# Energy Aware Path Planning and Guidance for Non-Holonomic Robots in a Manufacturing Workshop

MS Thesis
By

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**COMSATS University Islamabad**
**Pakistan**

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# Energy Aware Path Planning and Guidance for Non-Holonomic Robots in a Manufacturing Workshop

A thesis submitted to
COMSATS University Islamabad
In partial fulfillment of the
requirements for the degree of
Master of Science
in
Electrical Engineering

by

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This thesis is submitted to the Department of Electrical Engineering in partial fulfillment of the requirements for the award of the degree of Master of Science in Electrical Engineering.

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# Declaration

I, Rimsha Rehman, CIIT/FA23-REE-005/LHR, hereby declare that I have produced the work presented in this thesis, during the scheduled period of study. I also declare that I have not taken any material from any source except referred to wherever due to that amount of plagiarism is within an acceptable range. If a violation of HEC rules on research has occurred in this thesis, I shall be liable to punishable action under the plagiarism rules of HEC.

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# Certificate

It is certified that Rimsha Rehman, CIIT/FA23-REE-005/LHR, has carried out all the work related to this thesis under my supervision at the Department of Electrical Engineering, COMSATS University Islamabad, Lahore campus and the work fulfill the requirement for the award of the degree of MS in Electrical Engineering.

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# Dedication

In the Name of Allah, the Most Beneficent and the Most Merciful, Words can't express the ultimate depth of sentiments describing the grandeur of Prophet Muhammad (PBUH), they just bow in saying anything for Him with supreme modesty. To the beloved Prophet Muhammad (PBUH) who endured sufferings and agony for the whole mankind, to give the most prestigious teachings of amity and love to protect humanity from the bloodshed, fight, animosity in the form of most elevated religion of Peace, till the day of resurrection. Who not only defined but also established the moral principles of esteemed ethics to build a tolerant, humble and peaceful universal society.

# Acknowledgements

In the Name of Allah, the Most Beneficent and the Most Merciful

I must say that I could not have completed this work without the unconditional support of my family. In memory of my late father who has been my constant source of inspiration. My sister who set an example for me, my mother who ignited me to initiate this one.

I would like to mention the name of Dr. Mujtaba Jaffery, my mentor and supervisor, who not only trusted but motivated me to turn my passion into reality. He has been kind, generous and humble at every step of the research, without his ample conviction I would not have been able to complete my thesis. Dr. Zulfiqar Habib, my Co Supervisor with his profound domain expertise, infused me with confidence to take up the most challenging research topic, to contribute in the scholarly community.

At last, I owe special thanks to the ones who have been the prime reason to accomplish this essential and most fascinating goal of my life.

Rimsha Rehman

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# ABSTRACT


## Energy Aware Path Planning and Guidance for Non-Holonomic Robots in a Manufacturing Workshop

By

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Automated Guided Vehicles (AGVs) are now a core part of modern manufacturing workshops, enabling fast, reliable, and flexible material movement while reducing dependence on manual handling. Despite their importance, most existing path planning approaches still focus mainly on minimizing distance or travel time. These strategies overlook a crucial factor, energy consumption, which directly affects operational cost, battery health, sustainability goals, and overall system efficiency. Addressing this limitation, this thesis presents an Energy Aware Path Planning (EAPP) framework specifically designed for single-load, non-holonomic AGVs used in structured workshop environments. The proposed framework models the workshop layout as an undirected graph, where nodes represent workstation points or intersections and edges represent feasible routes that comply with AGV kinematic and turning constraints. Unlike traditional planners, our approach integrates a physics-based energy model into the A* algorithm, allowing each edge to be evaluated not only by its geometric length but also by its expected energy usage, considering acceleration, deceleration, rolling resistance, turning angles, and standby power. This enables the AGV to prioritize paths with fewer turns, even when they are slightly longer, ultimately reducing total energy consumption. The method is implemented and validated using MATLAB simulations, where both distance-based A* and the proposed energy-aware A* are compared under realistic AGV parameters. The results show that the EAPP framework significantly lowers energy consumption and maintains competitive travel times, while still producing feasible and safe navigation paths within constrained workshop networks. By directly embedding energy considerations into the path planning process, this work contributes to more sustainable intralogistics and provides a practical, scalable solution suitable for real-time AGV navigation and industrial deployment.

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## LIST OF ABBREVIATIONS AND ACRONYMS

A* – A-Star Path Planning Algorithm

ACO – Ant Colony Optimization

AGV – Automated Guided Vehicle

AI – Artificial Intelligence

ASV – Autonomous Surface Vehicle

CAGR – Compound Annual Growth Rate

CPU – Central Processing Unit

DoD – Depth of Discharge (Battery)

DWA – Dynamic Window Approach

EC – Energy Consumption

EAPP – Energy Aware Path Planning

EV – Electric Vehicle

FMS – Flexible Manufacturing System

GA – Genetic Algorithm

GPU – Graphics Processing Unit

GVRP – Green Vehicle Routing Problem

HEC – Higher Education Commission

IoT – Internet of Things

KPIs – Key Performance Indicators

MATLAB – Matrix Laboratory

ML – Machine Learning

MPC – Model Predictive Control

MS – Master of Science

PEMFC – Proton Exchange Membrane Fuel Cell

PSO – Particle Swarm Optimization

PBUH – Peace Be Upon Him

RL – Reinforcement Learning

ROS – Robot Operating System

SD – Standard Deviation

SDGs – Sustainable Development Goals

SoC – State of Charge (Battery)

VRP – Vehicle Routing Problem

# Chapter 1

# Introduction

## 1.1 Introduction

The last few decades have seen rapid progress in the use of robotics in industrial and manufacturing systems. Automation has transformed factories from labor-intensive spaces to smart environments where machines and intelligent systems perform most of the repetitive and precise tasks. Among different types of automation tools, Automated Guided Vehicles (AGVs) have emerged as one of the most important technologies for material handling. They are driverless vehicles designed to transport raw materials, semi-finished goods, and finished products within workshops, warehouses, and production lines. The adoption of AGVs allows industries to reduce labor costs, increase reliability, and improve efficiency in their overall production system [1].

AGVs follow predefined routes, usually controlled through markers, magnetic tapes, laser guidance, or more advanced navigation technologies. Unlike traditional forklifts or conveyors, AGVs can be programmed and reprogrammed, which gives flexibility to adapt to changing production needs. This makes them suitable for modern manufacturing systems where flexibility, customization, and quick responses are highly valued. Studies have shown that AGVs not only improve efficiency but also reduce errors that are common with human handling. This makes them essential in industries such as automotive, electronics, and general logistics, where precision and speed are critical [2].

### 1.1.1 Non-Holonomic Robots in Manufacturing

Many AGVs belong to the category of non-holonomic robots. A non-holonomic system is one where the robot’s motion is constrained by its kinematics. In simple terms, this means that the robot cannot move freely in all directions at once. For example, most wheeled AGVs can move forward and backward and can turn, but they cannot move sideways directly. This restriction makes the path planning process more complicated than holonomic robots, which have more degrees of freedom.

In manufacturing workshops, non-holonomic AGVs are common because they are simpler in design and more stable for transporting heavy loads. However, their limited movement creates a set of challenges. The robot must follow paths that respect its turning radius, acceleration and deceleration limits, and load stability. A path that looks optimal in terms of distance may not be feasible for a non-holonomic robot if it requires sharp turns or sudden maneuvers. As a result, the algorithms developed for path planning must take these constraints into account to ensure both safety and efficiency [4].

The study of non-holonomic robots has been an important area in robotics research. Classical algorithms such as A*, Dijkstra's algorithm, and variants of graph search methods have been used widely to find feasible routes. While these methods ensure collision free paths, they often ignore the vehicle's energy consumption, which is a vital concern for battery powered AGVs. Therefore, a more advanced approach is required that not only considers the kinematic feasibility of non holonomic robots but also integrates energy awareness into the planning process [5].

Figure 1.1. Overview of AGVs in manufacturing [6].

This figure 1.1 provides us a dual overview of Automated Guided Vehicles (AGVs) in manufacturing. one showing a real world fleet for large scale material transport, and the other illustrating the system's guidance path and technological integration with the workflow. AGVs are essential components of modern factories, enabling reliable, flexible, and autonomous movement of components to automate the production process.

### 1.1.2 Energy Efficiency Challenges

Traditional path planning algorithms in robotics usually optimize for distance or time. While these factors are important, they do not provide a complete picture of efficiency for AGVs. Since AGVs are battery driven, their ability to perform tasks continuously depends directly on energy consumption. Energy is used during different phases of motion. acceleration, cruising, deceleration, turning, and even standby. Ignoring these factors can lead to higher operational costs, frequent recharging, and shorter battery lifespans.

For instance, a path with minimum distance may involve frequent starts and stops, which require large amounts of energy due to repeated acceleration. Similarly, a path that minimizes time may push the vehicle to operate at high speeds, which also consumes more energy and increases wear and tear. Both situations reduce the overall sustainability of the system. Energy inefficiency not only impacts costs but also affects the reliability of AGVs when deployed in large fleets, as vehicles may need to be pulled out of operation for recharging more frequently [7].

### 1.1.3 Sustainability Context

Sustainability has become a global priority in all sectors, including manufacturing. The concept of sustainable or green manufacturing focuses on reducing waste, maximizing resource utilization, and lowering carbon emissions. This aligns with global frameworks such as the United Nations Sustainable Development Goals (SDGs), which call for responsible production and energy efficiency. In this context, AGVs, as continuous energy consuming machines, are an important target for improvement [9].

When AGVs operate without energy optimization, they contribute to unnecessary energy waste, which increases both costs and the environmental burden of manufacturing. By integrating energy efficiency into AGV path planning, industries can achieve a balance between productivity and environmental responsibility. This is particularly important as governments and international bodies are introducing stricter regulations on industrial emissions and energy use [10].

Therefore, energy aware path planning is not only an academic problem but also a practical necessity for industries that aim to remain competitive while meeting sustainability standards. By focusing on this challenge, this research contributes to the larger global effort toward reducing the environmental footprint of industrial activities. It connects robotics, optimization, and sustainability into a single framework that has the potential for real world impact.

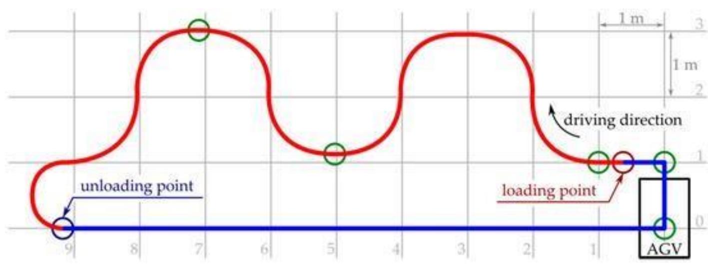


Figure 1.2. AGV energy model applied to PEMFC storage design [8].

Figure 1.2 illustrates an AGV's operational cycle used for energy consumption modeling, particularly for the design of a PEMFC (fuel cell) storage system. The path shows the AGV starting at a loading point, traversing a dynamic, winding red segment (representing high power demand driving), and then completing the circuit via a straight blue segment back from the unloading point. This defined, scaled trajectory allows for the precise calculation of energy demand variations throughout the cycle, which is essential input for accurately sizing and optimizing the vehicle's PEMFC power source.

### 1.1.4 Industrial and Research Context

In recent years, researchers have shown increasing interest in making robotics more energy efficient. Several studies in intralogistics have emphasized that AGVs should not only be fast and reliable but also energy conscious in order to support sustainable production systems [11]. Some authors have explored advanced methods such as reinforcement learning to reduce the overall energy use of AGVs, showing that intelligent algorithms can provide better results than traditional path planning [12]. Despite these advances, most research so far has focused on road based vehicles or simplified scenarios that do not fully reflect the conditions in structured workshop environments. In such environments, AGVs must operate under strict motion constraints, task sequences, and load handling requirements, which make the planning problem more complex.

This thesis builds on these existing studies and extends the discussion by introducing an Energy Aware Path Planning and Guidance (EAPP) framework. The framework considers energy consumption together with distance and travel time as part of a multi objective optimization approach. It also makes use of realistic modeling of AGV motion phases, such as acceleration, deceleration, cruising, and turning, to capture the true cost of movement. To test the effectiveness of the proposed approach, simulations are carried out in MATLAB environments, which allow for both mathematical validation and system level demonstration. The aim is to show how energy aware strategies can be applied to AGVs in workshop environments in a way that balances performance, efficiency, and sustainability.

### 1.1.5 Importance of Energy Aware Path Planning

The idea of energy aware path planning is not only important for research but also for real industrial practice. When factories use a large number of AGVs, even small improvements in energy use can save a lot of money and improve the overall flow of work. Using less energy means lower electricity bills, longer battery life, and fewer stops for charging, which helps the vehicles stay in operation for longer periods. At the same time, reducing wasted energy also means lowering carbon emissions, which helps companies meet environmental rules and standards for sustainable production [13].

This thesis therefore lies at the point where robotics, optimization, and sustainability come together. It looks at a real problem faced by industries while also adding to the academic discussion on multi objective optimization and path planning for robots. The work aims to provide both practical benefits for industry and meaningful contributions for research in energy efficient guidance of AGVs.

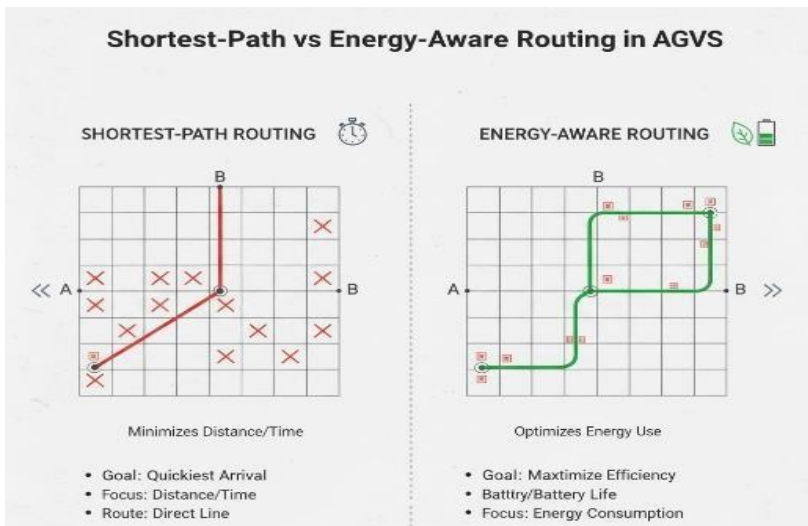


Figure 1.3. Shortest path vs energy aware routing [14].

Figure 1.3 contrasts Shortest Path Routing, which seeks the quickest route by minimizing time/distance, with Energy Aware Routing, which takes a longer path to maximize battery life and minimize energy consumption. This highlights the key trade-off in AGV operations between speed and energy efficiency [15].

## 1.2 Problem Statement

This research develops an Energy Aware Path Planning (EAPP) methodology for Automated Guided Vehicles (AGVs) working in manufacturing workshops. At the first stage, the focus is on optimizing AGV routing by considering transport distance and energy consumption. While these two factors are important, relying on them alone does not always give the most practical solution for real workshop operations. To make the model more flexible, a third parameter travel time is also included. This allows the AGV to balance distance, energy, and time together. By adjusting the importance of these factors, the user can choose routes that best match the operational requirements.

The study begins with the case of a single load AGV, which is capable of carrying one workpiece at a time. These AGVs usually operate on predefined tracks, often guided by magnetic tape or wires, which means their movement is limited to fixed paths. For each task, the AGV is given pick up and delivery points along with the order in which tasks should be carried out. The challenge is to find an optimal route that satisfies these restrictions while also keeping energy use and travel time efficient. By combining distance, energy, and time in the path planning process, the proposed approach aims to improve both the performance and sustainability of AGV operations. The effectiveness of the EAPP method will be tested by comparing it with existing path planning algorithms to show its advantages in real manufacturing scenarios.

## 1.3 Research Objectives

This research aims to achieve the following objectives.

1. Develop a software-based EAPP model for single-load AGVs in a manufacturing workshop environment, optimizing EC, transport distance, and time along predefined paths.
2. To design and implement an A* based path planner that integrates a realistic AGV energy model, minimizing total energy consumption instead of distance alone.
3. To compare standard distance-based A* with the proposed energy-aware A* in terms of energy usage, travel time, distance, and number of turns under identical workshop conditions.
4. Analyze the interplay between EC, transport distance, time, and task execution order in AGV path planning via MATLAB simulations.
5. Performance comparison of the proposed EAPP with existing path planning algorithm.

## 1.4 Overview of the Thesis

This thesis addresses a specific stage of the research while contributing to the overall development, implementation, and validation of the Energy Aware Path Planning and Guidance (EAPP) framework for non-holonomic Automated Guided Vehicles (AGVs). The structure has been designed to follow a logical flow, beginning with the contextual foundation and moving through technical formulation, simulation, experimental analysis, and concluding insights.

## 1.5 Research Contribution of the Thesis

The main contribution of this thesis is the development of an Energy Aware Path Planning and Guidance (EAPP) framework for non holonomic Automated Guided Vehicles (AGVs) in structured manufacturing workshops. The framework does not only aim to minimize travel distance and time but also explicitly incorporates energy consumption as a central optimization objective. This integration is essential for supporting sustainable manufacturing practices where energy efficiency is becoming a critical concern.

### 1.5.1 Development of a Comprehensive Energy Model

A detailed model of AGV energy consumption has been developed, which considers acceleration, deceleration, cruising, turning, and standby phases. Unlike many earlier studies that rely only on distance or speed as a measure of efficiency, this model captures the actual operational energy demands of AGVs. It provides a realistic way to evaluate the cost of different paths within a manufacturing workshop.

### 1.5.2 Multi Objective Optimization Formulation

The path planning problem is formulated as a multi objective optimization task. Instead of treating distance, energy, and time separately, the thesis integrates them into a single framework. This allows trade offs to be explored, so that AGV routes can be adapted to different operational requirements. Such a formulation is more practical for real world applications where reducing energy use cannot come at the expense of excessive delays.

### 1.5.3 Hybrid Path Planning Approach

The thesis introduces a hybrid approach that combines deterministic and metaheuristic techniques. The A* algorithm is used as the deterministic component because of its ability to find shortest feasible paths efficiently in structured environments. A* is preferred over Dijkstra's algorithm since it incorporates heuristics to reduce computation time while maintaining accuracy. However, shortest path solutions do not always minimize energy, so a Particle Swarm Optimization (PSO) method is added to evaluate and refine solutions. PSO explores a wide solution space and identifies Pareto optimal paths that balance energy, distance, and time. In this way, the framework gains both the precision of A* and the flexibility of PSO.

### 1.5.4 Distinction from Prior Work

Previous research in AGV path planning has mainly focused on minimizing distance or time. Only a few studies have included energy as an objective, and those often relied on simplified energy assumptions. This thesis differs by:

- Expanding the problem to a multi-objective framework that balances energy, distance, and time.
- Using a hybrid algorithmic approach that combines A* and PSO rather than relying on a single method.
- Providing validation through both MATLAB instead of purely mathematical analysis.
- Linking results directly to industrial needs such as reduced operating costs, battery life extension, and compliance with sustainability standards.

### 1.5.5 Academic and Industrial Impact

From an academic point of view, this research adds to the existing studies on AGV path planning by presenting a framework that is both theoretically sound and tested in practice. It strengthens the literature on multi-objective optimization in robotics and provides a basis for future work in areas such as multi AGV coordination, adaptive routing algorithms, and integration with digital twin technologies.

From an industrial point of view, the study offers practical value by showing how energy aware planning can reduce operating costs, improve sustainability, and increase the service life of AGVs in real manufacturing setups. Companies that rely on AGV fleets can benefit from reduced energy usage, fewer charging interruptions, and better alignment with sustainability standards that are now being required by governments and markets.

Overall, this thesis makes a contribution that is both innovative and relevant. It connects theoretical optimization approaches with industrial challenges, helping to achieve the twin goals of higher productivity and improved sustainability in automated manufacturing.

## 1.6 Research Publications Related to the Thesis

As part of this research effort, several academic publications have been planned and prepared to disseminate the findings to both the scholarly community and the industrial robotics domain. Since this thesis develops a novel Energy Aware Path Planning and Guidance (EAPP) framework for non-holonomic Automated Guided Vehicles (AGVs), the contributions are well aligned with leading journals and conferences in the fields of robotics, automation, optimization, and manufacturing systems.

The publications serve multiple purposes.

1. To document the theoretical formulation of the multi-objective optimization framework.
2. To report on the algorithmic innovations, including the two-stage method and PSO based approach.
3. To present the simulation results and validation studies, highlighting the industrial relevance of the research.
4. To contribute to the broader discourse on sustainable and green manufacturing practices in academic and professional settings.

# Chapter 2

# Literature Review

## 2.1 Introduction

The study of energy efficient routing has grown in two main directions. The first is the Green Vehicle Routing Problem (GVRP), which is mainly focused on transportation systems, and the second is the path planning of Automated Guided Vehicles (AGVs) in manufacturing. Both fields have made useful progress, but they also leave important gaps, which this thesis aims to address.

The GVRP was developed as an extension of the classical Vehicle Routing Problem (VRP), where energy use and environmental issues are considered in routing. Xiao et al. [15] introduced a fuel consumption model that used linear regression to capture the effect of vehicle load on fuel use. This was a meaningful step forward but still centered on outdoor transport, not on indoor workshop settings. Later, Schneider et al. [16] worked on electric vehicle (EV) routing, where charging station locations and variable energy use were included. Although this work deepened the understanding of battery based routing, it still dealt with road vehicles instead of AGVs.

Later studies showed that assuming constant speed in GVRP leads to inaccurate results. Demir et al. [17] developed models with time dependent speeds, which improved urban transport estimates but did not look at AGVs. Similarly, Turkensteen [18] showed that variable speed models are better than fixed speed ones. In EV routing, Zhang et al. [19] included charging and discharging efficiency in their models, and Xiao et al. [20] introduced time windows and load changes into their energy formulations. Yet, all of these were limited to road EVs and did not apply to AGVs, which are bound by workshop layouts and non holonomic motion limits.

Some researchers approached the issue from a sustainability perspective. Felipe et al. [21] developed heuristic models for battery management in EV fleets, but their application to AGVs was limited because the operating conditions are different. Yu et al. [22] studied AGVs in container terminals, analyzing emissions as speed and load changed. While this was related, it was more about port logistics than manufacturing. More recently, Hu et al. [23] proposed a reinforcement learning model for AGV routing that considered both load and energy consumption. This was an important step but was only tested in simulations, not in real workshop cases.

Overall, these studies show a slow but steady move from distance and time based routing models towards energy aware approaches. GVRP work gave the theoretical basis, and EV routing added energy considerations, but most of these stayed focused on road vehicles. At the same time, AGV research has only recently started to focus on energy as a main goal, and many models either simplify motion limits or lack validation in realistic workshop environments. This gap highlights the need for a dedicated framework that combines distance, energy, and time in AGV path planning, which is the main motivation of this thesis.

## 2.2 Early Developments in Energy Efficient Path Planning

The shift towards energy aware path planning began outside the direct scope of AGVs, largely within the domains of autonomous vehicles and sustainable transportation systems. These early works played an important role in establishing methods, models, and optimization techniques that were later adapted to AGVs in manufacturing environments.

One notable early contribution came from Rahman et al. [15], who investigated energy efficient navigation strategies for Autonomous Surface Vehicles (ASVs). Their study combined Particle Swarm Optimization (PSO) with visibility graphs to create paths that balanced energy savings and task rewards. The approach demonstrated the ability of metaheuristic methods like PSO to explore large solution spaces effectively, producing near optimal results in environments with dynamic conditions. Although ASVs differ considerably from AGVs in terms of their physical operating environment, the core idea of integrating energy awareness into routing was directlyrelevant. The use of PSO, in particular, provided evidence that swarm intelligence techniques could outperform classical shortest path algorithms when multiple objectives were involved.

Parallel to ASV studies, Li et al. [16] conducted performance analyses on energy efficient path planning in the context of sustainable transportation. Their research emphasized the trade off between energy use, travel time, and overall efficiency in routing models. By modeling energy consumption as a dynamic variable influenced by speed, load, and route selection, this study moved beyond simplistic assumptions of constant fuel rates. The findings underlined the importance of capturing real energy dynamics in routing models rather than relying on proxy measures such as distance. Although the study targeted large scale transportation networks, its contribution was significant for later AGV focused research. it highlighted that minimizing distance does not always correspond to minimizing energy, a principle that holds strongly in workshop based AGV operations.

These early contributions helped set the methodological foundation for subsequent energy efficient path planning. First, they established the need for multi objective optimization, where distance, energy, and time are treated as interdependent rather than independent goals. Second, they introduced computational intelligence techniques such as PSO that proved useful for handling the complexity of energy aware routing problems. Third, they demonstrated that environmental constraints and vehicle specific dynamics need to be integrated into any realistic optimization framework.

At the same time, these works also highlighted important limitations. The ASV study [15], while valuable, focused on open water environments where non holonomic motion constraints were less restrictive than in workshop layouts. Similarly, Li et al. [16] emphasized transportation systems that allowed long distance routing, recharging opportunities, and flexible path choices, which are not directly applicable to AGVs restricted to predefined paths in manufacturing settings. Furthermore, both studies dealt with single vehicle optimization rather than multi vehicle coordination or task scheduling, which are central concerns in AGV deployments.

Despite these limitations, the lessons learned from early ASV and transportation studies carried over into AGV research. In particular, the recognition that energy aware routing requires realistic energy models and advanced optimization techniques became a guiding principle. These early insights directly informed later efforts to design energy efficient path planning frameworks specifically tailored to AGVs operating in structured manufacturing environments.

In summary, early developments in energy efficient path planning made two key contributions. They demonstrated that energy cannot be ignored in routing models without sacrificing realism and efficiency, and they provided optimization techniques, such as PSO, that were later adapted to AGV problems. However, they also left a clear research gap. the absence of studies addressing the unique constraints and operational challenges of AGVs in workshop environments. This gap set the stage for more specialized studies on AGV path planning, which are reviewed in the following sections.

## 2.3 Energy Efficient Path Planning for AGVs

The application of energy aware path planning concepts to Automated Guided Vehicles (AGVs) marked a significant shift in the research field. Unlike surface or road based vehicles, AGVs operate in structured manufacturing workshops where paths are predefined, loads vary dynamically, and non holonomic constraints must be respected. The introduction of energy as an explicit optimization objective within AGV path planning represented a step forward in aligning intralogistics operations with the broader goals of sustainable manufacturing.

### 2.3.1 Single Load AGVs

One of the first major contributions in this direction was made by Rehman et al. [26], who investigated energy efficient path planning for single load AGVs. In their work, energy use was modeled across different phases of motion, such as acceleration, cruising, deceleration, and turning. Unlike earlier studies that mainly focused on reducing distance, this research provided a more complete energy model that reflected how AGVs actually consume power while moving.

The workshop layout was expressed as a graph, with nodes representing stations or intersections and edges showing the possible paths the AGV could take.

The study was novel in two main ways. First, it showed that energy use cannot be simplified as only a function of distance. For example, two paths of the same length might require different amounts of energy if one involves more turns or frequent stop and go movements. Second, it introduced the idea of treating energy and distance as separate but related objectives in AGV routing. Their findings proved that it is possible to achieve noticeable energy savings without greatly increasing travel distance, which makes the approach valuable for real workshop operations.

Still, this work also had some clear limits. The model assumed that each AGV would carry only one load at a time, which simplified the problem but did not reflect larger workshops where multiple transport tasks are common. In addition, the optimization was based on fixed task sequences and did not consider changing production needs or dynamic shop floor conditions. These restrictions pointed to the need for further studies to extend the framework to multi load AGVs and more flexible, real time planning methods [27].

### 2.3.2 Multi Load AGVs

To overcome the limits of the single load model, Rehman et al. [28] expanded their work to include multi load AGVs that could handle several transport tasks at the same time. This extension made the framework more complex, as it combined task scheduling with path planning. In this model, the AGV was not only treated as a vehicle following predefined paths but also as a resource capable of transporting multiple loads in sequence or in parallel, depending on the requirements of the tasks.

The multi load study had to balance three goals. reducing energy use, shortening travel distance, and minimizing task completion time. A multi objective optimization method was used to manage these conflicting aims. This approach better reflected real industrial situations, where

AGVs are expected to work productively and efficiently while still keeping energy consumption under control. Simulation results showed that multi load AGVs improved throughput compared to single load models, and the benefits in energy savings became more noticeable when both task scheduling and routing were optimized together.

Even so, the research also revealed new difficulties. Combining scheduling and routing made the optimization problem much more complex, raising doubts about whether the approach could scale well in large workshops with many AGVs. The framework also continued to assume mostly static conditions, with little flexibility for dynamic factors such as sudden obstacles, unexpected delays, or real time production changes [29].

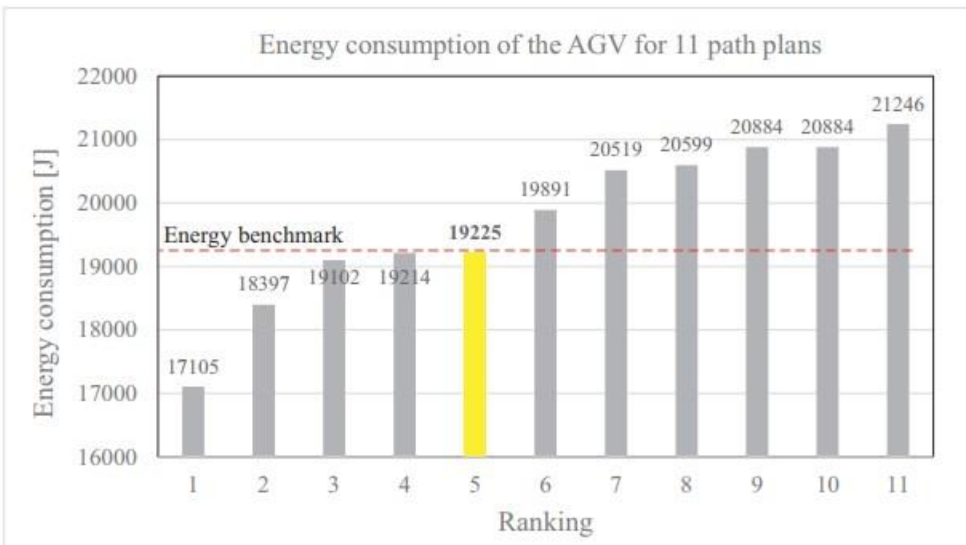


Figure 2.1. Energy benchmark of the Multiple AGVs [30].

Figure 2.1 illustrates the energy optimization in AGV operations by benchmarking the energy consumption of different path plans. It proves that intelligently planned routes (low energy consumption) yield substantial energy savings compared to inefficient routes, supporting the concept of Energy Aware Routing [31].

### 2.3.3 Research Gap and Synthesis

When considered together, the single load [26] and multi load [28] studies represent an important turning point in AGV path planning. They proved that energy aware routing is both possible and beneficial in manufacturing settings and introduced realistic models for capturing energy use across different phases of motion. These works also showed that energy efficiency and productivity are not in conflict. With proper optimization, both can be achieved at the same time.

However, the two approaches also left major issues unresolved. The single load model was too basic for complex workshop operations, while the multi load model struggled with computational demands and lacked real time adaptability. Neither study fully made use of advanced optimization methods like metaheuristics, and both relied mainly on simulations rather than real world validation. These gaps define the motivation for this thesis, which proposes an energy aware path planning and guidance framework that combines deterministic and metaheuristic approaches and is tested in both MATLAB simulation environments.

## 2.4 AGV Network Modeling in Manufacturing via Adapted Frameworks

The study of Zhongwei Zhang et al. was utilized as a theoretical reference for structuring the manufacturing workshop environment as an AGV transport network, which is illustrated in Figure 2.2 of the thesis. The concept of abstracting docking stations, work intersections, charging points, and transit pathways as graph nodes, and assigning edge weights based on inter node distances, was adopted from the reference to support the foundational modeling of the workshop layout [24]. This reference was not used for reproducing exact numerical results, but rather to validate that the workshop topology could be systematically mapped into a network that supports intelligent route planning. The reference also helped justify that realistic workshop components including automated machinery, material handling systems, and a centralized scheduling and monitoring unit form the core operational space in which AGVs navigate. By following this established modeling principle, the thesis methodology ensured compatibility with prior research frameworks while allowing further enhancement based on non-holonomic AGV motion behavior.

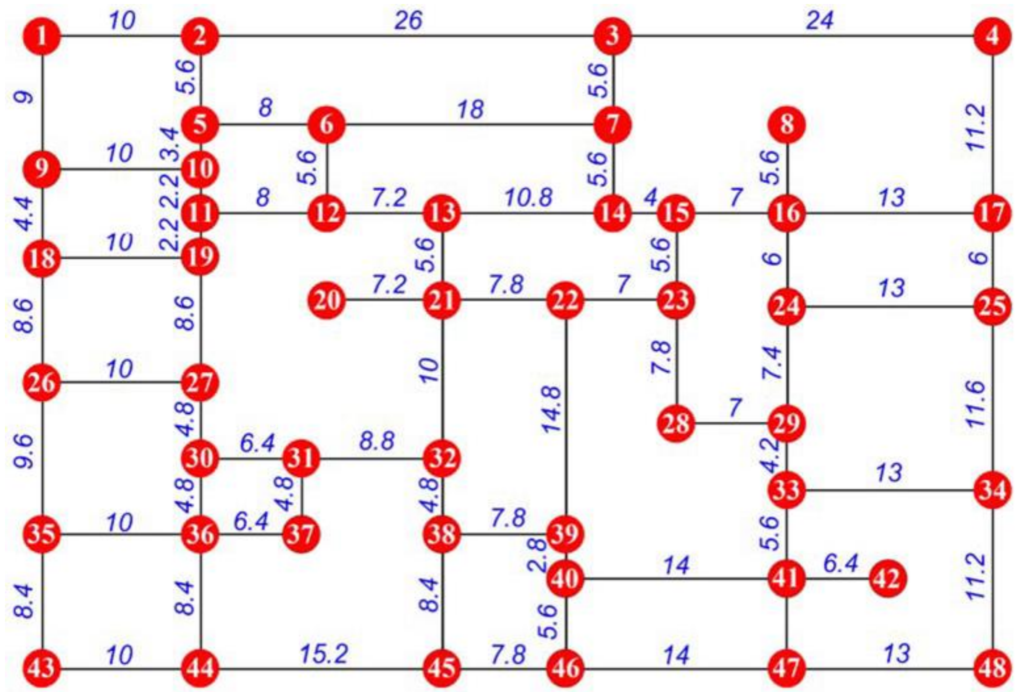


Figure 2.2. Topological map of the flexible manufacturing workshop [32].

In addition to network modeling, the same reference study was passively used as a benchmark in the literature review to support the comparative assessment of planning strategies presented in Table 2.1 of the thesis. The reference findings were used to theoretically deduce that energy consumption is not strictly dependent on shortest geometric distance, and that paths with equal lengths can still produce different energy demands due to motion dynamics such as acceleration, braking, and turning severity. These insights guided the modification of the classical A* algorithm within the thesis, where energy was embedded into the cost function to allow the planner to evaluate routes based on motion feasibility and speed stability rather than distance alone. The reference further supported the methodological decision to introduce flexibility in optimization objectives, ensuring that the thesis framework enabled path selection based on user operational priority, either time efficiency or energy efficiency, depending on requirement. Thus, the reference served to validate theoretical assumptions, justify algorithmic extensions, and reinforce that AGVs hold significant cumulative energy-saving potential in manufacturing workshops due to repetitive deployment and scaling effects.

Table 2.1 Performance Metrics for Minimum Distance Path Solutions.

| Sr No. | Path | D [m] | E(total) [kJ] | D(total) [m] | n(T) |
|---|---|---|---|---|---|
| 1 | 9 → 10 → 11 → 12 → 13 → 21 → 22 → 39 → 40 → 41 → 42 | 78.8 | 5.4902 | 91.91 | 6 |
| 2 | 9 → 10 → 11 → 12 → 13 → 21 → 32 → 38 → 39 → 40 → 41 → 42 | 78.8 | 5.5828 | 93.61 | 6 |
| 3 | 9 → 18 → 26 → 27 → 30 → 31 → 32→ 38 → 39 → 40 → 41 → 42 | 78.8 | 5.6341 | 93.25 | 7 |
| 4 | 9 → 18 → 19 → 27 → 30 → 31 → 32→ 38 → 39 → 40 → 41 → 42 | 78.8 | 5.6341 | 93.25 | 7 |
| 5 | 9 → 10 → 11 → 19 → 27 → 30 → 31 → 32 → 38 → 39 → 40 → 41 → 42 | 78.8 | 5.6753 | 95.31 | 6 |
| 6 | 9 → 10 → 11 → 12 → 13 → 14 → 15→ 16 → 24 → 29 → 33 → 41 → 42 | 78.8 | 5.5726 | 96.04 | 4 |

| | | | | | |
|---|---|---|---|---|---|
| 7 | 9 → 10 → 11 → 12 → 13 → 21 → 22→ 23 → 28 → 29 → 33 → 41 → 42 | 78.8 | 5.778 | 94.58 | 8 |
| 8 | 9 → 10 → 11 → 12 → 13 → 14 → 15 → 23 → 28 → 29 → 33 → 41 → 42 | 78.8 | 5.6753 | 95.31 | 6 |

## 2.5 Benchmarking and Comparative Analyses

As work on energy efficient AGV routing progressed, researchers realized that there was a strong need for standard benchmarks and comparative studies. The single load [26] and multi load [28] models showed how energy could be built into AGV routing, but their findings were mostly tied to specific case studies and simulations. Because there were no shared evaluation standards, it was difficult to judge which methods achieved the best balance between energy savings, travel distance, and time.

To fill this gap, Novak et al. [30] proposed a benchmarking framework for evaluating AGV energy use in path planning. Their framework offered a structured way to measure algorithm performance by considering factors like acceleration, deceleration, and turning energy. This was a step forward compared to earlier evaluations that only used distance as a proxy for energy. The benchmarking system also made it possible to test different algorithms under controlled conditions, so improvements in energy efficiency could be measured and compared fairly. This contribution was important not only for research but also for industry, as it provided the basis for standard testing practices that could guide AGV deployment.

At the same time, broader reviews of autonomous indoor robots stressed the industrial importance of energy efficient operation. Kumar and Singh [31] published a detailed review of load carrying robots in indoor environments, focusing on design, navigation methods, and efficiency challenges. They argued that energy efficient navigation was not just a research goal but also an urgent requirement for smart manufacturing, where fleets of robots are used continuously. Their review identified energy use as one of the main performance bottlenecks, along with obstacle avoidance, adaptability to real time changes, and computational efficiency. They also pointed out that while many path planning algorithms had been proposed, only a small number directly focused on energy efficiency in a comprehensive way.

Together, these studies offered two main lessons. First, benchmarking is necessary if progress in AGV path planning is to be measured and compared across studies. Second, energy efficiency should be treated as a central performance metric, on the same level as time and distance. Without shared standards, research risks becoming fragmented, with results that cannot be applied to real industrial systems.

Even so, some problems remained. The benchmarking study [30] was limited to simulations and had not yet been tested on real AGVs. Likewise, the review [31] highlighted the importance of energy efficiency but did not give specific methods for adding it into routing algorithms. These gaps suggest the need for continued work that links benchmarking with practical validation and the design of new optimization methods.

Table 2.2. Comparison of Key Studies on Energy Efficient AGV Path Planning.

| **Study** | **Focus** | **Strengths** | **Limitations** |
|---|---|---|---|
| Rehman et al. [17] | Single load AGV, energy model | Introduced motion phase based energy modeling | Simplified to single load tasks, no dynamic adaptability |
| Rehman et al. [18] | Multi load AGV, integrated scheduling | Balanced energy, distance, and time with multi objective optimization | High computational complexity, static conditions |

| | | | |
|---|---|---|---|
| Novak et al. [19] | Benchmarking AGV energy use | Standardized evaluation of energy efficient algorithms | Simulation only, limited industrial testing |
| Kumar and Singh [20] | Review of load carrying indoor robots | Identified energy efficiency as key performance challenge | No direct algorithmic framework proposed |

Table 2.2 summarizes four academic studies that focus on energy efficient path planning for Automated Guided Vehicles (AGVs), highlighting the evolution of research in this field.

- Studies by Rehman et al. [17] and [18]. These entries show a progression from a basic single load AGV energy model to a more complex multi load, integrated scheduling approach. The strength lies in introducing detailed motion phase based energy modeling and multi objective optimization (balancing energy, distance, and time). However, the limitations point to a struggle with real world applicability the initial study was simplified, and the latter involved high computational complexity and static conditions.

- Novak et al. [19]. This study focused on establishing a standardized way to benchmark

  AGV energy use. Its strength is creating a tool for standardized evaluation of different energy efficient algorithms, but it was limited to simulation only, lacking real industrial testing.

- Kumar and Singh [20]. This represents a literature review that theoretically solidified energy efficiency as a key performance challenge for indoor robots. Its limitation is that it provides no direct algorithmic solution or framework itself, but instead identifies the importance of the problem.

In conclusion, benchmarking studies and comparative reviews have played an important role in shaping AGV research. By creating standard evaluation frameworks [30] and carrying out broad reviews of robot performance [31], these works helped move the field beyond isolated case studies and toward results that are more general and useful for industry. Still, there remain open challenges, such as practical testing, real time adaptability, and the use of advanced optimization methods. These gaps provide the motivation for the work presented in this thesis.

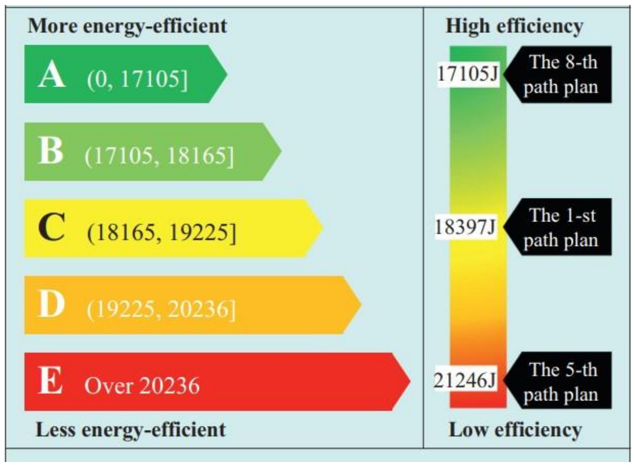


Figure 2.3. The improved rating system of energy efficiency for AGV path plans [33].

The figure 2.3 collectively illustrate the principle of energy aware routing for Automated Guided Vehicles (AGVs), demonstrating that optimizing a path's geometry for energy efficiency yields measurable and significant reductions in energy consumption compared to purely distance based routing.

Table 2.3**.** Comparative analysis of recent review papers on load carrying robots published in the last four years.

| **Reference** | **Year** | **Methodology** | **Purpose** | **Findings and Limitations** |
|---|---|---|---|---|
| [34] | 2020 | Particle Swarm Optimization (PSO) | Optimize AGV routing in manufacturing workshops environment. | Balanced exploration and exploitation; simplified AGV dynamics, ignored EC focus. |
| [35] | 2020 | Hybrid Genetic Algorithm for EV Routing | Reduce emissions in EV logistics routing. | Lowered emissions; not tailored to AGV workshop constraints. |
| [36] | 2022 | Multi-Objective EV Routing Model | Balance EC and time in EV routing with real-time data. | Improved scalability; focused on urban logistics, not AGVs. |
| [37] | 2022 | Deep Learning-Based VRP Solver | Enhance VRP scalability for energy efficient routing. | Reduced computation time; ignored AGV-specific constraints. |
| [38] | 2023 | Renewable Energy VRP Model | Optimize EV routing with renewable charging schedules. | Enhanced sustainability; road-based, not applicable to AGVs. |

| | | | | |
|---|---|---|---|---|
| [39] | 2023 | Reinforcement Learning for Dynamic VRP | Enable adaptive routing in dynamic environments. | Improved real-time adaptability; not tailored to AGV workshops environment. |
| [40] | 2024 | EC Model with Variable Acceleration | Optimize EC for EVs with dynamic motion. | Offered AGV-relevant insights; lacked workshop validation. |
| [41] | 2025 | Digital Twins for EV Routing | Explore real-time optimization for EV logistics. | Suggested AGV potential; not implemented for workshops environment. |
| [42] | 2022 | Ant Colony Optimization (ACO) | Dynamic AGV path planning in workshops environment. | Improved obstacle avoidance; ignored EC optimization. |
| [43] | 2023 | Neural Network-Based Path Planner | Real-time AGV path planning in manufacturing. | Enhanced adaptability; minimal EC focus. |
| [44] | 2024 | Hybrid PSO-A* Algorithm | Optimize AGV routing with reduced computation. | Lowered computation time; used basic EC models. |

| | | | | |
|---|---|---|---|---|
| [45] | 2024 | Digital Twins for AGV Simulation | Improve AGV path accuracy in workshops environment. | Enhanced path precision; did not prioritize EC. |

## 2.6 Alternative Approaches in Ground and Indoor Robotics

Although much of the progress in energy efficient navigation has focused on AGVs in manufacturing workshops, research in other areas of robotics has also looked at energy aware path planning. These related studies give useful ideas but also highlight why AGV specific frameworks are needed. Two research directions are especially relevant. energy efficient planning for ground robots using environmental data [32] and general studies on energy efficiency in indoor robots [33].

### 2.6.1 Energy Efficient Ground Robotics with Environmental Data

An important example is the study by Wang et al. [32], who examined how ground robots can improve energy efficiency by combining air and ground measurements. Their work focused on outdoor mobile robots, where factors such as terrain roughness, wind resistance, and surface friction all affect energy use. By combining aerial data from drones with ground based sensors, the robots could identify energy demanding areas in advance and adjust their routes to save power.

This study showed that including environmental information can greatly improve energy performance in path planning. It marked a step forward compared to traditional shortest path approaches that ignore real world variations in energy demand. However, its use for AGVs in manufacturing workshops is limited. Unlike outdoor robots, AGVs move on fixed, predictable floor layouts with little variation in terrain. Their challenges are instead linked to non holonomic movement restrictions, frequent turning, and the effect of carrying loads on energy use. For this reason, while the ground robot approach [32] provides valuable lessons in how to design energy aware routing, it does not fully address the industrial conditions faced by AGVs.

### 2.6.2 Indoor Robotics and General Navigation Challenges

A wider perspective on energy efficient robotics is provided by Patel and Singh [34], who reviewed path planning strategies for autonomous load carrying robots in indoor settings. Their survey covered a variety of applications, ranging from warehouse robots to service robots used in offices and hospitals. They stressed that energy efficiency is becoming increasingly important as fleets of indoor robots are deployed on a large scale.

The review identified several critical challenges, including dynamic obstacle avoidance, real time re routing, and the need to balance energy use with task completion time. A key observation was that most existing methods either optimize distance or time as the primary objective, while energy is often treated as secondary. This finding mirrors earlier AGV focused studies [28], [29], where energy considerations were also neglected as a central optimization goal.

Although the review by Patel and Singh [34] is broad and comprehensive, it applies to multiple types of indoor robots and does not specifically address AGVs. Service robots, for example, often work in semi structured or unstructured spaces, which require complex local navigation and adaptive decision making. In contrast, AGVs operate on predefined networks of nodes and edges inside workshops. This makes their navigation problem more restricted, but also more predictable. For AGVs, dedicated models are needed that explicitly represent motion phases such as acceleration, cruising, turning, and deceleration, as well as load dependent energy costs.

### 2.6.3 Comparison with AGV Path Planning

Taken together, the alternative approaches found in outdoor ground robots [32] and indoor service robots [34] show the diversity of strategies used in energy efficient navigation. Outdoor robots rely heavily on environmental data to anticipate energy intensive paths, while indoor service robots focus on adaptability and real time decision making. AGVs, however, fall somewhere in between. Their movement is constrained by fixed workshop layouts, yet they still need to balance multiple objectives. distance, time, and energy.

Compared to ground robots [32], AGVs face less environmental uncertainty, but they are strongly affected by repeated stop and go movement, turning, and load variations, which require more precise energy models. Compared to indoor service robots [34], AGVs benefit from predictable layouts, but they must also meet strict industrial standards, where even small inefficiencies can result in higher costs and reduced productivity.

This comparison highlights why a dedicated Energy Aware Path Planning (EAPP) framework for AGVs is necessary. While the broader robotics literature provides useful ideas, these methods cannot simply be applied to manufacturing workshops without major modifications. A tailored approach is required to capture the unique operational constraints and performance demands of AGVs in real industrial environments.

## 2.7 Limitations of Existing Approaches

Despite the progress made in energy aware routing and path planning across logistics, autonomous vehicles, and robotics, a number of important limitations remain. These limitations explain why existing approaches cannot fully address the requirements of energy aware path planning for Automated Guided Vehicles (AGVs) in structured manufacturing environments. The following subsections summarize the gaps across four key research domains.

### 2.7.1 Limitations in Green Vehicle Routing Problem (GVRP) Approaches

The Green Vehicle Routing Problem (GVRP) provided the starting point for research on energy aware logistics [15], [16]. Early work mainly focused on fuel consumption as a cost factor, and later studies extended this to electric vehicle (EV) routing with charging constraints [17], [18]. These studies were valuable for introducing energy as an explicit objective in routing. However, their focus remained on outdoor, road based systems rather than industrial environments.

A major limitation of GVRP based models is the simplification of energy consumption. In most cases, energy use is calculated only as a function of load and distance, sometimes with the assumption of constant speed [19], [20]. This ignores the dynamic behavior of Automated Guided Vehicles (AGVs), which undergo repeated acceleration, deceleration, and turning in workshop environments [21]. Another weakness is the emphasis on recharging infrastructure and traffic variability. While these are critical in road logistics, they are not directly relevant in factory settings, where AGVs run on fixed paths and controlled layouts.

Therefore, while GVRP studies built a strong foundation for energy aware optimization, their assumptions make them unsuitable as a direct solution for AGV path planning in manufacturing workshops. They provide theoretical insights but lack the realism needed for shop floor applications.

### 2.7.2 Limitations in AGV Specific Path Planning Studies

In contrast to GVRP, more recent work has focused directly on AGVs, especially their navigation in structured environments [22], [23]. These studies represented workshops as graphs, grids, or trajectory maps and applied classical algorithms such as A* and Dijkstra's for shortest path planning [24]. While these methods are efficient in computing minimal distance routes, they rarely optimize energy use. Even when energy is considered, it is usually treated as a secondary factor or modeled with simplified functions [25].

Some attempts have been made to address energy more explicitly. For example, Fazlollahtabar and Saidi Mehrabad [26] proposed grid based mapping for AGVs, which offered high spatial accuracy but required careful calibration. Similarly, Fragapane et al. [27] developed graph based models, and Li et al. [28] applied the Dynamic Window Approach (DWA) for local navigation. However, these methods face computational challenges when applied to large workshops or complex layouts.

Another limitation is the lack of adaptability to real time changes. Most AGV path planning frameworks assume static conditions, where routes are planned once and kept fixed. In practice, manufacturing workshops are dynamic, with task priorities, job orders, and layouts changing frequently. Current AGV routing algorithms still struggle to adapt to such variability while keeping energy consumption low [29].

In summary, AGV specific studies are more relevant to workshop logistics than GVRP approaches, but they remain incomplete. They either oversimplify energy use, suffer from computational complexity, or lack real time adaptability. This makes it necessary to develop new frameworks that integrate realistic energy models with optimization techniques capable of handling dynamic conditions.

### 2.7.3 Limitations in Benchmarking and Performance Analysis

Another limitation in the literature is found in benchmarking and evaluation methods. Some researchers have attempted to create frameworks for comparing energy efficient path planning approaches [30]. These studies usually rely on simulation based tests that measure energy use under controlled conditions [31]. While helpful, the benchmarking methods are often inconsistent, which makes it hard to compare results across different studies.

Most of these benchmarks are simplified. They often ignore important AGV specific factors such as non holonomic motion, load dependent energy costs, or the detailed layouts of manufacturing workshops [32]. In addition, many benchmarks are carried out only in mathematical models and do not make use of realistic robotic platforms or environments such as the Robot Operating System (ROS). This limits confidence in whether the proposed algorithms will actually work in real world factories.

Because of this lack of standardization, it is still difficult to identify which algorithms truly perform best in terms of balancing energy, distance, and time.

### 2.7.4 Limitations in Alternative Robotics Approaches

Related studies in other robotics fields also provide useful insights but show clear differences compared to AGVs. For instance, Wang et al. [33] proposed combining aerial and ground sensor data to improve energy efficiency for outdoor robots. Their method helped account for environmental factors such as terrain and surface conditions. However, such factors are not relevant in workshops where AGVs move on smooth and predictable floor paths.

In the same way, Patel and Singh [34] reviewed the performance of indoor service robots and underlined energy efficiency as an emerging concern. Their study, though broad, was not focused on AGVs. Robots in hospitals, offices, or warehouses must adapt to unstructured environments and obstacles, while AGVs usually follow fixed layouts with repetitive transport tasks. This difference means that the methods used in indoor robotics cannot be directly applied to AGVs without significant adjustments.

These comparisons show that while alternative robotics research highlights the importance of energy efficiency, the solutions remain too general for the specific challenges faced in manufacturing workshops.

## 2.8 Conclusion

The literature shows that while progress has been made in both logistics and robotics, existing methods fall short of addressing the specific challenges faced by AGVs in manufacturing workshops. GVRP based approaches simplify energy costs, AGV specific studies often neglect energy or real time adaptability, benchmarking frameworks lack standardization, and alternative robotics research is too broad. This thesis therefore addresses a clear gap by proposing a dedicated Energy Aware Path Planning (EAPP) framework. By explicitly modeling AGV energy consumption across motion phases and applying multi objective optimization methods, the research contributes both to academic understanding and to practical solutions for sustainable manufacturing logistics.

# Chapter 3

# Methodology

## 3.1 Energy-Aware Path Planning Framework Overview

This chapter presents the methodology used to develop the proposed Energy Aware Path Planning (EAPP) framework for Automated Guided Vehicles operating within a manufacturing workshop environment. The primary motivation behind this work is the recognition that AGV motion does not depend solely on geometric distance. Instead, total energy consumption depends on several dynamic factors including rolling resistance, turning behavior, acceleration, deceleration, and standby power. Traditional shortest path strategies assume that minimizing Euclidean distance naturally minimizes cost; however, this assumption does not hold true for AGVs whose motion phases are strongly influenced by route structure. For example, a slightly longer path with fewer turns often consumes less energy than a short path with multiple turns. Therefore, a path planner must evaluate both travel time and energy usage if the aim is to support sustainable, efficient workshop logistics.

To fulfil this requirement, an enhanced A* search algorithm has been developed. The planner operates in two modes. The first is classical shortest distance A*, used as a baseline reference to observe how distance minimization behaves under workshop constraints. The second is an energy aware A* method that integrates a physics based model of AGV energy consumption. Both versions run on the same undirected workshop graph where nodes represent workstations or intersections and edges represent feasible straight motions. Although the environment representation is identical for both modes, the two differ in how they evaluate edge costs, derive heuristics, and interpret turns and motion characteristics.

The energy aware version computes the energy cost of each edge by evaluating rolling resistance, acceleration energy required to regain cruising speed, braking losses during deceleration, additional rolling losses in turning arcs, and standby energy proportional to the total movement time. These calculations make the planner sensitive to the physical realities of AGV operation and provide a more realistic estimation of total energy usage.

The following sections describe the problem definition, the motivation for choosing A* as the search method, the formulation of the baseline and energy aware A* modes, and the details of the energy model used for evaluation.

## 3.2 Problem Definition

The workshop environment is modelled as a connected network of nodes and edges, where each node represents a workstation or intersection and each edge denotes a valid straight line segment for AGV movement. The core objective is to identify a path from the start node to the goal node that minimizes both travel time and energy consumption while respecting the AGV's non-holonomic motion limits. Earlier studies usually focused on a single metric, either optimizing travel time or reducing energy use, which does not reflect the varying operational priorities found in real manufacturing settings. In practice, users may value rapid task completion in some situations and energy conservation in others, especially when battery capacity or sustainability goals are critical. Because turning, braking, and acceleration cycles significantly influence energy demand, the shortest geometric path is not always the most efficient, making this problem inherently multi objective and sensitive to user preference.

### 3.2.1 Multi Objective Nature of the Problem

AGV routing is inherently multi objective, as different performance indicators interact with each other. However, instead of treating these objectives separately, this research embeds time and energy considerations directly into the cost structure of the A* algorithm. A* is suitable here because it is deterministic, handles static graph structures efficiently, and can be extended to incorporate energy terms while retaining optimality properties provided that the heuristic remains admissible. Furthermore, A* supports rapid re planning, a feature essential for dynamic manufacturing workshops.

### 3.2.2 Why A* Instead of Metaheuristic Methods

Metaheuristic methods like particle swarm optimization and genetic algorithms can search wide solution spaces but are computationally heavy and produce non repeatable results. AGV systems, however, require fast and predictable decisions, especially in real time. Therefore, this thesis uses a deterministic A* based approach with realistic energy modelling instead of stochastic optimization techniques.

## 3.3 Overview of the A* Search Algorithm

A* selects the most promising path by minimizing the function

$$f(n) = g(n) + h(n) \tag{3.1}$$

where g(n) represents the actual accumulated cost from the start node to the current node and h(n) is a heuristic estimate of the cost from the current node to the goal. If the heuristic never overestimates the true remaining cost, A* guarantees optimality. In classical implementations both g(n) and h(n) are based purely on geometric distance. However, to incorporate energy considerations, both components must be redefined in terms of realistic AGV motion energy [33].

## 3.4 Shortest Distance A* (Baseline Mode)

In the baseline mode, the cost of moving along an edge is simply its Euclidean length

$$Cost_{dist} = \mathrm{L} \tag{3.2}$$

This equation (3.2) is required to establish a pure geometric benchmark for comparison. It isolates the effect of distance by intentionally ignoring physical dynamics.

Without this baseline, the improvement of energy aware planning cannot be quantitatively validated [24].

This version represents the simplest possible planner. It ignores acceleration, deceleration, turning radii, or rolling resistance. It is included here to show that the shortest geometric path is often not the most energy efficient route. This baseline also provides a reference against which the effectiveness of the proposed energy aware approach can be measured.

## 3.5 Proposed Energy Aware A*

The energy aware A* modifies the cost evaluation to reflect the true physical work required by the AGV. It computes several energy components for each edge and sums them into a unified cost measure. This equation (3.3) is required because energy consumption depends on the total moving mass. Payload variations directly alter rolling, acceleration, and braking energies. Without incorporating payload mass, energy estimation would be physically incorrect. The first step is to define the total mass as

$$M = m_0 + Q \tag{3.3}$$

where $m_0$ is the mass of the AGV body and Q is the payload.

### 3.5.1 Importance of Turn Handling

The treatment of turns is fundamental because energy losses around corners are significantly higher than during straight motion. Each turn requires the AGV to decelerate to a lower turning speed, losing kinetic energy through braking, and subsequently re accelerating to regain cruising velocity. Additionally, the turning motion creates extra rolling resistance due to the arc length. Therefore, paths with many short edges and frequent turning consume substantially more energy than longer but smoother alternatives. This observation forms the theoretical rationale behind the proposed planner [24].

### 3.5.2 Physics-Based Energy Terms

Let M be the total mass.

a) Rolling Resistance

The equation (3.4) is required to model continuous energy loss during straight line motion. Rolling resistance is unavoidable and accumulates with distance traveled. Without this term, straight motion energy would be significantly underestimated [33].

$$E_{\mathrm{roll}} = \frac{M g c_r L}{\eta} \tag{3.4}$$

b) Acceleration Energy

This equation (3.5) is required to account for energy used to increase vehicle speed. Acceleration demands dominate energy usage in start stop industrial environments. Without this term, frequent speed changes would appear artificially inexpensive [33].

$$E_{acc} = \frac{1}{2}\frac{M\left(v_s^2 - v_c^2\right)}{\eta} \tag{3.5}$$

c) Deceleration Loss

The equation (3.6) is required to model energy dissipated when slowing down. Braking losses are unavoidable, especially before turns and intersections. Ignoring this term would incorrectly favor paths with excessive stopping [33].

$$E_{acc} = \frac{1}{2} \quad M(v_s^2 - v_t^2)\left(1 - k_{regen}\right) \tag{3.6}$$

d) Turning Arc Roll Loss

This equation (3.7) is required to represent energy loss during curved motion. Turns introduce additional friction and effective path length. Without this term, the planner would unrealistically prefer paths with many sharp turns [33].

$$E_{\mathrm{turn}} = \frac{Mgc_r(R\theta)}{\eta} \tag{3.7}$$

e) Standby Energy

This equation (3.8) is required to capture non motion energy consumption. Control systems and sensors consume power even when the AGV is stationary. Without this term, total mission energy would be underestimated [33].

$$E_{\mathrm{standby}} = P_{\mathrm{sm}}\, T \tag{3.8}$$

All these are computed edge by edge.

### 3.5.3 Combined Energy Aware Cost Function

The equation (3.8) is required to unify all physical energy components into a single metric. The distance penalty ensures numerical stability and path smoothness. Without this combined cost, energy aware A* cannot function effectively. The full cost of an edge in the proposed method is.

$$Cost_{energy} = E_r + E_{\mathrm{acc}} + E_{\mathrm{br}} + E_{\mathrm{tr}} + \lambda \mathrm{L} \tag{3.9}$$

The term λL lambda ensures that the algorithm still values distance but prioritizes energy [33].

### 3.5.4 Energy Proxy Heuristic

To keep the A* search efficient while incorporating a more realistic representation of AGV behavior, an admissible energy-based heuristic is introduced. The heuristic h(n) provides a conservative lower bound estimate of the minimum energy required to travel from the current node to the goal. This estimate is calculated by considering the smallest possible rolling resistance over a straight line between the two points and incorporating a minimal turning estimate derived from the geometric difference in direction. As long as these estimates do not exceed the true minimum energy required, the heuristic remains admissible and therefore preserves the optimality properties of A*. This energy aware heuristic ensures that the search remains guided and computationally efficient without compromising the physical realism of the solution.

## 3.6 Integrated A* Framework for Energy Aware Path Planning

The complete Energy Aware Path Planning framework integrates both the classical shortest distance A* and the proposed energy aware A* within a single system. This structure allows the AGV to switch between planning modes depending on operational requirements. When rapid route selection is the priority, the shortest distance mode is suitable because of its simplicity and fast convergence. When the goal is to minimize actual energy consumption, the energy aware mode becomes the preferred planner due to its detailed incorporation of motion phase energy components. The framework therefore provides the flexibility needed for experimentation, comparison, practical deployment, and validation of both approaches.

The overall workflow of the system begins with the construction of the workshop graph where all workstations, intersections, and travel lanes are represented as nodes and edges. The user or system then selects the planning mode. In the shortest distance mode the traditional Euclidean distance is used as the edge cost, while in the energy aware mode the cost is determined by the physics based energy model. A* expands nodes based on the minimum value of $f(n) = g(n) + h(n)$, where $g(n)$ accumulates the actual cost from the start to the current node and $h(n)$ estimates the remaining cost to the goal.

During the exploration process, the algorithm evaluates turns at each successive set of nodes. A turn is detected when the angle between the incoming and outgoing edges exceeds approximately ten degrees. This identification is essential because turning significantly increases energy usage due to braking losses, turning arc rolling resistance, and re acceleration energy requirements. After the search reaches the goal node, the final path is reconstructed through backtracking.

Once the path is obtained, it undergoes a detailed evaluation. Instead of assuming the path to be optimal based solely on A* cost, a high precision post analysis computes the exact distance, travel time, total energy, and each energy component including rolling, braking, acceleration, turning, and standby contributions. This evaluation ensures that the final comparison between distance based and energy based paths is grounded in precise physical modeling rather than simplified estimations.

## 3.7 Detailed Time and Energy Computation

The path obtained from either A* mode is subjected to a physically realistic evaluation. This evaluation is critical because the A* algorithm, even in energy aware mode, relies on approximated costs during the search. A more precise phase by phase analysis is therefore essential for confirming the validity of the selected route.

AGV movement along each edge is divided into multiple motion phases including cruising at a constant speed, deceleration before a turn, the turning motion itself, and the re acceleration phase after completing the turn. Each of these phases contributes differently to energy consumption.

This equation computes the total travel distance of the AGV by summing the lengths of all path segments. Each segment length $L_i$ represents either a straight or curved portion of the planned route.The total distance provides a geometric measure used for baseline comparison and performance analysis.

The total distance of the route is computed as

$$D_{\text{total}} = \sum_i L_i \tag{3.10}$$

where $L_i$ denotes the length of each segment.

This equation computes the time required for the AGV to traverse a straight segment at constant cruising speed. It assumes steady state motion after acceleration has been completed. This term is essential for estimating baseline travel time over linear paths. Travel time is then evaluated by summing the individual times associated with the cruise, turn, acceleration, and deceleration phases [24]. For example, the cruise time is computed as

$$t_{cruise} = \frac{L}{v_s} \tag{3.11}$$

This equation represents the time needed to negotiate a curved turning arc. The arc length $R\theta$ and reduced turning speed $v_c$ reflect safe cornering dynamics. It ensures that turning maneuvers are temporally distinguished from straight motion [24]. While the turning time is

$$t_{\text{turn}} = \frac{R\theta}{v_c} \tag{3.12}$$

This equation models the duration required to accelerate from turning speed to cruising speed. It captures the dynamic response of the AGV under limited acceleration capability. Without this term, speed transitions would be assumed to be instantaneous and unrealistic [24]. The acceleration and deceleration times are given by

$$t_{\text{acc}} = \frac{v_s - v_c}{a_{\text{acc}}} \tag{3.13}$$

This equation computes the time required for the AGV to decelerate from cruising speed to turning speed. The deceleration rate represents braking capability and operational safety constraints. It enables accurate modeling of speed reduction phases in complex AGV paths [24].

$$t_{\text{dec}} = \frac{v_s - v_c}{a_{\text{dec}}} \tag{3.14}$$

These time components form a timeline describing the AGV's speed transitions throughout the route. This equation aggregates all energy components incurred along the AGV route. It includes motion related losses as well as standby power consumption. The total energy metric enables direct comparison of alternative paths. The total energy consumption is calculated by summing all energy components associated with each segment. This includes rolling resistance, braking losses, acceleration energy, turning arc losses, and standby power [24]. The total energy is expressed as

$$E_{\text{tot}} = E_r + E_{\text{acc}} + E_{\text{br}} + E_{\text{tr}} - E_{\text{sb}} \tag{3.15}$$

Each of these terms is derived from the previously defined physics-based equations.

This detailed computation phase is indispensable because two routes with nearly identical distances can differ substantially in energy consumption if one of them has multiple turns or requires frequent speed changes. The evaluation highlights that a longer route may, in some cases, require significantly less energy and time compared to a shorter but highly segmented path. This supports the central claim that geometric shortest paths rarely translate into energy optimal solutions for AGV navigation.

## 3.8 Simulation Setup and Environment

To rigorously test the performance of both A* modes, a custom MATLAB simulation environment was constructed. The workshop layout includes forty nine nodes and more than sixty connecting edges arranged to resemble a realistic manufacturing setting. Coordinates were scaled by a factor of four to approximate the dimensions of an actual shop floor while maintaining the original topology.

AGV parameters used in the simulations, including mass, payload, rolling resistance, drivetrain efficiency, cruise speed, turning radius, acceleration limits, and deceleration limits, were selected based on typical industrial AGV specifications reported in recent research. This ensures that the simulation outcomes reflect realistic operational behavior.

The simulation interface accepts the start node, goal node, and desired planning mode. Visualization includes plotting of nodes and edges, labelled start and goal positions, and a highlighted representation of the final path. This graphical output allows intuitive comparisons between the routes generated by the shortest distance and energy aware A* modes.

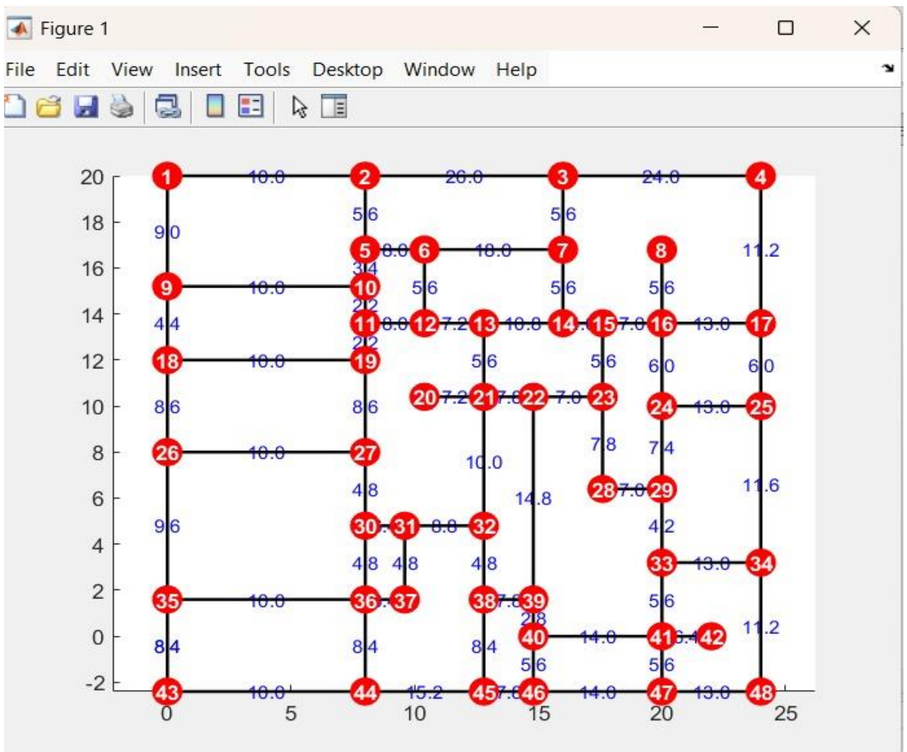


Figure 3.1. Topological map of the flexible manufacturing workshop [32].

This Fig 3.1. Topological map of the flexible manufacturing workshop, fundamentally represents the FMW as a weighted, undirected graph, which serves as the core spatial model for optimization. The nodes (red circles) correspond to discrete, critical locations or decision points, often representing machine centers, buffers, or load/unload stations. The edges (black lines) define the feasible set of direct connections or paths between these locations. The graph is characterized by the weight set (blue values), where each weight assigned to an edge quantifies a performance metric, typically Euclidean distance, travel time, or movement cost. This graph is instrumental for formulating and solving path-finding problems (e.g., finding the shortest path between any two nodes), flow problems (e.g., maximum flow analysis), and routing problems (e.g., determining optimal tours for Automated Guided Vehicles or material handlers).

## 3.9 Qualitative Analysis of the Framework

The enhanced A* framework demonstrates several strengths. It is deterministic and therefore suitable for real time AGV deployment where consistent and predictable results are required. Its energy model is based on realistic physical principles, allowing it to capture meaningful differences between paths that traditional distance based planners overlook. The framework also provides flexibility because the weighting parameter $\lambda$ can be adjusted to emphasize either energy efficiency or distance minimization depending on operational needs.

However, some limitations exist. A* returns only a single solution rather than a full set of Pareto optimal trade off paths. The accuracy of the energy aware cost function depends on correct tuning of model parameters and proper representation of AGV behavior. For extremely large or dense workshop graphs, the computational requirements of A* may increase, although for the scale of environments used in this research the performance remains efficient.

## 3.10 Time and Space Complexity

The computational complexity of A* in this context is O(E log V) when implemented with a priority queue. Since the workshop is represented as a sparse graph where the number of edges E is approximately twice the number of nodes V, the search remains computationally manageable. The space complexity is O(V), dominated by the storage requirements of the open and closed lists. The additional energy computations performed in the energy aware mode introduce only constant time operations per edge and therefore do not alter the algorithmic complexity. Both A* modes operate efficiently under the given workshop conditions.

## 3.11 Algorithmic Framework for Energy Aware AGV Path Planning

### 3.11.1 Process Flow of Energy Aware A* AGV Path Planning

The flow chart illustrates the logical workflow implemented in the MATLAB code for energy aware A* path planning of a single load AGV. The environment is first initialized by defining AGV physical parameters, loading the scaled node coordinate map, and constructing the adjacency graph from the edge list. The user inputs for start and goal nodes are then received, followed by selection of the planning mode. The A* search runs using either a distance-based cost or an energy aware proxy cost, where turns are detected based on angle thresholds, and motion phases are estimated only when required. Once the optimal path is identified, the route is reconstructed and passed to the physics-based evaluation module, which computes realistic energy consumption and travel time using rolling resistance, braking, acceleration, and turning arc motion constraints. The process concludes with visualization of the final path and performance metrics, ensuring that the decision making structure follows the same logic as executed in MATLAB, making the flow suitable for direct thesis documentation and future algorithmic extensions.

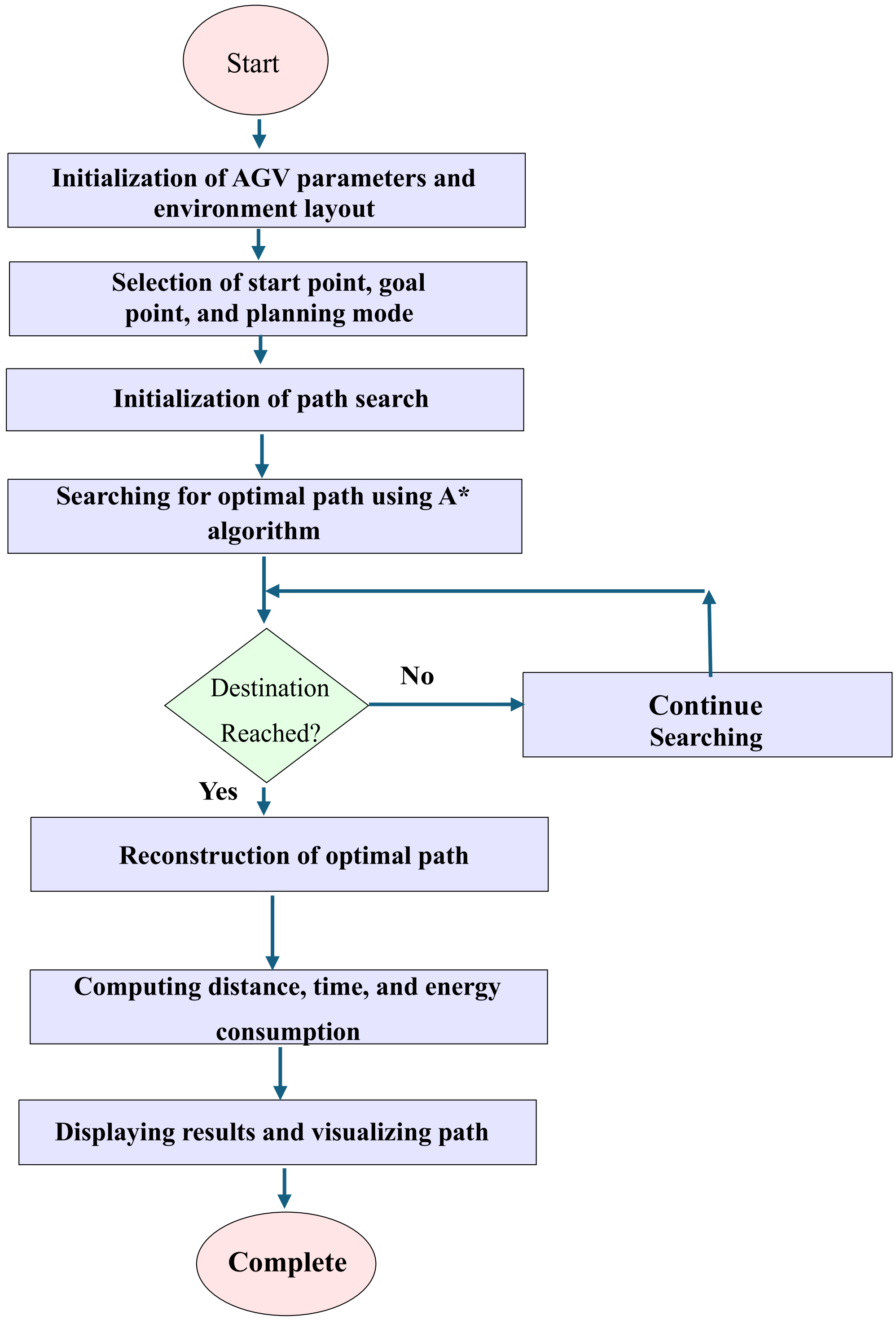


Figure 3.2. Flowchart of the AGV Path Planning Methodology

### 3.11.2 Algorithmic Logic of Energy Aware A Path Planning

#### Step 1. Initialization

This step establishes the foundation for the energy aware path planning process. All physical parameters of the Automated Guided Vehicle (AGV), including mass, payload, velocity limits, rolling resistance, and drivetrain efficiency, are defined at the outset. These parameters characterize the non holonomic nature of the robot and constrain its motion within the manufacturing environment. In addition, the spatial representation of the workshop is initialized using predefined nodes and connecting paths. Cost variables required by the A* algorithm are also initialized, including path cost estimates and heuristic values. The starting and goal nodes are assigned, and the initial search state is prepared. This step ensures that both the physical model of the AGV and the environment are consistently represented before path planning begins.

```
Compute total AGV mass M = m0 + payload
Build adjacency list G from edges
For all nodes n:
    gScore[n] = ∞
    fScore[n] = ∞
    prev[n] = null
gScore[startNode] = 0
fScore[startNode] = heuristic_energy_proxy(startNode, goalNode)
openSet = { startNode }
```

Figure 3.3. System Initialization

### Step 2. A Search Loop*

This step constitutes the central and most computationally intensive component of the proposed framework. The A* search algorithm iteratively explores feasible paths from the start location toward the goal while evaluating each candidate path based on the selected optimization objective.

At each iteration, the algorithm selects the most promising node according to a combined cost function. Unlike conventional distance based A* implementations, the proposed framework embeds energy consumption into the cost function. This cost accounts not only for the geometric length of a path but also for motion related energy factors, such as rolling resistance, speed transitions, braking losses, and turning behavior.

Special attention is given to turning maneuvers, which are particularly critical for non holonomic AGVs operating in confined manufacturing workshops. When a change in direction is detected, additional energy penalties associated with deceleration, turning arcs, and re acceleration are applied. This enables the planner to differentiate between geometrically similar paths that may have significantly different dynamic and energetic characteristics.

The algorithm continues expanding nodes and updating path costs until the destination node is reached. By integrating energy awareness directly into the A* search loop, the planner naturally favors smoother trajectories with stable motion phases, rather than simply selecting the shortest geometric path.

```
WHILE openSet is not empty:
  u = node in openSet with minimum fScore
  Remove u from openSet
  IF u == goalNode:
    BREAK (goal reached)
  FOR each neighbor v of u:
    Retrieve edge length L(u, v)
    IF mode == shortest-distance:
      edgeCost = L
    ELSE IF mode == energy-aware:
      Compute rolling energy over L
      IF a turn exists at node u:
        Add acceleration energy
        Add braking loss
        Add turning arc rolling energy
      edgeCost = energy_cost + λ × L
    tentativeCost = gScore[u] + edgeCost
    IF tentativeCost < gScore[v]:
      gScore[v] = tentativeCost
      prev[v] = u
      Update fScore[v]
      Add v to openSet if not already present
```

Figure 3.4. Energy Aware A* Search

### Step 3. Path Reconstruction

Once the destination node is reached, the optimal path is reconstructed by tracing back from the goal to the starting node. This is achieved by following stored predecessor relationships generated during the A* search.

The reconstructed path represents the most energy efficient or shortest distance route, depending on the selected planning mode. At this stage, the path is defined purely as an ordered sequence of nodes, without yet considering detailed timing or energy breakdowns. This separation allows the planning process to remain efficient while enabling accurate post processing evaluation in subsequent steps.

```
Initialize:
    Total distance D_total = 0
    Total time T_total = 0
    Energy components:
        E_roll = 0
        E_acc  = 0
        E_brake_loss = 0
        E_turnroll = 0
FOR each consecutive segment (u → v) in path:
    Retrieve segment length L
    D_total += L
    IF a turn exists at node v:
        Compute turn angle θ
        Compute deceleration distance and time
        Compute rolling energy on straight parts
        Compute braking energy loss
        Compute turning arc length = R × θ
        Compute rolling energy on turn arc
        Compute re-acceleration energy
        Update total time
    ELSE (straight motion):
        Compute rolling energy
        Update travel time
```

Figure 3.5. Optimal Path Reconstruction

### Step 4. Ultra Realistic Path Evaluation

This step constitutes a critical component of the proposed energy aware planning framework, as it bridges the gap between abstract path selection and realistic AGV operation. While the planning stage identifies a feasible and energy efficient route, this evaluation stage rigorously quantifies how the AGV would behave while physically traversing the selected path within a manufacturing workshop.

The evaluation process examines the path sequentially on a segment-by-segment basis, ensuring that motion continuity and dynamic transitions between segments are accurately represented. For each segment, fundamental performance metrics namely travel distance, traversal time, and energy consumption are computed in a manner consistent with the physical constraints of a non-holonomic AGV.

A clear distinction is made between straight motion and turning maneuvers, as these two motion modes exhibit significantly different energetic characteristics. During straight line travel, the AGV is assumed to operate at a steady cruising speed, and energy consumption is primarily governed by rolling resistance and drivetrain efficiency. This reflects typical AGV behavior in factory aisles where long, uninterrupted motion is common.

Moreover, this evaluation inherently accounts for the non-holonomic constraints of the AGV by enforcing direction dependent motion behavior and prohibiting unrealistic instantaneous changes in velocity or heading. Consequently, the resulting energy and time estimates closely reflect actual AGV operation rather than idealized or purely geometric motion assumptions.

Through this ultra realistic path evaluation, the proposed framework ensures that the selected path is not only optimal from a planning perspective but also viable and efficient under real operational conditions. This strengthens the practical relevance of the energy aware planning strategy and enhances its applicability to long term AGV deployment in automated manufacturing environments.

```
Initialize:
  Total distance D_total = 0
  Total time T_total = 0
  Energy components:
    E_roll = 0
    E_acc  = 0
    E_brake_loss = 0
    E_turnroll = 0
FOR each consecutive segment (u → v) in path:
  Retrieve segment length L
  D_total += L
  IF a turn exists at node v:
    Compute turn angle θ
    Compute deceleration distance and time
    Compute rolling energy on straight parts
    Compute braking energy loss
    Compute turning arc length = R × θ
    Compute rolling energy on turn arc
    Compute re-acceleration energy
    Update total time
  ELSE (straight motion):
    Compute rolling energy
    Update travel time
```

Figure 3.6. Path Energy Evaluation

### Step 5. Standby and Total Energy

In this step, auxiliary energy consumption is incorporated into the overall energy model. Even when the AGV is not actively accelerating or turning, onboard systems such as controllers, sensors, and communication modules continue to consume power.

Standby energy is therefore calculated as a function of total operation time and added to the motion related energy components. The total energy consumption of the path is then obtained by combining rolling energy, acceleration energy, braking losses, turning losses, and standby energy. This holistic approach ensures that the final energy metric reflects the true operational cost of AGV deployment in industrial settings.

```
Compute standby energy = standby_power × total_time
Total energy:
E_total = E_roll + E_acc + E_brake_loss + E_turnroll − standby_energy
```

Figure 3.7. Total Energy Computation

### Step 6. Output Results

The final step presents the results of the energy aware planning and evaluation process. The selected path is reported along with its total distance, travel time, and energy consumption. A breakdown of individual energy components is also provided to facilitate deeper analysis.

Additionally, the planned path is visualized within the workshop layout, highlighting the start and goal locations and the chosen trajectory. These outputs enable direct comparison between distance optimized and energy optimized paths, supporting performance evaluation and decision making for AGV routing in manufacturing environments.

Display:

- Selected path
- Total distance
- Total time
- Total energy
- Energy breakdown by component

Plot:

- Network layout
- Planned path
- Start and goal nodes

Figure 3.8. Planning Results Output

# Chapter 4

# Results and Discussion

## 4.1 Simulation Setup on MATLAB

The proposed algorithm operates by modeling the manufacturing workshop as a connected network and applying an informed search strategy to determine an optimal route between a start node and a goal node. The overall working of the code can be divided into three logical stages. environment modeling, path search, and realistic performance evaluation.

In the first stage, the workshop layout is transformed into a graph structure. Each workstation or intersection is treated as a node, while feasible travel corridors between them are represented as edges. This abstraction allows the AGV's navigation problem to be addressed using graph based search techniques while preserving the physical constraints of the shop floor. The adjacency relationships ensure that the AGV can move bidirectionally wherever the layout permits, which reflects realistic industrial movement.

In the second stage, an A* search algorithm is employed to explore possible paths. The algorithm maintains a list of candidate nodes and expands them based on a cost function that depends on the selected planning mode. When the shortest distance mode is chosen, the algorithm prioritizes paths that minimize geometric length only. When the energy aware mode is selected, the cost function is modified to include an energy related proxy, which biases the search toward smoother paths. A heuristic estimate based on the spatial separation between nodes guides the search toward the goal efficiently while avoiding unnecessary exploration.

A distinguishing feature of the algorithm is how it handles vehicle motion. The code explicitly identifies turning points by analyzing changes in direction between consecutive path segments. Acceleration and deceleration are assumed to occur only at these turning locations rather than continuously along the path. This assumption reflects real AGV behavior, where speed changes are mainly associated with direction changes rather than straight line motion. By embedding this logic into the search and evaluation process, the algorithm differentiates between paths that may have similar lengths but different dynamic characteristics.

In the final stage, once a path is identified, the code performs a detailed motion level evaluation. The selected path is traversed segment by segment to compute overall distance, travel time, and energy consumption. Different motion phases such as cruising, braking before a turn, turning movement, and re acceleration are treated separately. This ensures that the reported energy consumption reflects realistic physical behavior instead of idealized assumptions. Standby energy during travel is also considered to account for auxiliary power usage.

Overall, the code works by integrating classical graph based path planning with realistic AGV motion modeling. Instead of treating the AGV as a point moving at constant speed, the algorithm accounts for how real vehicles accelerate, decelerate, and lose energy during turns. This approach enables meaningful comparison between shortest distance and energy aware planning strategies and provides a reliable theoretical foundation for energy efficient AGV navigation in manufacturing environments.

### 4.1.1 Comparative Analysis of Results for Identical Start and Goal Nodes

For this experiment, both planners were evaluated using the same start node (1) and goal node (33) to enable a direct and fair comparison between the shortest distance A* planner and the energy aware A* planner under identical environmental and operational conditions, as illustrated in Fig. 4.1 and Fig. 4.2. This controlled setup ensures that any observed differences in performance arise solely from the planning strategy rather than from variations in path length or network topology.

As shown in Fig. 4.1 and summarized in Table 4.1, the shortest distance A*, which achieves the minimum geometric distance of 75.80 m. However, this path consists of multiple short segments and frequent direction changes, leading to repeated acceleration, deceleration, and turning maneuvers. These motion characteristics significantly affect the AGV's dynamic behavior, resulting in a total travel time of 102.16 s and an energy consumption of 3.406 kJ. The results reported in Table 4.1 clearly demonstrate that minimizing geometric distance alone does not account for motion stability or energy efficiency, particularly in non holonomic AGV operation.

In contrast, the energy aware A* planner, as illustrated in Fig. 4.2 and detailed in Table 4.2. Although this route maintains the same overall distance of 75.80 m, it is composed of longer, smoother segments with fewer directional changes. This structural advantage enables the AGV to sustain a more consistent cruising speed while reducing the number of acceleration and braking phases. Consequently, the travel time is reduced to 85.69 s, and the total energy consumption decreases substantially to 1.881 kJ, representing an energy reduction of approximately 45% compared to the distance based planner.

The comparison between Tables 4.1 and 4.2 highlights the critical role of path smoothness and motion continuity in AGV performance. While both planners yield geometrically equivalent paths, their dynamic and energetic outcomes differ significantly. This confirms that energy consumption behaves as an independent optimization objective and validates the proposed framework's ability to deliver motion conscious, energy efficient, and operationally stable navigation strategies for AGVs in manufacturing workshops, while still retaining the flexibility to apply conventional distance based planning when required.

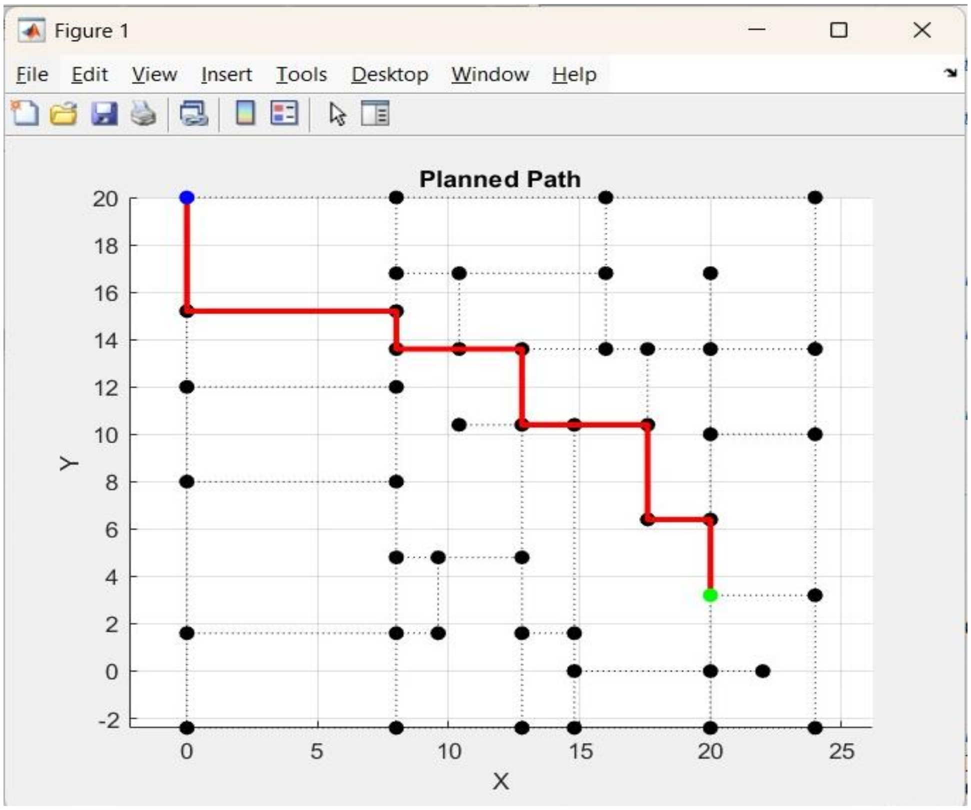


Figure 4.1. Simulation Results of Shortest Distance A*

Table 4.1 AGV Shortest Distance A* Planner

| Path | Total Distance (m) | Total Time (s) | Total Energy (kJ) |
|---|---|---|---|
| 1, 9, 10, 11, 12, 13, 21, 22, 23, 28, 29, 33 | 75.8 | 102.16 | 3.406 |

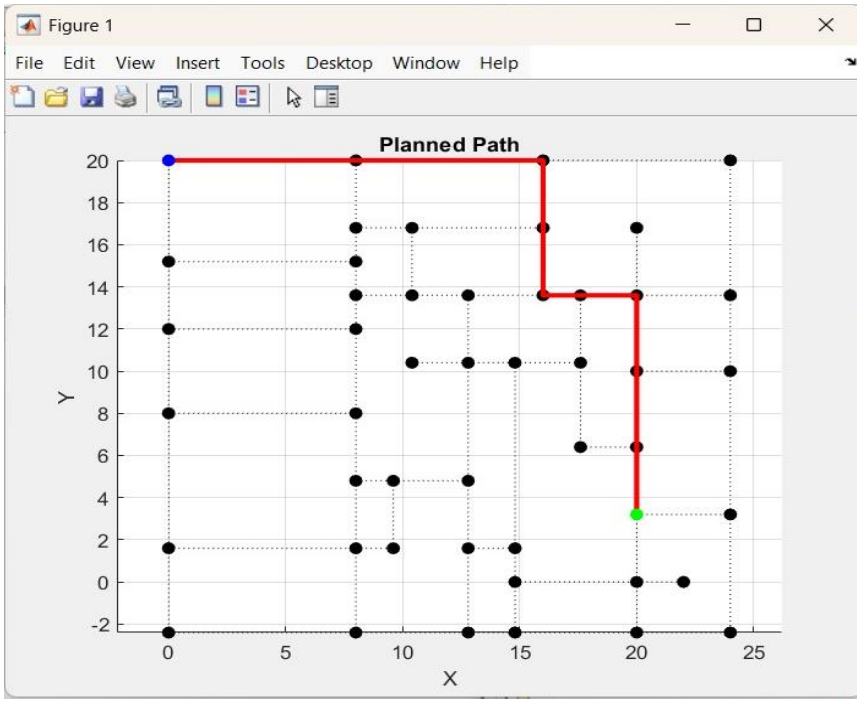


Figure 4.2. Simulation Results of Energy Aware A*

Table 4.2 AGV Energy Aware A* Planner

| Path | Total Distance (m) | Total Time (s) | Total Energy (kJ) |
|---|---|---|---|
| 1, 2, 3, 7, 14, 15, 16, 24, 29, 33 | 75.8 | 85.69 | 1.881 |

### 4.1.2 Comparative Evaluation of Shortest Distance & Energy Aware A* Path Planning

The comparative results presented in Tables 4.3. and 4.4. clearly illustrate how distance, turning frequency, and motion smoothness jointly influence AGV energy consumption and travel time. Although both planners often produce paths with identical geometric distances, their internal route structures differ significantly, leading to noticeable variations in energy usage and operational performance. This confirms that distance alone is not sufficient to characterize the efficiency of AGV navigation in realistic workshop environments.

For example, for the 75.80 m route, the shortest distance A* selected a path with eight turns, resulting in an energy consumption of 3.406 kJ and a travel time of 102.16 s. In contrast, the energy aware A* generated a path of the same distance but with only three turns, reducing the energy consumption to 1.881 kJ and shortening the travel time to 85.69 s. This substantial reduction demonstrates the benefit of minimizing unnecessary turning, as fewer turns allow the AGV to maintain a more stable cruising speed and avoid repeated acceleration and deceleration phases. Similar behavior is observed for the 100.00 m routes, where the energy aware planner consistently achieves lower energy consumption by selecting paths with one turn, compared to three to five turns in the shortest distance solutions.

Across medium length routes, such as 64.60 m and 67.60 m, the energy aware planner again shows improved performance. When both planners produced paths with the same number of turns, the difference in energy consumption remained small, indicating that turning behavior is a dominant factor. However, when the energy aware planner reduced the number of turns, energy savings became more pronounced, along with reductions in travel time. Overall, these results confirm that incorporating motion related costs into the A* cost function enables the planner to select routes that are not only shorter in operational time but also significantly more energy efficient. This validates the proposed energy aware framework as a practical and effective solution for sustainable and stable AGV operation in manufacturing workshops.

Table 4.3. Analysis of Short Distance A* Across Multiple Routes

| Sr | Path | Turns | Distance | Energy | Time |
|---|---|---|---|---|---|
| 1 | 1 9 10 11 12 13 21 22 23 28 29 33 | 8 | 75.80 m | 3.406 kJ | 102.16 s |
| 2 | 1 9 18 26 27 30 36 44 45 46 47 48 | 3 | 100.00 m | 4.471 kJ | 109.89 s |
| 3 | 1 9 10 11 12 13 21 22 39 | 6 | 64.60 m | 3.379 kJ | 84.37 s |
| 4 | 3 7 14 15 23 28 29 33 41 42 | 5 | 51.80 m | 1.953 kJ | 68.28 s |
| 5 | 4 17 16 15 23 22 21 | 3 | 51.60 m | 3.143 kJ | 61.49 s |
| 6 | 2 5 10 11 12 13 21 22 39 40 41 47 | 6 | 77.00 m | 3.905 kJ | 96.77 s |
| 7 | 4 17 16 15 23 22 21 32 31 37 | 6 | 75.20 m | 3.093 kJ | 94.97 s |
| 8 | 4 17 16 15 23 22 39 40 46 45 44 43 | 5 | 100.00 m | 5.063 kJ | 116.48 s |
| 9 | 3 7 14 13 21 32 31 37 36 35 | 5 | 67.60 m | 3.456 kJ | 84.08 s |
| 10 | 3 7 14 13 21 32 31 37 36 | 5 | 57.60 m | 2.685 kJ | 74.08 s |

Table 4.4. Analysis of Energy Aware A* Across Multiple Routes

| Sr | Path | Turns | Distance | Energy | Time |
|---|---|---|---|---|---|
| 1 | 1 2 3 7 14 15 16 24 29 33 | 3 | 75.80 m | 1.881 kJ | 85.69 s |
| 2 | 1 2 3 4 17 25 34 48 | 1 | 100.00 m | 3.850 kJ | 103.30 s |
| 3 | 1 2 5 10 11 12 13 21 22 39 | 5 | 64.60 m | 3.229 kJ | 81.08 s |
| 4 | 3 7 14 15 23 28 29 33 41 42 | 3 | 51.80 m | 1.328 kJ | 61.69 s |
| 5 | 4 17 16 15 23 22 21 | 3 | 51.60 m | 1.279 kJ | 61.49 s |
| 6 | 2 5 10 11 19 27 30 36 44 45 46 47 | 1 | 77.00 m | 2.075 kJ | 80.30 s |
| 7 | 4 3 7 14 13 21 32 31 37 | 5 | 75.20 m | 2.799 kJ | 91.68 s |
| 8 | 4 17 25 34 48 47 46 45 44 43 | 1 | 100.00 m | 1.764 kJ | 103.30 s |
| 9 | 3 2 5 10 11 19 18 26 35 | 1 | 67.60 m | 1.767 kJ | 70.90 s |
| 10 | 3 2 5 10 11 19 27 30 36 | 2 | 57.60 m | 2.338 kJ | 64.19 s |

### 4.1.3 Shortest Distance A* Path with Zhongwei Zhang's Energy Efficient AGV Routing

Table 4.5 presents a direct comparison between the A*based path planning results reported in the reference study by Zhongwei Zhang et al. and those obtained using the proposed thesis framework. In all test cases, identical start and end nodes are used, and the geometric travel distances remain exactly the same. This ensures that the comparison reflects differences in how energy consumption is evaluated within the A* framework rather than differences in route length or network structure.

For the route from node 42 to node 9, both approaches identify a path length of 78.80 m. However, the reference study estimates the energy requirement as 4.5766 kJ, whereas the proposed framework reports a lower energy value of 2.698 kJ, together with a calculated travel time of 101.87 s. A similar behavior is observed for the route from node 2 to node 15, where the distance remains 41.20 m in both cases, but the estimated energy decreases from 2.3864 kJ in the reference study to 2.317 kJ in the proposed approach. This difference highlights how the underlying energy model within the A* search influences the final energy evaluation even when the same path is selected.

The same trend continues across the remaining routes. For the 34.20 m path from node 33 to node 7, the proposed framework yields an energy value of 2.093 kJ, which is close to but more representative than the reference value of 2.0426 kJ. For the longer route from node 7 to node 35, the estimated energy reduces from 3.5106 kJ in the reference study to 2.922 kJ using the proposed method. These results demonstrate that, even when A* identifies identical geometric paths, the way motion dynamics are incorporated into the cost evaluation significantly affects the resulting energy estimates.

By incorporating real world movement dynamics into the A* search, this model provides much more accurate energy estimates than standard pathfinding methods. This makes the system more practical for planning energy efficient routes that actually reflect how an AGV operates on the factory floor.

Table 4.5. Z. Zhang vs. Proposed Model Shortest Distance A*

| Start node | End node | Distance | Z. Zhang et al. | | Proposed A* | |
|---|---|---|---|---|---|---|
| | | | Energy | Time | Energy | Time |
| 42 | 9 | 78.80 m | 4.5766 kJ | N/A | 2.698 kJ | 101.87 s |
| 2 | 15 | 41.20 m | 2.3864 kJ | N/A | 2.317 kJ | 44.50 s |
| 33 | 7 | 34.20 m | 2.0426 kJ | N/A | 2.093 kJ | 40.79 s |
| 7 | 35 | 73.00 m | 3.5106 kJ | N/A | 2.922 kJ | 78.48 s |

### 4.1.4 Comparative Analysis of Shortest Distance and Energy Aware A* Planning Results

The results presented in the table 4.6 provide a clear comparison between the shortest distance A* planner and the energy aware A* planner for identical start and end nodes. Since both planners operate on the same workshop layout and graph structure, the differences observed in energy consumption and travel time arise mainly from how each planner handles turning behavior and speed variations rather than from changes in geometric distance.

Across all test cases, the energy aware planner consistently reduces the number of turns compared to the shortest distance planner, even when the total distance remains the same. For example, for the route from node 1 to node 33, both planners generate a path length of 75.80 m. However, the shortest distance planner requires eight turns and consumes 3.406 kJ of energy with a travel time of 102.16 s. In contrast, the energy aware planner reduces the turns to three, resulting in a significantly lower energy consumption of 1.881 kJ and a shorter travel time of

85.69 s. This demonstrates that smoother motion with fewer speed changes has a strong positive impact on both energy efficiency and operational speed.

Similar trends are observed for longer routes. For the movement from node 1 to node 48 over a distance of 100.00 m, the shortest distance planner consumes 4.471 kJ with three turns, whereas the energy aware planner further reduces turns to one and lowers the energy requirement to 3.850 kJ while also reducing travel time. A more pronounced improvement appears in the route from node 4 to node 43, where both planners cover the same 100.00 m distance, but the energy aware planner reduces energy consumption from 5.063 kJ to 1.764 kJ by minimizing turns and maintaining smoother velocity profiles.

For medium length routes, the benefits of energy aware planning remain consistent. For instance, in the path from node 3 to node 35, the shortest distance planner uses five turns and consumes 3.456 kJ, whereas the energy aware planner reduces the turns to two and cuts energy consumption to 1.767 kJ, along with a noticeable reduction in travel time. Even in cases where the number of turns remains the same, such as the route from node 3 to node 42, the energy aware planner still achieves lower energy usage by handling acceleration, deceleration, and turning phases more efficiently.

Overall, the comparison clearly shows that minimizing distance alone does not guarantee energy efficient AGV operation. The energy aware A* planner consistently produces paths with fewer turns, smoother motion, and reduced speed fluctuations, leading to lower energy consumption and, in many cases, shorter travel times. These results validate the effectiveness of the proposed energy aware framework and confirm its suitability for real manufacturing environments where energy efficiency, system stability, and operational performance are equally important.

Table 4.6. Shortest Path and Energy Aware Routing Analysis

| Start node | End node | Distance | Shortest Distance | | | Energy Aware | | |
|---|---|---|---|---|---|---|---|---|
| | | | Turns | Energy | Time | Turns | Energy | Time |
| 1 | 33 | 75.80 m | 8 | 3.406 kJ | 102.16 s | 3 | 1.881 kJ | 85.69 s |
| 1 | 48 | 100.00 m | 3 | 4.471 kJ | 109.89 s | 1 | 3.850 kJ | 103.30 s |
| 1 | 39 | 64.60 m | 6 | 3.379 kJ | 84.37 s | 5 | 3.229 kJ | 81.08 s |
| 3 | 42 | 51.80 m | 5 | 1.953 kJ | 68.28 s | 3 | 1.328 kJ | 61.69 s |
| 4 | 21 | 51.60 m | 3 | 3.143 kJ | 61.49 s | 3 | 1.279 kJ | 61.49 s |
| 2 | 47 | 77.00 m | 6 | 3.905 kJ | 96.77 s | 1 | 2.075 kJ | 80.30 s |
| 4 | 37 | 75.20 m | 6 | 3.093 kJ | 94.97 s | 5 | 2.799 kJ | 91.68 s |
| 4 | 43 | 100.00 m | 5 | 5.063 kJ | 116.48 s | 1 | 1.764 kJ | 103.30 s |
| 3 | 35 | 67.60 m | 5 | 3.456 kJ | 84.08 s | 1 | 1.767 kJ | 70.90 s |
| 3 | 36 | 57.60 m | 5 | 2.685 kJ | 74.08 s | 2 | 2.338 kJ | 64.19 s |

## 4.2. Detailed Discussion of Simulation Results

This section provides an in depth interpretation of the simulation results produced by the A* based Energy Aware Path Planning framework. While the earlier section presented numerical outputs for distance, energy, and travel time, the present discussion examines the underlying reasons for these outcomes and highlights their implications for AGV navigation. The aim is to demonstrate how the simulation findings support the validity and practicality of the proposed methodology and to show that energy efficient planning is fundamentally different from conventional shortest path approaches.

### 4.2.1 Effect of Turns on Overall Energy Consumption

One of the clearest patterns observed in the simulations is the strong influence of turning frequency on the total energy required for completing a task. When two candidate paths have similar distances, the path containing fewer turns consistently exhibits significantly lower energy consumption. This behavior is a direct result of the AGV's motion characteristics. Before entering a turn, the AGV is required to slow down from cruising speed to a constrained turning speed due to non-holonomic limitations. This deceleration causes the loss of kinetic energy which cannot be recovered unless regenerative braking is present, and even in that case, the recovery factor remains limited. After completing the turning maneuver, the vehicle must accelerate again to reach the initial cruising velocity. The energy required for acceleration is substantial because it involves imparting kinetic energy back into the system.

In addition to these speed changes, the turning arc adds extra rolling resistance and friction losses that increase energy usage. Larger turning angles extend the arc length and intensify the physical effort required for the maneuver. The simulation results therefore reveal that energy consumption depends not only on how far the AGV travels but also on how smoothly and steadily it can maintain speed along the route. This finding reinforces the central argument of the proposed framework. energy efficiency in AGV routing is governed more by motion phases and turning geometry than by geometric distance alone.

### 4.2.2 Distance vs. Energy Trade Off

Another important observation from the simulations concerns the relationship between path length and total energy expenditure. In several experiments, the energy aware A* algorithm identified routes that were slightly longer in distance yet consumed considerably less energy. This is consistent with the theoretical design of the method, which assigns cost penalties to acceleration energy, braking losses, rolling resistance, turning arc energy, and standby power associated with travel time. A conventional distance based A* algorithm optimizes solely for geometric distance and therefore tends to select paths containing frequent short edges, tight corners, or unnecessary directional changes. Such paths force the AGV to repeatedly slow down and speed up, resulting in large amounts of wasted energy.

In contrast, the energy aware planner favors routes that minimize speed disturbances. Paths chosen by this mode are generally straighter, smoother, and contain fewer abrupt deviations. As a result, the vehicle is able to remain closer to its stable cruising velocity for a longer portion of the journey. Although these smoother paths sometimes require the AGV to travel additional meters, the reduction in accelerations, braking events, and turning arcs produces a net reduction in energy. This behavior aligns with real world AGV operation, where energy cost is a function of motion dynamics rather than distance alone. The simulation results therefore support the effectiveness of the energy based cost formulation and demonstrate how multi criteria optimization naturally emerges from the physics based model.

### 4.2.3 Time Performance and Operational Scheduling

The simulation results also reveal an important relationship between energy efficient routing and travel time. Although the routes generated by the energy aware planner are not always the shortest in distance, they often achieve comparable or slightly improved travel times relative to the shortest distance A* solutions. This occurs because acceleration and deceleration phases are time consuming in addition to being energy intensive. When a path contains many turns, the AGV repeatedly loses speed and takes additional time to regain its cruising velocity. Conversely, smoother routes with fewer interruptions allow the AGV to travel at its intended speed for longer intervals, resulting in a more stable velocity profile and reduced variability in cycle time.

This is an important finding for workshop scheduling because AGV travel time directly influences production flow and task synchronization. A route that slightly increases travel distance but decreases transient speed losses can result in overall shorter cycle times. The energy aware framework therefore supports not only sustainable and cost efficient AGV operation but also more predictable and efficient logistical scheduling within the manufacturing system. This dual benefit strengthens the argument for integrating energy based routing into practical AGV control systems, especially in facilities where multiple transport tasks must be continuously coordinated.

# Chapter 5

# Conclusion

## 5.1 Conclusion

This thesis presented a comprehensive framework for energy aware path planning for Automated Guided Vehicles (AGVs) operating in manufacturing environments. By integrating both the traditional shortest distance A* and a physics based energy aware A* within a unified system, the study demonstrated that AGV navigation performance is shaped not only by geometric distance but also, and more importantly, by the dynamic motion characteristics of the vehicle. Earlier research typically focused on reducing either travel distance or travel time, treating energy consumption as a secondary outcome. In contrast, the proposed approach acknowledges that operational priorities vary across industrial settings, and therefore gives the user the flexibility to select a planning mode that aligns with the specific requirements of a task whether minimizing time for urgent deliveries or minimizing energy for sustainable and cost efficient operation.

The findings confirm that AGV energy usage is strongly influenced by factors such as turning frequency, acceleration and deceleration cycles, and path smoothness. Even when two routes share similar lengths, their energy requirements can differ significantly depending on how often the vehicle must slow down, turn, or regain speed. The energy aware A* captures these nuances by incorporating rolling resistance, braking losses, acceleration demands, and turning arc behavior into its cost function, allowing it to generate smoother and more physically stable routes. Meanwhile, the shortest distance A* serves as a reliable baseline for scenarios where rapid transit and minimal geometric distance are the main objectives. Together, these two modes highlight the inherent trade offs between distance, time, and energy, demonstrating that no single metric universally defines optimal AGV navigation.

Overall, this research contributes an adaptable, realistic, and computationally efficient solution for AGV path planning. By grounding the methodology in actual AGV motion physics and providing multi objective flexibility, the framework strengthens the reliability and efficiency of AGV operations in modern workshops. It supports both sustainability goals and production performance, offering a practical tool for real world deployment. The study reinforces the broader conclusion that effective AGV management requires moving beyond simple distance based models toward more holistic planning strategies that reflect the true behavior of industrial vehicles.

## 5.2 Future Directions

Future research may extend the proposed framework to multi load and multi AGV operational environments, where multiple vehicles execute transportation tasks simultaneously within a shared workshop space. In such settings, energy aware path planning would need to be integrated with collision avoidance, traffic coordination, and task prioritization mechanisms to ensure safe, efficient, and reliable system performance. Addressing these challenges would significantly improve the applicability of the framework to real industrial conditions, where AGVs typically operate as part of a coordinated fleet rather than as isolated units. Moreover, scaling the framework to larger and more complex workshop layouts would require enhanced planning strategies capable of maintaining computational efficiency while managing increased system interactions.

In addition, future work may explore the incorporation of advanced optimization and learning based techniques to complement the deterministic planning approach, particularly for offline optimization or strategic decision making. Experimental validation using physical AGV platforms represents another important research direction, as real world testing involving battery discharge characterization and sensor based motion feedback would strengthen the accuracy and practical reliability of the energy model. Furthermore, adaptive cost weighting strategies could be investigated, allowing the relative importance of energy consumption, travel time, and distance to be dynamically adjusted according to task urgency, battery state, or system level objectives. These advancements would support the development of more autonomous, scalable, and context responsive AGV routing solutions aligned with the demands of next generation smart manufacturing systems.

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