Kaunas University of Technology

Faculty of Mechanical Engineering and Design

Impact of Automated Guided Vehicles on Logistics Operations in Manufacturing Enterprise "X"

Master's Final Degree Project

Hajar El Mastor

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Assist. Prof. dr. Laura Gegeckienė

Supervisor

Kaunas, 2025

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Industrial Engineering and Management (6211EX018)

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Task of the Master's Final Degree Project

Given to the student – Hajar El Mastor

1. Title of the Project

Impact of Automated Guided Vehicles on Logistics Operations in Manufacturing Enterprise “X”

(In English

Automatizuotų transporto priemonių įtaka logistikos operacijoms gamybos įmonėje „X“

(In Lithuanian)

2. Aim and Tasks of the Project

Aim: to assess the impact of automated guided vehicles on logistics operations in the manufacturing enterprise “X”.

Tasks:

1. to present the logistic processes that support operations in the manufacturing enterprise “X”;
2. to investigate the maturity level of the automated guided vehicles implementation in manufacturing enterprise “X”;
3. to study the performance of automated guided vehicles through statistical analysis;
4. to present the economic benefits of the application of automated guided vehicles in manufacturing enterprise “X”.

3. Main Requirements and Conditions

KPIs and operational cost savings are calculated for the case study of enterprise “X”.

4. Additional Requirements for the Project, Report and its Annexes

Not applicable

Project author	Hajar El Mastor		2025.03.07
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El Mastor Hajar. Impact of Automated Guided Vehicles on Logistics Operations in Manufacturing Enterprise “X”. Master's Final Degree Project, supervisor assist.prof.dr. Laura Gegeckienė; Faculty of Mechanical Engineering and Design, Kaunas University of Technology.

Study field and area (study field group): Production and Manufacturing Engineering (E10), Engineering Sciences (E).

Keywords: automated guided vehicle (AGV); manufacturing; performance; operational; logistics.

Kaunas, 2025. 57 p.

Summary

The research uses a mixed methods approach to study the impact of Automated Guided Vehicles (AGVs) on the logistics operations of a tier-1/2 automotive electronics supplier, namely enterprise “X”. Quantitative and qualitative tools are utilised to explore the impact of the implementation on the performance of plant operations. Logistics processes are mapped to show the scale of AGV implementation, and the preparations made for the robots' systematic integration and future scalability are presented. A maturity model is built based on industry practices discussed in the literature and company expectations for the automated solution. The model assesses implementation across six dimensions: system integration, autonomy, data and KPIs, workforce skills, efficiency, and AI/ML use. Expert professionals from the company are surveyed to diagnose the maturity stage of the AGV implementation. The maturity stage identified was “Standardised”. The strengths of the case company were in defining and tracking Key Performance Indicators (KPIs), while the weaknesses were in efficiency and AI/ML adoption. A quantitative statistical analysis was performed for the following KPIs: quality rate, utilisation rate, effective utilisation rate, performance rate, and total effective equipment performance (TEEP). Control charts that confirm system stability were graphed to identify that the underutilisation of the fleet was the limiting factor rather than technical performance, which was further confirmed by studying hourly average TEEP rates and performing correlation analysis. The economic section calculates the return on investment for the AGV fleet, yielding a positive IRR of 8%. The findings indicate that AGV deployment improves operational efficiency and provides scalable benefits at the operational and economic levels. The project presents a road map for industrial AGV/AMR systems implementation, using applied research methods to extract operational insights and assess maturity levels.

El Mastor Hajar. Automatizuotų transporto priemonių įtaka logistikos operacijoms gamybos įmonėje „X“. Magistro baigiamasis projektas, vadovė asist.dr. Laura Gegeckienė; Kauno technologijos universitetas, Mechanikos inžinerijos ir dizaino fakultetas.

Studijų kryptis ir sritis (studijų krypčių grupė): Gamybos inžinerija (E10), Inžinerijos mokslai (E).

Reikšminiai žodžiai: Automatizuotų transporto priemonių; gamyba; veiklos; logistikos; našumas.

Kaunas, 2025. 57 p.

Santrauka

Tyrime taikomas mišrus metodas siekiant ištirti automatizuotų valdomų transporto priemonių (AGV) poveikį automobilių elektronikos tiekėjo (1/2 lygio) gamyklos logistikos operacijoms, t. y. įmonei „X“. Naudojami kiekybiniai ir kokybiniai įrankiai, siekiant įvertinti AGV diegimo poveikį gamyklos veiklos rezultatams. Logistikos procesai yra suskirstyti ir aprašyti siekiant parodyti AGV įdiegimo poveikį, taip pat pateikiami pasiruošimai sistemingai integracijai ir robotų plėtros galimybėms ateityje. Sudarytas brandos modelis, paremtas literatūroje aprašyta pramonės praktika ir įmonės lūkesčiais dėl automatizuoto sprendimo. Modelis vertina įgyvendinimą šešiose srityse: sistemos integracija, autonomija, duomenys ir KPI rodikliai, darbuotojų kompetencijos, efektyvumas ir AI/ML naudojimas. Įmonės ekspertai buvo apklausti siekiant nustatyti AGV įgyvendinimo brandos lygį. Nustatytas brandos lygis – „Standartizuota“. Pagrindinės įmonės X stiprybės buvo pagrindinių veiklos rodiklių (KPI) apibrėžimas ir stebėsena, o silpnybės – efektyvumas ir dirbtinio intelekto bei mašininio mokymosi (AI/ML) diegimas. Buvo atlikta kiekybinė statistinė analizė šiems KPI rodikliams: kokybės rodiklis, naudojimo intensyvumo rodiklis, efektyvaus naudojimo rodiklis, našumo rodiklis ir bendras efektyvus įrangos našumas (TEEP). Kontrolinės diagramos patvirtino sistemos stabilumą, o koreliacijos analizė atskleidė, kad pagrindinis ribojantis veiksnys buvo sistemos neišnaudojimas, o ne techninės problemos – tai papildomai patvirtino valandinė našumo analizė. Ekonominėje dalyje nagrinėjamas AGV parko įsigijimo investicijų grąžos (ROI) skaičiavimas, atliktas remiantis darbo jėgos pakeitimu ir investicijų laikotarpio analize, parodė teigiamą 8 % vidinę grąžos normą (IRR). Rezultatai rodo, kad AGV diegimas pagerina veiklos efektyvumą ir suteikia plėtros galimybių tiek operaciniu, tiek ekonominiu lygmeniu. Projektas pateikia gairių žemėlapį pramoninės automatizacijos projektams, naudojantiems AGV/AMR sistemas, taikant tyrimų metodus praktinių įžvalgų gavimui.

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Abbreviations:

AGV – Automated Guided Vehicle;
AMR – Automated Mobile Robot;
IoT – Internet of Things;
RFID – Radio Frequency Identification;
ERP – Enterprise Resource Planning;
MES – Manufacturing Execution System;
KPI – Key Performance Indicator;
I-MR – Individual Moving Range;
FIFO – First In, First Out;
PCB – Printed Circuit Board;
SMT – Surface Mount Technology;
ROI – Return On Investment;
IRR – Internal Return Rate.

Introduction

Logistic processes lay the foundation for operational excellence in manufacturing organisations. The larger the organisation and the more diverse its product portfolio is, the more complex the supply chain becomes, and the more energy is needed to maintain it. The logistics department in a manufacturing organisation oversees ensuring the flow of material, information, and services from the start point at the suppliers to the endpoint at the customer. Logistics, however, is not a value creation discipline, and therefore, to stay competitive, it is critical to minimise cost while achieving the goal of delivering resources at the right time and quantity to the right place. In the modern day, logistics managers face challenges such as disruptions in global supply networks, labour shortages, current global uncertainty towards regulatory policies, etc. Logistics solutions are critical to achieving the overriding goals of reducing costs while ensuring the effective flow of resources. The industry has adopted various solutions to support manufacturing by scaling logistics operations, many of which are tied to automation. Automation solutions apply to physical material, information flow, network connections, and energy. The case company in manufacturing enterprise “X” is an international automotive tier 1/2 supplier that made the strategic decision to automate internal transport reducing the burden of relying on manual labour for repetitive transport jobs, eliminating the factor of human error in deliveries and improving workplace safety by cutting down strenuous movements associated with manual transport and handling activities. This move is replicated across the industry with big and small players adopting AGV/AMR systems for internal logistics automation in their warehouses and shop floors. As technology adoption levels increase, more and more companies are in the post-implementation phase of this technology, where it is essential to investigate its impact on operations by evaluating performance. Despite the unanimous recognition of this technology’s impact on operational efficiency, a gap in the literature persists in the post-implementation evaluation of operational performance. A quantitative assessment of the system’s efficiency is needed to support informed decision-making for future investments and for specialists to identify areas for improvement and align on target expectations. This research aims to comprehensively evaluate the implementation of an AGV/AMR system in the manufacturing enterprise “X”, focusing on operational performance evaluation.

Aim: to assess the impact of automated guided vehicles on logistics operations in the manufacturing enterprise “X”.

Tasks:

1. to present the logistic processes that support operations in the manufacturing enterprise “X”;
2. to investigate the maturity level of the automated guided vehicles implementation in manufacturing enterprise “X”;
3. to study the performance of automated guided vehicles through statistical analysis;
4. to present the economic benefits of the application of automated guided vehicles in manufacturing enterprise “X”.

Hypothesis: A combined quantitative and qualitative assessment of AGV implementation reveals the operational impact on the manufacturing enterprise.

1. Logistics Solutions in Manufacturing

Manufacturing or industrial logistics differs from service logistics in the complexity of its processes. Manufacturing organisations deal with challenges such as stringent industry-specific requirements, limited space for storage, workforce shortages, and increasing competition in markets that drive the profit margins down. A logistics solution in the industrial context is the product or service that addresses a specific gap to optimise operations. The driving factors of logistics solutions are industry trends, research findings, requirements of stakeholders, the behaviour of external players such as customers and competition, opportunities and risks in the market, legal and regulatory requirements, etc. Such factors continuously push decision-makers to reevaluate strategies and make calculated decisions to stay competitive. Decision makers choose to invest in solutions that strengthen their competitiveness and set them apart as industry leaders from the rest of the players [1].

1.1. Logistics 4.0 in Manufacturing

Coello et. al. summarise today's Logistic 4.0 strategies for logisticians in a manufacturing company and define the overarching concepts to be the combination of networking, digitisation, and automation [1]. A common challenge hindering an organisation's complete integration of manufacturing and logistics is the lack of effective data transmission between operations. In an ideal situation, operational excellence is achievable with both operations working synchronously. Technologies of Industrial Internet of Things (IIoT) aim to address this gap. However, the challenge lies in replicating the physical settings of both operations digitally. The overriding goal is to achieve real-time updates from both sides digitally, enabling real-time decision-making with no delays or lags [2]. Strandhagen et. al. study the manufacturing-logistics transformation necessary for the Engineer-To-Order operations model. They highlight the importance of digitisation in enabling processes and overcoming challenges identified in their case study. Fig. 1 highlights the challenges and the corresponding features that eliminate them.

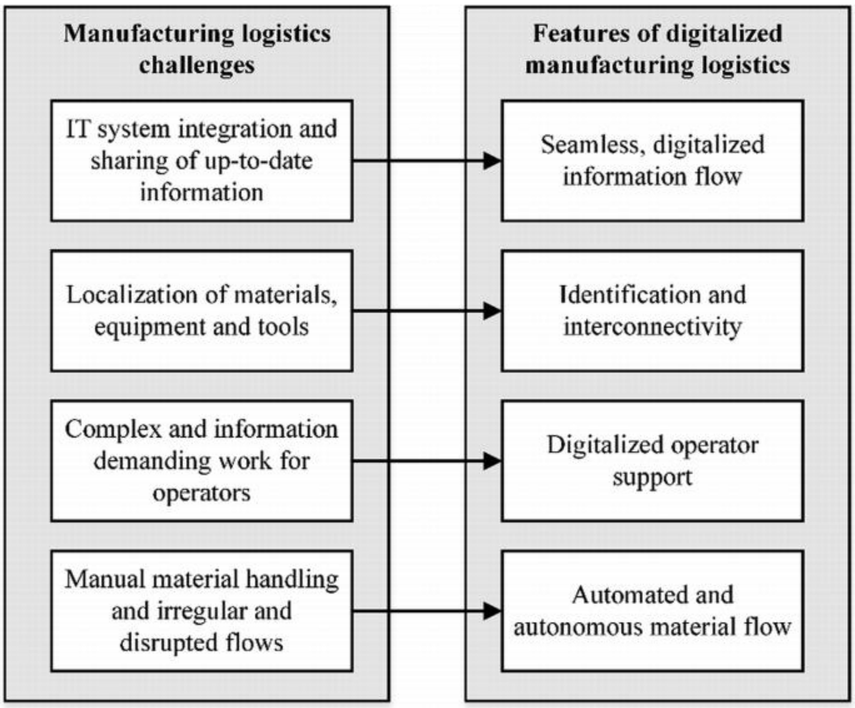

Fig. 1. Logistic challenges and digital features in solutions [3]

The authors propose digital information flows that update synchronously to tackle the need for real-time systematic updates. They also highlight the need to localise material of all kinds, aided by features that enable the identification and flagging of the position of the item in need. The nature of on-demand manufacturing increases the complexity of operations and puts increasing pressure on workers. The authors propose to provide support digitally to workers, improving work conditions and increasing productivity. Finally, to ensure a smooth and uninterrupted flow of materials, the authors recommend automating material flow using technologies such as AGV/AMR systems for autonomous transport [3]. Woschank et al. study the adoption of smart systems for industrial logisticians to target productivity and global competitiveness. In their research, they explain that a smart system uses progressive technologies to improve logistic processes, making them more responsive and effective by leveraging the early identification of errors and forecasting of demands through real-time assessment of inventory levels and consumption patterns [4]. Smart systems go hand in hand with IoT devices such as live location systems, sensors, RFID tags, fleet management systems, smart packaging, automated retrieval and storage systems. IoT devices support tracking material and equipment at various stages of handling, enabling visibility for traceability and navigation and reducing costs associated with waste. Additionally, using AI to process data collected from smart systems aims to shorten the time spent on decision-making or even automate it where possible. This applies to the augmentation of routes taken by automated vehicles on the shop floor and in warehouses. The goal is to reduce the time needed for the product to be produced, packaged, collected and prepared for dispatch and provide the organisation with more control over costs. Risks pertain to the security of the data against external dangers such as cyber-attacks, exposing companies' competitive practices and knowledge. Other challenges lie in the resistance to the change identified by research in the workforce when these technologies are implemented [5]. To model the value creation in manufacturing logistics, Meissner et. al. present the schematic in Fig. 2, which portrays how logistics creates value based on the assumption that customers will pay more for expedited delivery. The waiting time between production processes is eliminated, and distribution time is reduced to deliver the product to the market at a faster rate [6].

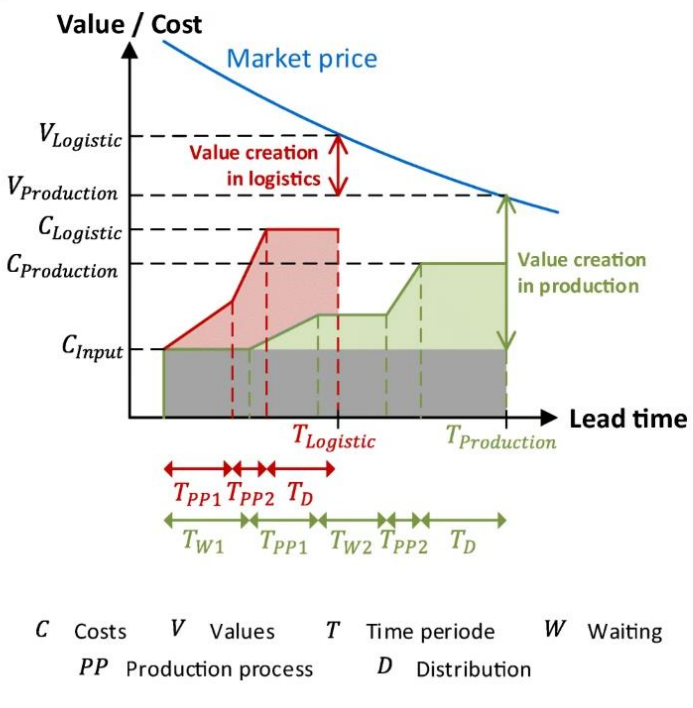

Fig. 2. A model that depicts how manufacturing organisations can increase value by improving logistics [6]

To target the challenges in employee perception, Cservenak et al. present an educational model that enhances students' engagement with Industry 4.0/5.0 technologies. The paper introduces the curriculum as a valuable tool within university settings to prepare future specialists with technological skills. Organisations can adopt this curriculum to educate their existing workforce and promote lifelong learning amongst their older employees to encourage them to remain updated with the technology landscape [7].

1.1.1. Maturity Assessment of Logistics 4.0 Implementations

Maturity assessments are highly relevant for transformative technology movements such as Industry 4.0, as they allow the organisation to benchmark its performance against other players and industry standards. Academic research provides practical models that evaluate performance through technology, process, safety, environmental, economic, operations, organisational preparedness, etc. There is an intersection between theoretical and practical research in maturity model studies. Researchers often prefer the case study approach to validate their models practically. The models assess organisations using the provided framework to provide an action plan for targeted areas of their implementation. The goal is to promote effective utilisation of existing resources and plan future investments productively. A popular Industry 4.0 maturity model that focuses on descriptive diagnosis of organisations is the 'acatech Industrie 4.0 Maturity Index'. The model supports individual adaptations of findings for roadmap creation. As shown in Fig. 3, the model adopts a structured approach that progresses naturally from the lowest maturity level (Computerisation) to the highest (Adaptability). This model rates organisations in the four target areas: existing resources, availability of information systems, the structure of the organisation, and finally, its culture. The paper tests maturity in 26 manufacturing organisations, aided by advanced questionnaires to identify the company's capability of achieving the proposed Industry 4.0 strategic targets. It offers a road map that proposes measures needed to achieve the targets [8].

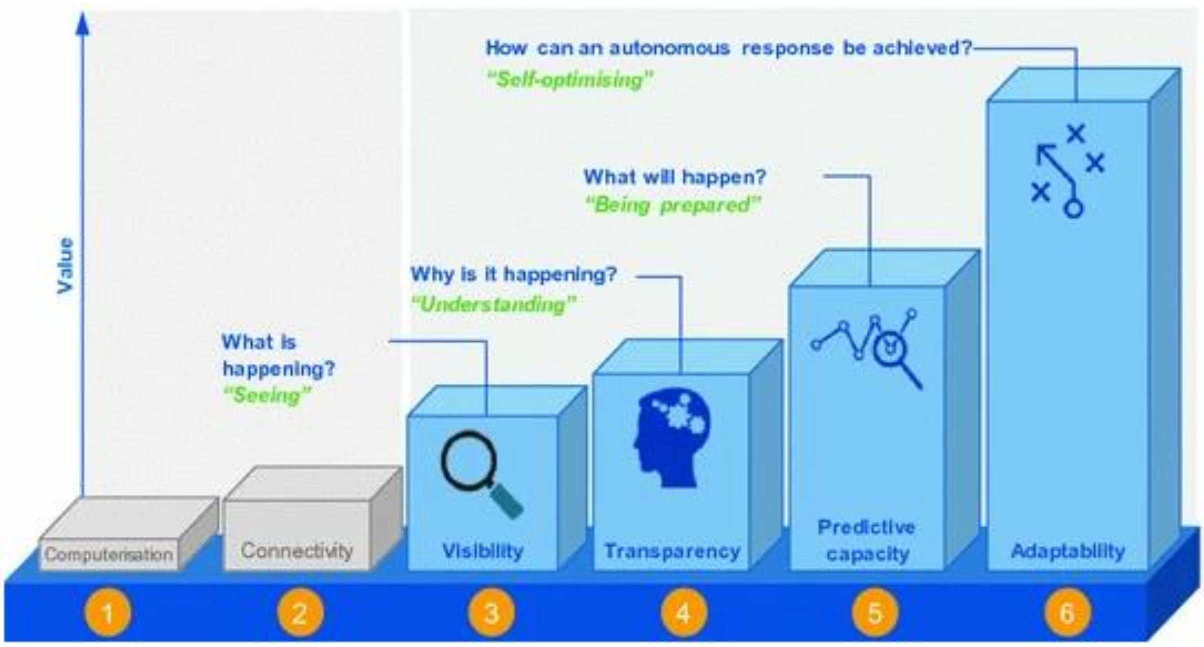

Fig. 3. Schematic illustration of the 'acatech Industrie 4.0 Maturity Index' model [8]

SIMMI 4.0 (System Integration Maturity Model Industry 4.0) is another popular maturity model that classifies enterprises based on their Information Technology systems and their fulfilment of Industry

4.0 requirements. The model performs at an enterprise level, assessing the horizontal and vertical integration, the digitisation, and technological resources. It does this in five levels, from level 1, which indicates basic digitisation, to level 5, which depicts optimisation of digitisation and value network simulation that performs in real time. The model assesses the communication between the physical assets (machinery, material, infrastructure) and enterprise management systems and data flow across functional areas and departments. It also evaluates the extent of digitisation of physical engineering processes throughout the product's lifecycle, the implementation of cloud computing, cybersecurity measures, and the adoption of big data in analysis. Compared to the previously discussed model, a limitation of SIMMI 4.0 is that it is derived from academic literature but not tested in practice. However, it does provide a systematic view for evaluating an organisation's technology readiness based on Industry 4.0 principles [9]. Alternatively, Facchini et. al. present a logistics-specific maturity model that evaluates organisations ' position based on three dimensions: management, material flow, and information flow. The model is empirically validated through application in two real manufacturing organisations, and radar charts were deployed to represent the results visually. The outcome is the organisation assessment that varies across five levels, rating the companies based on organisational readiness, technical infrastructure, and digital capability [10].

1.1.2. Automated Guided Vehicles in Manufacturing

E. A. Oyekanlu, et al. describe that AGV and AMR are names used interchangeably in literature to describe the same unmanned autonomous vehicles that automate transport tasks in industrial environments, with AMR referring to more autonomy and less reliance on guiding infrastructure [11]. In this paper, we refer to both types as 'AGVs', as they are commonly called in practice and at the company where the case study is performed. Steclik et al. describe that AGVs play a significant role in Industry 4.0 and are the equivalent of the conveyor belt that spearheaded the Second Industrial Revolution and was paramount to the rise of mass production. The authors also highlight that AGVs have been in the industry for decades, but their current mass adoption levels can be attributed to the new challenges faced by the industry [12]. Automation takes place when technology performs tasks that would otherwise require a level of human input. Transport waste is often disregarded in logistics practices, which leads to an exponential increase in costs in the form of wages, training, materials, space, energy, etc. Organisations enable cost savings through practices such as the implementation of AGVs [13].

Various industries adopt AGV technology to automate material handling, which is attributed to the technology meeting the following five criteria: mobility, universality, scalability, modularity, and compatibility with different applications. AGVs enable flexibility in intralogistics, which is important in highly dynamic environments such as manufacturing. Kopp et al. study the different points of view on AGV implementations: the perspective of the decision-makers against the beliefs of the operational staff in ten manufacturing organisations in Germany. The paper highlights the organisational factors that affect the success of AGV implementation with an emphasis on employee acceptance and how this affects the output of implementation projects [14]. Zuin et al. criticise the literature's focus on the technical aspects of AGV implementation and neglect of the operational characteristics that are equally important to the system's performance [15]. Coelho et al. delve deeper into the implementation of AGVs by building a model to simulate an automotive case study to identify improvements that decision-makers can use to optimise their in-house logistics processes. The authors comment that existing scientific research lacks a comprehensive evaluation that targets the internal logistics of manufacturing enterprises [16].

Kathmann et al. study the possibility of adapting existing autonomous vehicles' self-driving technology to improve AGV performance, inherently improving logistics efficiency. The authors present their aim that in automotive autonomous vehicles should act as AGVs that drive between workstations, eliminating the use of conveyors and performing the handover through machine-to-machine communication. VDA 5050 sets the guidelines for the interface, enabling communication between the master control and the vehicle. The aim is to accommodate flexible manufacturing systems, allowing the production of different product variants on the same equipment and shortening the time to market durations [17].

Invented in the USA at the beginning of the 1950s, the first AGV-like vehicle concept was currently inducted or what is known today as wire-guided vehicles. A few years later, the concept of similar self-guided vehicles entered Europe through England. Initial prototypes followed painted lines on the floor that were sensed by the robots using optical sensor technology. The automation boom in the 1970s, 80s, and 90s meant that early advancements in AGV technology were made and adopted for automating intralogistics. The rise of better electronic devices, processing capabilities, and stronger batteries enabled automated charging of these vehicles. The uses of AGVs varied from their usual application in intralogistics to acting as a moving station that connects production equipment. At that time, the main blocking point to the technology's wide expansion was the cost and lack of compatibility with manual processes. The automotive industry played a great role in enabling the technology by continuing to promote its use and supporting AGV research and development initiatives. In the late 1990s and early 2000s, AGV control systems became PC-based, allowing the vehicles' physical guidance to be eliminated with programmed free movement. Additionally, Wi-fi entered the picture, enabling optimal data transmission between system components. Today, AGVs are supported by separate modules that enable communication, driving, load handling, energy management, and safety control. Innovations in obstacle and deadlock prevention, smart handling of material coupled with other robotic applications as well as real-time data analysis and machine learning supported with AI sit at the top of the current and foreseen improvements in AGV technology as the vehicles remain a tool for enabling intralogistics across manufacturing shopfloors and warehouses [18].

Koreis et al discuss the value of human-robot collaboration in AGV-assisted picking activities and the importance of analysing the entire system to optimise the performance of the vehicles. The authors perform a comprehensive literature analysis, considering performance data and economic implications on decisions to invest in the technology. The paper looks at the effect of AGV-human collaboration on order picking efficiency and duration for task fulfilment. The findings showed that adding robots yielded higher results until the results plateaued, then eventually increased the time taken to pick up orders. The study takes into account the distance warehouse workers travel and the number of workers in the same work area. The authors acknowledge the limitations of their research due to the single case study approach taken. The authors use a mixed methods approach to evaluate over 140,000 data points of picking jobs in the same company over five months. The large dataset and the statistical model yield solid statistical findings supported by data collected from the warehouse management system. The study analyses the time taken for each order to be picked relative to the overall level of automation calculated by comparing the number of human workers to AGVs in that specific work area performing order picking activities. It is worth noting that the research focuses on a warehouse environment where both human and AGV pickers are needed, and full automation is not planned. The authors explain that less than 3% of warehouses are entirely automated, so studying the optimum mix between human and AGV pickers for high performance levels is highly relevant. The paper aims to fill a gap in the literature by moving from the isolated local level usually adopted in AGV performance analysis to provide an analysis that considers the entire logistics system [19].

Likewise, Shakeb et. al found that increasing the number of AGVs improves performance to a certain point, followed by a plateau of the results and a decline in efficiency perceived. The paper considers the combination of the fleet's size and the vehicles' velocity to evaluate the effectiveness of the utilisation of resources. The researchers perform a simulation experiment to model the flexible manufacturing system employing Design of Experiment (DOE) tools to shorten the process and improve experimental output [20]. Faccio et.al study different designs for the implementation of AGV/ AMR systems based on the level of automation of unloading and loading to manufacturing machines to select the most optimal operational and economic performance. They propose four different scenarios, starting with a completely manual model where the presence of operators is necessary to trigger the AGV/AMR job for the vehicle to arrive and pick up the load unit. In the second model, the operators are still needed to load and unload machines. However, buffers are stored to use material until the AGV/AMR arrives to collect or deliver. The author explains that an advantage of this model is that the use of operators eliminates the cost of quality issues, as operators perform inspection for visible defects, but also reduces the number of operators compared to the first model. The third case model eliminates the need for operators, as unloading and loading are done entirely by AGVs/AMRs.The fourth model proposes that the AGV/AMR stays parked at the machine until it collects load units; therefore, another empty robot must deliver. The authors build a mathematical model calculating the cost of each case for both the AGV and AMR options based on company-specific assumptions and input parameter values. The paper uses sensitivity analysis to estimate the possible variation of expected values. The overriding goal of the study is to determine which of the parameters influence the cost of the implementation. The authors use tools such as Pareto charts and contour plots to identify that cycle time and average route length are the parameters that influence the cost the most in all studied scenarios. The authors also conclude that the longer the travelled routes, the more economically viable it is to invest in AMRs compared to AGVs [21].

Prunet. et al study human factors that affect logistics and manufacturing systems. The paper aims to solve math problems in research using human factors to optimise industrial systems from the Operations Research (OR) perspective. OR is the discipline that aims to make better decisions by analysing work ecosystems, developing a model to compute factors affecting the ecosystem mathematically, designing algorithms to solve the problems and evaluating the results of the outcome of the solution. The authors evaluate application areas such as warehousing, vehicle routing, scheduling, etc., and modelling approaches such as mathematical programming, simulation, etc. As the paper is a literature review, the authors review 340 papers in their final corpus. They discuss underrepresented topics for future research to focus on. The authors highlight the need for more work to study optimisation problems to understand the impact of technological solutions and the importance of researching industrial applications to link theory to practice for better academic research [22].

1.2. Automated Guided Vehicles in Smart Warehouses

Van Geest et al. discuss the advantages of the ‘Smart’ Warehouse over a traditional warehouse, which is not optimised with advanced technologies, processes, and infrastructure. First, smart warehouses update information in real time, enabling immediate resolution of incidents and faster delivery times. Second, automated transport plays a great role in replacing ineffective manual labour, saving on costs and improving the working environment for workers. Third, the automation of processes improves definition and enables scalability. A process can be scaled up or down with minimal changes, which is advantageous for organisations in today’s volatile markets. Finally, smart warehouses use space more effectively and operate around the clock with lower manual intervention, allowing for better order planning and automated decision-making regarding inventory and its replenishment levels. The paper studies the example of an industrial warehouse that uses multiple smart technologies to propose a strategy for companies planning to transition from the traditional warehouse approach. The authors present their feature diagram of a smart warehouse shown in Fig. 4 [23].

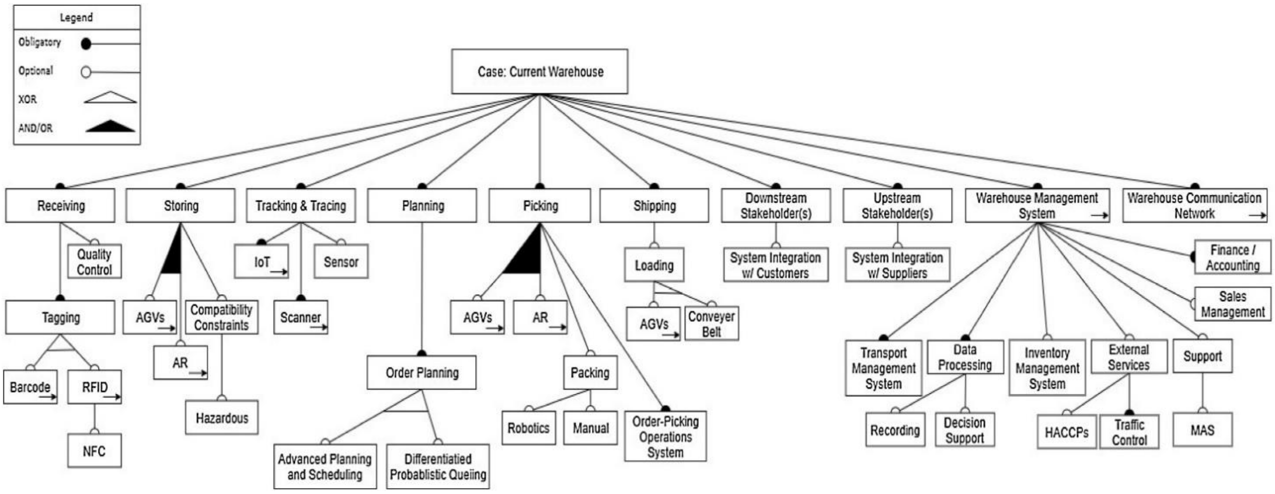

Fig. 4. Case study of industrial smart warehouse: Feature diagram [23]

The authors contrast the feature diagrams of smart and traditional warehouses and identify obligatory and optional elements present in either or both. In the discussed case, AGVs for storage are highlighted as optional, while tagging of received goods and tracking them using IoT devices are classified as obligatory [23].

Ellithy et. al discuss the shift of smart warehouses from the traditional order picking model, where workers travel to pick orders, to the approach where orders are delivered to the workers. Amazon‘s Kiva adopts this shift with robots bringing storage units to the workers' stations, reducing walking time and human error. The authors spotlight the role of AGVs in this application, supported by barcode scanning and light indicators to guide operators on actions needed to achieve optimal effective dispatching of orders. The paper discusses technologies that support autonomous AGV navigation and prospects for dynamic connections with other IoT devices within the warehouse. The authors foresee an increase in the adaptability of AGV systems for a “Plug and play” setup experience with minimal efforts for integration with existing interfaces, layout and robot fleet [24]. Patricio et. al. refer to distribution warehouses of mega sellers such as Amazon and Alibaba as fulfilment centres. They operate large numbers of AGVs/ AMRs in areas separated from humans to distribute products internally at higher speeds without compromising safety. The study spotlights AGV and AMR systems' methods to facilitate flexibility for just-in-time, dynamic storage, and cross-docking practices. In manufacturing, the vehicles enable a flow of materials to production instead of batch deliveries, reducing line-side storage and the costly space occupied in production shop floors. The paper notes that although AGV hardware improvements are underway, there is an implementation barrier due to the complexity of integration into local processes and digital systems. Machine learning, object recognition, and swarm intelligence are expected to enable easier adaptation and interoperability of these systems [25].

1.3. Chapter Summary

This chapter explores state-of-the-art literature on manufacturing logistics, starting with the impact of logistics solutions on the challenges faced by the industry, such as limited storage, labour shortages, etc. It identifies that automation and digitised data integration are fundamental discussion points in logistics 4.0-related research papers. Infrastructure readiness for automation systems, such as AGVs, is emphasised, looking deeper into the synchronisation of logistics and manufacturing modules. Research shows the industry’s commitment to AGV/AMR systems over the years as a solution for automating material transport. For manufacturing organisations, the implementation barrier is the complexity of the processes and the lack of know-how. There is still no solution in the market that is sufficiently universal to plug into any operations physically and digitally. Nevertheless, organisations view these systems as strategic investments that address market challenges, demonstrating that while the technology is not new, it remains exceedingly relevant in tackling current industry needs. Next, the chapter studies maturity models for assessing industrial technological solutions, presenting the acatech Industrie 4.0 Maturity Index and the SIMMI 4.0. Both models provide common criteria for evaluating organisation-wide 4.0 implementations in terms of data integration, organisation preparedness, system infrastructure, etc. The Facchini logistics-specific model deep dives into the maturity assessment of context-specific aspects. The model discusses criteria to diagnose system readiness of material transport automation systems, such as AGV/AMR. Furthermore, the chapter examines AGV technology to understand system-specific technical criteria related to network, control systems, connectivity, and supporting infrastructure. It also discusses operational factors that affect the success of the technology‘s implementation, such as employee acceptance, human-robot collaboration and process improvements. Additionally, smart warehouses and their role in achieving scalability, responsiveness to industry volatility, optimal inventory management practices, etc, are discussed. In summary, many industries deploy AGV/AMR systems to automate internal transport systems due to their adaptability, scalability, and strategic value in the manufacturing logistics interface. The challenge lies in the physical and digital integration into existing processes and infrastructure. The success of the implementation relies on the combination of robust technology, digital integration and operational adaptation.

2. Methodology for Research in the Company “X”

2.1. Research Methods in Literature

To assess the impact of the AGV system implementation in company “X”, we evaluate the research methods adopted in the literature to solve similar research problems. As a result, the following chapter discusses research methods commonly applied by similar experiments. The criteria for choosing the research methods are the following:

- The relevance to technological and industrial applications.
- The availability of the tools and practical feasibility based on knowledge and time constraints.
- The compatibility with the data available at the company “X”.

2.1.1. Case Study Research

Case study research is a common method for studies of technological implementations, as it allows both quantitative and qualitative analysis of practical applications with the possibility to test hypotheses in real settings. Namely, Ramos et. al. research the use of mining methods as a tool to discover inefficiencies in the performance of an AGV fleet, taking an automotive manufacturing plant as the object of their case study. The authors analyse extracted event logs from the AGV management interface to perform a comparative performance evaluation of over two hundred runs of an AGV fleet in seven days. Results compare the performance of the vehicles to expected values of cycle time and route fulfilment [26]. Similarly, this research aims to extract quantitative insights into the product's performance by analysing data extracted from the primary sources, such as the fleet management system. Likewise, Vlachos et al. present a case study of a manufacturing plant that adopts AGVs to automate material handling. The paper aims to develop a smart model for AGV implementation that suits flexible manufacturing systems. KPIs that exist in the organisation are used to measure the performance of AGVs in addition to workload and capacity calculations. The results show the implementation outcome before and after adding an IoT device that improves operational performance significantly. The authors emphasise the value of the results-based evaluation approach to derive practical insights into the system efficacy [27]. Furthermore, Correia et. al. adopt the case study approach to eliminate non-value-added activities using a tool for Value Stream Mapping (VSM). The authors extract data on the time an AGV spent on a transport job and the distance travelled by each vehicle from primary sources, starting with estimated values and comparing them against actual values post-experiment for validation. This approach is common amongst case studies that evaluate AGV system utilisation as it quantitatively predicts performance and benchmarks it against results of the real system [28].

The common point between these papers is that case study research allows data extraction from primary sources. Primary data is integral to the relevance and novelty of the authors’ empirical research findings. However, the limitation with case studies often lies in the researchers’ focus on single case scenarios (location, problem, application, etc.), which can affect the generalisability of findings. Results from case studies must be validated in other settings to confirm reliability.

2.1.2. Maturity Models Research

Assessing the maturity level of technology implementations is a must to measure the current levels of readiness at an organisation. Maturity models facilitate benchmarking against industry standards and other organisations’ performance. Halse et. al. assess the maturity of IoT technological implementation at four Norwegian manufacturing companies. The aim is to determine the companies' level in terms of technology adoption using the 8-level scorecard. The authors develop their model based on the methodology of the six consecutive stages illustrated in Fig. 5: scope, design, populate, test, deploy and maintain.

Fig. 5. Stages of maturity models development [29]

The authors start by defining an IoT object to scope the target of their maturity model. Next, they design their model according to the manufacturing automation pyramid. The next step is to populate the model. At the first level of maturity, the organisation implements means of traceability in the warehouse/shop floor and uses an ERP system to manage it. At the second level, the authors expect the company to have at least one Industry 4.0 object with technological assets controlled at a distance or programmed. At the third level, the enterprise has two to nine Industry 4.0 objects that communicate with each other using a central control system or internet-supported connection with external services or data. Next, at the fourth maturity level, automation increases with objects in the system forming networks that communicate together using robots. At the fifth level, the company uses ’smart manufacturing’ or ‘smart warehousing ’ concepts, whereby as many objects as possible communicate horizontally and vertically with planning and management systems. Additionally, robots are expected to have a large role in the automation of manual tasks and processes. Companies at the sixth level are expected to have robot-human interaction between their IoT objects and their workers, adopting machine learning methods to improve performance and control their lifecycle. At this level, data and its exchange and storage have great importance for the enterprise, as it can be used strategically to enhance value creation. Consequently, at the seventh level, organisations support big data management from both internal and external sources in analysis for business intelligence. The eighth level is also the last signifying full Industry 4.0 maturity, where all objects are connected using IoT, allowing constant communication and exchange of data. At this stage, full automation of warehouse and production systems is expected, with manual work where human value creation is critical. Performance of objects is monitored in real-time, and data collected is used to predict issues. The populated maturity model, as defined, is tested at four Norwegian manufacturing companies through interviews and surveys with the case companies [29].

Hetmanczyk builds the maturity model in his research by identifying the six most important key areas relevant for the robotisation of production processes. The author identifies the automation of production processes, robotisation of these processes, digitisation of intralogistics (warehouse), the flexibility of production processes and the integration between management and production processes. The five-level maturity model (ML) ranges from ML1 to ML5, assessing the current state of robotisation at 200 medium and small manufacturing companies against the target state of robotisation based on industry standards. The author scales this maturity model based on the characteristics of the current state, advantages and disadvantages, areas for growth and development recommendations. The author proposes an algorithm to assess the current level of maturity, sets a target level and identifies the action required to achieve it. Finally, the author validates the model empirically through a survey of companies. The survey consists of a diagnostic section and a strategic planning section where organisations share their development plans for the near future (3 years), resulting in a transformation readiness framework [30].

2.1.3. Statistical Analysis Reserach

Eschemann et. al. use metric-based control charts to detect unexpected variations in AGV fleet performance automatically. The research aims to integrate anomaly detection into the AGV system to improve awareness and mitigate the impact caused by operational variability. The authors acknowledge that dynamics in a production environment fluctuate significantly within a short duration, affecting the utilisation of robots and the number of transport jobs. To flag these scenarios, the use of Shewhart control charts to analyse process stability and deviation over time is proposed. The paper also introduces dynamic control charts, enabling dynamic thresholds calculated based on weighted moving averages. [31]. Similarly, López et. al. establish an approach to evaluate the efficacy of AGV performance in dynamic factory settings, integrating statistical analysis in the simulation of the AGV transport systems. The paper adopts normal and exponential distributions to test simulated variations in fleet size and demand for transport jobs, aiming to obtain optimal parameters for case-by-case settings [32]. Furthermore, Salazar et. al. apply a combination of DOE and simulation methods to analyse the performance of AGVs using statistical tools such as ANOVA to determine the effect of the change of the system design parameters on defined performance metrics such as utilisation, waiting time, and job flow durations [13].

2.2. Research Design

2.2.1. Maturity Model

This research adopts several methods to collect data about the target organisation’s operations. The aim is to provide relevant practical insights regarding the deployment of AGVs. First, the maturity level of the implementation at company “X” is identified. A model is developed according to the framework proposed by the literature. A diagnostic approach is adopted to assess the maturity level of the implementation at company “X”. The model has five levels of maturity, starting with Level 1, indicating the lowest maturity, to Level 5, with the highest maturity. The maturity level is described qualitatively in short form, with key processes, technological and operational factors listed. Table 10 presents a compilation of findings from the theory studied in the previous chapter, as well as insights examined at the case company.

An assessment framework is developed to quantitatively assess the maturity level of the implementation at company “X”. The framework rates maturity based on the six dimensions evaluated as critical for the success of AGV implementation. The framework is used in a survey for experts working at the case company to diagnose the maturity level based on their expertise. The participants are the directly involved professionals responsible for the AGV implementation at the case company. Their responsibilities include calculating the business case, planning operational integration, providing training to the workforce, and daily reporting of AGV KPIs at different levels. Participants are chosen due to their expertise in technical, operational, and organisational topics related to the implementation. It is important to note that the participants are not specialised in technical or maintenance engineering, as they are logistics specialists with a broad scope of knowledge sufficient for operational implementation. In Table 1, the profile of the survey participants is presented.

Table 1. Role of the participants and their experience

Participant's Role in Enterprise "X"	Experience
Head of Logistics Engineering	Works for 5 years as the head of the logistics engineering team at company "X". Oversees strategic logistics topics at the company. The Local sponsor of the AGV implementation. Reports AGV KPIs to the global logistics leadership.
Logistics Engineer	Works for 3 years at the logistics engineering team at company "X". Expert in charge of operational implementation of AGVs. Responsible for the setup of infrastructure, tracking of AGVs KPIs locally and workforce training on AGV operations.

As the implementation is a highly specialised process in company "X", the two participants are the directly responsible individuals with the right depth of knowledge to assess the maturity level. For this expert-based evaluation, data quality was deemed more important than volume, aligning with best practice in case study research design. The expertise of the first participant supports input from the perspective of operational readiness, while input from the second participant contributes a deep technical assessment of maturity. The template used for the survey is presented in Appendix 1. The participants were requested to rate the implementation on each category by selecting one level (from one to five) that describes the current state of AGV implementation in company "X". The levels were defined to them briefly in the survey document. The main aim was to rate each of the six dimensions: system integration, autonomy, data analytics and KPIs, skills of the workforce, efficiency and use of AI/ML. The assessment framework describes each maturity level as follows:

1. Initial (Level 1) represents an isolated approach adopted for the implementation pilot.
2. Managed (Level 2) represents the partial integration into the system with process limitations.
3. Standardised (Level 3) represents improved integration with the performance KPIs defined.
4. Optimised (Level 4) represents improved efficiency levels and active optimisation of processes.
5. Autonomous (Level 5) represents full automation of material transport, minimal human input and auto-optimisation of systems.

In Table 2, the first criterion of maturity is presented. The category assesses AGV systems' integration with operational management systems such as ERP and MES (most relevant to the case company). In level 1, the matrix assumes no integration between the AGV fleet management system and ERP or MES. Jobs are initiated strictly through the fleet management system interface. In level 5, the system is expected to use real-time AGV data in higher planning for dual-directional decision making and exchange of data, hinting at full integration with enterprise management software and its tools.

Table 2. Evaluation Category 1: System Integration

Evaluation Category	Descriptions by Maturity Level (1–5)				
	Initial (1)	**Managed (2)**	**Standardised (3)**	**Optimised (4)**	**Autonomous (5)**
System Integration	No integration with ERP/MES.	Partial integration with ERP/MES	Full integration with ERP/MES	Integration with ERP and data is used for forecasting	Connected in full to enterprise systems and cloud

In Table 3, the second criterion for the evaluation is presented. This category rates the robots‘ ability to perform independently with low levels of human input. It rates navigation, execution of jobs, and response to changes in the environment. At the first level of maturity, manual troubleshooting of robots is common, and autonomy is yet to be achieved. At the fifth level, robots are good at adapting to changes in their environment and are capable of navigating in complex scenarios.

Table 3. Evaluation Category 2: Autonomy

Evaluation Category	**Descriptions by Maturity Level (1–5)**				
	Initial (1)	**Managed (2)**	**Standardised (3)**	**Optimised (4)**	**Autonomous (5)**
Autonomy	Manual operation and no autonomy	Semi-autonomous with frequent manual input	Autonomous navigation in fixed paths	Dynamic rerouting and adaptive navigation	Self-adaptive with minimal intervention

In Table 4, the third criterion of maturity, data analytics and performance metrics, is presented. The category evaluates the level of digital tracking, analysis and reporting of performance meters. At the initial level, there are no defined performance metrics to be tracked, and the reporting is done arbitrarily. At the fifth level, the performance metrics are in place and are used for autonomous analysis of data that is fed back in a loop to the system to support job planning and execution.

Table 4. Evaluation Category 3: Data Analytics and Performance Metrics

Evaluation Category	**Descriptions by Maturity Level (1–5)**				
	Initial (1)	**Managed (2)**	**Standardised (3)**	**Optimised (4)**	**Autonomous (5)**
Data Analytics & Performance Metrics	No KPI tracking and manual reports only	Basic KPIs are tracked manually	Automated real-time KPIs. Dashboards used	KPIs are analysed for performance optimisation decisions	Predictive and prescriptive analytics

In Table 5, the fourth criterion of maturity, workforce skills, is presented. The criterion is an important indicator of organisational readiness, and it assesses the competency of the workforce in troubleshooting and working with robots to support the smooth flow of operations. At the first level of maturity, no training is provided to operators regarding AGV activities. At the autonomous level, the AGV system is self-managed; however workforce is trained to monitor performance, analyse data and implement new AGV use cases.

Table 5. Evaluation Category 4: Workforce Skills

Evaluation Category	**Descriptions by Maturity Level (1–5)**				
	Initial (1)	**Managed (2)**	**Standardised (3)**	**Optimised (4)**	**Autonomous (5)**
Workforce Skills	No AGV-related training and no workforce awareness	Limited training and support are needed from the supplier	All operational workforce is trained on the basic AGV problems	Proficient troubleshooting and optimisation by the workforce	Minimal human input and proactive system support

In Table 6, the fifth criterion of maturity, efficacy and usability, is presented. The category evaluates the utilisation of the AGV fleet and the efficiency of its performance. At the initial maturity level, AGV utilisation rates are low due to ineffective planning and the lack of resources and knowledge to optimise operations. The outcome is higher downtimes and lower performance levels. At the highest maturity level, the system achieves utilisation targets, performs at the highest level and enables effective logistics planning.

Table 6. Evaluation Category 5: Efficiency and Usability

Evaluation Category	**Descriptions by Maturity Level (1–5)**				
	Initial (1)	**Managed (2)**	**Standardised (3)**	**Optimised (4)**	**Autonomous (5)**
Efficiency and Usability	Very low utilisation and high downtime	Basic usability and high delays	Improved efficiency and reliable usage	High utilisation and low cost per move	Near 100% optimisation; peak efficiency

In Table 7, the sixth criterion, Artificial Intelligence (AI) and Machine Learning (ML) adoption, is presented. At the first maturity level, the AGV system is not supported by AI and ML algorithms and operates on PLC programmed instructions with no intelligent behaviour. At the fifth level of maturity, the system uses AI/ML to adapt and learn from previous jobs, self-troubleshoots and reprioritises jobs according to criticality.

Table 7. Evaluation Category 6: AI/ML Category

Evaluation Category	**Descriptions by Maturity Level (1–5)**				
	Initial (1)	**Managed (2)**	**Standardised (3)**	**Optimised (4)**	**Autonomous (5)**
AI/ML Use	No AI/ML use	Limited logic control algorithms	Rule-based optimization	Predictive logic and basic ML for route planning	Advanced AI for learning, planning, and self-repair

The survey results were collected and averaged equally to diagnose the level of maturity based on expert assessment. The results are presented in the next chapter in the form of a table and a radar chart.

2.2.2. Statistical Analysis

The main source of quantitative data for our research at the case company is the AGV metrics dashboard. The dashboard calculates performance metrics by extracting raw input data from the fleet management system, computing the input and displaying the KPIs in real time. Data on performance metrics of the AGV fleet for five weeks is exported from the dashboard for analysis. The data was, by default, aggregated for the entire AGV fleet and not individual robots. The selected data is filtered to remove outliers that skewed the overall trends in operations. Logs of data collected on the weekends, national holidays or other planned downtimes are filtered from the dataset. The dataset has operational variability across three different shifts. After pre-processing, the data sample consists of 586 log lines of hourly values of the five performance indicators. An important part of the data collection plan is the operational definition of the variables analysed. An operational definition describes an attribute or property and how it must be measured. In this research, the AGV KPIs are defined accordingly in Table 12. A product is evaluated based on its characteristics, and in this research, the evaluated product is the AGV fleet. The product characteristics can be quantitative or qualitative. Quantitative characteristics can be measured or counted and are classified into continuous or discrete categories, while qualitative characteristics are observed or described and are classified into ordinal and nominal categories. In statistical analysis, continuous data is preferred. In this research, continuous data of AGV operational metrics is analysed. The entire data pool is the population, and specific sub-groups are called subpopulations. Random samples refers to individual parts of the basic population or the subpopulation. In statistical analysis, selecting a random sample adequately can be used to estimate the parameters of the overall population within a defined margin of error. In industrial applications, enterprises aim to extract as much information as possible from as small a quantity of data as possible, as data collection and analysis are expensive. Statistical parameters compile information from the data and describe properties of data sets, allowing conclusions about characteristics of the product for business and operational processes. Mean, standard deviation, and variance are examples of statistical parameters. Parameters of the populations are often difficult and expensive to obtain, so sample indicators are obtained instead. For example, the mean value of the data population 'μ' is estimated by obtaining the sample mean '$\bar{x}$', and the standard deviation of the population 'σ' is summarised in the sample standard deviation 's'. One of the most important measures of the location of a variable characteristic is the arithmetic mean '$\bar{x}$', which is calculated as follows [33]:

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n} \tag{1}$$

where: $\bar{x}$is the arithmetic mean of the random sample; $\sum_{i=1}^{n} x_i$ is the sum of all observed values in the sample, from the first x_1 to the n-th x_n ; n is the total number of observations in the sample (sample size).

Minitab is a statistical and graphical analysis program that utilises data stored in worksheets or projects. Minitab was used to plot a time series chart for each performance metric. A time series plot represents data as a function of time and permits the detection of trends and period-specific events. In the research, time series visualises each metric's distribution over time. Additionally, Minitab is used to plot Individuals and Moving Range (I-MR) control charts that assess the stability of the process. Control charts monitor the process mean value and variation over time to determine if a process is in control. The control chart is similar to the time series plot but indicates the long-term process mean value and control boundaries. The moving average is calculated as follows [34]:

$$MR_i = |x_i - x_{i-1}| \tag{2}$$

where: $MR_i$is the moving range for the current observation; x_i is the current observation, x_{i-1} is the previous observation.

The average moving range (central line in the chart) is calculated as follows:

$$\overline{MR} = \frac{1}{n-1} \sum_{i=2}^{n} MR_i \tag{3}$$

where: $\overline{MR}$ is the average of all moving ranges; n is the total number of observations

The control limits for the Individuals chart are calculated as follows:

$$UCL_I = \bar{x} + 3\sigma \tag{4}$$

$$LCL_I = \bar{x} - 3\sigma \tag{5}$$

where: $\bar{x}$is the arithmetic mean of the sample; σ is the standard deviation of the sample.

The control limits for the Moving Range chart are calculated as follows:

$$UCL_{MR} = d \cdot \overline{MR} \tag{6}$$

where: $\overline{MR}$ is the average of all moving ranges.; d is a calculated function of the specific sample size (Minitab uses constants to estimate sample-specific functions).

$$LCL_{MR} = 0 \tag{7}$$

where: LCL_{MR} is zero because the range can not be negative.

Additionally, Pearson Method correlation analysis was used to map a matrix plot of dependencies between performance metrics to identify constraints to the system's overall effectiveness. A matrix plot compiles a group of scatterplots into one chart, making it possible to view the relationships between variables. The correlation coefficient computes the magnitude of the linear association (correlation) between two variables. The coefficient value is between -1 and +1, where 1 indicates that all points are in a straight line. A negative value indicates an inverse relationship between variables, while a positive value indicates a direct relationship. The correlation coefficient r formula is as follows [35]:

$$r_{xy} = \frac{1}{n-1}\sum_{i=1}^{n}\left[\frac{(x_i-\bar{x})(y_i-\bar{y})}{\sigma_x\sigma_y}\right] \tag{8}$$

where r_{xy} is the Pearson correlation coefficient between variables x and y; n is the total number of paired observations in the dataset; $\bar{x}$ is the arithmetic mean of all the x values in the dataset; $\bar{y}$ is the arithmetic mean of all the y values in the dataset; σ_x is the standard deviation of the x values; σ_y is the standard deviation of the y values.

2.2.3. Economic Analysis

The economic analysis is important for evaluating the financial benefits of an automated solution. The phased implementation meant that procurement of AGVs happened gradually, with more AGVs being added to the fleet every quarter. As the fleet grew, the investments started to be offset by savings from eliminating manual labour. The implementation began in the second quarter of 2023 and continues to the first quarter of 2025. The payback period for the investment planned was three years. The ROI was calculated using the IRR formula to determine if the investments in AGVs are offset positively by savings returns at the end of the payback period. Formulas in chapter four explain the calculation step by step. The savings calculation formula considers the operational efficiency of the system in its formula by multiplying it with an AGV efficiency coefficient E (the target value of the KPI TEEP). Calculations are done using the method used at the case company for the AGV business case. ROI calculation is expressed as follows:

$$ROI = IRR\left(\frac{Total\ Yearly\ Savings}{Total\ Yearly\ Investments}\right) \tag{9}$$

where: ROI is the Return on Investment over the AGV deployment period (%); IRR is the internal Rate of Return function applied to the yearly cash flow (%); *Total Yearly Savings* is the cumulative savings caused by the AGV system each year (€); *Total Yearly Investments* is the total capital spent on the AGV system each year (€).

2.3. Chapter Summary

This chapter presents the mixed methods research approach used to assess the impact of AGVs on manufacturing enterprise "X" in a case study approach that evaluates the current state of the implementation. The case study methodology supports the investigation of the real-life conditions in a manufacturing environment using quantitative and qualitative tools to extract practical observations. Starting with the first task, the qualitative case description aims to provide an understanding of the logistics processes at the company to draw the full picture of operations and the system's potential for scalability and integration into the rest of the logistics system. In the second task, a model is created to assess the maturity of the AGV system implementation. The model is based on the literature discussed in the previous chapter and the industry standards described at the manufacturing enterprise "X". Additionally, an assessment framework is developed based on the model proposed to survey experts at the case company. The goal is to diagnose the maturity of the AGV deployment based on the defined criteria presented. The results are visualised using a radar chart for the ease of interpretation of cross-dimensional ratings. In the third task, quantitative analysis of performance metrics is done by exporting AGV performance metrics data from the dashboard. Data pre-processing is done to eliminate noise. The statistical analysis is realised to present data as bar charts, time series plots, and I-MR control charts to assess process stability, variation in performance, utilisation and quality of AGVs. The Pearson correlation matrix describes the interdependence and limitations between metrics. Finally, formulas are used to calculate the return on investment by evaluating investments spent against savings due to AGV deployment, due to the elimination of redundant manual tasks. In summary, the research design adopts an applied, practical approach to assess the impact of the implementation on the case company and its operations.

3. Research at Company "X"

The case company enterprise "X" is a manufacturing plant that belongs to an international automotive tier 1/2 supplier that owns research and development centres and production plants worldwide. Fig. 6 illustrates the automotives sector supplier landscape in a triangle where the Original Equipment Manufacturer (OEM) is at the centre as the customer. The case company specialises in the production of compact, electronic subassemblies for automobiles. The products are typically small in size.

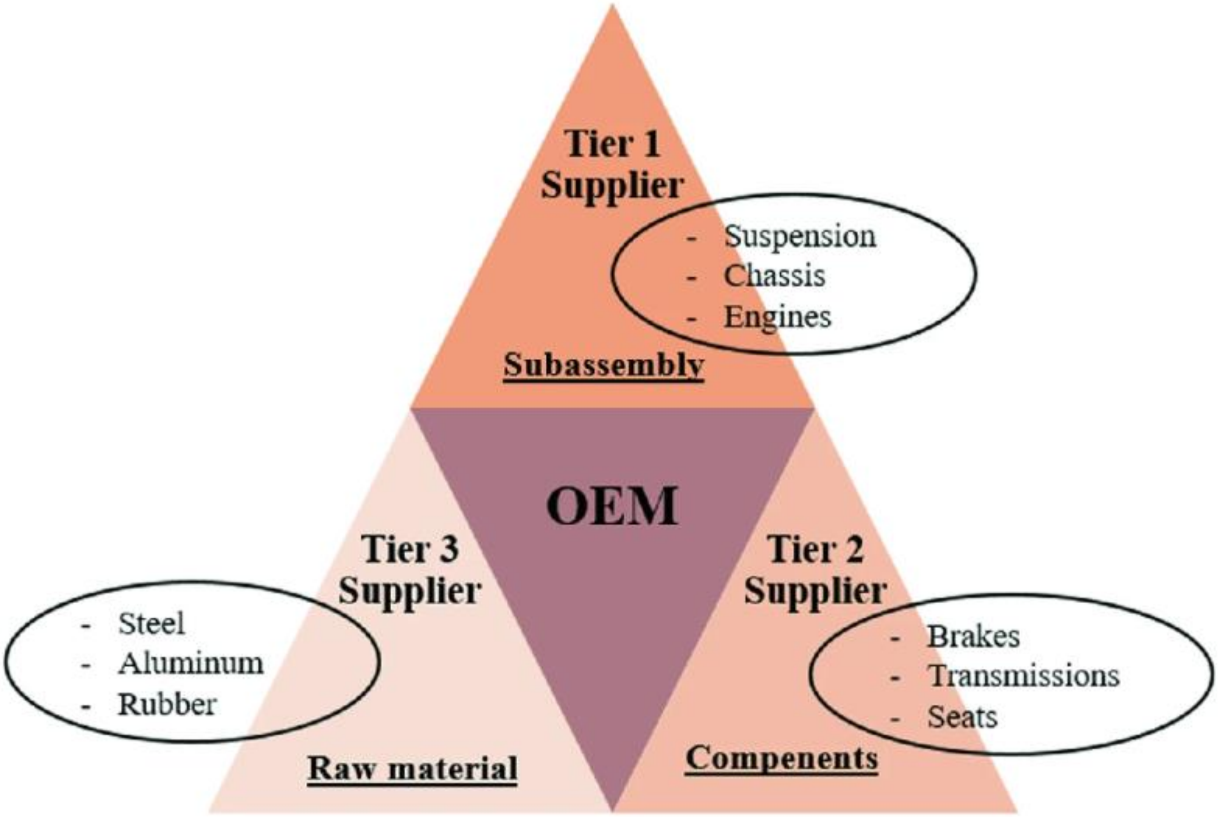

Fig. 6. Schematic of the automotive supplier landscape [36]

In Table 8, the main attributes of the case company are presented.

Table 8. Main characteristics of the case company

Operational Factor	**Contextual Conditions**
Company size	Plant headcount- approx. 450 workers. 7,592 m2 shopfloor and 5,670 m2 warehouse.
Company Specialization	Automotive electronics (e.g., sensors, lighting ECUs, radar systems)
Nature of Production Processes	Mostly automated production lines with minimal manual input
Complexity of logistics processes	Moderate to high
Complexity of manufacturing processes	Moderate

The company follows the standardised plant layout, business processes and ERP system that are uniformly defined across all the production plants within the organisation. Operational levers are defined centrally at the corporate level and cascaded to individual manufacturing locations, including the case company. The products manufactured at this site require strict technical cleanliness and traceability requirements. Production lines in the plant are highly automated and planned for minimal manual input. Logistics processes are of moderate to high complexity due to the diversity in product portfolio and range of materials handled in multiple storage systems. The plant itself is designed with a modular layout and limited storage capacity compared to industry norms, demanding efficient operational management.

3.1. Logistic Processes in Manufacturing Enterprise “X”

A manufacturing enterprise's main goal is to sell its manufactured goods to the customer. For this aim to be achieved, the logistics department must ensure that the material needed is delivered to production and the manufactured goods are delivered from production to the customer. Logistic processes in the manufacturing enterprise “X” can be categorised into four main functional areas: goods receipt, warehousing, material supply, and shipping. Packaging can be considered a bonus area however, the enterprise is moving towards the automated packaging of finished goods as part of the production line processes to eliminate the need for manual packaging activities.

3.1.1. Good receipt

The process of goods receipt starts upon receiving the notice that a delivery is incoming, with the transport arrival time being communicated to the warehouse. When the truck arrives, the responsible coordinator checks the documentation to identify if it is the correct load. If the delivery is recognised, the coordinator checks that the load is secure and undamaged before agreeing to unload. Load units are checked against the delivery documents, and only the received load units are confirmed in the ERP system as received to initiate the process of invoicing the supplier. The coordinator continues by checking if the delivered goods can be identified using part numbers or codes. The coordinator also checks if labels are present and compliant with standards before posting a goods receipt. It is worth noting that if the results of the previous steps are negative, additional inspection is needed, and goods quarantine may take place. Goods are quarantined in a closed-off storage area in the main warehouse. If the delivery is compliant, the goods receipt posting indicates that the parts are labelled correctly and are ready to be stored.

3.1.2. Warehousing

After goods receipt, the load units are picked up from the receipt area and moved to be stored in the assigned location indicated by the automatic transport order (TO) issued by the ERP Warehouse Management (WM) system. Once the transport is fulfilled physically, the worker confirms the action. If goods must be moved after initial storage, another transport order should be initiated on the ERP system before picking. The load unit(s) can be moved as a whole or partially; in the case of the latter, additional preparation is needed before picking the quantity in the TO. After the movement is done, relocation is also confirmed by posting TO systematically. The warehouse at Enterprise “X” is structured in storage areas for specific functions. A storage function is based on the type of material stored, e.g finished goods are stored separately from purchased parts. Fig. 7 shows the layout of the main warehouse in company “X”.

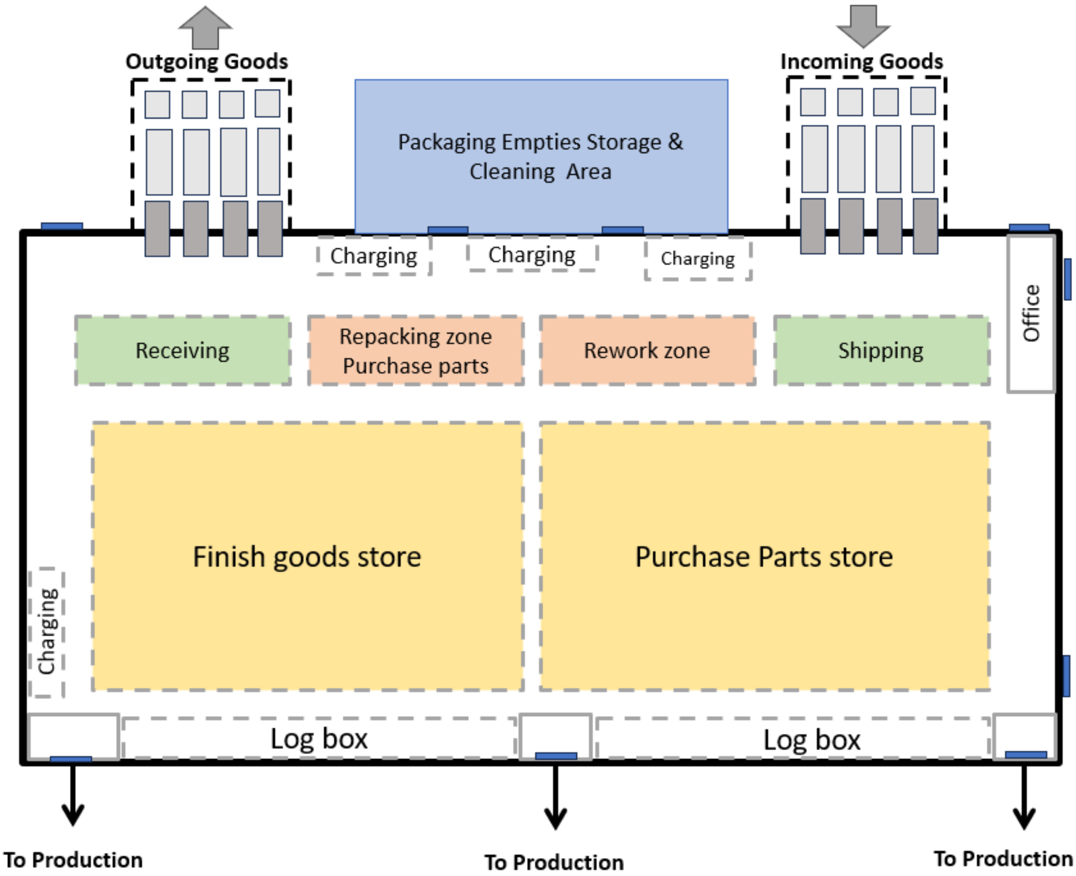

Fig. 7. Scheme of the central warehouse at the enterprise "X"

Storage is done based on the type of material, packaging, frequency of use, etc. As shown in Fig. 8, the most common storage types in this warehouse are pallet racks, flow racks, bin shelves, trolley lanes, etc. The storage type also affects the way of removing stock from the storage areas and, therefore, the equipment used to pick the material in stock. Warehousing applies to materials of all kinds: purchased material, work-in-progress parts, finished goods and also packaging. Packaging exists in two formats: one-way disposable packaging and returnable packaging, which is shared in loops with suppliers or customers. Returnable packaging necessitates additional activities such as transport, storing, handling and washing. Washing is especially relevant in the automotive sector, where components are subject to stringent technical cleanliness requirements and must be stored and packed accordingly. One way packaging must also be disposed of effectively, meeting sustainability criteria set by regulatory rules and the company's policies. In addition to the main warehouse depicted in Fig. 7, enterprise "X" stores electronic raw material such as Printed Circuit Boards (PCBs) using multiple Kardex machines in a side warehouse. Additionally, liquids are stored in a temperature-modulated cold room in the same location. Lastly, a fundamental pillar of modern warehousing activities is maintaining inventory traceability; scanning, labelling, FIFO maintenance, etc., are performed at every step.

Fig. 8. Storage types in company “X”: a. bin shelves,b. pallet racks,c. pallet bulk store,d. trolley lanes [37,38,39 ,40]

Bin shelves store smaller, low-volume components in a fixed, labelled storage bin for easy manual access. Pallet racks store palletised material and allow for high-density storage and forklift retrieval. Similarly, a pallet bulk storage location is an open storage of palletised material that utilises organised stacking in high-density without racking, making it suitable for low turnover goods and uniform packaging. Trolley lanes are the fixed floor lanes that stage the rolling trolleys that carry material to be transported to, from and between production lines. The lanes are also referred to as ‘dolly lanes’ in the case company and are fundamental infrastructure facilitating AGV pick up and drop off.

3.1.3. Material Supply

Next, material supply as a functional area encompasses all activities that involve moving material between taking material out of storage areas and bins to delivering those to production lines, as well as bringing back finished goods to the shipping area or back into storage. Material supply is done manually with tugger trains or automated using AGVs. After production, parts are picked up by the tugger train driver/AGV in load unit quantities after the TO is issued systematically. Finished goods are transported to the main warehouse, where they are unloaded to be stored or dispatched. Although the material supply area is supposed to handle the majority of transport activities, micro-transports are necessary within other functional areas. Purchased parts used in production are delivered by suppliers to the main warehouse if they are mechanical components. Electronic components are delivered to the SMT warehouse, where they are stored in the Kardex machines. Material flow in enterprise “X” follows a pull system, where as production orders are fixed based on customer orders, the necessary material needed for production is replenished promptly to minimise line-side storage. Pre-assembly consists of SMT production lines, intermediate production stations and Front-End production lines. The Work-In-Progress (WIP) parts travel down the manufacturing technological processes to reach the final assembly lines, where applicable. It is worth noting that the enterprise also sells WIP products to customers. Alternatively, the parts are delivered to the final assembly production lines where the last steps of the technological processes are performed, resulting in packaged finished goods in load units ready to be stored or shipped to the customer. In Fig.9, the flow of purchased parts is marked with green arrows, while the flow of WIP and finished goods is marked with blue arrows.

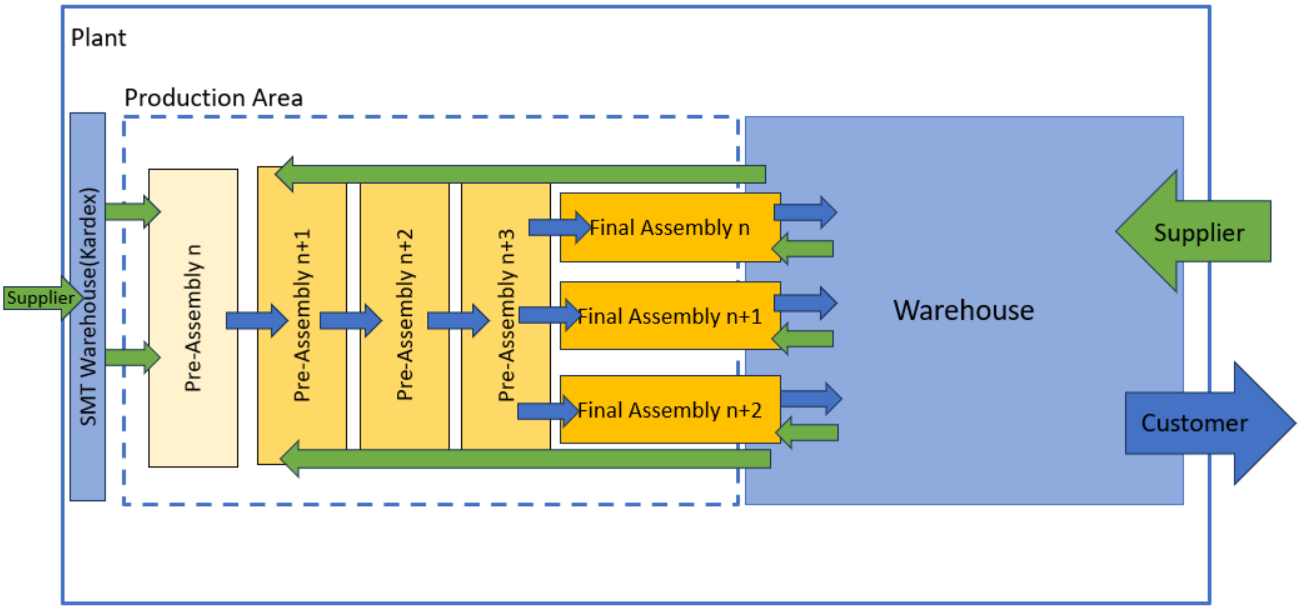

Fig. 9. Simplified diagram of the plant's material flow strategy

3.1.4. Shipping

Finally, the shipping activities take place in the form of preparation, execution and loading of parts into trucks to leave the plant. Tasks such as labelling, printing and attaching documentation to the outgoing pallets as well as wrapping, strapping and final inspection, are all part of the shipping functional area. When the material in pallets is ready for shipment, the delivery information is printed and brought with the material to the shipping desk. The shipping desk clerk initiates the shipping process through the ERP system by scanning the delivery note against the labelled physical goods and their packaging to identify if the shipment is complete and ready to be shipped. The pallets are then labelled for dispatch according to the customer's requirements, whereby customer-specific labels are attached, and internal production labels are removed. The verification takes place through the scanning of labels into the ERP system. The destination of the shipment is checked to identify the need for export documents. Once the shipment is successfully loaded onto transport, goods are issued, and the invoicing is initiated. Lastly, documents are handed over to the forwarder.

3.2. AGV Implementation Maturity Assessment

An industrial AGV is an unmanned robot that autonomously transports products or materials within a manufacturing facility or a warehouse. The movement of AGVs is controlled by software and sensor-based guidance systems. The vehicles move on a fixed path with precisely controlled acceleration and deceleration using automatic obstacle-detection bumpers. Typical AGV applications include transportation of raw materials, work in process, and finished goods in support of manufacturing production operations, as well as storage/retrieval in warehousing and distribution applications. The AGV system adopted in the manufacturing enterprise "X" is used primarily for in-house material transport. The system consists of 13 floor-supported AGVs, their guidance control system, position determination devices, data transmission equipment and supporting physical infrastructure. The system is used inside the company's logistics and production facilities. In terms of material transport to production lines, the goal of the enterprise is to achieve fully automated material replenishment to production lines for components and the collection of finished goods. To achieve this goal, systematic IT integration is required. The current system is semi-integrated with an enterprise resource planning (ERP) system and synchronises material and information flow with the MES.

3.2.1. Background on the Implementation

The case company belongs to a larger organisation, and relevant groundwork regarding AGV deployment was completed at the central corporate organisation level. A technical feasibility assessment was performed to identify vehicle types suitable for automation based on the plant's prerequisites. The evaluation took into account the plant's product portfolio, material handling limitations, layouts, operational constraints and specific systematic needs. Moreover, suppliers' evaluation was made to assess possible vendors against corporate criteria for a long-term strategic partnership that serves the corporation's vision for automation. Corporate also standardised the AGV system architecture across facilities and set predefined requirements for network and IT systems. Based on the suggestions provided on the central level, the type of AGV fleet suitable for local deployment was identified. Fig. 10 shows the AGV deployed at the case company.

Fig. 10 Rexroth Active Shuttle AGV with load (left) and trolley (right) []

Implementation activities began with the procurement of the AGV system components: the hardware (AGVs, charging station, network devices, etc.) and software. The local set-up of infrastructure was initiated, including the preparation of the network, such as mapping Wi-Fi coverage and system configurations to construct communication between AGVs, servers and plant infrastructure. The fleet management system, namely AGV Management System (AMS), communicates with external devices and software such as ERP, MES, etc. The system gathers inputs, processes, tracks, sorts and allocates the right task to the right AGV vehicle. The fleet operates with dynamic routing to plan utilisation of vehicles optimally according to fleet status, available floor space, storage buffers, and the jobs queue. The AMS also offers a graphical website interface for specialists to map the routes, set pick-up and drop-off points, trigger test jobs, etc.

Consequently, the number of AGVs that will be needed was calculated, driven by potential savings and operational goals. The implementation began with the testing phase. From the process perspective, the team selected a pilot use case. This use case served as a reference process for testing AGV functionality and reliability. The first use case involved the collection and transport of empty packaging from a production line to the empties area in the warehouse. Once successfully validated, AGV use cases were ramped up, gradually increasing transport jobs. Use cases were chosen based on the ease of their scalability, high frequency and job repeatability. As the ramp-up progressed, iterative operational improvements were made to support transport automation. As a part of the implementation, specific areas were defined for handover, pick up, deposit, parking spots and charging points. The availability of standard load carriers (such as ESD boxes or trays) and the compatible trolleys (shown in Fig. 10) was carefully evaluated as they are essential for AGV transport compatibility. Additionally, storage and replenishment requirements were determined, and a transparent storage logic was implemented. This includes clear, structured storage areas and systematic labelling of bins. The following processes were planned for automated material transport:

- Transport from the warehouse to the assembly lines (Raw material)
- Transport from work-in-progress shop stock to assembly lines (WIP parts)
- Transport from the assembly lines to the warehouse (finished goods)

The material to be transported is stored in a stackable box or tray that fits on a 600 mm by 400 mm trolley. Lanes that hold trolleys are defined at each pickup and drop-off point. Guide rails store larger quantities of trolleys, forming supermarkets that hold in-house produced parts, externally sourced parts and finished goods separately. The use of guide rails supports FIFO handling by allowing new material to be loaded from the rear, while older items are pulled from the front. This enables storage in fixed bin locations (dedicated lanes), where minimum and maximum quantities of each material are systematically defined and controlled in the ERP system.

3.2.2. Use Cases for Implementation

The types of use cases where material transport was automated in the manufacturing enterprise “X” are the following:

1. Delivery of PCB reels from the main warehouse to the SMT warehouse.
2. Delivery of magazines between Pre-assembly stations in production.
3. Delivery of empty packaging from production to the main warehouse.
4. Delivery of WIP parts between production stations.
5. Delivery of finished goods from production to the main warehouse
6. Delivery of purchased parts from the main warehouse to the final assembly lines in production.
7. Delivery of empty packaging from final assembly lines back to pre-assembly lines.

In Table 9, the number of AGVs implemented for the listed use cases, from the second quarter of 2023 to the first quarter of 2025, is presented.

Table 9. Timeline and number of AGVs adopted each quarter from 2023 to 2025

Use cases	Number of AGVs allocated	2023 Q1	2023 Q2	2023 Q3	2023 Q4	2024 Q1	2024 Q2	2024 Q3	2024 Q4	2025 Q1
1	3	0	1	1	1	2	2	2	2	3
2	2	0	0	1	1	1	2	2	2	2
3	3	0	0	0	1	1	2	2	3	3
4	2	0	0	0	0	0	1	1	1	2
5	1	0	0	0	0	0	0	1	1	1
6	1	0	0	0	0	0	0	1	1	1
7	1	0	0	0	0	0	0	0	0	1

The table indicates a clear trend in increasing AGV adoption in the manufacturing enterprise "X". Each use case starts with a small number of AGVs and then scales up the planned number of AGVs over time as it moves from manual transport to fully automated transport of material. In Fig. 11, a chart illustrates the quarterly deployment of AGVs across the seven types of use cases from quarter 1, 2023, to quarter 1, 2025.

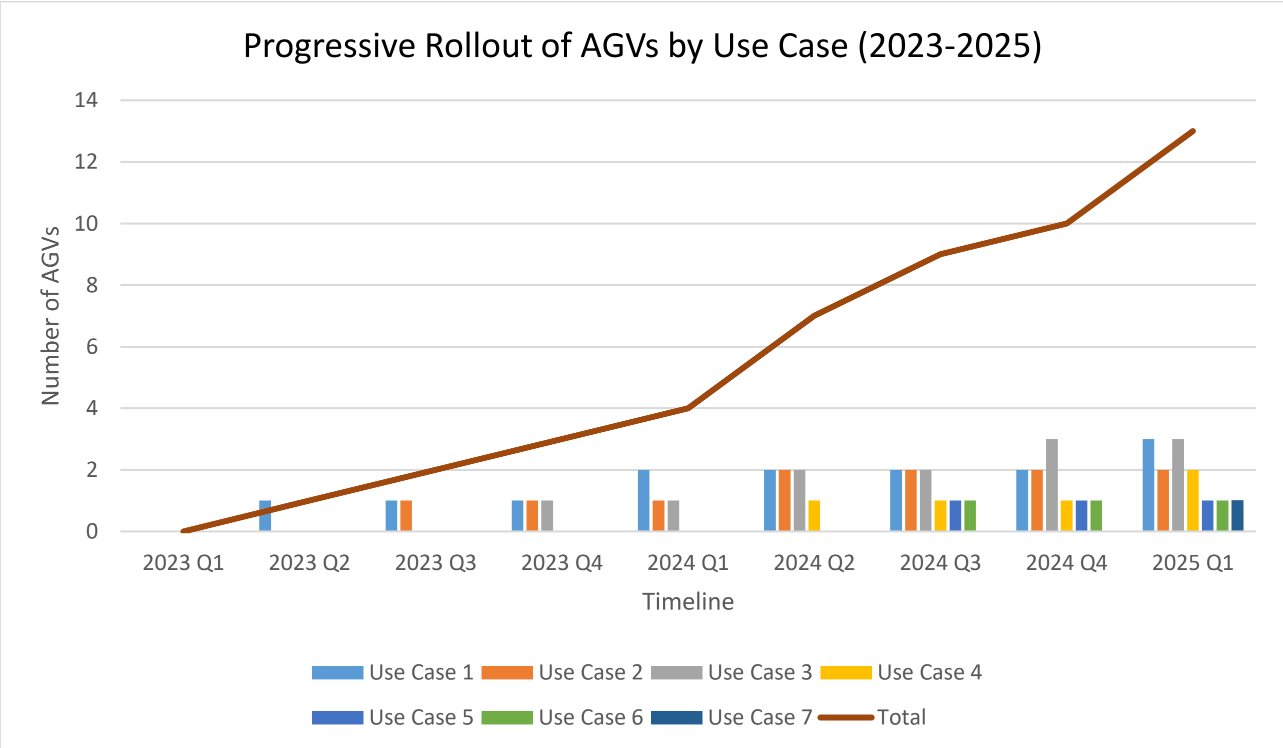

Fig. 11. Progressive AGV rollout by use case (2023–2025), reaching 13 deployed units by Quarter 1 2025.

In Fig. 11, the chart illustrates the phase-by-phase deployment of AGVs across the seven types of use cases. Each bar represents the number of AGVs allocated per use case per quarter. The first use case (PCB reels to SMT warehouse) is the first to be automated due to the limited system dependency, high volumes, and low variability logistics flow. Use cases 5 and 6 were introduced at later stages of the rollout due to their dependency on ERP and MES system integration.

3.2.3. AGV Maturity Model

The developed AGV implementation maturity model is presented in Table 10 and is defined in five levels, starting with the 'Initial' stage and ending with the 'Autonomous' stage. Literature presented maturity models for various technologies and concepts, such as Industry 4.0; however, a specific maturity model for AGV/ AMR system implementation is a novel output. The goal of this tool is to diagnose the current implementation status, benchmark it against industry practices and act as a road map for AGV deployment at the case company and beyond.

Table 10. The Automated Guided Vehicle (AGV) Maturity Model

Level	Maturity Stage	Description	Key Factors (Technology, Organisation, Process)
Level 1 – Initial	Pilot	AGV testing for limited use cases without systematic integration in controlled environments. Material transport is physical without information flow.	• At least one AGV is deployed. At least one charging station is installed. • A guidance control system and fleet management software. • Devices for position determination and localisation • Data transmission equipment • Infrastructure and peripheral units • Manual transport order input • No ERP/MES connection
Level 2 - Managed	Partial Automation	Systematic integration for select use cases. Limited automation is achieved with low efficiency levels due to operational delays and manual interventions.	• The connection between MES and AGV fleet management system is established. • The transport orders are triggered manually. • The workforce lacks AGV troubleshooting skills.
Level 3 - Standardised	Integrated	AGVs operating according to standards with systematic integration, established training and KPIs defined. Performance shows improvement.	• KPIs are defined. And tracked (e.g., utilisation rate, completion rate, etc.) • The connection with the ERP system is established. • Dashboard for performance monitoring • Training is provided to all shopfloor and warehouse employees. • Daily tracking of KPIs by the responsible department.
Level 4 - Optimised	Efficiency-focused	AGVs achieve expected utilisation rates. Optimisation efforts are	• Automated task triggering using sensor technology.

Level	Maturity Stage	Description	Key Factors (Technology, Organisation, Process)
		reducing cost and improving performance.	• Cost performance and optimisation cycles. • High competence amongst the workforce. • Optimised routes to reduce AGV travel time and the chances of obstacles.
Level 5 - Autonomous	Fully Automated	AGVs self-optimise using AI and only need minimal human intervention.	• Integration with Digital twin or use of simulation models to optimise performance. • Data-driven predictive planning of intralogistics transport. • Optimised task distribution enhanced by ML algorithms

3.2.4. AGV Implementation Maturity Assessment Framework

As explained in the methodology, the two experts in company "X" were surveyed to determine the maturity of the AGV implementation. The maturity model in Table 10 was used to create the quantitative AGV implementation maturity assessment framework presented in Table 11. The average rating from the expert evaluation collected through the survey in Appendix 1 is also shared in the last column of Table 11.

Table 11. The AGV Maturity Assessment framework

Evaluation Category	Initial (1)	Managed (2)	Standardised (3)	Optimised (4)	Autonomous (5)	Average Rating (1–5)
System Integration	No integration with ERP/MES.	Partial integration with ERP/MES	Full integration with ERP/MES	Integration with ERP and data is used for forecasting	Connected in full to enterprise systems and cloud	3
Autonomy	Manual operation and no autonomy	Semi-autonomous with frequent manual input	Autonomous navigation in fixed paths	Dynamic rerouting and adaptive navigation	Self-adaptive with minimal intervention	3
Data & Performance Metrics	No KPI tracking and manual reports only	Basic KPIs are tracked manually	Automated real-time KPIs. Dashboards used	KPIs are analysed for performance optimisation decisions	Predictive and prescriptive analytics	3.5
Workforce Skills	No AGV-related training and no workforce awareness	Limited training and support is needed from the supplier	All operational workforce is trained on the basic AGV problems	Proficient troubleshooting and optimisation by the workforce	Minimal human input and proactive system support	3.5

Evaluation Category	Initial (1)	Managed (2)	Standardised (3)	Optimised (4)	Autonomous (5)	Average Rating (1–5)
Efficiency	Very low utilisation and high downtime	Basic usability and high delays	Improved efficiency and reliable usage	High utilization and low cost per move	Near 100% optimization; peak efficiency	2.5
AI/ML Use	No AI/ML use	Limited logic control algorithms	Rule-based optimization	Predictive logic and basic ML for route planning	Advanced AI for learning, planning, and self-repair	2.5

A radar chart is used to visualise the results of the assessment in Fig. 10.

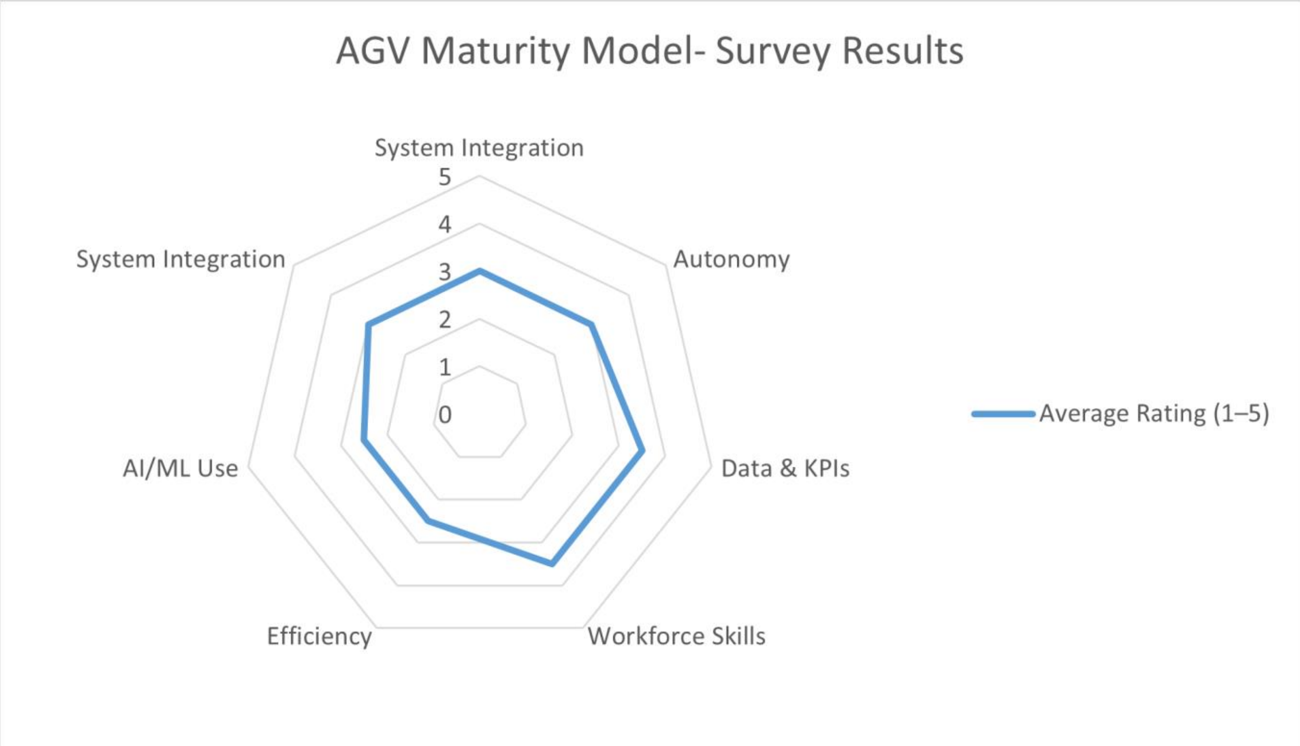

Fig. 12. Radar Chart of Surveyed Maturity Assessment

The results of the maturity survey across all categories indicate that the enterprise's current maturity level is 3, as defined by “Standardised”. The two dimensions in which the company performed the highest, data and performance metrics and workforce skills, rated 3.5/5, indicating a focus on operational performance development. System Integration and Autonomy categories scored moderately at 3/5, hinting at the semi-integrated systematic connection to the planning system, and lower than expected autonomy perceived of the AGVs. Lastly, efficiency and AI/ML use were the categories that scored the lowest average (2.5/5), implying the necessity to improve the system‘s intelligent decision-making and utilisation rates. Overall, a foundation is laid for good performance by AGVs, but further investments into the technology, both from the organisational and technical perspective, are a must to extract the highest value from the system. Variations in the results from the two participants were not studied in this research. Future research could explore the variation in perspective between management and execution specialists and its effect on their maturity assessment.

3.3. Performance Analysis

Following the assessment of AGV maturity at plant "X", we will study the performance of the AGV fleet quantitatively according to the metrics defined on the corporate level. The metrics apply to AGV fleets of the same type in the organisation's branches worldwide. Table 12 presents the operational definition of the relevant KPIs.

Table 12. AGV KPIs

Key Performance Indicator (KPI)	**Definition**
Quality Rate	Proportion of successful runs to total runs
Utilisation Rate	Proportion of operating time to working time
Effective Utilisation Rate	Proportion of operating time to working time, excluding robots that are not operational.
Performance Rate	Proportion of ideal time to real time
Total Effective Equipment Performance (TEEP)	The arithmetic product of the metrics: effective utilisation rate, quality rate, performance rate.

The KPIs provide key insights into the operational aspects that are important for an AGV system. All the metrics take the average data across all the robots in the fleet, and the values are displayed as percentages. The quality rate is the calculated proportion of successful runs against the total runs performed by the fleet. Quality losses occur when a job fails or is manually completed. The utilisation rate is the availability metric that calculates the proportion of time the fleet is operating against its theoretical working time. The theoretical working time is calculated by evaluating the number of AGVs in a fleet multiplied by the number of hours per day. The operating time excludes planned and unplanned downtimes. Examples of planned downtime can be charging time, cleaning time, time allocated for planned maintenance activities, idle time, etc. Alternatively, unplanned downtime can be due to IT issues, accidents or the lack of orders due to production stops. The effective utilisation rate is calculated in the same way, additionally omitting the number of AGVs that are not operating in the working time calculation for a more accurate representation of the theoretical availability of the fleet. Performance Rate is the proportion of the expected job completion times against the actual job completion times recorded for the AGV fleet. Performance losses can occur due to reduced velocities or routes blocked by obstacles, stopping the robots from reaching their destinations on time.

3.3.1. Analysis of AGV Operations

The dataset adopted for analysis is 5 weeks of hourly values of the five KPIs presented in Table 12. The results from the five-week observations were analysed, focusing on identifying the patterns in the KPIs. The chart in Fig. 13 shows overall high levels of quality with clusters of values between 90-100%, and an average ($\bar{x}$) of 92.45%, indicating robust task execution by the AGV fleet. In two instances, the quality rate dips to 0%, signalling that rare systematic disruptions seem like a one-off issue as they don't repeat in further observations.

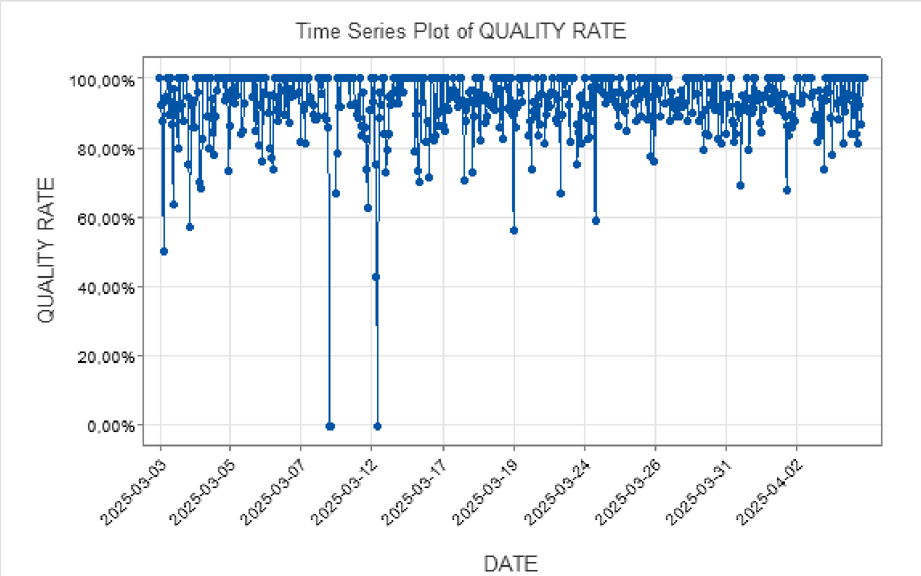

Fig. 13. Time Series Plot of AGV Fleet Quality Rate

The I-MR control plot examines the variability across observations calculated using individuals and moving average values. Fig 14 shows that most individual quality rate values fall within statistical control limits, while the moving average also shows a quick recovery of the spikes beyond the upper control limit. The occasions of disruptions are seen to reduce in frequency and volume in further observations. Process control is generally stable, with rare exceptions of failures. The narrow control range describes tight process control, suggesting performance repeatability.

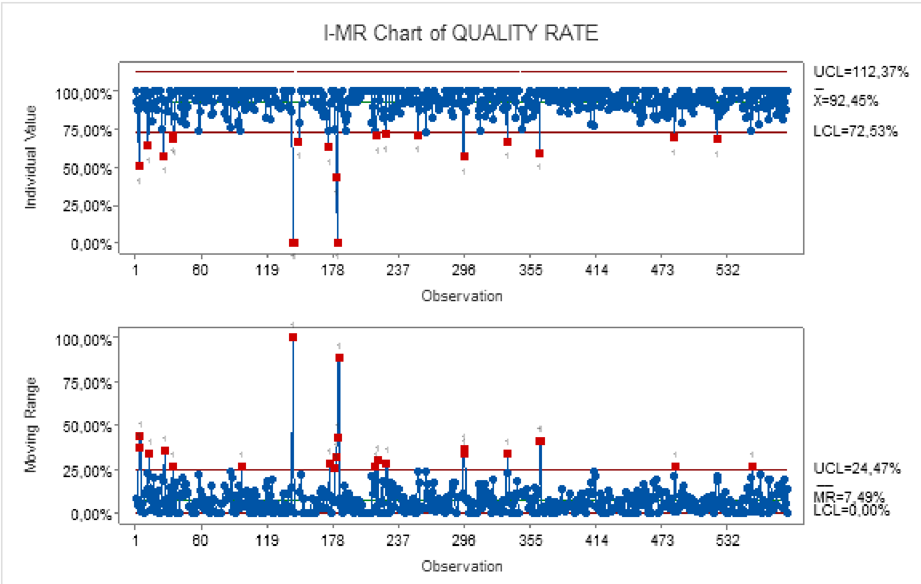

Fig. 14. I-MR Chart of AGV Fleet Quality Rate

The hourly utilisation rate is plotted in Fig. 15, representing the proportion of theoretical operating time relative to the total working time of the entire AGV fleet. There is a large variability with points clustering between 20% and 60%. Utilisation rates vary significantly even in the short term, indicating that variation in AGV task load is likely due to shift-specific factors or production schedules. Low utilisation matches with periods of idle production or shift changes.

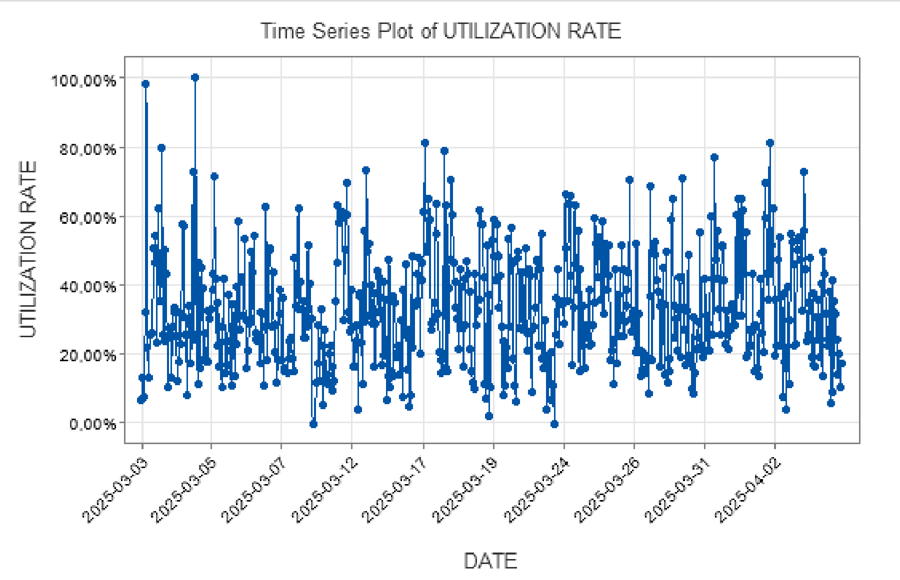

Fig. 15. Time Series Plot of AGV Fleet Utilisation Rate

The I-MR analysis using the chart in Fig. 16 provides the statistical process control view for utilisation rate values with an average ($\bar{x}$) of 33.00% indicates that the fleet is operating at a third of its working time, with most points falling between control limits, except for points that fall beyond the UCL, indicating higher demand windows associated with higher production trends. The moving average rates indicate the quick change from one hour to another, highlighting the inconsistent demands for AGVs.

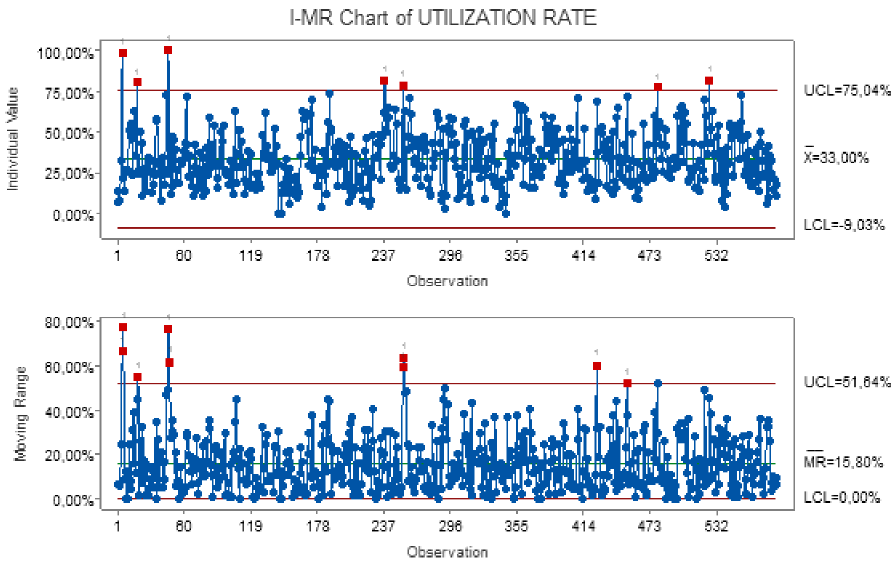

Fig. 16. I-MR Chart of AGV Fleet Utilisation Rate

Fig. 17 shows the time series plot for the effective utilisation rate. It only considers the active robots in the fleet; therefore, the values are effectively higher than the previously analysed utilisation rate. Values cluster mostly between 40% and 80%, with values concentrating in the higher part of the range.

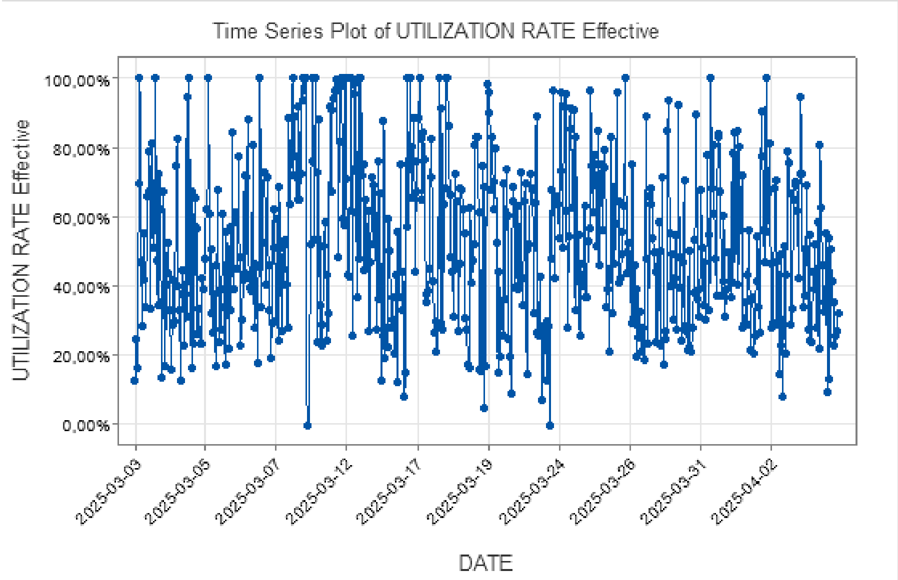

Fig. 17. Time Series Plot of AGV Fleet Effective Utilisation Rate

Similarly, the results are improved in the I-MR chart in Fig. 18. The average ($\bar{x}$) of 52.10% has increased by 19.1% in comparison to the average of the non-adjusted utilisation rate, validating the advantage of discounting the unavailable AGVs. Overall, the effective utilisation rate is statistically under control as individual values fall within statistical control limits. The moving average chart indicates significant hourly variations within expected limits, indicating process instability caused by demand inconsistency. These inefficiencies can be improved by optimising production planning and fleet scheduling.

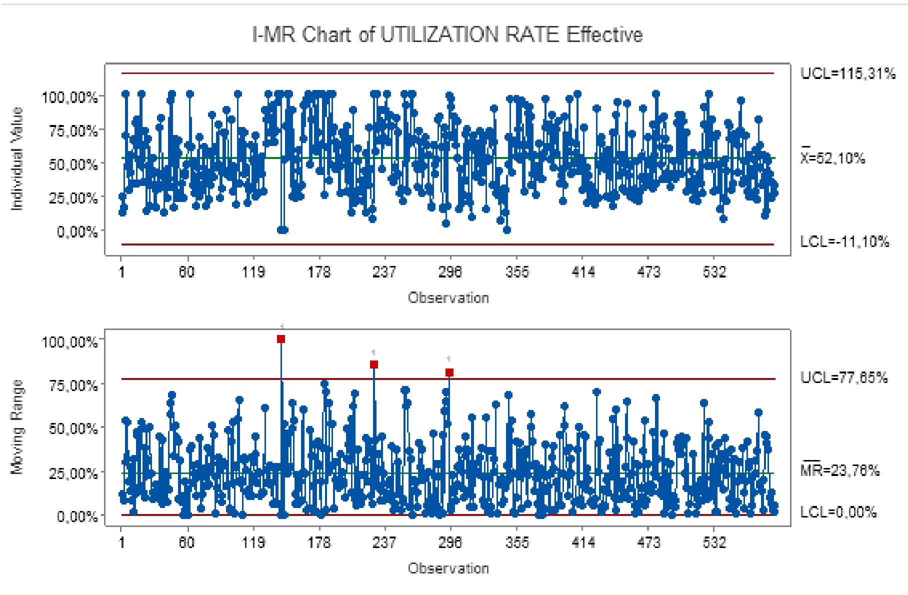

Fig. 18. I-MR Chart of AGV Fleet Effective Utilisation Rate

In Fig. 19, the time series plot of performance rate shows fluctuation between 60% and 100%, with most values clustering between 80% and 95%, with an average ($\bar{x}$) of 78.92%, signifying a 20% performance loss on average.

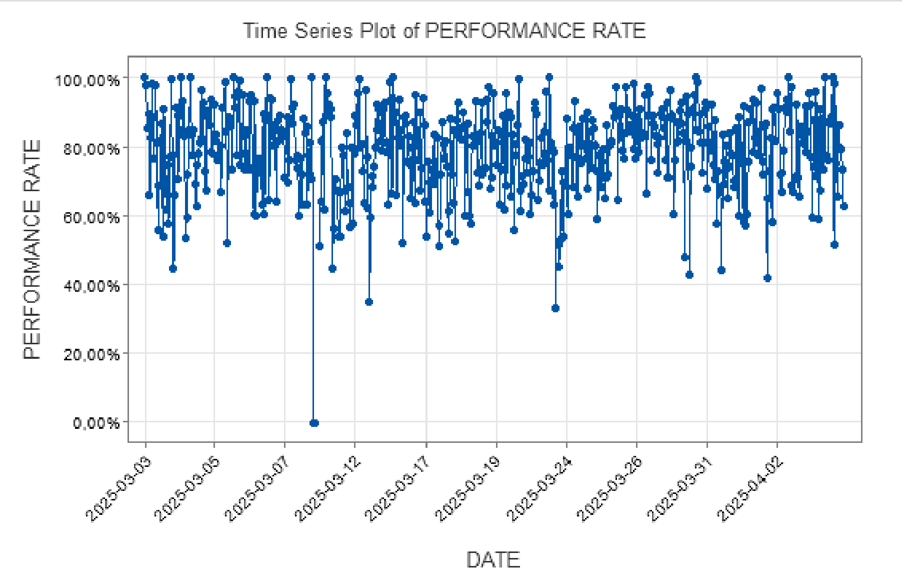

Fig. 19. Time Series Plot of AGV Fleet Performance Rate

The I-MR chart in Fig. 20 shows consistent strong performance with AGVs generally operating at expected speeds. The few lower outliers can be traced to systematic errors or organisational problems obstructing AGV paths. Overall, performance rates are stable within statistical bounds, but optimising route planning and technical obstacle avoidance can reduce the dips in performance rates.

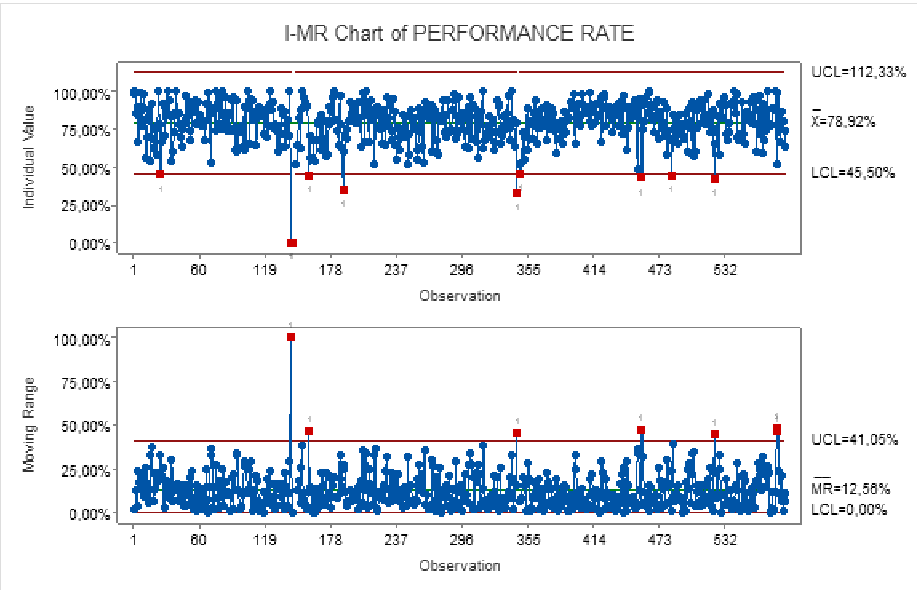

Fig. 20. I-MR Chart of AGV Fleet Effective Utilisation Rate

Fig. 21 presents the time series plot of TEEP. Values cluster between 20 % and 30%. The arithmetic product of the effective utilisation rate, the quality rate, and the performance rate is TEEP. Compared to the previously discussed KPIs, TEEP shows higher variability due to the accumulation of inefficiencies from other KPIs, such as utilisation rate. The company‘s current TEEP target is 35%.

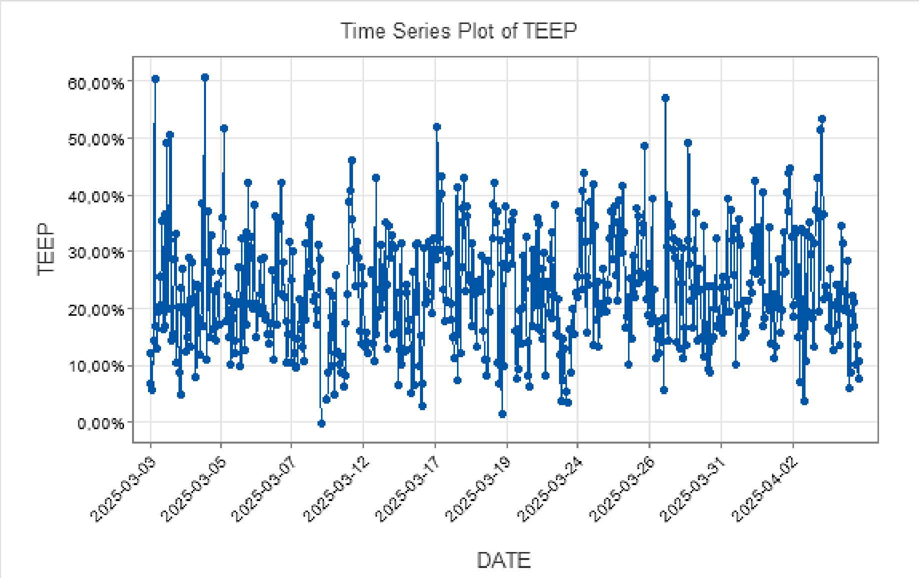

Fig. 21. Time Series Plot of TEEP

In Fig. 22, the I-MR chart shows the statistical control analysis for TEEP, which shows the sample's mean at ($\bar{x}$) of 23.26%. The MR chart indicates significant changes in operational performance between one hour and the next, but fewer than the quality rate and performance MR charts. Overall, the I-MR chart shows low equipment effectiveness even though individual components, such as quality rate, remain high. This suggests that underutilization and operational inconsistency limit the fleet's effectiveness, not technical failures.

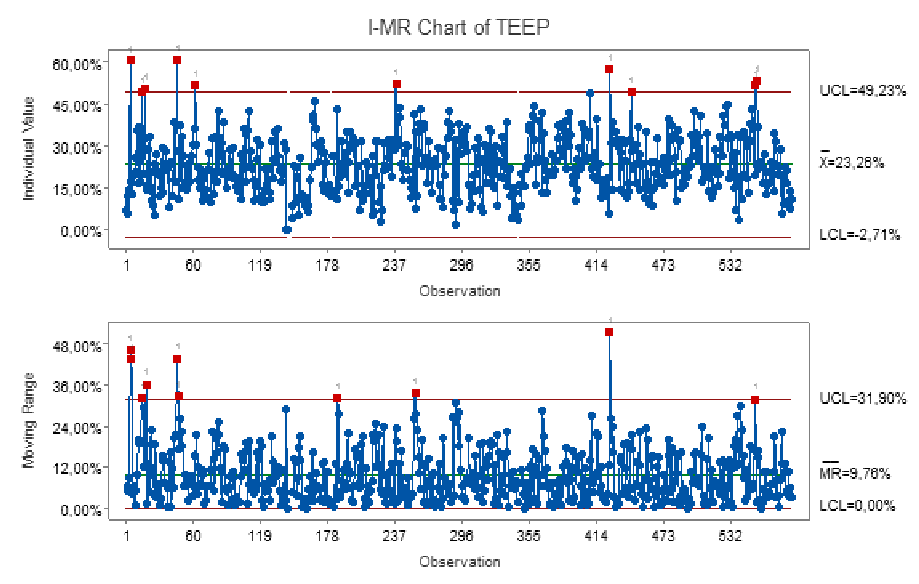

Fig. 22. I-MR Chart of TEEP

A correlation analysis is needed to test the hypothesis that TEEP follows the underlying patterns of utilisation rate. Fig. 23 presents the Pearson correlation matrix. Pearson correlation analysis evaluates the linear relationship between the KPIs for the given sample population.

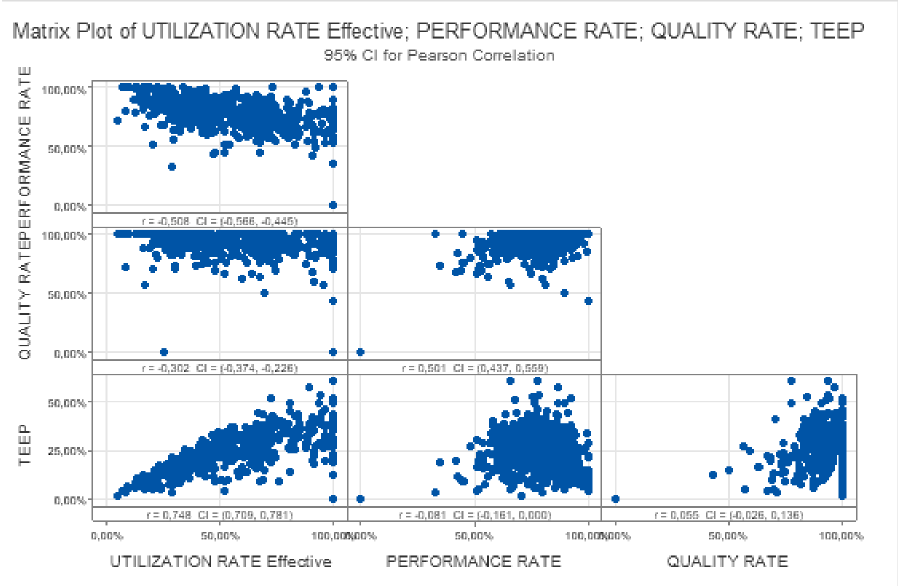

Fig. 23. Correlation Matrix of the KPIs (scatterplots with Pearson coefficients)

As expected, the strongest linear relationship was seen between Effective Utilisation Rate and TEEP, with a Pearson correlation coefficient of r=0.748, suggesting that AGV fleet utilisation and occupancy play a primary role in the effectiveness of the system. The low positive coefficient of quality rate at r=0.055 entails that the KPI doesn‘t limit the efficiency of AGVs but acts as a baseline for good results that can be expected from the system. The relationship between the performance rate and TEEP is a weaker negative one at r=-0.081, indicating that faster deliveries by AGVs don‘t influence the overall efficiency and even have a slightly inverse relationship. This suggests that the speed of deliveries doesn‘t improve operational efficiency, as better performance might occur at periods of lower demand for the robots. Additionally, utilisation rate demonstrated a relatively strong negative correlation with performance and quality, confirming the observation that there is a trade-off with higher performance and quality compromising utilisation and vice versa. Overall, the results confirm the influence of the utilisation rate on the TEEP. It can be concluded that the factor limiting TEEP outputs is the lower utilisation rate. Table 13 compiles the Pearson correlation coefficient values of the 5 KPIs.

Table 13. Pearson Correlation Coefficients for KPIs

Key Performance Indicator	**Effective Utilisation Rate**	**Performance Rate**	**Quality Rate**
Performance Rate	-0.508	-	-
Quality Rate	-0.302	0.501	-
TEEP	0.748	-0.081	0.055

In Fig. 24, we analyse the hourly average of the TEEP KPI to shed light on the variation of performance by time of the day and consequently shifts. The chart records peak output between 12:00 and 13:00, averaging 32.73%. nearing the plant's target of 35%. The lowest average values recorded are in the early hours between 01:00 and 02:00 at 15.83%. A trend can be seen due to the expected workload cycle based on the production shifts.

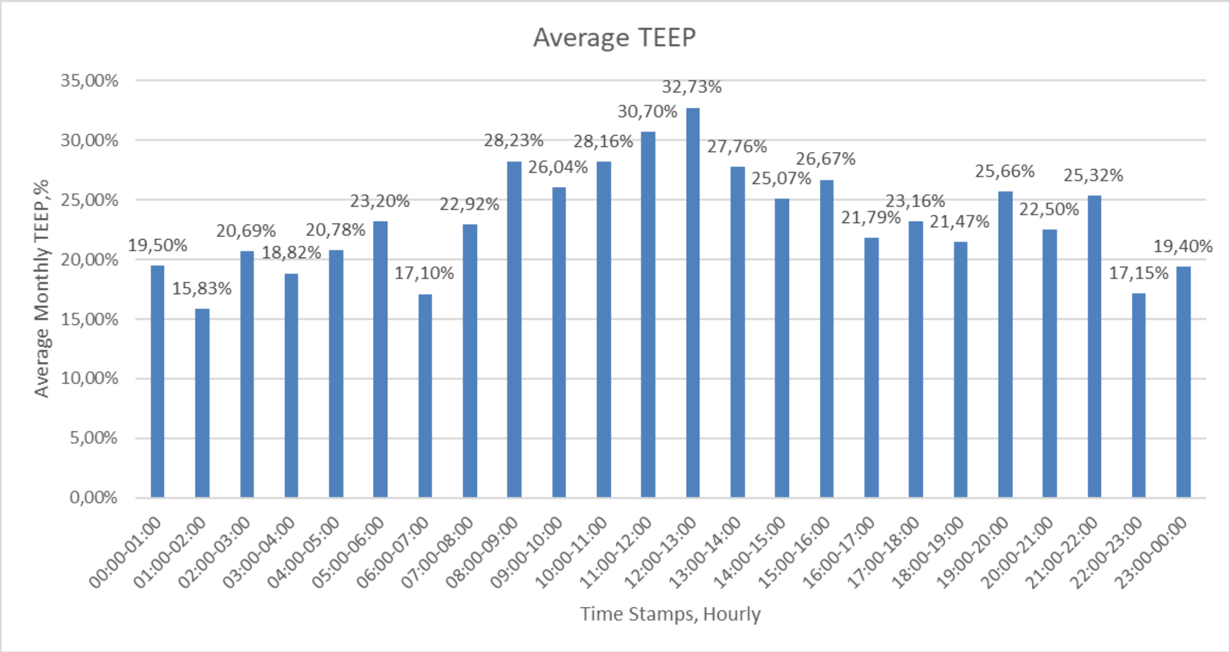

Fig. 24. Hourly Average TEEP Chart

As per the statistical analysis performed, AGVs perform at a high quality in the case company, and dips in performance rates are not due to technical failures. Underutilisation and variation in utilisation explain the drop in utilisation rates due to drops in job demand. The Quality rate indicates robots' technical capability, suggesting minimal manual troubleshooting necessary to correct the jobs and consequently reducing indirect labour costs. The hourly average chart for TEEP indicates a period of low activity during later shifts of the day, confirming the conclusion of underutilisation of the AGV fleet's capacity. Table 14 compiles the information concluded from the statistical analysis.

Table 14. Summary of KPIs with operational and economic insights extracted

KPI	Sample Mean Value	Key Insights	Economic Result
Quality Rate	94.25%	Jobs completed at a high quality imply reliability and minimal technical errors.	Reduces the indirect labour cost associated with manual intervention
Utilisation Rate	33.00%	AGVs are underused during night and early morning shifts	The plant is not utilising the AGV fleet's maximum capacity and is not extracting maximum savings.
Effective Utilisation Rate	52.10%	Discounting unavailable robots calculates a more accurate utilisation rate.	Unavailable AGVs incur ownership costs, reducing savings.
Performance Rate	78.92%	AGVs are performing at expected speeds with some occasional path-related delays.	A path optimisation will increase cost effectiveness by reducing transport waste.
Total Effective Equipment Performance (TEEP)	23.26%	The target of 35% is achievable with improvements to process constraints (underutilisation).	There is an opportunity to increase ROI if underutilisation is tackled.

3.4. Chapter Summary

In this chapter, the implementation of an AGV fleet at a manufacturing enterprise was described, providing insights on the company‘s logistics processes, system implementation maturity and operational performance. Factors such as material flow and plant layout play a great role in the success of material transport automation. The description of storage areas and analysis of the material supply process framed the problem being solved by AGVs in company “X”. The case study demonstrated potential and current limitations of AGV deployment in a manufacturing environment. The company gradually implemented 13 floor-supported AGVs, beginning with high-volume and high-frequency use cases. A novel AGV maturity model was developed and applied to diagnose AGV deployment on a five-level scale. The model was applied to create an assessment framework structured based on the five dimensions identified through literature as critical to the success and scalability of an AGV system. The average maturity score was 3, categorising the implementation at the “Standardised” level. The diagnosis scored the organisation highly on data-driven performance and workforce preparedness. On the other hand, efficiency and AI/ML use were identified as areas of improvement. Although a foundation for good performance exists, the fleet can be utilised more effectively by enabling intelligent system improvements through AI/ML. In the third task, we studied the fleet’s impact through performance analysis of the five KPIs: quality rate, utilisation rate, effective utilisation rate, performance rate and TEEP. The statistical process analysis revealed high average quality rate (94.25%) - highlighting the technical reliability of the system, low average utilisation rate (33.00%) - due to underutilisation of the fleet, moderate average effective utilisation rate (52.10%) - improving the measurement accuracy by excluding inactive robots, relatively good average performance rate (78.92%) and a low average TEEP (23.26% compared to target of 35%) - demonstrating the cumulation of efficiency losses mostly due to lower utilisation rates as the output from the Pearson correlation analysis concluded. Quality and performance rates, although high, do not influence TEEP significantly in this case. Results provided key insights that guide future improvement measures. To summarise, the implementation system was found technically dependable, however, the system is deemed constrained by operation planning factors at the plant level, such as variation in production volumes and their fulfilment, lower AGV demand in the night shifts, etc. Further research should aim to perform a root cause investigation, such as a Pareto-based evaluation, to identify and prioritise the factors leading to the underutilisation of AGVs to perform high-impact improvements that unlock the full value of the automation

4. Economic Evaluation of the AGV Deployment

As highlighted in previous chapters, the AGV implementation is a strategic decision to achieve economic and operational benefits. From the perspective of engineering management, both capital expenditure (CAPEX) and operational expenditure (OPEX) are important to consider when evaluating the impact of an investment. CAPEX is the one-time cost associated with the procurement and installation of the AGV system. The costs are amortised over the expected service life of the AGVs. In this case, CAPEX is estimated as €45,000 per AGV shuttle (comprising €40,000 based on the supplier pricing agreement and an estimated €5,000 installation cost). OPEX includes the repetitive costs required to operate and maintain the system, such as energy costs, maintenance costs, labour costs, etc. For reference, OPEX investments are estimated at €5,000 per AGV annually. However, to maintain a clear and consistent scope, the ROI calculation in the analysis will focus on initial capital recovery.

The implementation was phased across eight consecutive quarters. The total investment per AGV is estimated at €50,000. To calculate the quarterly investment amount, the number of AGVs added in the current quarter is multiplied by the unit investment cost of €50,000. In Eq. 10, the formula used to calculate the quarterly investment value C_{Q_n} is presented:

$$C_{Q_n} = \Delta N_k \cdot C_k \tag{10}$$

where: C_{Q_n} is the investment value in quarter n (€); ΔN_k is the number of new AGVs added in quarter n, compared to the previous quarter (units); C_k is the unit cost for one AGV k (€)

To estimate cost savings from the deployment of AGVs in each quarter, a formula is used that calculates operational savings per unit. The model assumes that once an AGV is deployed, it generates a predefined amount of cost savings per shift (€ 9250 in company X‘s case). Company X operates on a three-shift model. Additionally, the savings formula is adjusted to take into account the efficiency of the AGV fleet. The efficiency factor used to calculate is derived from the target TEEP value (35% or 0.35). In Eq. 11, the formula used to calculate the estimated quarterly savings value C_{Q_n} is presented:

$$S_{Q_n} = N_k \cdot S_k \cdot c \cdot E \tag{11}$$

where: S_{Q_n} is the estimated savings in quarter n (€); N_k is the number of AGVs operating in quarter n (units); S_k is the quarterly saving for one shift per AGV k (€); c is the number of shifts per day; E is the performance efficiency factor

Table 15 presents the number of AGVs deployed every quarter to the current quarter (2023-2025), calculated quarterly investment values and estimated quarterly savings values. The savings represent the cost reduction achieved by deploying the AGV.

Table 15. Quarterly Investment and Savings from AGV deployment (2023-2025)

Year	**Quarter**	**AGVs deployed N_k**	**Investment C_{Q_n}(€)**	**Savings S_{Q_n} (€)**
2023	Q2	1	50,000	9,713
	Q3	2	50,000	19,425
	Q4	3	50,000	29,138

Year	Quarter	AGVs deployed N_k	Investment C_{Q_n}(€)	Savings S_{Q_n} (€)
2024	Q1	4	50,000	38,850
	Q2	7	150,000	67,988
	Q3	9	100,000	87,413
	Q4	10	50,000	97,125
2025	Q1	13	150,000	126,263
	Q2	13	-	126,263
	Q3	13	-	126,263
	Q4	13	-	126,263

To assess the profitability of the implementation, the Return on Investment (ROI) is calculated using the Internal Rate of Return (IRR) method, as it considers both the investment and the savings incurred across each quarter. The IRR measures the percentage rate of return by evaluating the efficiency of an investment based on its cash flows over time. IRR calculation returns a percentage value on computing the given series of yearly cash flows. Eq. 12 expresses the ROI calculation using this method:

$$ROI = IRR(\{-C_1, -C_2..., -C_m, S_1, S_2, ..., S_m\}) \quad 12$$

where: C_n are the investment value in each year m (€); S_m are the savings in each year m (€); negative signs represent cash outflows (investments), and positive values represent cash inflows (savings).

Table 16 presents the yearly sum of investments and savings used to calculate the ROI value. The payback period is considered to be three years.

Table 16. Yearly Sum of Investments and Savings for AGV deployment (2023-2025)

Year	Sum of Investments (€)	Sum of Savings (€)
2023	150,000	58,275
2024	350,000	291,375
2025	350,000	505,050

The IRR function in Excel calculates the return on investment for the implementation as 8%. As the IRR is positive, the investment is viable if the cost of capital is lower than the IRR value. However, it is worth noting that the initial business case is based on a target TEEP of 35%. The calculated experimental value of TEEP is 23.26%. At this lower efficiency, the projected ROI would not be achieved. This emphasises the importance of performance optimisation to justify the investment.

Conclusions

1. The logistic processes in enterprise ‘X ’ are structured across four functional areas: goods receipt, warehousing, material supply and shipping. Automation of transport has an impact on the efficiency of all the functional domains, but it belongs to the material supply domain. The company implemented a fleet of 13 floor-supported AGVs to automate high-volume and high-frequency material supply jobs.
2. A novel AGV maturity model was developed and applied to diagnose AGV deployment on a five-level scale. Overall, the AGV implementation in enterprise “X” is at the ‘standardised’ level. The diagnosis scored the organisation highly on data-driven performance and workforce preparedness (3.5/5), validating the operational readiness. System integration and autonomy are rated moderately (3/5), due to limited ERP integration and the need for path optimisation. On the other hand, efficiency and AI/ML use were identified as areas of improvement (2.5/5).
3. The AGV fleet performs at a high-quality rate (mean=94.25%) and a moderate performance rate (mean=78.92%), confirming the fleet’s reliability from the technical perspective. The effective utilisation rate (mean =52.10) is a better metric than the utilisation rate (mean = 33%), highlighting the value of removing unavailable robots from the calculation to understand the real system capacity. The utilisation rate is the limiting parameter hindering AGV performance due to underutilisation. The TEEP metric (mean=23.26; target=35 %) depicts the overall operational effectiveness of the AGV system.
4. The AGV deployment business case demonstrates progressive cost savings over time, reaching an estimated quarterly saving of €126,263 by Q1 2025. Over the full implementation period, the calculated ROI reaches 8%, assuming the system maintains target performance efficiency. The results justify the financial viability within the planned three-year payback period ending in 2025. However, the ROI is dependent on the efficiency of operations, emphasising the criticality of achieving target performance metrics.

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Appendices

Appendix 1. Maturity Level Determination Survey Template

Please rate each category by selecting one level (1 to 5) that best reflects the current state of AGV deployment at your company. This survey aims assess the current level of maturity of the AGV implementation.

Evaluation Category	**Initial (1)**	**Managed (2)**	**Standardised (3)**	**Optimised (4)**	**Autonomous (5)**	**Average Rating (1–5)**
System Integration	No integration with ERP/MES.	Partial integration with ERP/MES	Full integration with ERP/MES	Integration with ERP and data is used for forecasting	Connected in full to enterprise systems and cloud	
Autonomy	Manual operation and no autonomy	Semi-autonomous with frequent manual input	Autonomous navigation in fixed paths	Dynamic rerouting and adaptive navigation	Self-adaptive with minimal intervention	
Data Analytics & Performance Metrics	No KPI tracking and manual reports only	Basic KPIs are tracked manually	Automated real-time KPIs. Dashboards used	KPIs are analysed for performance optimisation decisions	Predictive and prescriptive analytics	
Workforce Skills	No AGV-related training and no workforce awareness	Limited training and support are needed from the supplier	The entire operational workforce is trained on the basic AGV problems	Proficient troubleshooting and optimisation by the workforce	Minimal human input and proactive system support	
Efficiency	Very low utilisation and high downtime	Basic usability and high delays	Improved efficiency and reliable usage	High utilisation and low cost per move	Near 100% optimisation; peak efficiency	
AI/ML Use	No AI/ML use	Limited logic control algorithms	Rule-based optimisation	Predictive logic and basic ML for route planning	Advanced AI for learning, planning, and self-repair	

Each level is defined as follows:

1. Initial (Level 1) represents an isolated approach adopted for the implementation pilot.
2. Managed (Level 2) represents the partial integration to the system with process limitations.
3. Standardised (Level 3) represents improved integration with the performance KPIs defined.
4. Optimised (Level 4) represents improved efficiency levels and active optimisation of processes.
5. Autonomous (Level 5) represents full automation of material transport, minimal human input and auto-optimisation by systems.

Appendix 2. Industrial Engineering Conference Participation Certificate

12th International Young Researchers' Conference

INDUSTRIAL ENGINEERING 2025

Certificate

This certificate confirms that

Hajar El Mastor

attended in 12th International Young Researchers Conference "Industrial Engineering 2025" and published the article

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in the conference proceedings

15 May 2025, Kaunas, Lithuania

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Dean of the Faculty of Mechanical Engineering and Design

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