automation, Robotics and Vision Singapore, 18-21 November, IEEE,* pp. 48-53.

Liu, J., Li, Z., He, L. P. and Shi, W. (2020), "Energy Efficient Path Planning for Indoor Wheeled Mobile Robots", *In 2020 Global Reliability and Prognostics and Health Management Shanghai, China, 16-18 October, IEEE,* pp. 1-7.

Artal-Sevil, J. S., Bernal-Agustín, J. L., Dufo-López, R. and Domínguez-Navarro, J. A. (2017), "Forklifts, Automated Guided Vehicles and Horizontal Order Pickers in Industrial Environments. Energy Management of an Active Hybrid Power System based on Batteries, PEM Fuel Cells and Ultracapacitors", *Renewable Energy and Power Quality Journal*, Vol. 1, pp.859-864.

Kim, H. and Kim, B. K. (2012), "Minimum-energy trajectory planning and control on a straight line with rotation for three-wheeled omni-directional mobile robots", *In 2012 IEEE/RSJ International Conference on Intelligent Robots and Systems Vilamoura-Algarve, Portugal, 07-12 October, IEEE,* pp. 3119-3124.

Kim, H. and Kim, B. K. (2017), "Minimum-energy cornering trajectory planning with self-rotation for three-wheeled omni-directional mobile robots", *International Journal of Control, Automation and Systems*, Vol. 15, pp.1857-1866.

Kojima, T., Tanabe, H., Imakiire, A., Fuji, K., Kozako, M., Hikita, M., Imoto, Y. and Honda, K. (2015), "Characterization of contactless power transfer system and investigation of core shape for AGV application", *In 2015 IEEE 11th International Conference on Power Electronics and Drive Systems Sydney, NSW, Australia, 09-12 June, IEEE,* pp. 703-706.

Vasunina, Y. and Saveliev, A. (2022), "Algorithm for Replacing the Battery of a Robotic Tool Using Serving Mobile Robots", *In 2022 International Russian Automation Conference Sochi, Russian Federation, 04-10 September, IEEE,* pp. 700-705.

Góra, K., Kujawinski, M., Wroński, D. and Granosik, G. (2021), "Comparison of Energy Prediction Algorithms for Differential and Skid-Steer Drive Mobile Robots on Different Ground Surfaces", *Energies*, Vol. 14, pp.6722.

Lee, M. S. and Jae Jang, Y. (2022), "The AGV Battery Swapping Policy Based on Reinforcement Learning", *In 2022 IEEE 18th International Conference on Automation Science and Engineering Mexico City, Mexico, 20-24 August,IEEE,* pp. 1479-1484.

Lee, T. S., Hung, T. C. and Huang, K. C. (2023), "Wireless power transfer for mobile robot with capacity optimization and dynamic protection considerations", *Journal of the Chinese Institute of Engineers*, Vol. 46, pp. 128-140.

Liu, L., Chen, J., Brocanelli, M. and Shi, W. (2019), "E2M: an energy-efficient middleware for computer vision applications on autonomous mobile robots", *In Proceedings of the 4th ACM/IEEE Symposium on Edge Computing Arlington,Virginia, 7-9 November, IEEE* ,pp. 59-73.

Wieckowski, L. and Klimek, K. (2020), "Development of a hybrid energy storage system for a mobile robot", *In 2020 International Conference Mechatronic Systems and Materials Bialystok, Poland, 01-03 July, IEEE* ,pp. 1-6.

Chaudhari, M., Vachhani, L. and Banerjee, R. (2014), "Towards Optimal Computation of Energy Optimal Trajectory for Mobile Robots", *IFAC Proceedings Volumes*, Vol. 47, pp. 82-87.

Visca, M., Powell, R., Gao, Y. and Fallah, S. (2022), "Probabilistic Meta-Conv1D Driving Energy Prediction for Mobile Robots in Unstructured Terrains", *IEEE Access*, Vol. 10, pp. 107913-107928.

Sperling, M. and Kivelä, T. (2022), "Concept of a Dual Energy Storage System for Sustainable Energy Supply of Automated Guided Vehicles", *Energies*, Vol. 15, pp. 479.

Jaramillo-Morales, M. F., Dogru, S., Gomez-Mendoza, J. B. and Marques, L. (2020), "Energy estimation for differential drive mobile robots on straight and rotational trajectories", *International Journal of Advanced Robotic Systems*, Vol. 17, pp. 172988142090965.

McNulty, D., Hennessy, A., Li, M., Armstrong, E. and

Ryan, K. M. (2022), "A review of Li-ion batteries for autonomous mobile robots: Perspectives and outlook for the future", *Journal of Power Sources*, Vol. 545, pp. 231943.

Stampa, M., Rohrig, C., Kunemund, F. and Hes, D. (2015), "Estimation of energy consumption on arbitrary trajectories of an omnidirectional automated guided vehicle", *In Proceedings of the 2015 IEEE 8th International Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications Warsaw, Poland, 24-26 September, IEEE* ,pp. 873-878.

Mitschke, M., Uchiyama, N. and Sawodny, O. (2018), "Online Coverage Path Planning for a Mobile Robot Considering Energy Consumption", *In 2018 IEEE 14th International Conference on Automation Science and Engineering Munich, Germany, 20-24 August, IEEE* ,pp. 1473-1478.

Mohammadpour, M., Kelouwani, S., Gaudreau, M.A., Allani, B., Zeghmi, L., Amamou, A. and Graba, M. (2022), "Energy-Efficient Local Path Planning of a Self-Guided Vehicle by Considering the Load Position", *IEEE Access*, Vol. 10, pp. 112669–112685.

Morales, M. F. J. and Mendoza, J. B. G. (2018), "Mixed Energy Model for a Differential Guide Mobile Robot", *In 2018 23rd International Conference on Methods & Models in Automation & Robotics Miedzyzdroje, Poland, 27-30 August, IEEE* ,pp. 114-119.

Won, M., George, S. M. and Stoleru, R. (2011), "Towards robustness and energy efficiency of cut detection in wireless sensor networks", *Ad Hoc Networks*, , Vol. 9, pp. 249-264.

Nguyen, T. T., Nguyen, N. D. and Nahavandi, S. (2020), "Deep Reinforcement Learning for Multiagent Systems: A Review of Challenges, Solutions, and Applications", *IEEE Transactions on Cybernetics*, Vol. 50, pp. 3826–3839.

Pamungkas, L., Chiu, H.J., Shih, B.C. and Chi, P.C. (2022), "Combined Frequency and Phase-Shift Control for Constant-Voltage Charging Mode of Wireless Power Transfer System in AGV Applications", *In 2022 International Conference on Technology and Policy in Energy and Electric Power Jakarta, Indonesia,* 18-20 October, *IEEE* ,pp. 305-310.

Pan, S., Xu, Y., Lu, Y., Liu, W., Li, Y. and Mai, R. (2022), "Design of Compact Magnetic Coupler With Low Leakage EMF for AGV Wireless Power Transfer System", *IEEE Transactions on Industry Applications*, Vol. 58, pp. 1044–1052.

Flocchini, P., Omar, E. and Santoro, N. (2019), "Effective Decentralized Energy Restoration by a Mobile Robot", *In 2019 Seventh International Symposium on Computing and Networking Nagasaki, Japan, 25-28 November, IEEE* ,pp. 73-81.

Partovibakhsh, M. and Liu, G. (2015), "An Adaptive Unscented Kalman Filtering Approach for Online Estimation of Model Parameters and State-of-Charge of Lithium-Ion Batteries for Autonomous Mobile Robots", *IEEE Transactions on Control Systems Technology*, Vol. 23, pp. 357–363.

Pavliuk, O., Steclik, T. and Biernacki, P. (2022), "The forecast of the AGV battery discharging via the machine learning methods", *In 2022 IEEE International Conference on Big Data Osaka, Japan, 17-20 December , IEEE* ,pp. 6315–6324.

Benecki, P., Kostrzewa, D., Grzesik, P., Shubyn, B. and Mrozek, D. (2022), "Forecasting of Energy Consumption for Anomaly Detection in Automated Guided Vehicles: Models and Feature Selection", *In 2022 IEEE International Conference on Systems, Man, and Cybernetics Prague, Czech Republic, 09-12 October, IEEE* , pp. 2073–2079.

Jaroszek, P. and Trojnacki, M. (2014), "Model–based energy efficient global path planning for a four–wheeled mobile robot", *Control and Cybernetics,* Vol. 43.

Kumar, P., Bensekrane, I., Singh, M. and Merzouki, R. (2018), "Bond Graph based Power Consumption Estimation of a Non-holonomic Wheeled Mobile Robot with Multiple Driving Modes", *In 2018 7th International Conference on Systems and Control Valencia, Spain, 24-26 October, IEEE* , pp. 441–446.

Qiao, H., Wu, Y.-X., Zhong, S.-L., Yin, P.-J. and Chen, J.-H. (2023), "Brain-inspired Intelligent Robotics: Theoretical Analysis and Systematic Application", *Machine Intelligence Research*, Vol.20, pp. 1–18.

Ren, W.-Q., Qu, Y.-B., Dong, C., Jing, Y.-Q., Sun, H., Wu, Q.-H. and Guo, S. (2023), "A Survey on Collaborative

DNN Inference for Edge Intelligence" *Machine Intelligence Research*, Vol. 20, pp. 370–395.

Rosenbaum, M. and Schröder, U. (2010), "Photomicrobial Solar and Fuel Cells", *Electroanalysis*, Vol. 22, pp. 844–855.

Lee, S. D. and Jung, S. (2015), "Power estimation of a battery in a single-wheel mobile robot by a motion analysis approach", *In 2015 12th International Conference on Ubiquitous Robots and Ambient Intelligence Goyangi, South Korea ,IEEE ,* pp. 77–80.

Fadlo, S., Elmahjoub, A. A. and Rabbah, N. (2021), "Energy Performance Analysis of a Differential Wheeled Mobile Robot with Fuzzy Logic Controller", *In 2021 IEEE International IOT, Electronics and Mechatronics Conference Toronto, ON, Canada, 21-24 April, IEEE ,* pp. 1–5.

Fadlo, S., Rabbah, N. and Elmahjoub, A. A. (2020), "Energy Modeling for a Differential Guide Mobile Robot Using Simscape", *In 2020 International Symposium on Advanced Electrical and Communication Technologies Marrakech, Morocco, 25-27 November , IEEE ,* pp. 1–4.

Shukla, S. and Kumar, A. (2022), "Energy Optimized Dynamics Incorporated A-star Algorithm For A Four-Wheeled Mobile Robot", *SSRN Electronic Journal* .

Dogru, S. and Marques, L. (2016), "Power Characterization of a Skid-Steered Mobile Field Robot", *In 2016 International Conference on Autonomous Robot Systems and Competitions Bragan, Portugal, IEEE ,* pp. 15–20.

Liu, S. and Sun, D. (2011), "Optimal motion planning of a mobile robot with minimum energy consumption", *In IEEE/ASME International Conference on Advanced Intelligent Mechatronics Budapest, Hungary, 03-07 July, IEEE ,* pp. 43–48.

Liu, S. and Sun, D. (2014), "Minimizing Energy Consumption of Wheeled Mobile Robots via Optimal Motion Planning", *IEEE/ASME Transactions on Mechatronics*, Vol. 19, pp. 401–411.

Tomy, M., Lacerda, B., Hawes, N. and Wyatt, J. L. (2019), "Battery Charge Scheduling in Long-Life Autonomous Mobile Robots", *In 2019 European Conference on Mobile Robots Prague, Czech Republic, 04-06 September, IEEE ,* pp. 1-6.

Deshmukh, V., Deshmukh, K. and Patil, S. R. (2017), "Energy estimation and comparison for a dynamic trajectory planning mobile robot intercepting a moving target using Bezier curve", *In 2017 2nd IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology Bangalore, India,19-20 May, IEEE ,* pp. 1027-1032.

Singh, V., Barai, R. K. and Mandal, P. (2015), "Real-time heuristic search based minimum energy path planning of wheeled mobile robot", *In Proceedings of the 2015 Conference on Advances In Robotics Goa ,India, 2-4 July, IEEE ,* pp. 1-6.

Wang, C., Jin, C. and Li, Z. (2019), "Bilevel programming model of low energy consumption AGV scheduling problem at automated container terminal", *In 2019 IEEE International Conference on Smart Manufacturing, Industrial & Logistics Engineering Hangzhou, China, 20-21 April, IEEE ,* pp. 195-199.

Wang, G.-Y., Cheng, D.-D., Xia, D.-Y. and Jiang, H.-H. (2023), "Swarm Intelligence Research: From Bio-inspired Single-population Swarm Intelligence to Human-machine Hybrid Swarm Intelligence" *Machine Intelligence Research*, Vol. 20, pp. 121–144.

Wei, H., Wang, B., Wang, Y., Shao, Z. and Chan, K. C. C. (2012), "Staying-alive path planning with energy optimization for mobile robots", *Expert Systems with Applications*, Vol. 39, pp. 3559–3571.

Wongwirat, O. and Anuntachai, A. (2011), "Searching energy-efficient route for mobile robot with ant algorithm", *In 2011 11th International Conference on Control, Automation and Systems Gyeonggi-do, South Korea, IEEE ,* pp. 1071–1075.

Zhao, X., Su, Z. and Dou, L. (2014), "A path planning method with minimum energy consumption for multi-joint mobile robot." *In Proceedings of the 33rd Chinese Control Conferenc Nanjing, China, 28-30 July, IEEE ,* pp. 8326–8330.

Yacoub, M. I., Necsulescu, D. S. and Sasiadek, J. Z. (2013), "Energy consumption optimization for mobile robots in three-dimension motion using predictive control", *In 2013 9th Asian Control Conference Istanbul, Turkey, 23-26 June, IEEE ,* pp. *1-6.*

Yi, W., Ming, L., Zhongping, Y. and Fei, L. (2020), "Analysis and Comparison of SP and S/SP

Compensated Wireless Power Transfer System for AGV Charging", *In 2020 IEEE 3rd International Conference on Electronics Technology Chengdu, China, 08-12 May*, *IEEE ,* pp. 485–488.

Chuang, Y. C., Chuang, H.S., Yang, C.H. and Fan, S.Y. (2020), "A Novel High-Frequency Sinusoidal Pulse-Charging Method Based on a Contactless Battery Charger for Mobile Service Robots", *In 2020 IEEE 29th International Symposium on Industrial Electronics Delft, Netherlands, 17-19 June, IEEE ,* pp. 612–617.

Yuan, Q., Lu, Q. and Xi, Z. (2017), "Optimal path selection for mobile robots based on energy consumption assessment of different terrain surface", *In 2017 36th Chinese Control Conference Dalian, China, 26-28 July, IEEE ,* pp. 6755–6760.

Zhang, C., Dou, J., Wang, S. and Wang, P. (2023), "Hybrid particle swarm optimization algorithms for cost-oriented robotic assembly line balancing problems" *Robotic Intelligence and Automation*, Vol. 43, pp. 420–430.

Zhang, J., Chen, D. and Zhang, C. (2019), "Enhanced power transmission for on-road AGV wireless charging systems using a current-optimized technique", *Progress In Electromagnetics Research C*, Vol. 96. pp. 205–214.

Zhang, J., Zhang, N., Tian, L., Zhou, Z. and Wang, P. (2023). "Robots' picking efficiency and pickers' energy expenditure: the item storage assignment policy in robotic mobile fulfillment system", *Computers & Industrial Engineering*, Vol. 176. pp.108918.

Zhang, X. and Zhu, H. (2023), "The Impact of Industrial Intelligence on Carbon Emissions: Evidence from the Three Largest Economies", *Sustainability*, Vol. 15. pp. 6316.

Zhao, Y. and Tsiotras, P. (2011), "A quadratic programming approach to path smoothing", *In Presented at the Proceedings of the American Control Conference San Francisco, CA, USA, 29 June -01 July, IEEE ,* pp. 5324–5329.

Zhang, Z. W., Wu, L., Zhang, W., Peng, T. and Zheng, J. (2021), "Energy-efficient path planning for a single-load automated guided vehicle in a manufacturing workshop", *Computers & Industrial Engineering*, Vol. 158. pp. 107397.