Master's thesis

NTNU
Norwegian University of Science and Technology
Faculty of Engineering
Department of Mechanical and Industrial Engineering

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Intralogistics System Design with Autonomous Mobile Robots

Master's thesis in Global Manufacturing Management
Supervisor: Fabio Sgarbossa
Co-supervisor: Mirco Peron
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"It was all a dream…"
-Christopher Wallace

Abstract

This thesis studies the intralogistics system design based on Autonomous Mobile Robots (AMR) for the purpose of recommending the most suitable AMR type to different manufacturing environments. Today's intralogistics systems are being put under pressure by customization and personalization requirements from the market, requiring solutions that are both flexible and responsive to the current market trends. However, a lack of procedures, frameworks, and models that provide an overview of the characteristics and considerations that guide the practical design process of using AMRs is evident in the current scientific literature. A Decision Support System (DSS) linking the most suitable AMR type to the configuration of the manufacturing environment is proposed to address this, along with an overview of the characteristics that impact this decision. The results show the recommended AMR type or types for 192 scenarios across three common manufacturing environments found in industrial manufacturing. The DSS is further validated through mathematical modeling. The results show that the configuration of the characteristics guides what AMR type is most suitable in the manufacturing environment. The thesis contributes to our understanding of how the new and emerging AMR technology can be applied in industrial manufacturing for the purpose of increasing flexibility to meet the trends and requirements that characterize competing in today's markets. Future research should apply and validate the DSS through practical case studies and take additional characteristics the step towards decision support.

Sammendrag

Denne avhandlingen studerer intralogistikksystemdesign med Autonome Mobile Roboter (AMR) for å anbefale den mest egnende AMR typen i forskjellige produksjonsmiljøer. Intralogistikk i dag blir presset av kundetilpassede produkter, noe som krever løsninger som er fleksible for å svare på de nåværende markedstrendene. Til tross for dette er det en mangel på prosedyrer, rammeverk og modeller som gir en oversikt over karakteristikkene som har innflytelse på den praktiske designprosessen for AMRer i nåværende vitenskapelig litteratur. For å adressere dette, er det foreslått et beslutningsstøtteverktøy som har til hensikt å knytte de mest egnede typene AMR til konfigurasjonen av produksjonsmiljøet, samt en oversikt over de karakteristikkene som påvirker denne avgjørelsen. Resultatene viser de foreslåtte typene av AMR for totalt 192 scenarioer over tre vanlige produksjonsmiljøer som man finner i industriell produksjon. Beslutningsstøtten er også validert gjennom matematisk modellering. Resultatene viser at karakteristikkenes konfigurasjon bestemmer hvilken type AMR som er mest egnet for produksjonsmiljøet. Avhandlingen bidrar til vår forståelse av hvordan den nye og fremadstormende AMR teknologien kan bli tatt i bruk i industriell produksjon med den hensikt å øke fleksibiliteten for å møte trendene og kravene fra markedet. Videre forskning burde bruke og validere beslutningsstøtteverktøyet i praktiske casestudier og ta flere av karakteristikkene steget videre til beslutningsstøtte.

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Abbreviations

Abbreviation	Meaning
AGV	Automated guided vehicle
AI	Artificial intelligence
AMR	Autonomous mobile robot
AS/RS	Automated storage and retrieval systems
ATO	Assemble to order
CODP	Customer order decoupling point
CPS	Cyber-physical system
DSS	Decision support system
ETO	Engineer to order
FGI	Finished goods inventory
HSE	Health, safety, and environment
IoT	Internet of Things
KPI	Key performance indicator
L/U	Loading/Unloading
MH	Material handling
MiR	Mobile Industrial Robots
ML	Machine learning
MTO	Make to order
MTS	Make to stock
NTNU	Norwegian University of Science and Technology
PPC	Production planning and control
PQRST	Product, Quantity, Routing, Supporting Services, Time
QR	Quick response
RMI	Raw material inventory
ROC	Rank order clustering
ROI	Return on investment
RQ	Research question
SC	Supply Chain
SHA	Systematic handling analysis
SLAM	Simultaneous localization and mapping
SLC	Small load carrier
SLP	Systematic layout planning
UR	Universal Robots
WIP	Work in process

1 Introduction

Increasing needs for flexibility among manufacturers have come due to current market trends such as customization and personalization of products (Pei et al., 2019). Ensuring efficient and flexible intralogistics solutions are essential for addressing this challenge. Along with the challenges posed by the market, Industry 4.0 technologies now see their application in industrial manufacturing. Among the most promising Industry 4.0 technologies for intralogistics is the Autonomous Mobile Robot (AMR), providing much-needed flexibility to the Material Handling (MH) operations (Andersen et al., 2017). Although the AMR can effectively respond to the challenges set forth by the market trends, their use and application must be carefully considered to make sure the system reaches the required flexibility and efficiency.

Although the AMR has been researched for various purposes and use cases, especially the development of both hardware and software solutions, such approaches have failed to address the practical design process of AMR systems in industrial manufacturing (Bøgh et al., 2012). This includes the link between suitable AMR types and the specific configuration of the manufacturing environment. Effectively, this has neglected the needs of practitioners, and lacking decision support towards designing intralogistics systems with AMRs is an evident shortcoming of the current scientific literature.

This thesis seeks to address this literature gap by providing easy-to-grasp decision support to practitioners regarding the intralogistics system design with AMRs. A Decision Support System (DSS) linking the most suitable type of AMR to the configuration of the manufacturing environment's characteristics is proposed through a review of the scientific literature, AMR vendor solutions, Delphi study, and mathematical modeling. Three AMR types are identified and described to achieve this, along with three manufacturing environments commonly found in industrial manufacturing. Furthermore, an overview of the characteristics that impact the intralogistics system design with AMRs is developed. Finally, mathematical models are developed and used to validate the proposed DSS. Thus, the thesis contributes to our understanding of how the new and emerging AMR technology can be applied in industrial manufacturing for the purpose of increasing flexibility to meet the trends and requirements that characterize competing in today's markets.

1.1 Problem Background

Due to globalization and high competition in virtually every business sector, today's market trends have brought along an increasing desire for more customization and personalization by the customers. Manufacturing started as craft production of exclusively one-of-a-kind products (Koren, 2010). With Henry Ford, we entered the era of mass production, and where beneficial for the specific manufacturer, it evolved into Toyota's lean manufacturing and mass customization. With today's personalization, manufacturing systems are again changing to accommodate personalized production of one-of-a-kind products, as well as remanufacturing (Hu et al., 2011, Koren, 2010). Personalization is the trend of *"consumers' desire to influence and participate in the design of products"* (Hu et al., 2011). Customer interaction in the design process has previously been non-existent in mass-produced consumer goods but can be traced back to craft production, as illustrated in Figure 1.1.

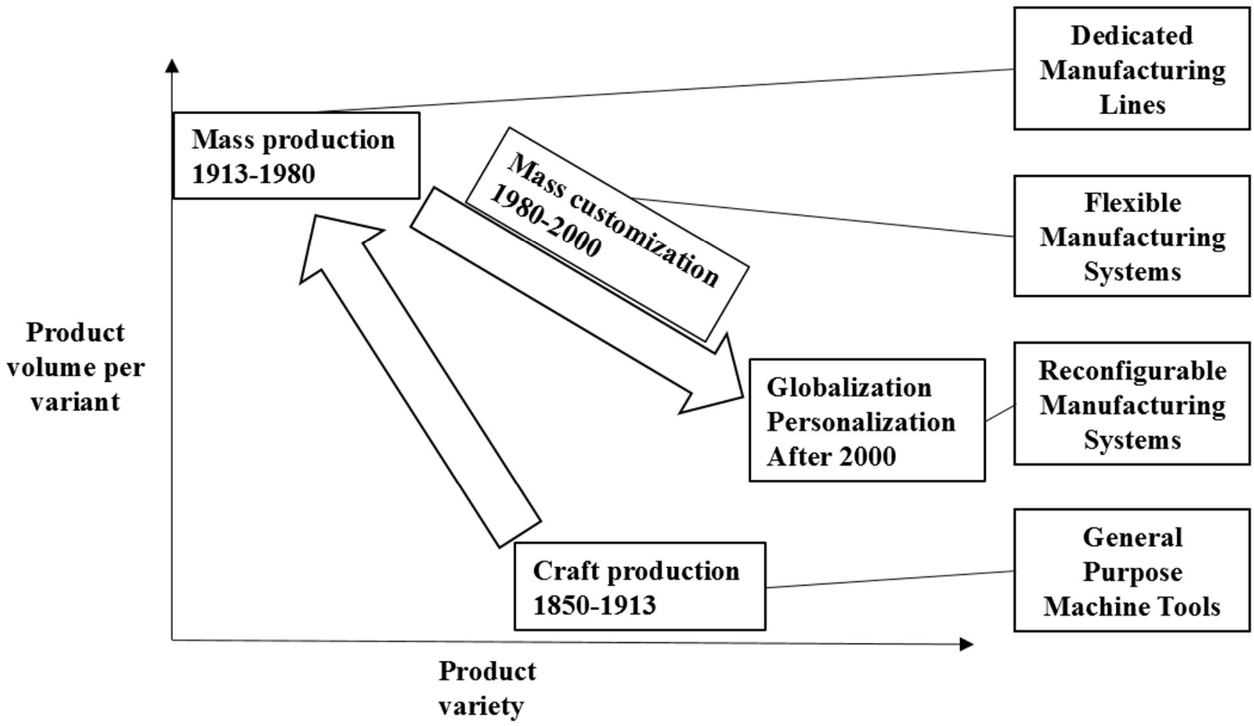

Figure 1.1 – The evolution of production systems from 1850-Today, adapted from Koren (2010)

This paradigm change affects manufacturers whether they still run mass production or if they have taken steps towards mass customization. Increased productivity has been the hallmark of the other paradigm changes, and this change should be no different (Rüßmann et al., 2015). The challenge is to produce high varieties in an economically viable way. Mass production systems do not have the flexibility the current demand requires (Fragapane et al., 2020b), and mass customization systems are faced with the complexity of personalization, e-commerce, and omnichannel distribution (Custodio and Machado, 2020).

Due to the increased pressure to create personalized products, globalization factors, and fierce market competition, the need for flexibility among manufacturers is immense (Pei et al., 2019). Flexibility is defined as *"the ability of a system to respond cost-effectively to changes in volume requirements, product-mix requirements, machine status, and processing capabilities"* (Custodio and Machado, 2020). Dang et al. (2011) stated that the tradeoff is usually focused on being efficient in volumes and inflexible, or highly flexible and less efficient. Achieving increased productivity through flexibility is the balancing act of manufacturing today. Economies of scope are crucial to master, and value differentiation is transitioning as the order winner under these market trends. This emphasizes the just-in-time philosophy and increased agility and customization abilities (Custodio and Machado, 2020). The stretch goal from lean manufacturing with a batch size of one has turned into reality, combined with higher product variation and shorter life cycles of both products and technology, posing a significant challenge to manufacturers (Andersen et al., 2017, Pedersen et al., 2016).

An example of the flexibility challenge is found in the research by Kousi et al. (2019), which stated that mixed-model assembly lines experience unbalanced inventory levels and the need for frequent, high product mix deliveries due to high variation in the produced variants and the different items they require. This effectively puts pressure on the current production and logistics systems, which are now turning towards more flexibility and reconfigurability (Čech et al., 2020). The realization of these attributes is trending towards decentralizing and modularizing the production or assembly systems, which opens up for higher autonomy within production or assembly cells (Michalos et al., 2016b).

The paradigm change has popularly been called Industry 4.0, which is the trending name for the fourth industrial revolution. It is called the fourth revolution because it sequels the three earlier revolutions, namely steam power and mechanization, electricity and mass production, and computers and automation. Industry 4.0 started as a German Government initiative and has spread rapidly due to the application pull created by industry, much due to the need for flexibility and faster market response (Lasi et al., 2014). While Industry 4.0 lacks a clear definition, it is common to view Industry 4.0 as an umbrella term, built on nine technologies that have greatly advanced in the last years. These are often referred to as the nine pillars: Autonomous robots, simulation, horizontal and vertical systems integration, the industrial Internet of Things (IoT), cybersecurity, the cloud, additive manufacturing, augmented reality, and big data and analytics (Rüßmann et al., 2015). While some of these technologies have existed for some time already, quite fundamental changes can be made when they are combined. For example, the industrial IoT combined with simulation and big data can effectively create digital twins of factories - allowing for real-time control and optimization of production systems. Autonomous robots are at the heart of Industry 4.0 advancements (Lasi et al., 2014) and allows factories to realize the aspiration of virtualization, decentralization, and network building in Industry 4.0 (Fragapane et al., 2020b). Although automation has existed for a long time, autonomy is powerful due to the integration of several technologies, making the sum of the components greater than their individual contributions. This increases efficiency and reduces the need for infrastructural interventions (Indri et al., 2019).

Logistics 4.0 has been proposed as a term for the developments and impacts Industry 4.0 and other factors have on today's logistics operations. As defined by Winkelhaus and Grosse (2020), *"Logistics 4.0 is the logistical system that enables the sustainable satisfaction of individualized customer demands without an increase in costs and supports this development in industry and trade using digital technologies"*. This definition also summarizes the trends we see from the market and industry. The framework by Winkelhaus and Grosse (2020) described the technological building blocks, external changes, human factors, logistics tasks, domains, and Logistics 4.0 characteristics under the Logistics 4.0 umbrella. Within this framework, personalization of globalized products is important in the domain of intralogistics, where new methods must be applied to accommodate the flexibility needs on the shop floor.

Reconfigurable manufacturing systems are starting to emerge from discrete manufacturing as a response to the changes in the market trends (Koren and Shpitalni, 2010); however, process industries are not necessarily following this (Fragapane et al., 2020b). High volume and low variety products are produced on dedicated and inflexible equipment. The consequences of this configuration are reduced utilization due to setup times, fixed and rigid layouts, and routings with conveyors, which ultimately reduces their flexibility in terms of product mix. In the case of expanding the number of variants or production output, long setup times or the addition of new production lines results in low utilization and high investment costs (Fragapane et al., 2020b). This is a major deficit with the increasing need for flexibility.

In assembly systems, modularity is a prominent solution for added flexibility. Examples from the automotive sector show a growing trend for this. For example, with the introduction of electric cars, Audi experienced difficulties assembling these on the same line they assembled fossil fuel cars due to the differences (Rendall, 2016). Furthermore, the number of possible variants in the automotive market keeps growing. Their aim is now to modularize the assembly lines to accommodate the need for flexibility. Presented by Kern et al. (2017), modular assembly systems should have three main characteristics: 1) Uncoupled workstations, 2) Flexible assembly systems with transportation of Automated Guided Vehicles (AGV), and 3) Integrated production logistics, decentralizing the logistics areas to uncouple supply from demand. Buffering of components for the different variants to be produced is possible through decentralized logistic areas and introducing Small Load Carriers (SLC) to increase the standardization of MH operations. Combined with AMRs, this allows for smaller and frequent deliveries at the point of use (Urru et al., 2017). In other sectors, autonomous robots are already being used in, for example, military applications (Hvilshøj and Bøgh, 2011), aeronautics and space exploration (Natarajan et al., 2014), and in the medical industry such as home-care (Hvilshøj and Bøgh, 2011) and healthcare (Fragapane et al., 2020a).

In addition to the flexibility challenges, the operator's role is changing and becomes a factor in Logistics 4.0 intralogistics. Machine and workstation operators want to stay at their workstation and perform value-added work instead of exhausting walking and lifting. This is aligned with the goals of many improvement programs to reduce wasted time, unnecessary costs, improve ergonomics, and to increase time spent on value-added activities in the factory. Low-level logistics employees are getting harder to employ since unskilled labor is often occupied by migrant workers seeking better lives in industrialized countries (International Labour Organization, 2021). Especially during the corona crisis, travel restrictions have stopped migrant workers who normally occupy unskilled labor positions such as MH. We also face an aging workforce, requiring us to reduce the amount of heavy and repetitive tasks related to MH (Markis et al., 2019).

With the current market and industry trends it is evident that intralogistics is being put under pressure. Yet, at the same time, it could be the key to success. All these external factors, together with new and improved technology for autonomous MH solutions for intralogistics, have sparked the interest of both practitioners and researchers in this field. One of the enablers for reconfigurable production systems and modular assembly systems is the introduction of autonomous intralogistics. As defined by Fottner et al. (2021), *"Autonomous intralogistics systems enable self-contained, decentralized planning, execution, control, and optimization of internal material and information flows through cooperation and interaction with other systems and with humans".* Among the most studied and applied solutions is the AMR (Andersen et al., 2017). AMRs as a general concept challenges any existing MH equipment and can have a wide range of applications. For example, their level of flexibility due to autonomous navigation puts them ahead of AGVs and conveyors.

Designing intralogistics systems with AMRs differs from the traditional design due to the added capabilities of the vehicle. AMRs operate without drivers, have a small physical footprint, and can be configured to operate in a wide range of environments performing various activities. If the vehicles are deployed in an existing environment, two important decisions are the fleet size and design of the top module. Fleet size largely depends on the layout, travelling distances, Loading/Unloading (L/U) activities, and the material flow. The top module design is influenced by product characteristics such as the weight and size of the products. When undertaking a larger project or designing a completely new system, every step in the design process can be questioned and seen in a new light with the introduction of AMRs. For example, the L/U activity can significantly impact the number of vehicles to purchase and congestion issues (Alizon et al., 2009). L/U stations on machines can be redesigned, fitted with new equipment, or removed depending on the top modules of the AMR. The layout and manufacturing environment can be restructured to allow more flexibility, such as modularizing production cells to allow higher variety in production routing, due to the AMR having fewer restrictions than its predecessors. There is also the possibility of performing various additional tasks based on different top module designs. Employees can be relieved from intralogistics tasks and focused on value-added activities. The aim for any practitioner is to create an efficient, flexible, and scalable intralogistics system that satisfies the production system's requirements in terms of correct and timely delivery.

1.2 Problem Description

Although AMR vendors promise to offer a wide range of capabilities with little integration effort, practitioners are faced with a complex decision with a myriad of options. There are a range of AMR types to choose from, top module variations, L/U activity design, and combined with the manufacturing environment, layout setup, and the likes, create a complex decision. This can be relating the AMR type to the weight & size/shape of the products, the unit load design, or the product mix representing the variety of products. Some AMRs are beneficial, for instance, in high throughput environments due to their low cost and queue-avoidance capabilities, while others are preferred when space consumption is most critical. Ensuring that the most suitable vehicle-system match is achieved can reduce investment costs and allow for conceptual changes to the production system, which can be highly beneficial.

Although existing procedures, models, and frameworks have been proposed on the topic of intralogistics design for several years, such as Systematic Layout Planning (SLP) (Muther and Hales, 1987), expanding the literature beyond the established and well-proven methods for the various parts of intralogistics design must be pursued with the innovative abilities of the AMR. Understanding the consequences of the characteristics the manufacturing environment has is important to properly understand how AMRs can support and improve the future of intralogistics. In the scientific literature, little research has focused on precisely this use and application of the AMR (Nielsen et al., 2017). Instead, there has been a strong focus on optimizing the different subsystems, including the individual technologies of the hardware and the software controlling the vehicles, neglecting aspects such as integration, implementation, and application (Bøgh et al., 2012). This has effectively neglected the needs of the MH system and the system-level design (Kousi et al., 2019). The literature also lacks a classification to support the development and implementation of autonomous systems in intralogistics (Fottner et al., 2021). State-of-the-art research on intralogistics applications of the AMR has been performed by practitioners and business analysts, which is unavailable for researchers and the public domain (Van Meldert and De Boeck, 2016). Furthermore, research on the economics behind AMR solutions remains scarce in the scientific literature (Winkelhaus and Grosse, 2020). Consequently, manufacturers and practitioners require performance metrics and implementation procedures which are non-existent today (Schneier and Bostelman, 2015).

The correct design of the intralogistics system can significantly reduce waste and increase throughput and flexibility, essentially being a key to enhancing manufacturers' competitiveness in today's markets. AMRs can allow practitioners to make conceptual changes to the production system, effectively adapting to the current market conditions. The literature gap can be summarized as the lack of procedures, frameworks, and models that provide an overview of the characteristics and considerations that guide the practical design process of AMR systems, including the link between suitable AMR types and the specific configuration of the manufacturing environment. The practical design process is seen as the execution of layout planning, AMR type selection, fleet sizing, and similar activities in relation to facilities and intralogistics planning. Pursuing research on this topic is considered crucial decision support for practitioners undertaking intralogistics projects using AMRs in a manufacturing environment, which is becoming increasingly common in the Industry 4.0 era.

1.3 Research Objective and Questions

The research objective of this thesis is to address the gap in the literature regarding the lack of procedures, frameworks, and models that provide an overview of the characteristics and considerations that guide the practical design process of AMR systems, including the link between suitable AMR types and the specific configuration of the manufacturing environment. The intention is to develop a DSS that can connect the characteristics and capabilities of AMRs (e.g., payload capacity, costs, L/U activities), characteristics of the manufacturing environment (e.g., product weight & size/shape, throughput requirements, travel distances), and established design procedures (e.g., layout design, material handling equipment selection). This thesis addresses the following two Research Questions (RQ) to reach the research objective:

RQ 1: *What are the characteristics to consider when designing intralogistics systems based on AMRs?*
RQ 2: *What is(are) the most suitable AMR type(s) in different manufacturing environments?*

RQ1 is concerned with making an overview of the characteristics to consider, which is answered using a literature review and a review of AMR vendor's solutions available on the market. RQ2 is answered by developing a DSS that builds on the characteristics from RQ1 and a Delphi study, proposing the most suitable AMR type in different manufacturing environments. Simplified mathematical models are developed to validate the DSS. By developing the overview of characteristics and DSS, practitioners are provided with the characteristics to consider, what they entail, and which AMR type suits their manufacturing environment. The RQs, their objective, the methodology, and resulting tools are linked as shown in Table 1.1.

Table 1.1 – Research questions, objectives, methodology, and tools

Research question	Objectives	Methodology	Tools for practitioners
What are the characteristics to consider when designing intralogistics systems based on AMRs?	Identify characteristics of the system and AMR relevant for the design of the final system	• Literature review • AMR vendor solutions review	Overview of characteristics
What is(are) the most suitable AMR type(s) in different manufacturing environments?	Recommend the most suitable AMR depending on the configuration of the manufacturing environment	• Based on the overview from RQ1 • Delphi study • Validation through mathematical modeling	Decision support system

1.4 Research Scope, Outline, and Structure

This thesis is concerned with the use of AMRs in industrial manufacturing environments for the purpose of intralogistics MH. A range of other application areas such as warehousing, fulfillment centers, hospitals, and the likes are discussed in the literature and applied in industry but are not a part of this study. Other types of MH equipment are not discussed, as they remain thoroughly covered in the existing scientific literature. An additional part of the intralogistics system design is the information flow. This thesis does not address the information flow part of the intralogistics system. The information flow is better suited for studies related to the other parts of planning and control, such as scheduling, dispatching, and control systems. Hence, this thesis effectively considers the intralogistics system design based on AMRs as the organization of the internal flow of materials with AMRs for industrial manufacturing environments.

The thesis is restricted to three main manufacturing environments: Production lines, job shops, and cellular manufacturing. The literature review is restricted to reviewing design procedures for manufacturing environments, layout, MH equipment, cellular manufacturing, intralogistics with AMRs, and AMR vendor solutions. The focus is directed at covering the main design decision and the most common methods for making these decisions. The purpose is not to create new design procedures, e.g., for layouts, but rather analyzing the existing procedure and addressing the impact of AMRs. This serves as input to the proposed overview and DSS. This is done to relate the overview and DSS to the common and accepted research in the scientific literature as well as creating them unifying and easy-to-grasp for practitioners. The overview and DSS can also be used to evaluate AMRs in more detail when comparing them with other MH equipment if there are several seemingly equal alternatives; however, directly addressing this is not the objective of this thesis. Thus, this thesis proposes the most suitable AMR, but does not address whether the AMR is suitable or not when compared to other MH equipment. Worth noting is the large body of research on AMRs from the robotics, information technology, and electronics research strings. Brief discussions are presented from these strings to describe the hardware and software of the AMR, but it is not the aim of this thesis to directly address this literature.

The research outline and thesis structure are presented in Figure 1.2. This shows the research steps taken and where they are located in respect to the thesis structure.

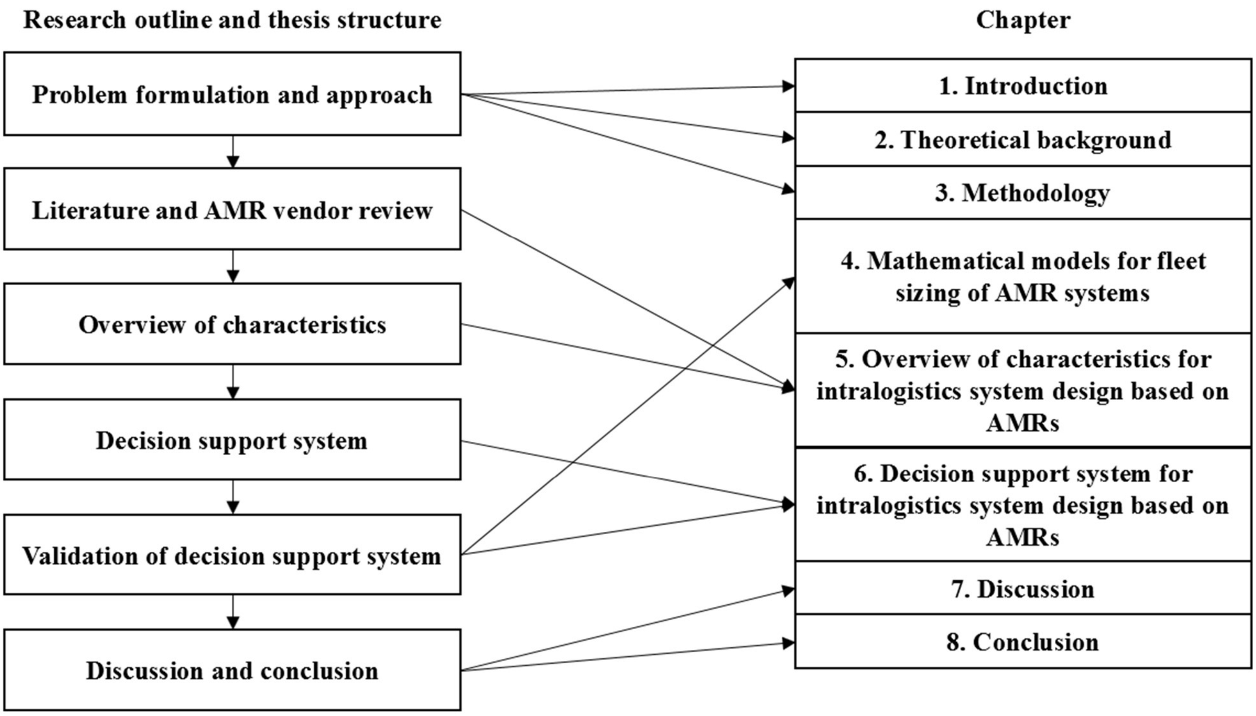

Figure 1.2 – Research outline and thesis structure

2 Theoretical Background on AMRs and Manufacturing Environments

This chapter starts with the theoretical background for the AMR by defining, describing, and presenting the AMR and the challenges and benefits regarding its industrial application. Then, the intralogistics properties of the three manufacturing environments considered in this thesis; production lines, job shops, and cellular manufacturing; are described.

2.1 Autonomous Mobile Robots

The AMR is one of the nine pillar technologies in Industry 4.0 and is becoming a prominent tool for MH and especially intralogistics. They are being put to use in manufacturing companies worldwide proving their efficiency, suppliers keep developing new and better robots, as well as it is becoming a popular topic for researchers (Andersen et al., 2017, Horňáková et al., 2019). Along with technological developments, decreasing costs for the AMR has been an important enabler. It is expected that smart factories will be increasingly common, which will integrate production and assembly lines with AMRs, cobots, and enhanced manual workstations (Indri et al., 2019). Like Industry 4.0, giving a precise definition of AMRs is a difficult task. They come in a wide range of types with different applications and equipment. Additionally, the rapid development of new types makes it more challenging (Indri et al., 2019). This thesis uses the definition from Fragapane et al. (2021) because it properly describes the AMRs for the purpose of this thesis. As defined by Fragapane et al. (2021), *"Autonomous mobile robots are industrial robots that use a decentralized decision-making process for collision-free navigation to provide a platform for material handling, collaborative activities, and full services within a bounded area"*.

Simply put, an AMR consists of a battery powered mobile platform. The vehicle is equipped with various vision systems and sensors to sense and navigate autonomously in an environment. This allows the vehicle to model and map the environment, localize itself, and perform path planning and motion control decisions (Lynch et al., 2019). The basic form of an AMR is also equipped with a top module capable of safely transporting items and parts. Various equipment and top module designs can be equipped which allows the AMR to perform a wide range of activities. This can, for instance, be manipulators with various tools or a conveyor top. Equipping a manipulator on the AMR allows it to pick and place the objects it is transporting, removing the need for L/U equipment. The first AMR equipped with a manipulator was created in 1984 and was called MORO (Mobile Roboter) (Andersen et al., 2017). The MORO transported parts, handled tools, and navigated the shop floor. However, due to limitations in processing power, battery capacity, and its high cost, it never got any industrial applications (Andersen et al., 2017). In the work by Hvilshøj et al. (2012a) the evolution from the 1984 MORO to the modern-day AMRs pre 2011 was described. This highlighted the technological improvements made in hardware and software which has turned AMRs into a viable option for industrial applications.

The technological improvements in hardware have enabled the development of AMRs as a viable concept. With these improvements, software has been developed for the efficient control and operation of the vehicles. A description of how these improvements have impacted AMRs on planning and control of AMR systems is found in the work by Fragapane et al. (2021). The hardware anatomy of the vehicles consists of power-efficient sensors such as tactile sensors, LIDAR, 3D-cameras, accelerometers, gyroscopes, magnetometers, wheel encoders, and powerful processors (Wang and Du, 2016, Alatise and Hancke, 2020, Rubio et al., 2019). Rapid developments in the field of battery technologies allows for ever smaller and lighter vehicles, due to the high energy densities in for example lithium-ion batteries. To sustain the advanced vehicles over extended periods of time and 24-hour operations, wireless charging and autonomous battery change has been proposed (Zou et al., 2018). In terms of software solutions, path planning and navigation in dynamic environments are crucial challenges to solve. Several technologies, sensors, and vision systems are deployed to accommodate autonomous navigation, as well as the introduction of Simultaneous Localization And Mapping (SLAM) and Artificial Intelligence (AI) together with Machine Learning (ML) to enhance and optimize path planning (Zhang et al., 2016). All the data input from sensors are fused together to successfully localize and navigate, using fusion methods such as Kalman and particle filters, and decision-making algorithms for sensor fusion based on Bayesian networks or Dempster-Shafer Theory (Alatise and Hancke, 2020).

AMRs as a general concept can challenge virtually any existing intralogistics MH equipment. Although its application must be carefully considered, as is the purpose of this thesis to address, it provides a range of benefits compared to its competitors. The established industrial AGVs face limitations with its predefined paths requiring permanent installations for navigation support, normally integrated in the floor. In the case of redesigning the layout or assigning new routes, there is a need for infrastructural changes to the guidance installations. Since the paths are predefined, AGVs cannot dynamically change their path and will stop if an object is blocking its path. Furthermore, planning activities and L/U of AGVs are mainly performed manually (Kousi et al., 2019). Neither of these limitations are facing the AMRs, as they can plan their path dynamically and autonomously without any additional infrastructure interventions. The popular assembly line feeding equipment, tugger trains, forces a lot of design constraints on the layout design. When replaced with AMRs, less design effort is needed because the need for one-way lanes, U-turn areas, spacious turn radiuses, fixed routes, and long milk-runs are no longer needed (Urru et al., 2017). Using AMRs also removes conveyors who act as barriers that make some routes inaccessible.

Automated equipment has been around in industry for some years, and an early focus was to dedicate them to perform tasks that are dumb, dull, dangerous, and dirty (Hvilshøj and Bøgh, 2011). This helps to improve ergonomics and job satisfaction with operators. Providing flexibility; however, often comes with high investment costs due to extra equipment with low utilization, and few studies have looked at configuring flexible automation solutions to reduce costs (Yamazaki et al., 2017). As much as 40% of the investment cost in automotive part manufacturing can be accredited to the MH equipment (Yamazaki et al., 2017). Based on new strategies this can be reduced, such as integrating MH equipment in the early design process, and not designing the MH solutions after the machine structures are ready (Yamazaki et al., 2017). The consequence of the wrong approach is low utilization and waiting times, which is commonly recognized as waste in lean manufacturing (Nicholas, 2011). The increased agility and reduced infrastructure investment for the AMR allows for quick re-organization to produce new variants (Marvel et al., 2018). Selected researchers report the following improvements and benefits when using AMRs for various logistics applications:

- AMRs in assembly lines: *"Higher reconfigurability, reduced duration of breakdowns, lower commissioning time, higher reliability and flexibility, minimum need for human intervention due to their autonomous behavior and higher production variability"* in addition to an increase in output volume, utilization, and availability (Michalos et al., 2016a).
- AMRs in factory environments: *"Higher flexibility in processes, improved degree of capacity utilization for robots, higher economic efficiency and process stability and automation of currently not automatable processes"* (Unger et al., 2018).
- AMRs in logistics systems: *"Autonomous planning and high level of flexibility, the system operates steadily and safely, high degree of intelligence and fewer staff members and battery driven, green and environmentally friendly"* (Zhang et al., 2019).
- Providing real-time data from the shop floor to the smart factory ecosystem (Indri et al., 2019).
- Communicating and negotiating independently with production resources to optimize itself (Fragapane et al., 2021).
- Important decision categories and future development possibilities: Degree of autonomy, degree of freedom, application, ease of integration, scalability, safety standards, AI, and costs (Indri et al., 2019).

Despite its benefits, some technical areas remain challenging, such as the level of accuracy, the flexibility of the AMR system, and the safety in operation. Accuracy is one of the major concerns, as accuracy and repeatability are important features of the AMR (Cronin et al., 2019). Combining manipulators with AMRs increases the complexity of control. Ideally, the AMR base provides a free path for the manipulator, but additional degrees of freedom and uncertainty in sensors and actuators can impair the operation (Natarajan et al., 2014). Accurate position for e.g., machine tools and Automated Storage and Retrieval Systems (AS/RS) is crucial and usually have narrow margins of error (Vosniakos and Mamalis, 1990). An offset of ±10cm was encountered by Andersen et al. (2017) using a MiR100 robot, which significantly impairs the operation of the vehicle. Lourenço et al. (2016) encountered similar challenges with alignment to supermarkets and workstations on the ROBO-PARTNER project. Additional adjustments and computations to successfully align reduces the battery charge (Lim et al., 2019). If the manipulator is placed on the workstation, alignment is even more crucial due to the restricted reach radius of the manipulator. Quick Response (QR) codes can decouple the manipulator from the AMR and improve environment recognition, position of loaded material, and position referencing (Pedersen et al., 2016, Andersen et al., 2017).

AMRs move and operate slower than MH equipment operated by humans (Čech et al., 2020). This leads to an increase in the number of vehicles, which in the worst case could create congestions and bottlenecks. As seen from a real-world implementation of AMRs at Whirlpool in Poland, three AMRs only replaced one manual forklift driver (Crowe, 2019). With autonomous technologies, a higher level of standardization is needed. Standardized cases regularly used for storing smaller items must be stored in a highly structured environment, which can impair space utilization due to low utilization of the space inside the case. In addition, AMRs can struggle with identifying the correct case when neighboring cases look the same (Huang et al., 2015). The AMR must also be able to recognize its cargo, update, and correct inventory status. QR codes are suggested by Čech et al. (2020) for this purpose.

It is crucial for the AMR itself to be flexible to accommodate higher product variety. Identified by Huang et al. (2015), affordable AMR manipulator tools pre 2015 were not able to handle a wide range of items, but were restricted to standardized cases, bags, bins, and pallets. This is an important shortcoming because accommodating an increasing product variety is what the AMR is set to do, and so it must be able to handle products of different weights, sizes, and shapes (Custodio and Machado, 2020). Tool exchange can be useful for this purpose, as well as in terms of breakdowns, and for reducing tool-changing costs (Dang and Nguyen, 2017). Other important areas are rapid reprogramming (Custodio and Machado, 2020, Cronin et al., 2019). Custodio and Machado (2020) further stated that AMRs should have *"The ability to be rapidly re-tasked without the need to be shut down for an extended period of time when a new operation needs to be performed; the ability to recover from errors; the ability to quickly swap in and out from different manufacturers, so that a company is not tied to a single robot brand"*. Thus, AMR vendors must pay attention to scalability and co-existing with other AMR brands - allowing the AMR to become as close to plug-and-work as possible. To provide added flexibility to the smart factory ecosystem, the connectivity of the vehicles is important. Oyekanlu et al. (2020) covered challenges regarding localization and navigation, scheduling algorithms, path planning algorithms, and wireless and 5G technologies for the control and connectivity of the AMR. Reported difficulties include precise and reliable docking, reliable networking, and communication issues.

AMRs must be safe and collaborative when coexisting with humans on the shop floor (Cronin et al., 2019). Studies show improved ergonomic ratings of workstations in proximity to AMR operations (Unger et al., 2018), and some of this can probably be accredited to making the AMRs perform the dumb, dull, dangerous, and dirty operations. However, challenges still exist in regard to navigating freely and safely on the shop floor with dynamic obstacles (Lourenço et al., 2016). Previous safety measures including placing autonomous robots in safety zones or cages can no longer be utilized due to the mobility of the robots. Especially manipulator AMRs create new and unexplored situations where injuries could occur. As suggested by Custodio and Machado (2020), human-robot collaborations are hindered and slowed down due to safety issues. Marvel et al. (2018) stated that increasing the variety and quantity of vehicles in a work cell increases the complexity of control, coordinating, and debugging, effectively creating a need for expensive software solutions to preserve safety and efficiency.

Safety should be emphasized in the development of the future AMRs although new restrictions could limit the capabilities suggested by researchers and practitioners. As pointed out by Markis et al. (2019), no fully compliant standards, guidelines, or design proposals exist for AMRs with active equipment such as a manipulator. The American based Association for Advancing Automation and the American National Standards Institute are working on this exact standard, called the ANSI/RIA R15.08. The aim of this standard is to bridge the gaps between AGV, AMR, and manipulator AMR roaming a shop floor with humans (Markis et al., 2019). It contains *"Technical requirements for the design and integration of industrial mobile robots"* (Rose, 2021). Due to the wide range of applications for AMRs, the standards being developed trend towards an individual responsibility with basis in the standards, rather than a full listing of requirements and needs (Markis et al., 2019). At the time of writing, the ANSI/RIA R15.08 is not yet fully complete, and only the guidelines towards manufacturers of mobile robot equipment are done (Rose, 2021).

2.2 Manufacturing Environments

To address the industrial manufacturing application of the AMR, first the considered manufacturing environments are identified and described. Among the most popular tool for characterizing and classifying manufacturing environments is the product-process matrix developed by Hayes and Wheelwright (1979). The matrix combines the product and process structure (manufacturing environment), and each intersection has its common manufacturing strategy. Using this matrix, the manufacturing plant can be properly structured according to what place it occupies in the matrix.

Table 2.1 – Product-process matrix

Product structure →	**Custom**	←	→	**Commodity**
	Differentiated	←	→	**Standardized**
Process structure	**Low volume**	←	→	**High volume**
Job shop	X			
Batch		X		
Repetitive flow			X	
Continuous flow				X

The matrix, shown in Table 2.1, suggests four general strategies, and additionally project oriented products such as buildings or ships can be included. Projects are usually carried out in a fixed location with tools and material being brought to the site, and thus, they are not considered further in this thesis. Moving along the diagonal from the upper left corner to the bottom right corner, four general strategies are identified. Job shops are found in the upper left corner and have the highest flexibility, used for low volume and high variety products. The next environment on the diagonal is the conventional batch production, moving towards what can be referred to as production lines. These have better efficiency for a narrower range of different products. The next environment is repetitive flow, which are adapted towards standard products with higher volumes. The bottom right corner is occupied by continuous flow lines, where production volume is the highest and product differentiation is the lowest. The most common conception is that only product/process combinations along the diagonal are competitive. This has been challenged and competitive positions off the diagonal have been proved to be competitive, such as mass customization. However, the basics of the product-process matrix still provide a useful tool. Cellular manufacturing has emerged as a combination of job shops and production lines, gathering required machines for a given product family together. This is further presented in one of the following paragraphs.

Additionally, it is common to classify the manufacturing strategy in four categories: Make To Stock (MTS), Assemble To Order (ATO), Make To Order (MTO), and Engineer To Order (ETO) (Stavrulaki and Davis, 2010). Other names might appear due to different nomenclature (e.g., Build to order instead of Make to order). This classification depends on the Customer Order Decoupling Point (CODP), which is the center piece for the level of customization. The CODP is linked to the manufacturing strategies as shown in Table 2.2. These are simple but powerful analysis tools, which guides the rest of the design process. Managers should always be on the lookout for where they are placed, if they should reposition, or differentiate some of their product categories.

Table 2.2 – Customer order decoupling points

Customer order decoupling points	Engineer	Fabricate	Assemble	Deliver
Make to stock				CODP
Assemble to order			CODP	
Make to order		CODP		
Engineer to order	CODP			

To address the intralogistics design procedures, a differentiation of the manufacturing environments commonly found in industrial manufacturing is necessary. Each manufacturing environment has different considerations to make, and the intralogistics design heavily relies on this. To address these differences, three distinct types of manufacturing environments are chosen: Production lines, job shops, and cellular manufacturing. These are based on the product-process matrix from Hayes and Wheelwright (1979) and what is commonly found in industrial manufacturing, as well as being general environments that have their own specific characteristics related to the intralogistics design. Variations within these three are naturally limitless; however, the main concepts of intralogistics can be reasonably described by dividing them into these three environments. A description of the manufacturing environments and their intralogistics properties is now provided.

2.2.1 Production Lines

Production lines are normally preferred where there are medium to high volumes of a given product range to produce (Hayes and Wheelwright, 1979). Some can have lower volumes of larger product mixes, while some have higher volumes with smaller product mixes. For example, continuous flow lines have a very low number of products with a high sales volume per product (Ketokivi and Jokinen, 2006). The raw material or components are processed at the required machines and then sent to the Finished Goods Inventory (FGI). Routing and required processing steps can vary based on the product although usually follows the sequence of the machines on the shop floor. Layout designs depend on the required machines, available floor space and building specifications. The layouts are usually highly sequenced according to the main flows between machines to reduce transport distances for the routes with the highest flow intensity, following the SLP methodology (Muther and Hales, 1987). This means that the majority of the parts starts with the first machine in line, moves on to the second machine in line, and so on. Some variety in routing can be expected when the product mix is large. ATO and MTS are the most utilized strategies for production lines, as they can have high efficiency for a certain range of products (Stavrulaki and Davis, 2010). Intralogistics can be handled with any type of equipment, ranging from forklifts to conveyors, depending on the volume and product mix to handle. Differentiating the equipment can also be a possibility based on the sequence of machines and routings of the products, as some routing steps are equal for all products, while others are not. Figure 2.1 depicts a generic production line which can be considered a reference throughout this thesis.

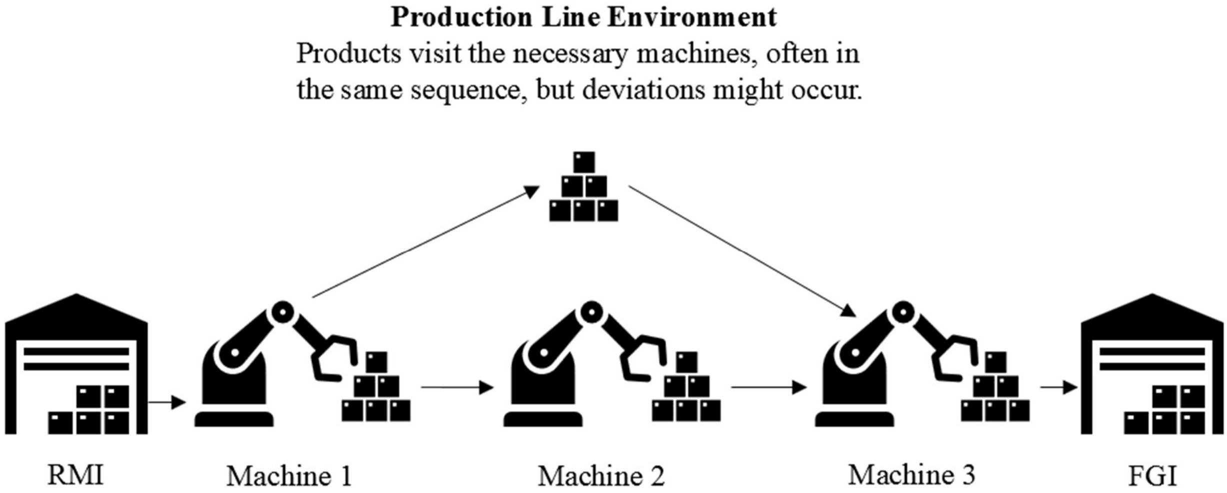

Figure 2.1 – Production line environment

2.2.2 Job Shops

In a job shop, all machines related to a specific activity are gathered into a department, e.g., the welding or painting department. The raw material or components are processed in the required departments and is then sent to the FGI. Routing and required processing steps vary based on the product. Job shops are usually preferred where there is a low volume of a wide variety of products (Hayes and Wheelwright, 1979), and therefore flexibility is preferred over efficiency. Layouts can take on a wide range of shapes, depending on the required equipment, size of the departments, available floor space, and building specifications. However, layouts are usually organized according to the main flows between departments to reduce transport distances for the routes with the highest flow intensity, following the SLP methodology (Muther and Hales, 1987). Job shops especially create a lot of material movement, as the shop floor is split into different departments. For example, all welding activities take place in the welding department and nowhere else. Parts requiring multiple visits to the welding department will have to be transported back and forth across the shop floor, which challenges the transportation and information systems for intralogistics. ETO and MTO are most commonly utilized in job shops due to the level of flexibility (Stavrulaki and Davis, 2010). Intralogistics are generally handled by manual trip-based equipment, such as manual forklifts. Job shops can have both flexible manufacturing equipment and labor-intensive operations (Stavrulaki and Davis, 2010). Figure 2.2 depicts a generic job shop which can be considered a reference throughout this thesis. Not all routing options are visible for illustration purposes.

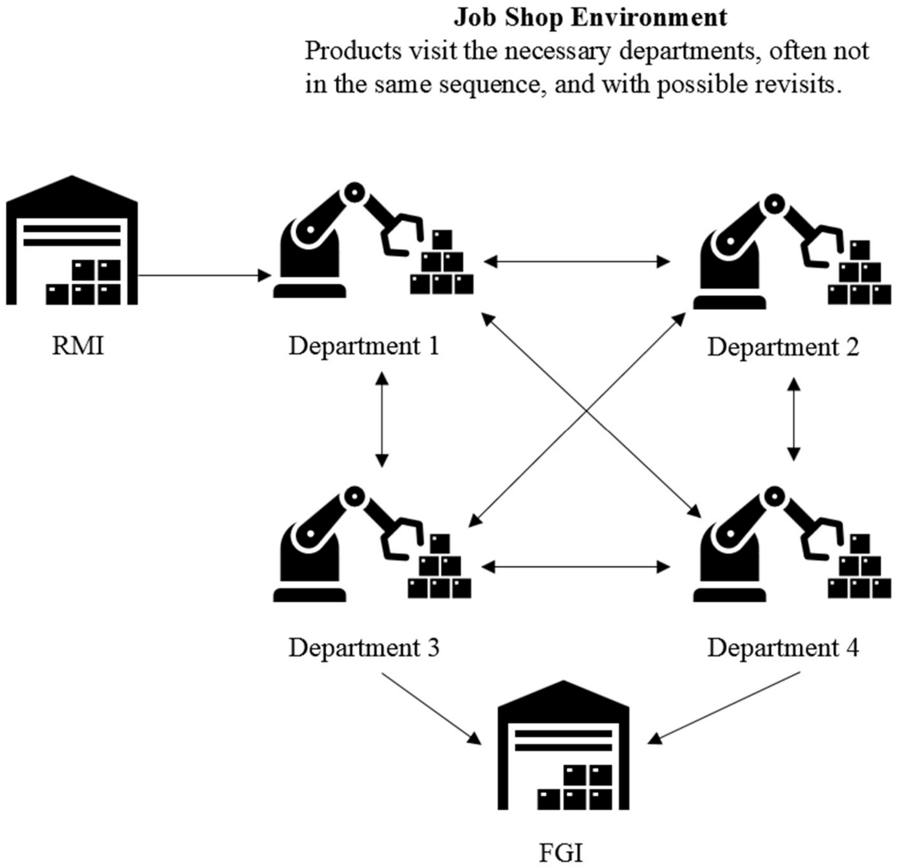

Figure 2.2 – Job shop environment

2.2.3 Cellular Manufacturing

Group technology and the introduction of product families can help create focused factories, or a plant within a plant, and can combine benefits from job shops and production lines (Nicholas, 2011, Skinner, 1974). Popularity has grown especially in the formation of production cells under the lean manufacturing domain. The anatomy of a production cell resembles a job shop with features from a production line sequence of the layout. The cells gather machines, material, intralogistics equipment, and operators to produce product families dedicated to that cell (Nicholas, 2011). The materials or components enter the cell in one end, get processed on the machines in the cell, and are then sent to FGI. A production cell can be utilized for either assembly operations or conventional processing of materials. Often, items are passed manually from one workstation to the next, or simply carried over by the operator if they are performing the next task as well. In the case of long distances or heavy products, small, automated vehicles or manual trolleys can be utilized. For supplying and retrieving items from the cells, AGVs or tugger trains can be used. The cells can take on a range of different shapes, most commonly resembling the letters U, T, S, and Z. This can depend on the nature of the process, or constraints from the building such as pillars and available space. U-cells have received a lot of attention in both research and practice. In U-cells, volume flexibility is highly accommodated due to the ease of adding/removing operators. The distances are kept short for operators to be able to operate several machines at once. Worker flexibility is an important feature in this case (Nicholas, 2011). In the case of assembly, products are not processed but rather assembled together, and the cells are fed from a supermarket with the required components. They often use a modular approach in both the products and processes to address the trade-off between efficiency and flexibility (Stavrulaki and Davis, 2010). A focused factory with cellular manufacturing will be less flexible than a job shop but can provide added efficiency depending on the demand for the designated product families. ATO and MTS are most utilized. The design focus meeting todays' requirements should be on reconfigurability of the cells regarding workers and machines to support more flexibility due to changing market demands (Nicholas, 2011). Figure 2.3 depicts a generic structure of a U-cell which can be considered a reference for cellular manufacturing throughout this thesis.

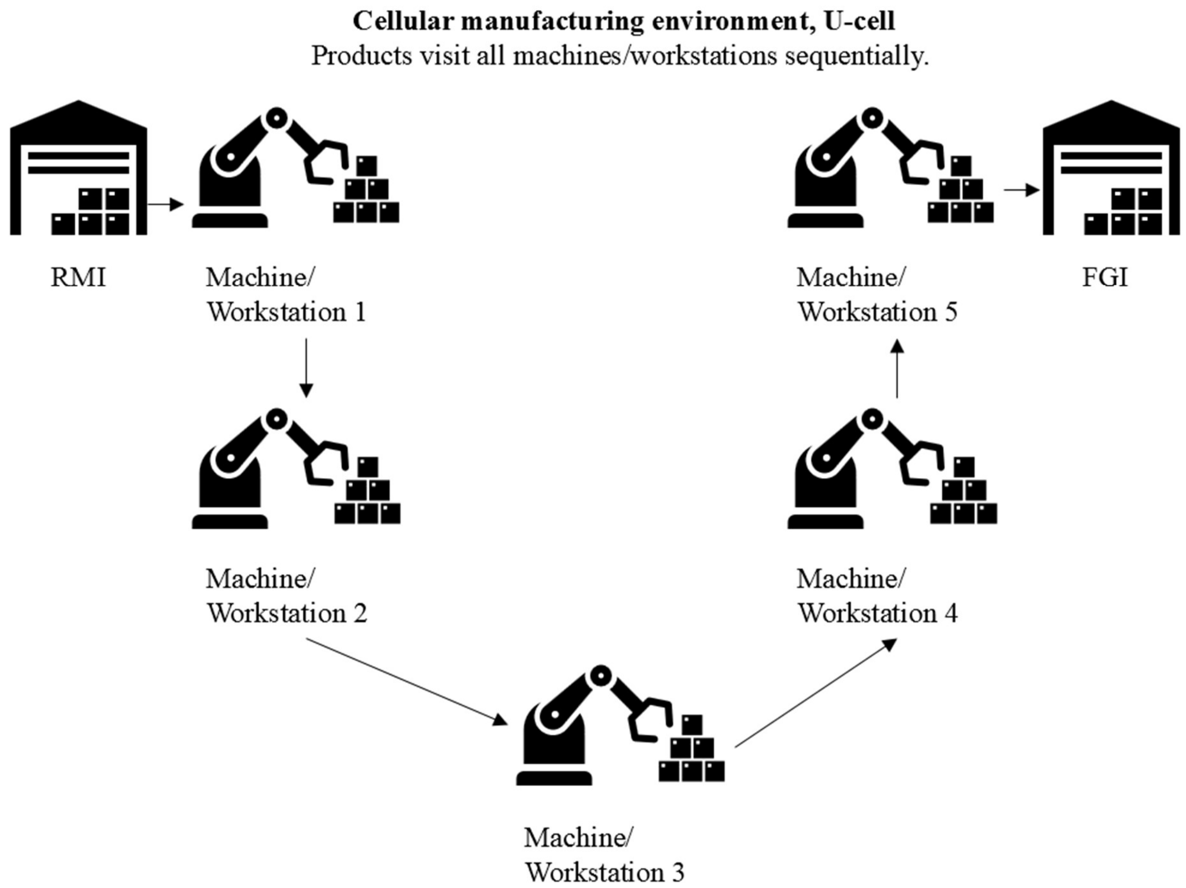

Figure 2.3 – Cellular manufacturing environment, U-cell

2.2.4 Mass Customization

Mass customization has come as a consequence of stronger customer requirements and higher customization of products, shorter product life cycles, and more flexible manufacturing technologies (Da Silveira et al., 2001). Mass customization promises to deliver highly customized products with close to the same efficiency as mass production, thus placing it off the diagonal in the product-process matrix. The idea of mass customization emerged in the 1980s (Da Silveira et al., 2001), and today we can see an ever-increasing desire for customization, which has evolved into personalization of products and shorter life cycles of products. Therefore, mass customization is not described as its own manufacturing environment, as the trend in both market and industry is a desire for more flexibility and efficiency regardless of manufacturing environment.

3 Methodology

This chapter describes the methodology used to address the two RQs. RQ1 is answered by performing a literature review and a review of AMR vendors' solutions, which is described in Chapter 3.1. RQ2 is answered through the development of a DSS, based on the procedure described in Chapter 3.2. Validation of the DSS is performed through mathematical modeling, as described in Chapter 3.3.

3.1 Literature & AMR Vendor Review

To find the relevant characteristics of the manufacturing environment and AMRs to consider, addressing RQ1, a review of the scientific literature and AMR vendors were conducted. By reading the resulting articles and information, the findings were obtained by looking at the areas that impact the intralogistics design, choice of AMR, or the interaction between them. This resulted in the overview of characteristics to consider when designing intralogistics systems based on AMRs. Articles from this literature review are also present in the introduction, theoretical background, and for addressing RQ2 when useful for either defining or addressing the research objective of the thesis.

This two-fold approach of reviewing the scientific literature and AMR vendors was appropriate because the two fields of intralogistics and AMRs are very different. The field of intralogistics design is well explored in prior research and describing the main and general concepts was considered appropriate and adequate. Hence the use of textbooks such as Tompkins et al. (2010) and Muther and Hales (1987), which extensively covers the relevant concepts from this field. Additional literature and more recent research articles have been used when deemed appropriate and to expand the view with more recent research. The AMR field is the direct opposite of an established research field, and this required extensive literature searches in online databases for contemporary research articles, as well as reviewing AMR vendors online to discover different AMR types currently on the market. The literature and AMR vendor review allowed the thesis to develop the results based on prior research conducted and available AMR types on the market.

The literature review was conducted as an integrative review because the intention was to *"combine perspectives to create new theoretical models"*, and not to review all published material on the topic (Snyder, 2019). In line with Torraco (2005), the integrative review fits better for assessing prior research when new theoretical frameworks and perspectives should be the outcome. This suited the thesis best, as this method of literature review is aligned with the aim of the thesis - namely getting a new perspective on an established field. Since this type of literature review lacks a rigid structure, the search strategy, databases, phrases, and screening process are presented to allow for replication and validation.

The three databases Google Scholar, Scopus, and Oria were used for searching in the scientific literature, which covers a wide and satisfying range of scientific journals. Some factors have limited the literature study which was out of the author's control. Only articles accessible through the Norwegian University of Science and Technology (NTNU) license could be used, as well as only articles in English. The search results are limited to what was accessible and published in the two time periods September-October 2020, and January-April 2021. The time period from 2020 was due to a specialization project performed in connection to this thesis. Relevant articles referenced in the obtained articles from the literature searches are also included when deemed appropriate, using a backwards snowballing method.

The search strategy is based on building blocks searches using Boolean operators. Different levels of search terms are combined to allow the database to return relevant articles of interest. Together with the Boolean operators OR and AND, the search terms are checked against the titles, abstracts, and keywords of the published articles. Table 3.1 presents the search terms used. The level 1 terms are general search phrases which are combined with the level 2 terms to specify the context of the search. Level 2 A represents the different nomenclature to the topic of AMRs and aims to find relevant research on AMRs in the level 1 terms. A lack of clear definitions is present due to the rapid development of the field, and thus variations occur between authors regarding the AMR nomenclature. Level 2 B helps to specify the level 1 terms and produce more reliable results within the specified areas of interest. Level 2 A and 2 B terms were also combined to identify research directly related to the objective of this thesis. The selection of search terms is based on common nomenclature in the field known to the author and experience from conducting relevant searches and reading relevant articles.

Table 3.1 – Search terms

Level 1	Level 2 A	Level 2 B
Material handling	Autonomous mobile robot(s), AMR(s)	Design
Intralogistics	Mobile robot(s)	Planning
Material flow	Autonomous mobile manipulator robot(s), AMMR(s)	Application
Manufacturing	Mobile manipulator(s), MM(s)	Vehicle
Production	Autonomous intelligent vehicle(s), AIV(s)	System
Assembly		
Layout		

When the search terms and strategy was executed, screening of the articles based on title, abstracts, and full texts were conducted. The screening process significantly helped to identify the relevant articles, as the topic of AMRs is fragmented among engineering disciplines. AMR literature is found in manufacturing and logistics, but also in robotics, electronics, information technology, and related fields. Evaluating the title and abstract eliminated articles from the wrong fields, and full text screening revealed the relevant articles for the studied problem. The field of AMR research is rapidly developing, and the most recent articles are considered the most relevant. However, less recent articles are used both for describing the established field of intralogistics and manufacturing logistics and for historical developments.

Due to the fragmented nature of the AMR field, a wide range of scientific journals represents the applied literature. Also, conference papers from the Institute of Electrical and Electronics Engineers (IEEE) are included to capture state-of-the-art AMR designs. Selected AMR vendors have been studied to find the existing solutions on the market and to help quantify some technical specifications of the vehicles. The vendors Universal Robots (UR), KUKA, Mobile Industrial Robots (MiR), and Robotnik were chosen as references due to their references in scientific literature, industrial applications, and information presence available to the author. The information gathered is collected from their respective homepages on the internet (Universal Robots A/S, 2021, KUKA AG, 2021a, Mobile Industrial Robots A/S, 2021c, Robotnik Automation S.L.L., 2021c).

Since AMRs are of growing popularity and highly relevant as of the time of writing, media outlets, industrial magazines and the likes also supply a steady stream of available information and convey application stories from industry. Selected publications have been included because the source of the information is likely to come directly from the manufacturer, thus providing input to a more nuanced discussion. Few scientific articles discuss the implementation in companies (Van Meldert and De Boeck, 2016), and this lack of case studies justifies this resort towards alternative sources of information. However, no conclusions are based on this type of information, but as stated earlier, it adds a perspective to the discussion which is lacking in the scientific literature. Application stories originating from AMR vendors are disregarded due to their high level of bias. Full details of journals and sources used are available in the References section.

3.2 Decision Support System

To address RQ2 and provide decision support to practitioners, a DSS is proposed for choosing the most suitable AMR type within a manufacturing environment with given characteristics. The need for a new tool was quickly identified because current intralogistics design tools does not consider the innovative capabilities of the AMR. The presented DSS has its origins in the overview of characteristics from RQ1 and is developed through the following four steps.

Step 1 - Selection of the most important characteristics

The characteristics in the overview from RQ1 were shortlisted to create the DSS. The characteristics include weight & size/shape, throughput, space requirements, travel distance, unit loads, and product mix. A shortlist was appropriate to base the DSS on, because a lot of the characteristics does not impact the choice of AMR type, but rather has high significance for other parts of the design process. The intention was to propose the most suitable AMR types, and only the characteristics that separated the different AMR types was relevant to look at. The full reasoning and discussion leading to the excluded and included characteristics are found in Chapter 6.1. Briefly summarizing the results of the exclusion and inclusion process, the characteristics which do not separate the different AMR types, and where type of AMR does not matter, were excluded. One example of an excluded characteristic is for instance the speed of vehicles, which can be assumed to be similar for all vehicles and restricted in some cases by industrial standards. Opposed to the speed, the product mix is included because it has significant impact for the choice of AMR and interaction with the products. The selection of the characteristics was based on this line of reasoning, supported by literature findings from similar studies, and input from the AMR vendors and their available AMR types obtained from RQ1.

Step 2 - Grading of the characteristic's importance to the manufacturing environments
Since the manufacturing environments are compared on the same characteristics, a grading of their importance to the specific manufacturing environment was needed to propose the most suitable AMR type in all scenarios. To grade the characteristics, a Delphi study was conducted. A Delphi study seeks to achieve consensus among experts on a specific topic, and the procedure should result in a good approximation of the actual situation due to the knowledge of the participants and the benefits of the Delphi process (von der Gracht, 2012). A Delphi study was chosen because it allowed to study a wide range of manufacturing environments in a limited time frame and the available expertise at NTNU. The Delphi study had four participants, including the author. These were chosen based on their experience and expertise, as the participants were all actively engaged in AMR research for manufacturing logistics at NTNU. Their experience ranged from Professor to PhD candidate and the author as a master student. The participants were given a thorough description of the considered manufacturing environments, the characteristics, their definition and scope, and the intended use of the results.

The Delphi process builds on the four elements anonymity, iteration, controlled feedback, and statistical group response (Rowe and Wright, 2001). The use in this thesis assured anonymity of the results, but the participants were aware of and knew the other participants, thus a form of quasi-anonymity was obtained (Hasson et al., 2000). The process was iterated two times to allow the participants to argue for and revise their suggestions in the light of the results from the first round. Two rounds were considered appropriate due to the low number of participants (Hasson et al., 2000). The author of this thesis was the facilitator of the process and controlled the feedback the participants received. The grades were given on a Likert scale (Likert, 1932) of one to five, where the grade one = least amount of impact and grade five = highest amount of impact. This ensured that the Likert scale had five response categories (Allen and Seaman, 2007). In the first round, the mean of the grades given by the four participants were used as a measure for the statistical group response and rounded to the closest integer. As proposed by

Norman (2010), opposing the view of Allen and Seaman (2007), the mean can be used even though a Likert scale is strictly using ordinal data. The mean is used here on the basis that these results were only a measure of the first-round results subject to further discussions. Additionally, several researchers strongly refute that using the mean provides a high probability of reaching an erroneous conclusion (Norman, 2010). Hence, using the mean of the results from the Delphi study was considered appropriate for the first-round results. These results were then forwarded to the participants. Through a discussion they arrived at consensus for the final grades, thus fulfilling the objective of achieving consensus among experts. The results from the second round were used for development of the DSS. Four characteristic-manufacturing environment combinations changed with plus or minus one point in the second round. The results from the Delphi study are presented in Chapter 6.1, while all results from both rounds of the Delphi study are found in Appendix 1 and Appendix 2.

Step 3 - Grading of how well each AMR type performs on the characteristics

A grading process of the AMRs was also needed to propose the most suitable type for each scenario. The AMRs are graded relative to each other depending on how well they perform on the various characteristics. Since there were three AMR types, the highest performer gets three points, the middle one gets two points, and the lowest performer gets one point. Due to considering only three AMR types, and the high customizability of AMRs in terms of tools and adaptations to specific environments, an exact grade is highly difficult to determine. Using a relative grading scale, the uncertainty of the grades was highly reduced, since there are obvious features of the AMR types that would allow them to perform better than the others on the shortlisted characteristics. The grades were given based on the features that the different AMR types had, studying the solutions from the AMR vendors, prior research available in the literature, and how they impact the performance on the shortlisted characteristics. This made the relative grading scale appropriate to use and the grades were based on both prior scientific studies and AMRs currently available on the market. The grades and their explanation are presented in Chapter 6.1.

Step 4 - Evaluation and selection of the most suitable AMR types

With the obtained results from the Delphi study and the grading of the AMRs, the proposed DSS was developed. The DSS consists of a decision tree structure for each of the three manufacturing environments. In the decision trees, for each of the shortlisted characteristics, the scenarios of high and low were considered. With the six characteristics, this resulted in $2^6 = 64$ unique branches of the decision tree, representing 64 scenarios for each manufacturing environment. To propose the most suitable vehicle types, the grade of the AMR was multiplied with the grade of the characteristic for the manufacturing environment when the characteristic was set to “high”. When the characteristics were set to “low”, it was multiplied by zero, and hence did not influence the recommended AMR type. The results from each characteristic were then summed to arrive at the final score for each AMR type in each scenario, following the equation:

$$Score = \sum_{n=1}^{6} Characteristic\ grade_n * AMR\ grade_n \tag{3.1}$$

Due to the subjectivity and uncertainty in the grades, the scores for all AMR types in every scenario were divided by the highest score in the scenario, creating a ratio. A threshold was determined to include or exclude the type as a recommended solution based on the ratio. In many cases, the score was close, and due to the uncertainty in the grades, more than one AMR type was recommended if they surpassed this threshold value. The threshold value was determined by the equation:

$$Threshold = 1 - \left(\frac{Theoretical\ maximum - Top\ performer}{Theoretical\ maximum}\right) \tag{3.2}$$

Where the theoretical maximum is equal to the grade for the characteristic to the manufacturing environment multiplied with the value 3, which is the highest possible grade for the AMR. This equation has several advantages rather than using a static and predetermined threshold. The observed mean for the threshold was 85%, meaning that for all three environments a score within 85% of the top performer will get recommended. However, instead of using 85% as a static threshold, the dynamic threshold better reflected the specific scenarios of being on, close to, or far off the theoretical maximum, as is described now:

- If a vehicle scores the theoretical maximum, no other vehicle is included, as a consequence of the relative grading scale. The relative grading scale does not allow two or more types to score the theoretical maximum in one specific scenario. This is beneficial as a vehicle scoring the theoretical maximum is likely to be a prime choice for the specific environment.

- The closer the top performer is to the theoretical maximum, the smaller the threshold is to include more types. This means that when one type is close to the theoretical maximum, the other types are only recommended if they are close to the same performance. This has nearly the same effect as the scenario of scoring the theoretical maximum, precisely to include only the high scorers when one type performs especially well.

- When the top performer is further away from the theoretical maximum, the bigger the threshold is for other types to be recommended as well. This indicates to the practitioner that other characteristics and considerations should be closely evaluated, such as the proposed qualitative ones from the overview. This is beneficial as it suggests considering more types and possibly other solutions when the performance of the given types is low. This also supports the validity of the DSS, since it cannot capture and reflect every manufacturing environment imaginable, and hence going back to the overview of characteristics and existing tools in the literature might be the better choice for the practitioner.

This procedure for AMR type selection will recommend the most suitable AMR type because the higher the importance of the characteristic is for the manufacturing environment, and the better the AMR performs on this characteristic, the higher the score it receives. In addition, when the characteristic is set to “low”, no vehicles are awarded points. This also reduces some of the uncertainty in selecting the shortlisted characteristics, as the characteristic is essentially ignored in the calculation of scores when not considered important. This allows practitioners to follow the branch of the decision tree that most closely resembles their specific environment and indicates AMR type or types that support their specific configuration. The recommendation(s) should then be subject to more detailed analysis before determining the final design of the system.

3.3 Mathematical Modeling

To validate the proposed DSS, mathematical models for fleet size and cost determinations were developed for the three manufacturing environments: Production lines, job shops, and cellular manufacturing. These are based on generalized and simplified scenarios for the manufacturing environments. Fleet sizing models were used because they allowed to model differences between the AMR types, and combined with the differences in costs and cost structures, it allowed to propose recommendations of different AMR types for different manufacturing environments.

The models include the shortlisted characteristics from the DSS, which impacts the models in various ways. The characteristics throughput, travel distance, and unit loads were included in the fleet size determination, as they will directly impact the fleet size. The characteristics weight & size/shape, space requirements, and product mix will not impact the fleet size under the definitions given in this thesis but are included in the costs of the AMR types. This means these characteristics influence either the cost of the different AMR types or corresponding L/U station, depending on the characteristic and AMR type. For instance, if weight & size/shape is set to “high”, an additional +15% is added to the AMR cost because of the increased payload capacity it requires.

Several assumptions are limiting the mathematical models presented, and they are not to be considered applicable for accurate fleet sizing, but rather a simplified way of validating the DSS, which is this thesis’ main contribution. The models estimate the required fleet size of the system based on input values for certain characteristics, and hence evaluate which AMR type can provide the lowest cost given the input data. Despite the dynamic environment of fleet sizing considering the autonomous operation of the vehicles, a mathematical model allows for a good starting point and a rough fleet size estimation that can be further built into a simulation model specifically developed for a given scenario (Ganesharajah et al., 1998). In addition, a simplified and generalized picture of the manufacturing environments is considered, where additional analysis by for instance discrete event simulation becomes unnecessary, as it is not related to a specific case study.

Additional literature was needed to develop the mathematical models. The search terms of fleet sizing, number of vehicles, autonomous mobile robots (AMR), and automated guided vehicle (AGV) were combined to find relevant literature on this topic. The same databases and procedure of screening as presented in Chapter 3.1 were conducted. The term AGV was included because most fleet sizing articles are related to the AGV and not the AMR, due to the limited timeframe that the AMR has been researched. However, fleet sizing techniques based on mathematical modeling does not differ significantly. Chapter 4 presents the literature review for the models, the line of reasoning for developing the models, along with the considered environments, assumptions, and formulas. This allows for an evaluation of the mathematical correctness to be performed, in line with Karlsson (2016). To validate the DSS, parametric analysis is performed on the mathematical models, and the input values and highlighted results are presented in Chapter 6.3, while the full results are found in Appendix 7, Appendix 8, Appendix 9, Appendix 10, Appendix 11, Appendix 12, Appendix 13, Appendix 14, and Appendix 15. This was based on input data from similar theoretical and case studies, since this made it possible to use approximated values without a case study being performed in this thesis.

4 Mathematical Models for Fleet Sizing of AMR Systems

This chapter presents the literature review and mathematical models developed for each manufacturing environment to estimate the fleet size and costs. In Chapter 6.3, parametric analysis is performed on the models to validate the proposed DSS. The chapter starts off by discussing the various fleet sizing techniques found in the literature review. Then, the three manufacturing environments and their corresponding mathematical model is presented one by one.

4.1 Literature Review of Fleet Sizing Techniques

Fleet sizing is one of the most central challenges when designing an AMR system. It is also a complex operation due to the decentralized decision making and autonomous path planning of the vehicles. In its essence, the fleet size can be formulated by this basic equation:

$$Number\ of\ vehicles = \frac{Time\ required}{Time\ available} \tag{4.1}$$

The time required represents the travel and MH time of the vehicle. Travel time is based on the acceleration, speed, and travel distance, while handling time considers the time for L/U operations and their frequency within a given time period (Čech et al., 2020). Time available represents the considered time period and the availability of the vehicle. It should be noted that a highly accurate fleet size usually requires detailed simulation or even a trial-and-error procedure when implementing to account for all situations that might appear. However, mathematical models are a good starting point because they can provide rough estimates without requiring a whole lot of resources. Therefore, several researchers have expanded the basic equation to specific scenarios to attempt the estimation of the fleet size.

A normal adaptation of the formula is the use of a traffic factor due to lost time in the AMR operation. Time spent waiting at stations, intersections, blocking of machines, and poor routing are examples of situations where time is lost (Urru et al., 2017). Ilić (1994) is a good starting reference for fleet sizing because it sufficiently covers the basics of the fleet sizing problem. The paper modeled a flexible manufacturing system served by AGVs, but the thought process can be applied to AMRs. Ilić (1994) proposed the use of efficiency losses, where the efficiency loss is dedicated to time spent L/U and empty return travel. The number of vehicles is then determined by the required throughput of the system divided by the efficiency of the vehicle fleet - or simply put, required time divided by the available time. Urru et al. (2017) raised the discussion on the assumption of always considering that the AMR are allowed to travel fully loaded. In fact, this is a production batch sizing issue, since it relates to the buffer sizes at the pickup point and the delivery point. On this issue, Ozden (1988) found that increasing buffer sizes to match the vehicle carrying capacity will allow higher utilization of the vehicle carrying capacity, and effectively reduce the fleet size. The conclusion from this is that buffer sizes and vehicle carrying capacity should be equal. Furthermore, the results from Ozden (1988) simulation's showed that the optimal number of vehicles is an increasing concave function. This is due to the traffic problems discussed earlier, where there is a threshold for how efficient the vehicles can be when the fleet size increases. This threshold value determines the utilization of the vehicles, and is explored e.g., in Ferrara et al. (2014), which combined laser-guided vehicles and pallet shuttles. Utilization is viewed as the number of missions and time per mission divided by the number of vehicles, accounting for the travel time and handling operations.

The cycle of one AMR mission is the loading of items, loaded travel to destination, unloading of items, and unloaded travel to the next mission. When breaking down the basic equation of required time and available time, the numerator can usually be broken down into three components: L/U time, loaded travel, and unloaded travel. The L/U time is usually expressed as a deterministic time value in most papers. However, it can be argued this is dependent on the top module design of the vehicle, which can have significant impact on L/U times, fleet size, and congestion issues (Alizon et al., 2009). The loaded travel time is based on the acceleration and speed of the vehicle, and the determination of the length of travel. The problem is to determine the length of travel, which depends on the location of the destination. Different manufacturing environments and layouts will have varying degrees of complexity in determining the length. For instance, job shops require more detailed procedures because it is not obvious which department is the destination, since it is highly dependent on the product mix. In sequential assembly lines the length is given by the distance to the next workstation in line. Building on the work of Ilić (1994) was Urru et al. (2017), which introduced combinatorics and probability theory for determining the loaded travel times when supplying workstation from a central supermarket. They apply the Symmetric Travelling Salesman Problem to determine the length of travel.

Determining the unloaded length of travel is complex in most manufacturing environments besides in a loop layout of the vehicle route. A loop travel route was studied by Fragapane et al. (2020b), which determined the fleet size based on the required throughput of the system and the effective capacity of the vehicles. Here, the travel distance was equal to the length of the loop, reducing the need for a split between loaded and unloaded travel times. For rail-guided vehicles, the loop route can be applied. Calzavara et al. (2018) determined a threshold value of vehicles in relation to congestions on the rail. The threshold value is dependent on the interference space between the vehicles and the total length of the rail, influenced by the speed of the vehicles and L/U times. For instance, long L/U times or high speed reduces the threshold value and the number of vehicles that are most efficient to deploy. Determining unloaded travel times in non-loop scenarios is highly specific to the manufacturing environment, layout, and route availability. The use of probability theory and combinatorics as seen in Urru et al. (2017) can be applicable if the Symmetric Travelling Salesman Problem can be applied. The procedure of calculating the net flows and assigning unloaded trips to stations with negative net flow is another procedure, seen in Koo et al. (2004b). The net flow is the difference between inbound and outbound transportation missions from a station. Some stations will emerge with a positive net flow, meaning they have unloaded trips originating from the station, while some are negative meaning they need to be the destination for some unloaded trips. The net flow can also equal zero, meaning no unloaded trips occur to/from the station. Solving the assignment of empty trips can be done as a linear optimization model, where the objective is to minimize the length of unloaded trips. Constraining the net flows can relieve the model from this optimization problem, such as assuming a net flow of zero for machines in a sequenced line. Under the assumption of unlimited buffers, the net flow approach to the problem can be highly useful and allow for simpler fleet size models. The unlimited buffer assumption is limiting and can in some cases underestimate the unloaded travel times but can be used as a lower bound on the fleet size (Koo et al., 2004b).

The denominator of the basic equation can usually be expressed as the time period considered, usually 1 hour - or 3600 seconds, multiplied by the availability of the vehicle. The availability of the vehicle can be collected from the vehicle vendor and their experience in similar environments. The availability can also be calculated after implementation, although this is not useful when designing the system. When considering the availability, factors like charging time and maintenance needs are likely to have a significant impact.

Other ways than mathematical models to determine the fleet size more accurately include queuing theory, linear programming models, and discrete event simulation. Queuing theory can be found in e.g., Koo et al. (2004a). With the use of queueing theory, the fleet size can be calculated based on an acceptable waiting time between a transport request and the response time of the vehicle. Queueing theory is applied on the premise that the number of servers is the vehicles, customer arrivals are delivery requests, and service time is the L/U and travel time. An M/M/m system is applied to determine the waiting times, which has exponentially distributed interarrival and service time, and with m servers. Other variations of queueing theory, represented by Kendall's notation, allows different systems to be modelled, e.g., D/D/1, using deterministic arrival and service times, and with one server.

A linear programming model was used by Choobineh et al. (2012) to calculate the fleet size. The objective was the minimization of the number of vehicles constrained by the utilization of machines. The utilization was determined by the required throughput of the system, and the model allowed for large product and routing mixes. Relevant to the question of designing L/U stations was the work by Ozcelik and Islier (2011). While studying the unidirectional loop layout problem, the tradeoff between the variable costs of transporting material and fixed cost of adding L/U stations was addressed. They removed the artificial constraint of only having one loading and one unloading station in unidirectional loop layouts, and this created opportunities for more efficient layouts since the number of L/U stations also became a decision variable. Discrete event simulation for analyzing the use of AMRs in automotive assembly was studied in the work by Kousi et al. (2019). They analyzed the fleet size, carrying capacity of the vehicle, and the trigger point for ordering of parts to a workstation. Briefly summarized, fleet sizing problems can be analyzed with the use of the basic equation which must be properly adapted to the specific system considered and its characteristics. Other more sophisticated tools have been studied in the current literature, but with the attempt of reaching higher accuracy, it usually increases the resources needed to perform the analysis.

4.2 Mathematical Models for Fleet Sizing different Manufacturing Environments

The mathematical models proposed in this thesis are all based on the basic Equation (4.1). The time required is split into loaded and unloaded travel, which are determined in different ways depending on the manufacturing environment. Following are the notations used for the mathematical models, and one by one each considered manufacturing environment is presented along with the developed mathematical model.

Indices:

$$N = Number\ of\ production\ cells/departments/lines$$

$$n = 1, \ldots, N\ production\ cells/departments/lines$$

$$K = Number\ of\ machines\ in\ the\ cell/department/line$$

$$k = 1, \ldots, K\ machines$$

$$G = Number\ of\ products$$

$$g = 1, \ldots, G\ products$$

$$p = Pickup\ station$$

$$d = Delivery\ station$$

$$r = Repair\ station$$

$$in = Intratransportation\ between\ cell\ n, machine\ k, or\ department\ n$$

Cost variables:

$$C_T = Total\ cost$$

$$C_I = Investment\ cost$$

$$C_{AE} = Cost\ of\ ancillary\ equipment$$

$$C_O = Operational\ cost$$

$$C_{AMR} = Cost\ of\ AMR$$

$$C_{L/U} = Cost\ of\ L/U\ station$$

Vehicle variables:

$$v = Vehicle\ speed\ \left[\frac{m}{s}\right]$$

$$a = Vehicle\ acceleration\ \left[\frac{m}{s^2}\right]$$

$$T_{L/U} = Time\ for\ loading/unloading\ [s]$$

$$U_{L/U} = Utilization\ of\ loading/unloading\ equipment$$

$$C_v = Carrying\ capacity\ of\ vehicle\ [Unit\ loads]$$

$$T_a = Time\ available\ for\ vehicle\ or\ L/U\ station\ [s]$$

$$A_{amr} = Availability\ of\ vehicle$$

System variables:

$$Q = Required\ throughput\ [\frac{pcs}{hr}]$$

$$Q_n = Required\ throughput\ for\ system\ n\ [\frac{pcs}{hr}]$$

$$U = Unit\ load\ size\ [pcs]$$

$$q = Quality\ level\ of\ machines$$

$$d_{ij} = Distance\ between\ point\ i\ and\ j\ [m]$$

$$T_{c\,ij} = Time\ for\ one\ mission\ between\ i\ and\ j\ [s]$$

$$N°T_{ij} = Number\ of\ trips\ between\ i\ and\ j$$

$$R_t = Required\ time\ [s]$$

$$NF_i = Net\ flow\ of\ inbound\ and\ outbound\ transport\ at\ point\ i$$

$$Mix_{ng} = Portion\ of\ product\ mix\ for\ product\ g\ at\ department\ n$$

$$N°L/U = Number\ of\ L/U\ stations$$

$$V_{amr\,ij} = Number\ of\ vehicles\ needed\ in\ area\ between\ i\ and\ j$$

4.2.1 Production Lines

The production line environment reference is shown in Figure 4.1. In the considered production line, there is one pickup location at the Raw Material Inventory (RMI), three machines in sequence, and a delivery station at the FGI. The determination of the fleet size includes the transportation missions from the pickup at the RMI to the first machine, between all machines in the line, from the last machine to the FGI, quality defects to the repair station, and unloaded trips.

The loaded travel is based on the required throughput, where all products visit the same machines in the line sequentially, and quality losses occur at every machine. Together with the travelling distances, speed, acceleration and L/U time of the vehicle, the time for one mission is determined and is multiplied with the number of trips to determine the required loaded time, following the equations from Fragapane et al. (2020b).

The unloaded travel time is based on the calculation of net flows, under the assumption of unlimited buffers and a negative net flow for all stations except the RMI. This means every unloaded trip has the RMI as its destination, and the unloaded travel time can be determined by the distance and net flow surplus at each station. This relieves the model from an optimization problem, and will, in most cases, account for the longest possible trip for the unloaded travel, since the number of unloaded travels increases the further away from the RMI due to quality losses. The distances between the RMI, machines, and FGI are equal, while the distance to the repair shop is unique. Quality losses are included in the required throughput. This means that the material delivered to the FGI is the required throughput, while material delivered from the RMI is higher than the required throughput. In the case of using a basic AMR, which relies on ancillary equipment for L/U, the time for L/U will increase if the utilization of the ancillary equipment surpasses 100%.

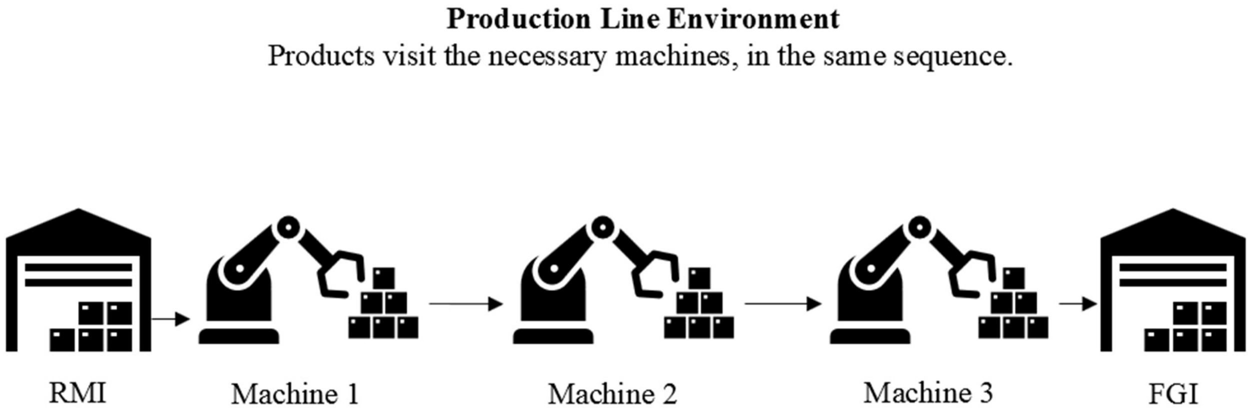

Figure 4.1 – Production line environment

Fleet size determination

The required loaded travel time is determined by the following equations:

$$N°T_{pn} = \left\lceil \frac{Q_n}{U * C_v * q^K} \right\rceil \tag{4.2}$$

$$N°T_{in} = \sum_{k=1}^{K} \left\lceil \frac{Q_n}{U * C_v * q^{(K-k)}} \right\rceil \tag{4.3}$$

$$N°T_{nr} = \left\lceil \frac{Q_n}{U * C_v * q^K} - \frac{Q_n}{U * C_v} \right\rceil \tag{4.4}$$

Quality losses from all machines are accounted for in the input to the first machine in the cell, between machines, and the number of trips to the repair station. For the basic AMR or other types not capable of simultaneous L/U of several vehicles:

$$R_{t\,L/U\,p} = N°T_{pn} * T_{L/U} \tag{4.5}$$

$$U_{L/U\,p} = \frac{R_{t\,L/U\,p}}{T_a} \tag{4.6}$$

$$T'_{L/U} = \begin{cases} T_{L/U}, U_{L/U\,p} < 1 \\ T_{L/U} * U_{L/U}, U_{L/U\,p} > 1 \end{cases} \tag{4.7}$$

Where p is used because throughput is the highest at this point. For other AMR types, the utilization will always be less than 1.

$$T_{c\,pn} = T_{c\,in} = T_{c\,nd} = T_{c\,general} = \frac{d_{in}}{v} + 2 * \frac{v}{a} + 2 * T'_{L/U} \tag{4.8}$$

$$T_{c\,nr} = 2 * \left(\frac{d_{nr}}{v} + 2 * \frac{v}{a} + T'_{L/U}\right) \tag{4.9}$$

This includes the empty return trip from the repair shop.

$$R_{t\,loaded} = (N°T_{pn} + N°T_{in} + N°T_{nd}) * T_{c\,general} + N°T_{nr} * T_{c\,nr} \tag{4.10}$$

Using the procedure of calculating the net flows, under the following assumptions, the required unloaded travel time can be determined.

$$\mathit{Unlimited\ buffers}$$

$$\mathit{Assuming}\ NF_p \leq 0\ \mathit{and}\ NF_k \geq 0\ \forall\ k$$

$$NF_k = \left\lceil \frac{1}{U * C_v} * \left(\frac{Q_n}{q^{[(K+1)-k)}} - \frac{Q_n}{q^{(K-k)}}\right) \right\rceil \tag{4.11}$$

$$NF_d = \left\lceil \frac{Q_n}{U * C_v} \right\rceil \tag{4.12}$$

$$T_{c\,kp} = \frac{d_{in} * k}{v} + 2 * \frac{v}{a} \tag{4.13}$$

$$T_{c\,dp} = \frac{d_{in} * (K+1)}{v} + 2 * \frac{v}{a} \tag{4.14}$$

$$R_{t\,unloaded} = \sum_{k=1}^{K} \left(NF_k * T_{c\,kp}\right) + NF_d * T_{c\,dp} \tag{4.15}$$

The resulting total fleet size is expressed as:

$$V_{amr} = \left\lceil \frac{R_{t\,loaded} + R_{t\,unloaded}}{T_a * A_{amr}} \right\rceil \tag{4.16}$$

4.2.2 Job Shops

The job shop environment reference is shown in Figure 4.2. Not all routing options are visible for illustration purposes. The layout shows one RMI, four different departments (e.g., cutting, drilling, milling, and washing), and one FGI. Material starts at the RMI, is transported to and from departments depending on its routing, and when finished it is brought to the FGI. The fleet size is determined by the number of transportation missions from the pickup location at the RMI, between the different departments, delivery to the delivery station at the FGI, and unloaded empty trips. In this model, it is considered that the distance between all departments, the RMI, and the FGI, is equal. The distance between delivery at the FGI to the pickup at the RMI is unique.

The loaded travel times are based on the product mix, routing, and throughput. This means that the number of visits to each department is calculated, and assuming all distances between all departments are equal, the required loaded travel time is determined based on the travel distance, speed, acceleration, and L/U times, following the equations from Fragapane et al. (2020b). The product mix must be directly related to the throughput, so that if part 1 visits department 2 twice, and 20% of the throughput is dedicated to part 1, 40% of the throughput visits department 2.

Unloaded travel times are determined by calculating the net flows based on the product mix, under the assumption that net flows for all departments are zero, and the only unloaded trips occur from the FGI to the RMI. This can be applied because when we do not include quality losses, every product must be transported both to and from the department, and all products end up in the FGI. This relieves the model from an optimization problem. This procedure is likely to underestimate the fleet size, but it can be used as a lower bound for the fleet size (Koo et al., 2004b). In the case of using a basic AMR, which relies on ancillary equipment for L/U, the time for L/U will increase if the utilization of the ancillary equipment surpasses 100%.

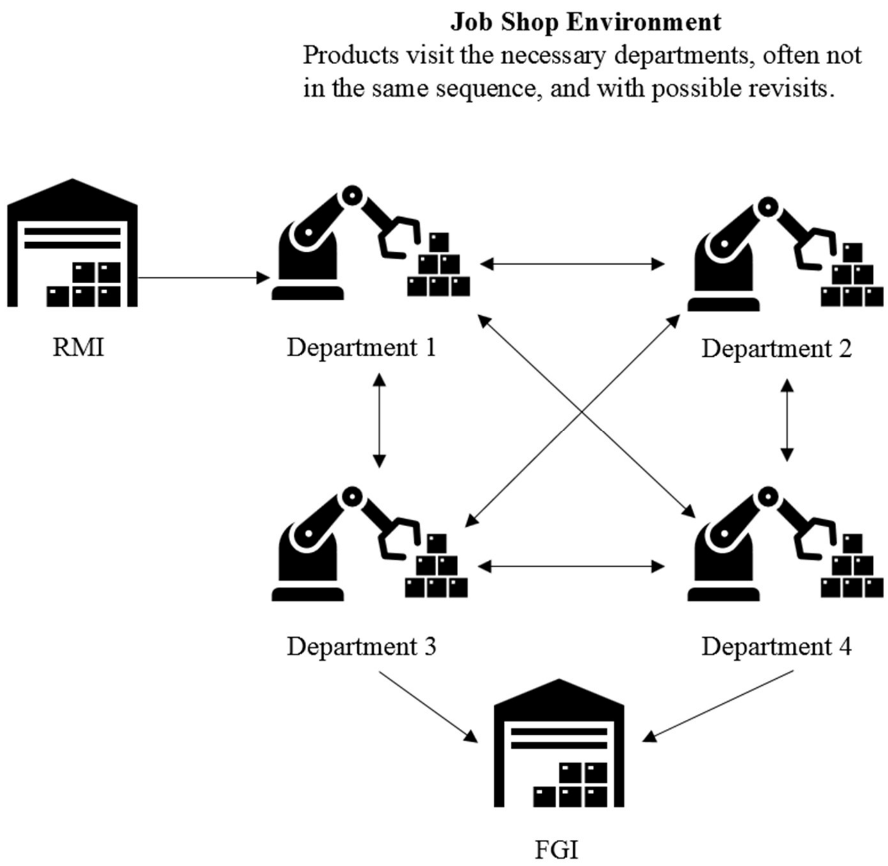

Figure 4.2 – Job shop environment

Fleet size determination

The required loaded travel time is determined by the following equations:

$$N°T_{loaded} = \sum_{n=1}^{N}\sum_{g=1}^{G}\left\lceil\frac{Q * mix_{ng}}{U * C_v}\right\rceil \tag{4.17}$$

For the basic AMR or other types not capable of simultaneous L/U of several vehicles:

$$R_{t\,L/U\,n} = \sum_{g=1}^{G}\left\lceil\frac{Q * mix_g}{U * C_v}\right\rceil * T_{L/U} \tag{4.18}$$

$$U_{L/U\,n} = \frac{R_{t\,L/U\,n}}{T_a} \tag{4.19}$$

$$T'_{L/U} = \begin{cases} T_{L/U}, \max\left(U_{L/U\,n}\right) < 1 \\ T_{L/U} * U_{L/U}, \max\left(U_{L/U\,n}\right) > 1 \end{cases} \tag{4.20}$$

Where n is used because throughput is the highest at the departments due to revisits of material depending on the routing. For other AMR types, the utilization will always be less than 1.

$$T_{c\,pn} = T_{c\,in} = T_{c\,nd} = T_{c\,general} = \frac{d_{in}}{v} + 2 * \frac{v}{a} + 2 * T'_{L/U} \tag{4.21}$$

$$R_{t\,loaded} = N°T_{loaded} * T_{c\,general} \tag{4.22}$$

Using the procedure of calculating the net flows, under the following assumptions, the required unloaded travel time can be determined:

$$Assuming\ unlimited\ buffers$$

$$Assuming\ NF_p < 0\ and\ NF_n = 0\ \forall\, n$$

$$T_{c\,dp} = \frac{d_{dp}}{v} + 2 * \frac{v}{a} \tag{4.23}$$

$$N°T_{unloaded} = \left\lceil \frac{Q_n}{U * C_v} \right\rceil \tag{4.24}$$

$$R_{t\,unloaded} = N°T_{unloaded} * T_{c\,dp} \tag{4.25}$$

The resulting total fleet size is expressed as:

$$V_{amr} = \left\lceil \frac{R_{t\,loaded} + R_{t\,unloaded}}{T_a * A_{amr}} \right\rceil \tag{4.26}$$

4.2.3 Cellular Manufacturing

The cellular manufacturing environment reference is shown in Figure 4.3. This shows one pickup station at the RMI, one production cell resembling the letter U, and one delivery station at the FGI for finished products. To calculate the fleet size of the cell production environment, three different areas are considered. The areas consist of transport from the pickup station to the input of the production cell, the intracell transport, transport of defective items to the repair station, and the transport from the exit of the cell to the delivery area. The calculations for all three areas follow the same procedure. The first step is to determine the number of trips, *N°T*. Then, the time for one trip within that area, the T_c, is determined. To determine the time required for transportation, R_t, the time for one trip is multiplied by the number of trips. Then, the fleet size is determined by the required time and the available time of the AMR.

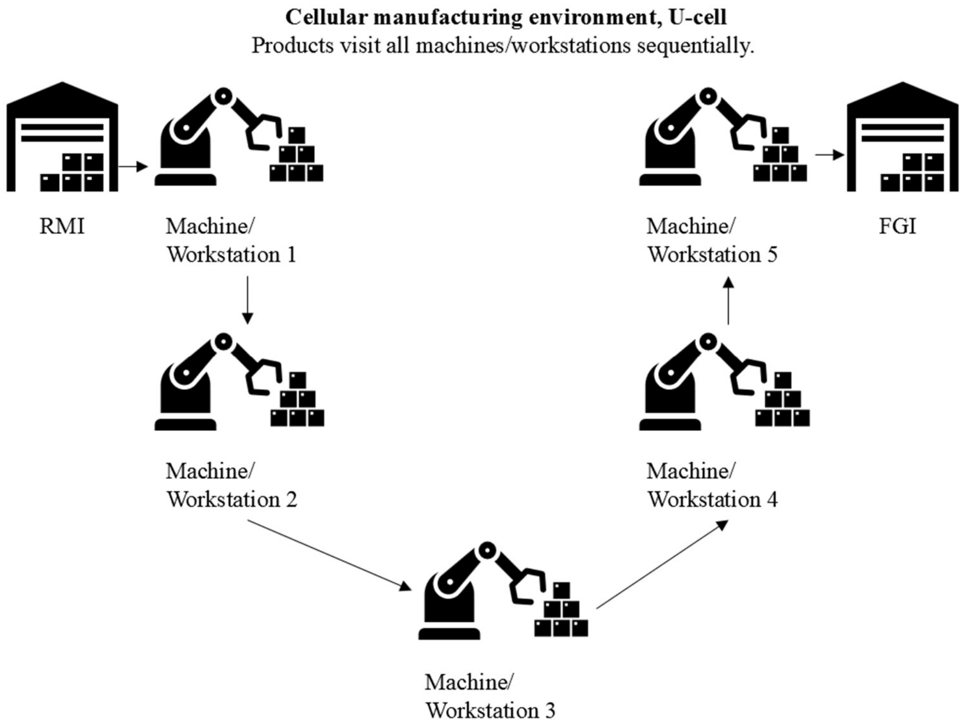

Figure 4.3 – U-cell environment

Deliveries to and from the cells follow the same logic: The loaded and unloaded travel is equal because it returns to the cell unloaded for its next mission, travelling along the same route. The time for one mission is then based on the required throughput, accounting for quality losses, the travelling distance, speed, acceleration, and L/U time of the vehicle, following the equations from Fragapane et al. (2020b). In the case of using a basic AMR, which relies on ancillary equipment for L/U, the time for L/U will increase if the utilization of the ancillary equipment surpasses 100%. The transport to the repair station resembles the deliveries to and from the cell, where loaded and unloaded travel is the same because it follows the same route and returns empty to the cell.

The loaded travel within the cell is calculated using the sequential steps in the production cell and the required throughput. The distance between every machine in the sequence is considered to be equal. Unloaded travel times are determined using the Euclidean distance as an estimate for the unloaded travelling distance using the Pythagoras theorem, where the sides are the distance between the machines in the cell, illustrated in Figure 4.4. This is done because the Symmetric Travelling Salesman Problem can be applied due to the AMRs free path choosing, and the intracell distances satisfy the triangle inequality, which states that (Ilavarasi and Joseph, 2014):

$$Distance\ AC \leq Distance\ AB + Distance\ BC$$

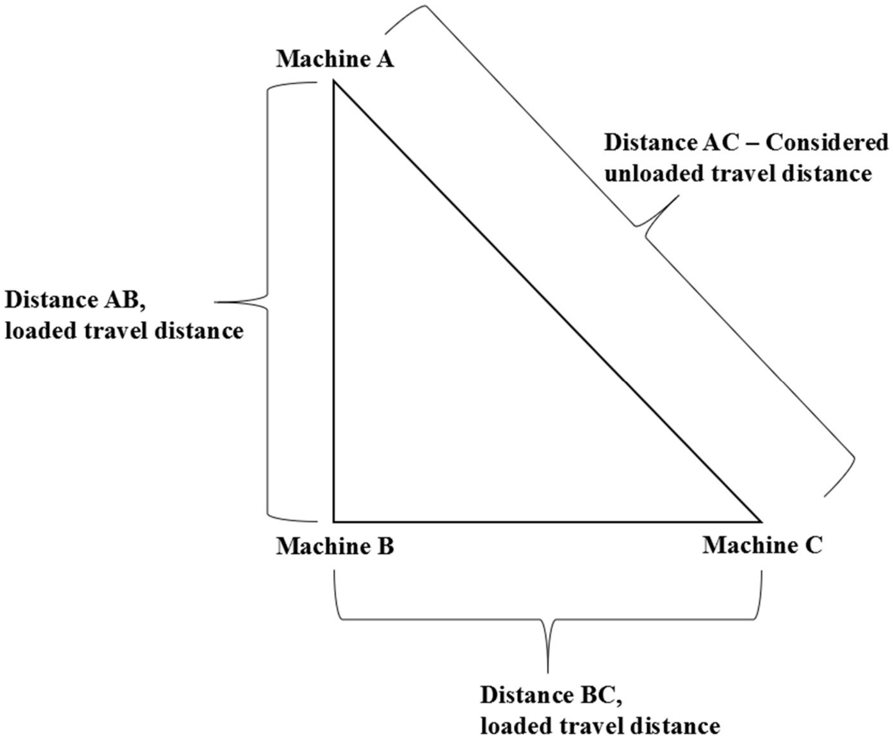

Figure 4.4 – Considered unloaded travel distance

Fleet size determination

Fleet size for area pickup station to production cell:

$$N°T_{pn} = \left\lceil \frac{Q_n}{U * C_V * q^K} \right\rceil \tag{4.27}$$

Quality losses from all machines are accounted for in the input to the first machine in the cell. For the basic AMR or other types not capable of simultaneous L/U of several vehicles:

$$R_{t\,L/U\,p} = N°T_{pn} * T_{L/U} \tag{4.28}$$

$$U_{L/U\,p} = \frac{R_{t\,L/U\,p}}{T_a} \tag{4.29}$$

$$T'_{L/U} = \begin{cases} T_{L/U}, U_{L/U\,p} < 1 \\ T_{L/U} * U_{L/U}, U_{L/U\,p} > 1 \end{cases} \tag{4.30}$$

Where p is used because throughput is the highest at this point. For other AMR types, the utilization will always be less than 1.

$$T_{c\ pn} = 2 * \left(\frac{d_{pn}}{v} + 2 * \frac{v}{a} + T'_{L/U}\right) \tag{4.31}$$

The unloaded travel time equals the loaded travel time since the AMR returns empty to the pickup station for its next mission, travelling the same route.

$$R_{t\ pn} = T_{c\ pn} * N°T_{pn} \tag{4.32}$$

$$V_{amr\ pn} = \left\lceil \frac{R_{t\ pn}}{T_a * A_{amr}} \right\rceil \tag{4.33}$$

Fleet size for area intracell and repair station:

$$T_{c\ in} = \frac{d_{in}}{v} + \frac{\sqrt{d_{in}^2 + d_{in}^2}}{v} + 4 * \frac{v}{a} + 2 * T'_{L/U} \tag{4.34}$$

The unloaded travel trip length is based on the Euclidean distance using the Pythagoras theorem. Since the highest throughput is from pickup to the cell, the new L/U time remains the same.

$$T_{c\ nr} = 2 * \left(\frac{d_{nr}}{v} + 2 * \frac{v}{a} + T'_{L/U}\right) \tag{4.35}$$

The unloaded travel time from the repair station equals the loaded travel time since the AMR returns empty to the production cell for its next mission, travelling the same route.

$$N°T_{in} = \sum_{k=1}^{K} \left\lceil \frac{Q_n}{U * C_v * q^{(K-k)}} \right\rceil \tag{4.36}$$

$$N°T_{nr} = \sum_{k=1}^{K} \left\lceil \frac{1}{U * C_v} * \left(\frac{Q_n}{q^{[(K+1)-k]}} - \frac{Q_n}{q^{(K-k)}}\right) \right\rceil \tag{4.37}$$

Quality losses are accounted for in the output from each machine. The number of defects is the difference between input and output from each machine.

$$R_{t\ inr} = T_{c\ in} * N°T_{in} + T_{c\ nr} * N°T_{nr} \tag{4.38}$$

$$V_{amr\ inr} = \left\lceil \frac{R_{t\ inr}}{T_a * A_{amr}} \right\rceil \tag{4.39}$$

Fleet size for area production cells to delivery station:

$$T_{c\ nd} = 2 * \left(\frac{d_{nd}}{v} + 2 * \frac{v}{a} + T'_{L/U} \right) \tag{4.40}$$

The unloaded travel time equals the loaded travel time since the AMR returns empty to the production cell for its next mission, travelling the same route. Since the highest throughput is from pickup to the cell, the new L/U time remains the same.

$$N°T_{nd} = \left\lceil \frac{Q_n}{U * C_V} \right\rceil \tag{4.41}$$

$$R_{t\ nd} = T_{c\ nd} * N°T_{nd} \tag{4.42}$$

$$V_{amr\ nd} = \left\lceil \frac{R_{t\ nd}}{T_a * A_{amr}} \right\rceil \tag{4.43}$$

Total fleet size:

Option 1: The three areas are considered in isolation.

$$V_{amr} = V_{amr\ pn} + V_{amr\ inr} + V_{amr\ nd} \tag{4.44}$$

Option 2: The areas of delivering to and from the cells are joined together.

$$V_{amr} = \left\lceil \frac{R_{t\ pn} + R_{t\ nd}}{T_a * A_{amr}} \right\rceil + V_{amr\ inr} \tag{4.45}$$

In some instances, due to the rounding of the theoretical number of vehicles and increased utilization of the vehicles, option 2 will result in a smaller fleet size. This requires the AMRs to be equipped with the correct equipment for handling all material both being delivered to the cells and the finished products brought away from the cells. In the following parametric analysis, option 2 of the total fleet size is used in all scenarios.

4.3 Cost Modeling

The total cost of the AMR system is used to compare the performance of each AMR type. With the differences between the AMR types, the scenarios result in different costs for the different AMR types. The cost of the system has three components: Investment cost, operational costs, and the cost of ancillary equipment. Hence, the total cost can be formulated as:

$$C_T = C_I + C_{AE} + C_O \tag{4.46}$$

The investment cost is the cost of the vehicles:

$$C_I = V_{amr} * C_{amr} \tag{4.47}$$

The cost of ancillary equipment depends on the type of AMR, but is considered here to be related to the number of L/U stations:

$$C_{AE} = N°_{L/U} * C_{L/U} \tag{4.48}$$

Operational costs are the sum of each contributing costs:

$$C_O = C_1 + C_2 + \cdots + C_n \tag{4.49}$$

For practical purposes, the operational costs are omitted from the parametric analysis. Hence, the costs of the AMR system will depend on the cost of vehicle, number of vehicles, cost of L/U stations, and the number of L/U stations. Parametric analysis is performed on the presented mathematical models to validate the results of the DSS. The input data and results of the parametric analysis is presented in Chapter 6.3.

5 Overview of Characteristics for Intralogistics System Design based on AMRs

This chapter presents the reviewed literature and findings for addressing RQ1. It starts off with presenting the existing procedures for intralogistics system design. Then the AMR is classified into three main types considered in this thesis, followed by selected AMR vendor solutions. Following this is the literature concerning intralogistics system design based on AMRs and descriptions of the characteristics identified. The chapter is rounded off with answering RQ1 by presenting the overview of characteristics for intralogistics system design based on AMRs.

5.1 Intralogistics System Design Literature Review

Intralogistics is defined by VDMA, the German material handling and intralogistics association, as *"the organization, control, implementation and optimization of the internal flow of materials, the flow of information and the handling of goods in industry, retail and public facilities"* (Friedrich, 2021). This definition covers the broad domain of intralogistics, while the point being that intralogistics is concerned with all logistics activities within the four walls of industrial companies, retail, or public facilities. The operating context of intralogistics, as suggested by Mörth et al. (2020), must account for the characteristics of the orders, environment, physical goods, transport system, service, and human operators. A complete intralogistics system would account for the material flow from inbound to outbound transport, information flow, and storage locations for RMI, Work In Process (WIP) buffers, and FGI. Since the term intralogistics is relatively new, the literature is fragmented, and considering the scope of this thesis, the literature findings are limited to the topics concerning the physical design of the intralogistics material flow. The selected topics are layout planning, cellular manufacturing design, and equipment selection for the MH system. The scope is presented in Figure 5.1. These selected topics are now introduced together with tools commonly used for their design process.

5.1.1 Layout Planning

The intralogistics design for all three manufacturing environments, but especially production lines and job shops, are heavily based on the layout planning. Cellular manufacturing has additional design constraints and characteristics which is introduced in the following section. Layout planning also plays a vital role when designing the MH system. The layout will determine the distances to travel, what routes are possible, and one of the goals of layout planning is to minimize MH requirements. Muther and Hales (1987) presented the SLP methodology, and many of the tools proposed are well established and have been around for several years. They remain valid because they are all built on the two elements which govern virtually any layout decision: What will be produced (Product) and how much will be produced (Quantity). There are also three other elements impacting this decision: Routing, supporting services, and time. The routing governs how the product is to be made, supporting services include storage areas, maintenance, utilities, and other auxiliaries required, while time includes the information about when to produce, how often, cycle times, takt times and the likes. These five elements, Product, Quantity, Routing, Supporting Services, and Time (PQRST) hold the key to unlocking layout problems (Muther and Hales, 1987). The SLP procedure is illustrated in Figure 5.2.

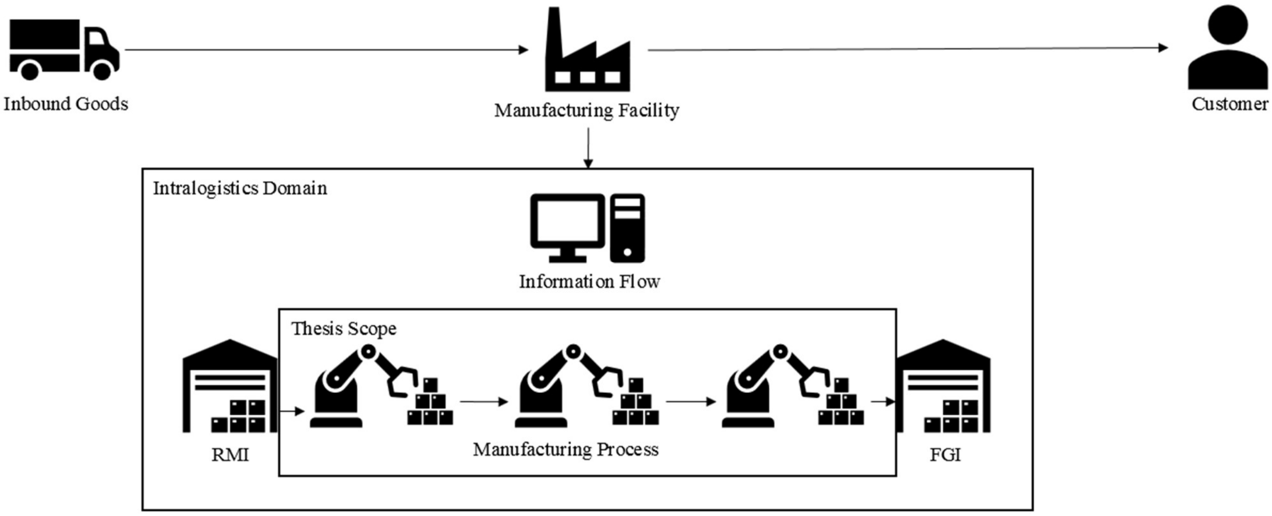

Figure 5.1 – Intralogistics domain and thesis scope

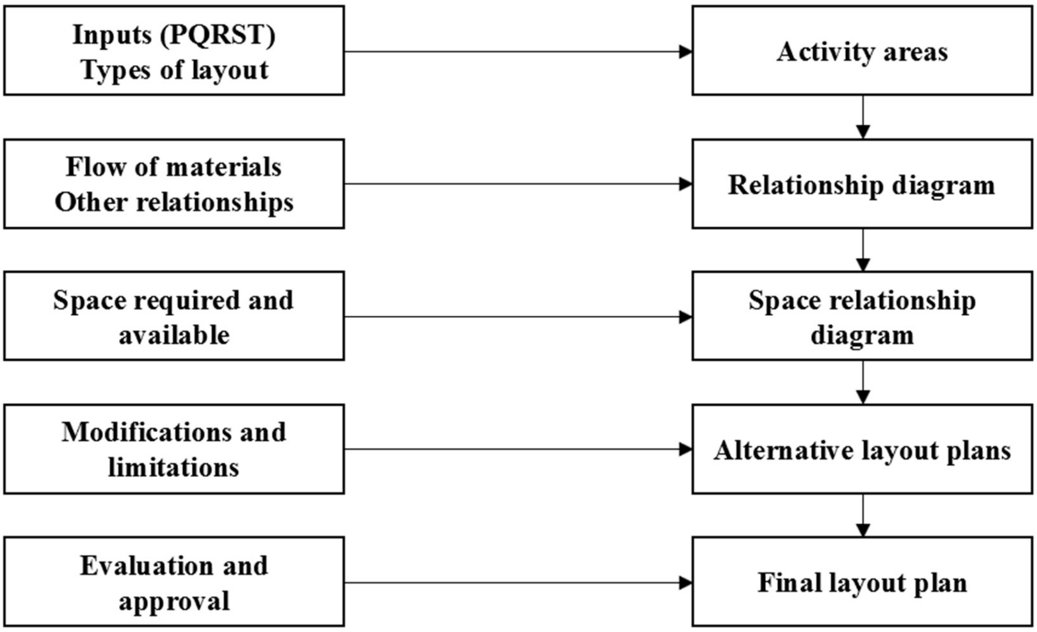

Figure 5.2 – The SLP procedure, adapted from Muther and Hales (1987)

The SLP procedure from Muther and Hales (1987) follows a number of steps which builds on the PQRST. The input from the PQRST will determine the activity areas needed to produce the products. Here, new technologies and design procedures for both the product and processes are important to recognize to not go ahead with activity areas that are outdated or not suited for competitive manufacturing. When the areas are determined, a relationship chart is constructed consisting of a grading system based on whether two areas should be adjacent or not. This is based on both the material flow presented in e.g., a from-to-chart and other relationships such as dirty and clean zones, fire hazards, supporting services required and the likes. When the relationship chart is complete, a relationship diagram is constructed to visualize the departments and their flows. Then, space requirements for the different departments are calculated and a space relationship diagram is formed, further visualizing what the layout designer must fit into the layout. Equipped with the space relationship diagram, the actual layout alternatives can be made. To create realistic layout alternatives, all limitations of the building, building area and shape, auxiliaries required, MH considerations, Health, Safety, and Environment (HSE) considerations, and the likes must be included in the layout. When different layout alternatives are ready, they must be further evaluated, and management must agree on the final layout design and begin implementation. The impact from the MH system is a crucial piece in the step of generating alternative layout plans (Muther and Hales, 1987), and the choice will either put limitations and constraints on the layout design, or new MH solutions such as AMRs can allow for new and innovative designs. This is related to e.g., the space requirements of the equipment and travel route options. Brief examples of constraints originating from the MH equipment could be mobile equipment creating congestion issues and conveyors forming a barrier to hinder movement (Muther and Hales, 1987).

The layout part of the intralogistics design for production lines and job shops are satisfyingly described by the SLP since the variations within these two categories are virtually limitless. More specific procedures and recommendations are out of the scope of this thesis and would typically require case studies of specific environments. However, cellular manufacturing has other considerations which is addressed in the following section.

5.1.2 Cellular Manufacturing System Design

Although cellular manufacturing can be based on the same principles and tools from the SLP, some other considerations are commonly guiding the process. There are three main activities related to the design of the production cells: The identification of product families, allocating product families to the cells, and the creation and design of the cells (Heragu, 1994). The product families and the allocation must be economically feasible and desirable to proceed with the cellular manufacturing environment (Kulak et al., 2005). To form families, a large number of procedures exists in the literature, and the Rank Order Clustering (ROC) algorithm developed by King (1980) is among the most common (Nicholas, 2011). This utilizes the product-machine matrix to identify suitable product families. The rows and columns are given binary weights, sorted in order, and then the user can identify families based on what the matrix displays. Despite its appealing simplicity, the ROC does not consider demand, sequence, and setups, and can only be seen as a provisional result (Nicholas, 2011). Furthermore, by estimating takt times and cycle times, the needed number of resources and workers can be identified (Kulak et al., 2005).

Several researchers have looked at both the creation of product families and the constraint-based design of the production cells, and a review of such methods is provided by Heragu (1994). Akturk and Turkcan (2000) studied the product family, cell formation, and cell layout problem simultaneously, maximizing the profit under the constraints of routing, layout, cell size, utilization, and profit levels. The design of production cells must account for the following design constraints: Machine capacity and utilization; technological and safety requirements; number of machines in a cell and number of cells; costs related to machine investment, operation, and WIP; scheduling of jobs; and achieving maximum production throughput (Heragu, 1994). The layout design of the cell, which makes up the production flow strategy, is where MH will impact the design process. This is linked to the decisions on layout, automation level, space requirements, flexibility requirements and workstation types. AMRs can help create more flexibility in the cell layout, and enable dynamic reconfiguration when market demand changes, as well as performing tasks with poor ergonomics, unacceptable safety levels, and tedious tasks such as kitting and palletizing relevant to the various operations (Schneier and Bostelman, 2015).

In many ways, cellular manufacturing can combine benefits from the production line and job shop environments. This is especially true when the manufacturing facility consists of several cells, where high efficiency can be obtained for a broad range of product families. Cellular manufacturing facilitates the following beneficial properties (Nicholas, 2011, Akturk and Turkcan, 2000):

- Efficiency through repetitive manufacturing of a given product family.
- Greater control over planning, routing, scheduling, costs, and quality.
- The smaller the cell the more efficient due to employee’s higher involvement, motivation, a single supervisor/manager, short distances, improved communication, and reduced coordination needs.
- The cell operators can work together with their specific suppliers and customers.

Typical benefits occurring from the creation of production cells are reduced WIP, lead times, travelling distances, and setup times (Kulak et al., 2005). As a result, production throughput can be increased with a reduction in wasted resources, which is in accordance with lean manufacturing principles (Nicholas, 2011).

5.1.3 Design of Material Handling Systems

MH through the lean manufacturing lens is a necessary, but non-value-added activity, referred to as Muda type 1 (Nicholas, 2011). Although lean is not a universal solution and might not be a strategic priority for all companies, the concept of waste is generally applicable. Hence, efforts should be made to reduce the time and resources spent on MH as much as possible while still providing the necessary service level. MH in its essence is defined by Tompkins et al. (2010) as: *"Material handling means providing the right amount of the right material, in the right condition, at the right place, in the right position, in the right sequence, and for the right cost, by the right method(s)"*. Combining these two together suggests a system that should operate flawlessly without wasting valuable time. The starting point for any project on the MH system is to fully understand the environment of its operation. In this manner, the material handling system equation is highly useful. The material handling system equation states: Materials + Moves + Methods = Recommended system (Tompkins et al., 2010), together with the connected questions presented in Table 5.1.

Table 5.1 – Material handling equation and questions

Category	Questions
Materials	What?
Moves	Where?
	When?
Methods	How?
	Who?
Preferred system	Which?

The material is what should be transported, the moves are where and when to transport from/to, and the methods are how to transport it and by who. When properly analyzed, this will effectively connect product and process characteristics, layouts, and advantages and disadvantages of the MH equipment, to achieve the best possible synergy to create the recommended system. Similar to the SLP, Muther and Hales (1987) proposed a Systematic Handling Analysis (SHA). SHA combines the PQRST input, layout plan, and MH methods to create a quantified flow diagram. To create realistic alternatives; modifications and limitations, as well as fleet sizing, costs, and operating times are added to generate and evaluate the MH system alternatives. The similarity with the material handling equation is evident, as the materials, moves, and methods represent the PQRST, which governs the recommended MH system, but with a slightly different nomenclature. In addition to these two procedures, The Material Handling Institute (2021) stated ten MH principles for designing MH systems, summarized in Table 5.2.

Table 5.2 – The ten material handling principles from The Material Handling Institute (2021)

Principle	Description
Planning principle	The MH system should be the result of a deliberate plan reflecting the business goals, formed by involving all stakeholders and promote concurrent engineering of product, process, layout and MH design.
Standardization principle	MH activities and equipment should be standardized without sacrificing flexibility or modularity.
Work principle	Reduce the amount of time and resources spent on MH while still providing the necessary service level.
Ergonomic principle	Recognizing the limitations, physical, and mental stress on human operators of MH tasks.
Unit load principle	Unit loads must be appropriately configured based on supply chain stage, promoting ease of flow, just-in-time deliveries, and reducing WIP.
Space utilization principle	Efficiently use the available space, avoid messy environments, and consider the tradeoff between storage density and accessibility.
System principle	All MH activities must be integrated to a system, which minimizes inventory levels, and satisfies customer requirements.
Automation principle	Where feasible, automation should be considered, considering all interface issues and the requirements from the equipment.
Environmental principle	Environmental impact, energy consumption, load carrier reusability, and transportation of hazardous materials must be considered when evaluating the alternatives.
Life cycle cost principle	The cost of equipment from acquisition to disposal must be considered, as well as maintenance plans. Strategic considerations should be a part of the cost perspective when possible, and always a part of the decision process.

Further descriptions of other types of MH equipment and related equipment such as load carriers are not covered, due to the thorough descriptions provided in previous literature, e.g., in Tompkins et al. (2010) and Muther and Hales (1987). To summarize, the generalized procedures for designing MH systems must ensure the timely delivery of correct materials with the least amount of waste possible, based on the specific characteristics of the materials, moves, and methods, following some general principles which have appeared from experience in a well-studied problem area. The bottom line is that each piece of MH equipment has its advantages and disadvantages, which together with the mentioned procedures and principles provides a good understanding of how to design the system.

5.2 AMR Types

Equipped with the design procedures presented above regarding intralogistics design, a look at the AMRs is necessary to identify the different characteristics that will impact the intralogistics design. AMRs can be equipped with a range of different tools and equipment, allowing different configurations to perform different activities. The possibility is also there to choose the equipment that best suits the manufacturing environment, even down to the specific task level if it can be financially justifiable. Which vehicle type and equipment to choose is one of the main decisions that must be made before implementation can begin. As an example, from order fulfillment, AMRs can be used to follow the picker, guide the picker to the correct shelves, or bring the goods to the picker. These are usually categorized as either goods-to-person or person-to-goods. Other strategies are of growing interest currently being researched, such as meet in aisle or last mile delivery (Ghelichi and Kilaru, 2021). Each of these strategies require the AMR to perform different tasks, which requires different equipment and different vehicle types.

For this thesis to cover a satisfying range of AMR types, while at the same time grouping them into appropriate classes, three different vehicle types are discussed. The three types are those that can be considered applicable for material handling in manufacturing environments, while other types not included here can be applicable in different settings, such as for use cases in hospitals and the likes (Fragapane et al., 2021). The differences among the chosen AMR types are concerned with the top module design. The same grouping of AMRs is also used by the Association for Advancing Automation, which categorizes them in the following way, shown in Figure 5.3 (Gerstenberger, 2019).

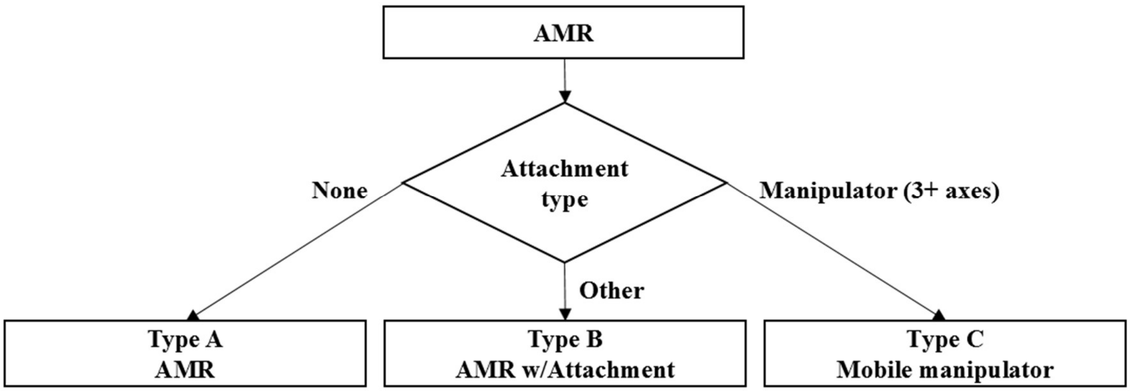

Figure 5.3 – AMR types classified in Gerstenberger (2019)

Note that substantial differences exist within these types, for example the manipulator AMR can have a wide range of manipulators attached, with even more types of end effectors. However, to break down the general concept of AMRs to a reasonable quantity, this thesis refers to these three types. Note that the nomenclature used in this thesis is slightly different from what was used by Gerstenberger (2019), because this thesis focuses only on AMRs, and the term mobile manipulator can also mean AGVs. The three considered types in this thesis are listed as follows:

- The first type is referred to as the basic AMR. This vehicle type has a top module without any interaction with the goods, but it is suited for transporting the goods safely. Manipulators at workstations or manual operators are utilized to perform L/U of the goods. Figure 5.4 shows an example of the basic AMR.

Figure 5.4 – Basic AMR (MiR 1000), collected from Mobile Industrial Robots A/S (2021a)

- The second type of AMR is referred to as the manipulator AMR, which is a basic AMR equipped with a manipulator. When equipping a manipulator, it increases the number of possible activities, enabling the capability of both locomotion and manipulation. This creates a range of new application areas, and effectively increases its operational capabilities and flexibility (Hvilshøj and Bøgh, 2011). Mobility obtained from the vehicle provides an unlimited workspace for the manipulator, which is able to carry out complex manipulation tasks in structured and unstructured environments (Mersha et al., 2018). When capable of both locomotion and manipulation, the AMRs are able to perform human-like tasks (Hvilshøj and Bøgh, 2011). Figure 5.5 shows an example of the manipulator AMR.

Figure 5.5 – Manipulator AMR (KUKA KMR iiwa), collected from KUKA AG (2017)

- The third type of AMR is referred to as the special top module AMR. These can have various top modules, and those considered in this thesis is a conveyor top, lifting/lowering mechanism, and towing. These top modules can be advantageous in situations where the AMR must interact with the goods, and a manipulator is not suitable. Furthermore, they can be cheaper and handle a wider range of goods than manipulator AMRs. Figure 5.6 shows an example of a special top module AMR, namely the conveyor top AMR.

Figure 5.6 – Special top module AMR (Conveyor top), collected from Mobile Industrial Robots A/S (2021f)

5.3 AMR Vendor Review

To collect characteristics from currently available AMR types and designs on the market, different AMR types are presented from three AMR vendors and one manipulator vendor. The vendors are chosen due to their references in scientific literature, industrial applications, and information presence available to the author. The following paragraphs summarizes the findings from the considered vendors, classified into the three AMR types. The most relevant information, namely payload capacity and top module design, related to the ability to handle various items and determining the L/U abilities, are presented.

5.3.1 Basic AMR

The basic AMR has a platform suited for safely transporting goods. A total of four solutions from MiR and Robotnik are considered as references for this vehicle type. Additionally, manipulator arms and manual L/U is included because the basic AMR relies on this for L/U of the items. Universal robots is selected as the reference on manipulator arms. For manual L/U, the payload capacity is restricted to 25 kg, as this is the recommended maximum lifting weight for a human operator advised by The Norwegian Labor Inspection Authority (2021). Table 5.3 summarizes the different models and their capacity.

Table 5.3 – Basic AMR vendor solutions

Basic AMR	Fixed manipulator arm	Manual loading/unloading
MiR 200: 200 kg payload (Mobile Industrial Robots A/S, 2021c)	UR3: 3 kg payload and 500 mm reach radius (Universal Robots A/S, 2021)	Maximum payload of 25 kg (The Norwegian Labor Inspection Authority, 2021)
MiR 1000: 1000 kg payload (Mobile Industrial Robots A/S, 2021c)	UR5: 5 kg payload and 850 mm reach radius (Universal Robots A/S, 2021)	
Robotnik RB-1: 50 kg payload (Robotnik Automation S.L.L., 2021c)	UR10: 10 kg payload and 1300 mm reach radius (Universal Robots A/S, 2021)	
Robotnik Summit-XL steel mobile robot: 250 kg payload (Robotnik Automation S.L.L., 2021c)	UR16: 16 kg payload and 900 mm reach radius (Universal Robots A/S, 2021)	

5.3.2 Manipulator AMR

The manipulator AMR is essentially a basic AMR equipped with a manipulator, where the manipulator can be equipped with a range of various end effectors. The end effectors are not considered here; however, they will determine the capabilities of the manipulator. The chosen references for this type of AMR are from Kuka and Robotnik, and the chosen models are the ones with the highest payload capacity, shown in Table 5.4.

Table 5.4 – Manipulator AMR vendor solutions

Manipulator AMR
Kuka LBR iiwa 14 R820: 14 kg payload manipulator (KUKA AG, 2017)
Robotnik RB-Kairos 16: 16 kg payload manipulator, the UR16 (Robotnik Automation S.L.L., 2021c)

5.3.3 Special Top Module AMR

The special top module AMR has the highest variety within its specific type. There can be a multitude of options, but this thesis considers the options of a lifting/lowering mechanism, conveyor top, and towing AMR. The vehicles from MiR are frequently represented in this category, as they have a modular approach to their vehicle designs where different partners can supply different top modules. Table 5.5 summarizes the different models and their capacity.

Table 5.5 – Special Top Module AMR vendor solutions

Lifting/Lowering mechanism	**Conveyor top**	**Tow**
Robotnik RB-2: 200 kg payload (Robotnik Automation S.L.L., 2021a)	MIR 500: 500 kg payload Types of conveyor: Pallet, belt, roller, tilt, and height-adjustable conveyor (Mobile Industrial Robots A/S, 2021e)	MIR 200: 500 kg payload with hook (Mobile Industrial Robots A/S, 2021b)
MiR 1000: 1000 kg payload (Mobile Industrial Robots A/S, 2021c)	MIR 1000: 1000 kg payload Types of conveyor: Pallet, belt, roller, tilt, and height-adjustable conveyor (Mobile Industrial Robots A/S, 2021e)	

5.4 Intralogistics System Design based on AMRs Literature Review

Intralogistics system design with AMRs comprises the definition from Friedrich (2021): *"The organization, control, implementation and optimization of the internal flow of materials, the flow of information and the handling of goods in industry, retail and public facilities"*, as well as specific considerations made towards the AMRs such as choice of vehicle, top module design, and fleet sizing. In its essence, it can be seen as the process concerned with designing the most effective material and information flow system served by AMRs. Due to the gaps in current research and application in industrial settings, several researchers have looked at the possible use cases for various types of AMRs. These are now summarized to create a basis for application areas for AMRs.

5.4.1 Use Cases

Table 5.6, Table 5.7, and Table 5.8 is adapted from Unger et al. (2018), Bøgh et al. (2012), and Fragapane et al. (2021), respectively, and presents their findings for potential use cases for various industrial applications and type of tasks.

Table 5.6 – Use cases from Unger et al. (2018)

AMR use cases
Machine tending
Delivery into automated safety zones
Consignment
Repair delivery
Mobile material exchange
Transport with added value
Conveyor following
Cleaning and maintenance
Flexible worker support
Packaging and palletizing

Table 5.7 – Use cases from Bøgh et al. (2012)

Assistive tasks	Logistics tasks	Service tasks
Machine tending	Transportation	Maintenance, repair, and overhaul
Pre-assembly	Multiple part feeding	Cleaning
Inspection	Single part feeding	
Process execution		

The collaborative AMR has received a lot of attention in both research and practice. The idea is to have human operators and manipulator arms work together to perform the tasks needed. For example, the suitability of a collaborative robot performing the sorting in kitting operations was studied by Fager et al. (2019) and Fager et al. (2020), and the introduction of digital instructions and cobots in assembly activities was studied by Peron et al. (2020). AMRs with manipulators are for now only used in large sized industries and enterprises, proving to be effective, but are not yet proven in other application areas and for small and medium enterprises. Mersha et al. (2018) suggested this is due to their high price, as manipulator AMRs come off quite expensive.

Table 5.8 – Use cases from Fragapane et al. (2021)

Tasks → Environment	Material handling	Collaborative and interactive	Full service
Manufacturing	Anchor/Tow/Train	Collaborative robot	Robot arm with sanding equipment for windmill
	Shelf unit		
	Lifting equipment		
	Conveyor top		
Warehousing	Order fulfillment	Collaborative fetching	Picking and fetching
	Picking	Surveillance	
	Sorting	Collaborative order picking	
	Localization and inventory		
	Puzzle-based storage systems		
Other intralogistics environments	Secured drug transportation in hospitals	Patient guidance in hospitals	Disinfection of hospital rooms
	Luggage carrier in hotels	Robot with telepresence device in hospitals	
	Robot in container terminals		
	Car valet robot at car parks		

5.4.2 Planning and Control

Due to the complexity and importance of planning and control of AMRs, it has received a strong focus in literature (Bøgh et al., 2012). The planning and control of AMRs include the control centralization level, vehicle types, service points, resource management, scheduling, dispatching, path planning, and robustness and resilience of the vehicle fleet (Fragapane et al., 2021). Mixed Integer Programming (MIP) based on time windows for pickup and delivery of items, controlled by the s,Q inventory system is utilized by e.g., Dang et al. (2011), Yao et al. (2019), and Xiao et al. (2020). These were aimed at scheduling AMRs to and from various workstations. Manipulator AMRs face the challenge of dynamically adapting the manipulator to new tasks. Pedersen et al. (2016) discussed how manipulators can be self-sustained by defining a set of basic skills combined with real-world sensing. This reduces the need for programming and robotics specialists on the shop floor (Arrais et al., 2019). Decentralized control is key for AMRs and further distinguishes them from AGVs. Decentralization allows better fleet control through negotiations between vehicles (Draganjac et al., 2016). The overall goal of the controlling software is to arrive at close to optimal scheduling, path, and motion planning with the least number of computations and time. The outcome should be a reliable fleet size which ensures high utilization of the vehicles to minimize the required fleet sizes. Furthermore, these algorithms can see significant improvements with IoT, big data, and AI (Čech et al., 2020). The further development of planning and control algorithms are important for the control of ever larger fleet sizes and can be considered one of the most central areas where further research is needed. However, further analysis on this area is out of the scope for this thesis.

As for the intralogistics system design, several researchers have identified requirements and trends for automated and autonomous MH solutions. Furmans et al. (2010) presented five design patterns for the future of so-called plug-and-work MH systems: 1) Modularity - Independent modules can easily be combined to create a system, 2) Functions integration - Each module holds the ability to perform every required activity, 3) Decentralized control - The modules are independently making decisions, 4) Interaction - Modules can exchange tasks and materials, 5) Standardized physical and information interfaces - Removing the need for centralized control, easing the modular approach. Furmans et al. (2019) suggested the need for better human-machine interaction, sensing, and adaptation to the intralogistics requirements. The automation principle from The Material Handling Institute (2021) suggests that operations should be automated where feasible - improving efficiency, responsiveness, consistency, and predictability, as well as integrating the material and information flow. Also stated by The Material Handling Institute (2021), is the commonly used approach of simplifying and re-engineering the process before automating. Bányai et al. (2019) argued that conventional equipment is now being replaced by flexible, responsive, intelligent, and networking equipment within the Industry 4.0 domain.

Fottner et al. (2021) proposed a classification matrix for autonomous intralogistics systems, based on the task level and automation stages. The task levels cover the overall planning, operations control, process control, device control, and the physical process. The automation stages cover the stages from no automation to full autonomy. Case study findings from Fottner et al. (2021) reported that although most companies' intentions are to reach as high automation stages as possible for intralogistics, most rarely reach full autonomy. For operational tasks, they settle on conditional to high automation, while for tactical and strategic tasks the automation level is significantly lower. This is largely explained by the need for standardization due to shortcomings in object manipulation and recognition, and decision algorithms which need operator support in unfamiliar situations (Fottner et al., 2021).

Intralogistics is concerned with the MH operations within the four walls of a facility. In contrast to classic distribution logistics outside the facility, a range of other criteria should guide the design process other than choosing the shortest path. First, intralogistics is a non-value-added but necessary activity. Hence, efforts should be made to reduce the time and resources spent on it. Second, the equipment occupies valuable floor space from production and storage equipment and requires certain aisles width and generally more spacious areas than what is strictly needed. Third, it plays a role in the safety of shop floor employees, as they share the same floor space. Fourth, it has a direct impact on starving and blocking issues, queuing, waiting times, and cycle times. If the material is delivered late, utilization will suffer.

A separation can be made between trip-based systems such as the AMR, and connection-based systems such as conveyors (Furmans et al., 2019). The industry pull for Industry 4.0 technologies has spawned the term of Logistics 4.0 where new technologies are introduced for intralogistics. The center of attention has undoubtedly been given to the AMR. Hence, the popularity of trip-based systems is increasing since connection-based systems struggle to accommodate flexibility. As previously stated, intralogistics could be the key to success for manufacturers in the future, and manufacturers should always be on the lookout for accommodating new productivity improvements. Pei et al. (2019) proposed an assessment tool for intralogistics and Cyber-Physical Systems (CPS). The tool can be utilized by practitioners to identify their current state and improvement potential regarding CPS enabled intralogistics on a total of 16 assessment criteria. Among their findings through case studies was that big enterprises generally have more CPS technology implemented than smaller enterprises. Most criteria are concerned with the information flow such as machine to machine communication and resource planning, while few are concerned with the material flow, where transport, supply and storage, and handling of objects are the only ones included.

From the findings discussed above, it is evident that AMRs hold, or have the possibility to hold, the properties needed in the future of intralogistics system design. This is linked to the reduction of non-value-added activities and required floor space, safety considerations, reduced blocking and starving, increased flexibility, modularity, and decentralized control. As previously stated, the practical design and application of AMRs in intralogistics systems has received little attention in the literature, and selected studies that directly addresses this issue is now presented.

5.4.3 Findings from Theoretical and Case Studies

Fragapane et al. (2020b) presented analytical models for the cost, throughput, and flexibility of a system comparing conveyors in the process industry production lines with the use of AMRs. In its essence, a system based on AMRs would be beneficial if the increase in throughput and corresponding profit increase, generated by the increase in routing flexibility, would surpass the cost of the AMR solution. Through parametric analysis, the key parameters found to support the investment in AMRs were the cost of the AMRs and the number of shifts.

The case study conducted by Čech et al. (2020) at the automotive assembly line at Skoda, proposed an 8-step procedure for using AMRs in assembly lines. The 8 steps are described in Table 5.9.

Table 5.9 – AMR implementation procedure proposed by Čech et al. (2020)

Step	**Description**
Benchmarking	Comparing implemented system to other systems
Current state analysis	Analysis of workplaces, parts, loading/unloading, flow intensity, and supply principles
AMR market analysis	Analysis of available and relevant vendors and technologies
Technological solution proposal	Selecting the most appropriate technologies and vendors
AMR vendor selection	Evaluating business offers and vendor technology
Fleet size determination	Determining the required number of vehicles based on technology and characteristics
Cost-benefit analysis	Considering the life cycle cost of the investment, and returns
Final decision	Final selection of vendor, technology, and fleet size

Čech et al. (2020) further presented findings in the areas of technology, management, economics, capacity, and vendor characteristics. Important highlights include the wide range of AMRs to choose from, the lack of experience from large fleet implementations, difficult Return On Investment (ROI) calculations due to ancillary equipment and theoretical vs. actual AMR performance, lack of proper capacity calculations, and possible difficulties in vendor relationships. Angerer et al. (2012) presented findings on the criteria for deploying manipulator AMRs in the automotive sector in a collaboration with Audi. The proposed criteria are industrial requirements made based on the input from Audi in their case study. Table 5.10 summarizes these requirements.

Table 5.10 – Manipulator AMR requirements proposed by Angerer et al. (2012)

Properties	**Industrial requirements**
Navigation	Robustness in unstructured environment
Gripping technology	Applicability for different part geometries
Hardware components	Economic components with compliance of industrial standards
Workload	20 kg
Workspace	1.8 m
Availability	99%
Energy supply	24 hours
Safety	CE labelled application for man-machine interaction

The case study by Melo and Corneal (2020) addressed the concurrent design of an AMR system and layout design. The study was based on an automotive parts supplier, with the goals of reducing manual MH, improving floor space utilization, and optimizing the material flow. The background for the study was the increasing desire to focus operators on value-added work and easier traceability of parts and WIP in the manufacturing process. The considered Key Performance Indicators (KPI) include throughput; response time; manual labor; buffers; avoidance of starvation, blocking, deadlocks, and disruptions; and capital cost. The reported challenges in the design process included the coexistence of AMRs and manual forklifts, navigation to avoid deadlocks and blocking, and determining the most effective service areas for the AMRs. The final design relied on reducing travel distance on high flow intensity routes and tandem AMR loops that avoided interaction with manual forklifts.

5.4.4 Matrix Production

The manufacturing environment is determined by the product, which is determined by demand. Hence, the manufacturing environment must account for the market situation and is therefore linked with the demand (Greschke et al., 2014). With the changing market trends, new layout types should be considered. Layout type should always follow the manufacturing environment, like the product-process matrix. One emerging trend is the matrix production layout, suggested by KUKA AG (2021b). Essentially, matrix production is a cluster of equal and flexible machine cells, which is supplied raw materials and tools through AMR systems. A matrix production layout of the shop floor is by definition off the diagonal in the product-process matrix, representing a high variety high volume position much alike what is proposed as mass customization. However, matrix production takes mass customization a step further. In addition to modularizing product design, translating and effectively responding to various customer needs (Pine et al., 1993), it modularizes the manufacturing environment. Hence, matrix production is an off-diagonal option - but its layout follows the manufacturing environment: High variety and high volumes requires flexibility and efficiency. Therefore, matrix production can be considered a viable off-diagonal position. Simulation results also confirm that matrix production is outperforming production lines when variety is high, which is a promising start for the relatively new concept (Fries et al., 2020). The matrix layout is similar to a job shop, but combines this with elements from the production line, making the manufacturing cells much more versatile (Schönemann et al., 2015). An example of a matrix layout is depicted in Figure 5.7, while a more thorough discussion is provided in Chapter 7.3.

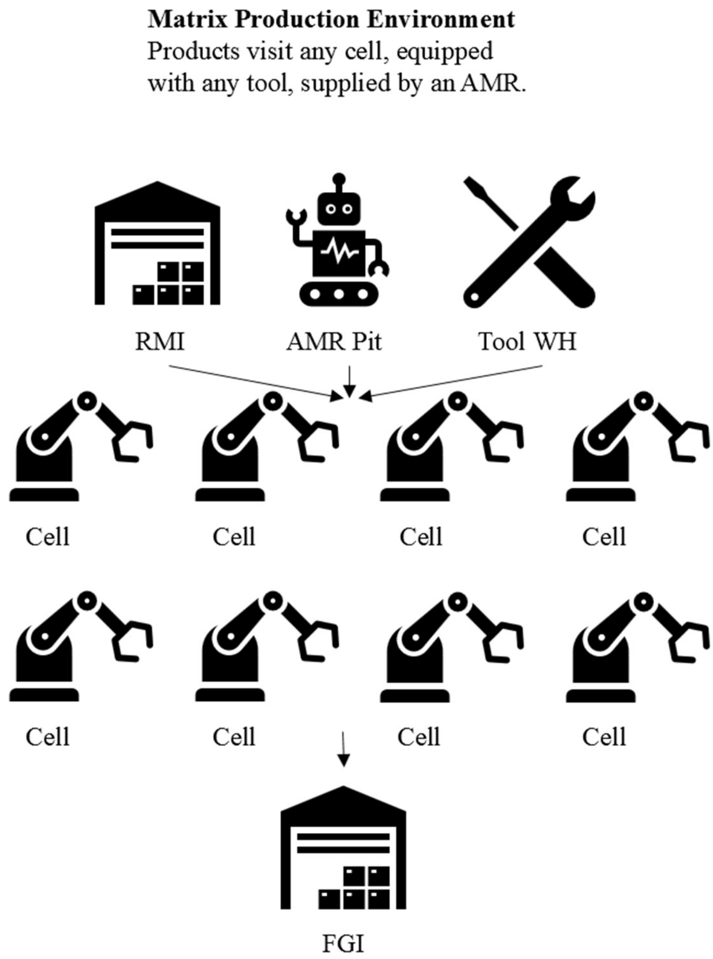

Figure 5.7 – Matrix production environment

5.4.5 Summary of Literature and AMR Vendor Review Findings

Important highlights from the literature review and theoretical background are the three main manufacturing environments and AMR types chosen for this thesis. The manufacturing environments are production lines, job shops, and cellular manufacturing, while the AMR types include the basic AMR, the manipulator AMR, and the special top module AMR. AMR vendor's solutions on these AMR types have been presented. Furthermore, the impact of AMRs in the procedures for layout planning and MH system design are identified. The material handling equation is a central piece of any MH equipment selection process but has its shortcomings in the specificity. Matrix production is identified and presented as a new layout concept as a response to the changes in market and demand trends.

Prior research on AMRs has focused on use cases, planning and control architecture, and conceptual requirements for AMR systems. Among the few directly addressing the intralogistics system design based on AMRs, Fragapane et al. (2020b) used analytical models to address whether the AMR as a concept is suitable or not, but not which AMR types. Čech et al. (2020) offered an implementation procedure for AMRs in assembly lines, but offered little insight into the choice of AMR type. Angerer et al. (2012) presented industrial requirements for manipulator AMRs in the automotive sector, but only limited insight into the solutions towards these requirements. Melo and Corneal (2020) performed a study on concurrent layout and AMR system design, but only evaluating one AMR type.

As evident from these findings, little research has been devoted to the practical design process of AMR systems, as well as linking specific AMR types to different manufacturing environments. The choice of AMR type, layout design, and connected decisions could benefit from a concurrent design process, with a large potential for synergies. In addition to this, AMRs hold unique properties not previously found in common MH equipment. This emphasizes the need for an overview of these characteristics rather than adapting the established models which does not properly cover the innovative AMR capabilities. The following sections present the characteristics to consider for intralogistics system design based on AMRs, descriptions of them, and an overview which groups and connects all the different characteristics and considerations for the evaluation and selection.

5.5 Characteristics for Intralogistics System Design based on AMRs

Based on the findings from the literature and AMR vendor review, RQ1 can be addressed. It must be further emphasized that, within the scope of this thesis, the information flow part of the intralogistics system is not considered. This thesis effectively considers the intralogistics system design based on AMRs as the organization of the internal flow of materials with AMRs for industrial manufacturing environments.

Figure 5.8 shows an overview of the different categories that the literature and AMR vendor findings are grouped into. The intralogistics design concerning layout, cellular manufacturing design, and MH system design fit into the categories of product, quantities, mix, manufacturing environment, layout, and routes. The AMR types, AMR vendor solutions, and use cases fit into the vehicle and top module categories. Planning and control, theoretical studies, and case studies fit into the product, vehicle, fleet sizing and evaluation & selection category. The center piece of the figure is evaluation and selection, where additional considerations towards making the final decision are included. These categories are grouped further in three main categories, following the material handling equation from Tompkins et al. (2010): Materials, moves, and methods. The next sections elaborate on each of these categories.

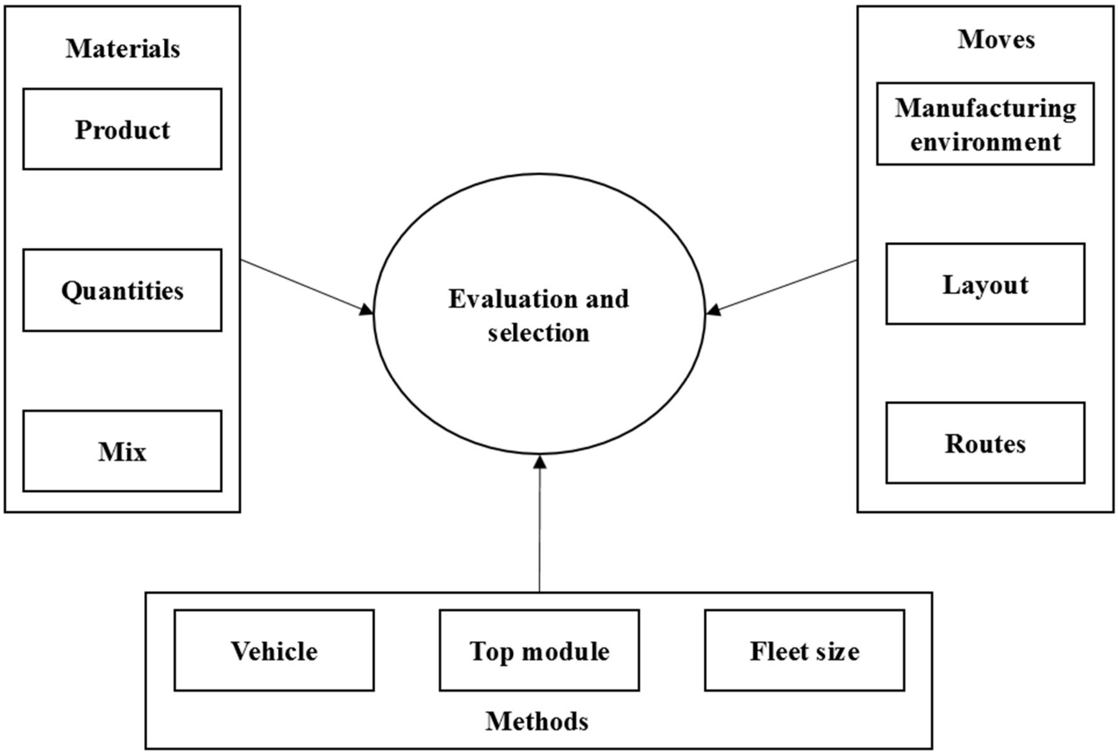

Figure 5.8 – Category grouping of characteristics

5.5.1 Materials

Product

The first consideration to make in any decision regarding the MH equipment is the products to be moved. The AMR must be able to handle the specific geometry and weight of the loads and their varieties (Angerer et al., 2012). Is it discrete products, are they batched together, are they in bulk? What is the shape of the items, boxes, barrels, pallets, or other load carriers that should be moved? What is the weight of each unit load? Is the product costly or fragile, and is it covered in protective packaging or transported as is? Answering these questions gives a good perception of what is being moved (Tompkins et al., 2010). This information is possibly the biggest factor in terms of choosing the type of vehicle and top module. For example, the payload capacity of an AMR is often directly linked to the design options and price ranges, as seen from various AMR vendor solutions (Mobile Industrial Robots A/S, 2021c, KUKA AG, 2021a). More rugged vehicles require more enduring materials and equipment that increases the price, and fewer options become available. In addition to weight, geometry of the product or load carrier is essential for interacting with the goods. For instance, could a manipulator AMR independently perform L/U for this type of product, or is a conveyor top more suitable? Within this category is where we find the typical exclusion criteria, for example payload capacity of a vehicle and weight of each unit load. Mismatches in these properties will deem some of the AMR solutions not feasible.

Quantities
When the products and load carriers are identified, the next step is to look at the quantities of products to move. The total throughput of the manufacturing unit in question is the guiding number. When the total number is acquired, this number can be broken down into different items based on how they are transported. A simple example would be a production line with a throughput of 100 pcs/day, where 50 pcs are transported individually on pallets, and the other 50 pcs are transported in boxes of 5 pcs/box. Hence, the system must transport 50 pallets and 10 boxes per day. Important to consider here is the use of the unit load principle - Where a unit load is *"A single item, a number of items or bulk material which is arranged and restrained so that the load can be stored and picked up and moved between two locations as a single mass"* (Tompkins et al., 2010). The unit load design plays a vital role in the number of transports, since smaller unit loads correspond to more frequent transportation and vice versa. It also determines the weight of the unit loads, which applies to the payload capacity of the vehicle. The design of unit loading and MH system should be done simultaneously, because they impact each other in such a large way (Tompkins et al., 2010). The life cycle of the product will play a role in the quantity - Is it a mature product with stable demand, is it being phased out, or has it just been introduced and expected to grow? This should impact the level of reserve capacity and scalability designed into the system. The characteristics of orders, customers, and timing of orders is linked to the market and Supply Chain (SC) configuration of the company (Mörth et al., 2020). This can significantly impact the quantities we need to plan for. Are we allocated production orders based on our capacity from a central SC planning office or are we independent and must prepare for accommodating all our customers placing orders at their convenience? How often do we receive new orders and how do we level our production output? How many shifts do we operate, and what level of throughput must we accommodate?

Mix
By understanding the products and quantities to move, an outline of the system to design should begin to appear. To specify this further, the production mix is the key. This is especially important under the current market trends, as the number of variants is increasing, and this requires increased flexibility (Pei et al., 2019). The first is the volume mix - How will the system handle peaks and valleys in production volume? Can we have enough reserve capacity for all peaks, or will the system reach a threshold for transportation volume? In times where demand is low, how much will the idle time cost us? These are typical issues regarding sales & operations planning, and awareness of how the intralogistics system is designed and what it can handle is important. The next is the product mix - How many unique products are we producing? Different products may have different transportation needs as discussed earlier. They may also have different cycle times, creating an unbalanced flow. In addition to this, different products may have entirely different routing through the shop floor, requiring flexible transportation. This is mainly covered in the discussion of "moves" but understanding the level of flexibility needed to accommodate these challenges are important. Last, as a consequence of

the production mix, a range of other factors comes into play. The setup times for machines can impact the ability to handle the product mix. A setup reduces productivity and can create starvation and blocking of other machines (Custodio and Machado, 2020). Machines and series of workstations will produce defects, and the quality component of the overall equipment efficiency can indicate how many products need to be rerouted or transported to a repair station. How should the intralogistics system respond to these challenges? The Production Planning and Control (PPC) policies and systems will to a large degree control the production mix released to the shop floor and can be a valuable resource for designing the intralogistics system.

5.5.2 Moves

Manufacturing environment

The manufacturing environment is the decision that will guide virtually any move conducted within the shop floor. Often, the manufacturing environment is directly linked to the product structure as suggested by Hayes and Wheelwright (1979). The three main manufacturing environments used in this thesis are production lines, job shops, and cellular manufacturing. The reasoning is that their intralogistics needs, and design procedure similarities, can be grouped reasonably in these three environments. The three environments' intralogistics characteristics can be generally described this way (Hayes and Wheelwright, 1979, Stavrulaki and Davis, 2010, Nicholas, 2011):

- Production lines move medium to high volumes of products in sequential steps, visiting the processing steps required to the product. Usually, this means visiting every machine in the production line sequence.
- Job shops gather common machines into departments, and the routing is specific to the product being produced. This means different products visit different departments at different stages in the production process, and departments may be revisited.
- Cellular manufacturing requires the cell to be fed from a warehouse or supermarket, then the product enters the cell, passes through all required machines/workstations, and is sent from the cell to the FGI.

The manufacturing environment determines the outline of the moves to be performed, while being further defined by the layout.

Layout

The layout of the shop floor is a detailed plan of the manufacturing environment. Here, machines, departments, supporting services and the likes are puzzled together based on transportation frequency between them and other requirements such as clean zones and fire hazards, commonly based on the SLP procedure (Muther and Hales, 1987). The space of machines and departments are calculated, and a map of the shop floor is created. An important consideration for the intralogistics system is how flexibility is accommodated. The flexibility in layout planning represents the modularity, reconfigurability, and scalability of the system. By reaching good solutions within these keywords, the shop floor's ability to handle increased production mixes is strengthened. The supporting services and factory environment are also essential elements for a world class factory. How the factory looks aesthetically, and functions can be important for the physical and psychosocial health of workers. For example, securing ventilation, correct temperatures, natural light, and green plants can create a better environment (Tompkins et al., 2010). Such considerations become important when introducing AMRs, as it brings new and mobile technology to the shop floor.

Routing

With a set layout, the routes for transportation are determined. The objective of the routes is to provide a passage, as short and fast as possible, between one step in the production to the next. Therefore, the efficiency of the layout will depend on the travel distance of the routes and the flow intensity on the routes (Muther and Hales, 1987). The travel distance should always be kept as short as possible, while the flow intensity can become a bottleneck. Highly occupied routes can create congestions, queues, and operations can be starved of material to process (Melo and Corneal, 2020). Buffer inventories are commonly utilized to decouple machines with different cycle times, reducing the possibility for starvation or blocking. A quick fix to intralogistics problems is to increase buffer sizes; however, lean principles show us the disadvantages of keeping large WIP inventories around the shop floor (Nicholas, 2011). Another consideration is if the route has special requirements. Some manufacturers can have areas with high temperatures, hazardous environments, clean environments, and the likes. This can deem routes inaccessible in some cases, requiring the MH equipment to take detours adding to the transportation time (Tompkins et al., 2010).

5.5.3 Methods

Vehicle

In existing systems, the first step is to look at the current MH equipment being used. It must be determined what should be replaced with AMRs, what can be kept and interact adequately with the AMR system, and what must be changed to accommodate the AMRs (Mörth et al., 2020). The range of existing MH equipment can be large and highly fragmented, with various levels of suitability for AMR interaction. When these questions are answered, the process of finding the suitable AMR can commence. It can be difficult to distinguish different AMR types without including the differences in top modules. However, some characteristics must be taken into consideration apart from the top module. The features of the vehicle represent what it can provide. AMRs should, by definition, operate autonomously and some examples of such tasks are: Safe and timely transport of materials, obstacle avoidance of what is present on the shop floor, charging or battery change, and capability to attach various top modules (Angerer et al., 2012). The payload is important, as stated earlier. Knowing how heavy each unit load is, a vehicle with the proper payload capacity must be selected. The scalability of the AMR system must be considered. This should be both in terms of scaling up for more capacity or scaling down. Relevant questions include: Does this AMR vendor have the correct software in place to effectively add and remove vehicles? Can the AMRs from this brand effectively co-exist with AMRs from other vendors? Life cycle of the vehicle itself: Is this a mature and well-proven technology, is it immature and unstable, is it outdated, what is happening in the industry within the next few months? Other important considerations towards the vehicles include hardware and software: Is safety properly accounted for in terms of sensors and backup solutions, what sensors and technology guides the navigation and localization (Alatise and Hancke, 2020)? Is this effective in the specific environment? Can we operate, maintain, and solve problems on our own through the software solution or is the need for technical experts frequent (Arrais et al., 2019)? How accurate are the vehicles? How flexible are they in terms of new products, routes, stations, and addition/removal of vehicles? Are the solutions standardized so that we can retain operator flexibility, or does every vehicle behave differently with different properties?

Top module

The top module decision should be heavily influenced by the materials to be moved. Some products will favor certain types of top modules. For instance, using pallets as load carriers can favor e.g., an AMR with a lifting and lowering mechanism, since it can handle it autonomously. The three main types; Basic AMR, manipulator AMR, and special top module AMR is favored for some specific characteristics similar to the load carrier. Additionally, the design and use of L/U stations impacts the decision. Requiring the workstation to perform L/U can create queues in times of peak demand, while letting the AMR do this autonomously removes this problem (Alizon et al., 2009). Naturally, the cost of the AMR will increase with its level of complexity, type of equipment, and tasks to perform. However, the use of manual operators or ancillary equipment increases when using only basic AMRs, and this cost must be considered. Here, a middle ground must be found.

Some essential keywords should influence the choice of top module. The first is capacity: Linked to our unit load design, how many loads can we move at the same time? Is it practical to move more than one load? The second is capability: What tasks do we want it to perform and what can the vehicle perform? Third is reliability: A more complex and well-equipped AMR could be more prone to error, reducing the availability of the vehicle. Fourth, if using manipulators, what is the capability of the end effectors, does this suit our product range? Through answering some of these questions, the suitability of the solution can be evaluated. Then the performance of the solution can be evaluated by testing some of the vehicles, performing simulations, or visiting other companies with the same vehicles. Worth keeping in mind is also value adding or other tasks performed by the vehicle while transporting. For example, the AMR can count items, correct inventory status, sort items, test and perform quality inspections, perform simple assembly operations, or pack items if equipped with the correct equipment. In the end, each top module design has its advantages and disadvantages, and these must be evaluated against the materials and moves.

Fleet size

The number of vehicles to deploy depends on the required and available time. This is determined by a wide range of factors including, but not limited to, travel distance, speed of the vehicle, L/U time, required throughput of the factory, and routing. The fleet size is important for two reasons: The correct amount of vehicles must be deployed to satisfy the demand on the intralogistics system, and it determines the majority of the cost of the solution based on the price of the vehicles (Čech et al., 2020). Hence, fleet sizing is a part of the decision-making process while selecting a solution and supplier, as well as when releasing the vehicles on the shop floor. When evaluating the total cost of the system, three types of costs can be distinguished: Investment costs, operational costs, and cost of ancillary equipment. The investment cost is the upfront cost of vehicles. The operational costs are maintenance and other costs agreed upon not to be paid in the upfront investment. Ancillary equipment is usually needed, and this could be charging stations, adjustments to the routes of the AMRs (such as repairing the floor and ensuring Wi-Fi connection), and equipment on the L/U stations, depending on what operations the AMR performs. The cost is a crucial factor for the suitability of the AMR in the first place, as suggested by Fragapane et al. (2020b). Here, the vendor business model is also relevant for the decision. Do they charge the full amount upfront, can the vehicles be leased, or can they be purchased as a service based on meters travelled or kilograms moved?

5.5.4 Evaluation & Selection

The intention of the proposed overview is to include all characteristics the practitioners should analyze or be aware of when undertaking AMR projects. However, when evaluating and selecting different alternatives, other considerations can quickly come into play. Some of these are not under the AMR projects' control, while others require different skills and resources to evaluate than the intralogistics planner normally has. These are briefly introduced now to complete the overview.

The first consideration is the strategic priorities of the company, which can influence the materials, moves, and methods. For instance, future product portfolios might be changing, the structure of the SC network is being redesigned, or a specific supplier might be preferred due to collaborations at the corporate level. These are long term decisions and plans not necessarily known to the head of the AMR project, and will usually guide the process in a certain direction.

The human-machine interaction must also be properly evaluated when deploying autonomous vehicles in a system with humans. In addition to safety concerns, four typical problems identified by Hoc (2000) were: Loss of expertise, complacency, trust and self-confidence, and loss of adaptability. Briefly summarized, these cause operators to put too much trust in the systems, not get practice on the tasks and feedback from the machines if the tasks must be performed manually, and the difficulty achieving dependability and predictability of the human-machine system. The work by Gorecky et al. (2014) discussed the human-machine interaction in the Industry 4.0 era and pointed to four requirements for human-machine interaction: Access to the automated technologies through mobile devices with user interfaces, account for the higher system complexity operators will experience, tracking component positions, and tracking the operators to supply the current and correct information for them to effectively solve problems. These are general guidelines and problems which should be accounted for in the AMR project.

Ergonomics on the shop floor is also important to consider. AMRs for intralogistics can remove ergonomically challenging tasks such as lifting and extensive walking, and even workstations close by can have improved ergonomics ratings after the deployment of AMRs (Unger et al., 2018). It is important to not lose sight of this objective when choosing an AMR solution. For example, using a basic AMR might require the operator to lift large unit loads off the vehicle. To better respect the ergonomics of the worker, a manipulator could be tasked with unloading the vehicle. Psychosocial ergonomics can be affected severely in this kind of project. There might be a reduction in the number of manual intralogistics workers, meaning some might be re-tasked to other functions, or even let go, and the operators now work in close relation to robots. Keeping an eye on the impact on both the physical and psychosocial ergonomics of the workers is considered highly important both for the workers' health and the acceptance of the new intralogistics system (Berx et al., 2021).

In addition to the strategic priorities, human-machine interaction, and ergonomics, selecting the most suitable solution should focus on the topics discussed in the following paragraphs. The fit between the materials, moves, and methods is above all the most important (Tompkins et al., 2010). The clearest example of this is the match between payload capacity of the vehicle and weight of the unit loads. Other mismatches can be further filtered out by studying the specifics of the scenario. For example, basic AMRs requiring a lot of ancillary equipment for L/U might not be favorable when space is severely limited. If required throughput is high, and variety is low, the question whether AMRs are suitable in the first place should be revisited. If throughput and variety is high, quick L/U solutions may prove important to avoid congestions. Recommendations in the fit of the solution for the defined manufacturing environments are found in Chapter 6.2. Although the fit is most important, this may leave the practitioner with a handful of possible solutions. To further evaluate these, the following considerations may guide the process.

The desired autonomy level of the intralogistics system, as proposed by Fottner et al. (2021), must be determined and thus forming the AMR system to fit into this. The ambition is to not only have autonomous vehicles, but also autonomous planning, control, and decision-making processes. If the ambition of the company is to reach full autonomy on all intralogistics activities, the AMR system must be suited for it. For example, this could mean including the necessary computational power onboard the vehicles or making sure the AMRs can interact with other MH equipment deployed for other purposes.

The software infrastructure for collecting, analyzing, sharing, and receiving relevant data to and from the vehicle must be considered. The vehicle fleet should be connected to the manufacturing execution system or similar tools to effectively schedule the fleet and supply the correct workstations at the right time. Reporting inventory status, and counting items can also be conducted, increasing inventory accuracy and control over the WIP. For effective decision making, the vehicles must have access to information collected by the entire fleet and supplying information to the smart factory ecosystem (Indri et al., 2019). This will allow for improvements in the vehicle fleet's performance and to the production system as a whole, enabling a dynamic PPC process. When deploying AMRs, it is arguably easier to ensure that the MH activities are part of a coordinated and integrated system (The Material Handling Institute, 2021), as the AMRs require a more rigid system structure than manual MH solutions would. In addition to this, the question of whether the new MH solution reduces the amount of time and resources spent on MH should be raised. As per the definition from lean, necessary but non-value adding activities should be kept to a minimum (Nicholas, 2011). The outcome should reduce the resources spent on MH.

Finally, the cost of the system cannot be left out of the equation. As previously stated, the cost can be split between investment, operation, and ancillary equipment costs. When the fleet size, type of solution, and vendor business model has been identified, the total cost of the system is determined through an offer from the vendor. Evaluating offers from the vendors can prove difficult, due to the lack of standardized metrics and experience with the technology (Schneier and Bostelman, 2015). Therefore, the cost question is important but can be misleading. One way of evaluating the cost is to look at the ROI. The ROI must be based on the reduction of labor hours on MH, the possible benefits from adding robots (higher accuracy, less human errors, better ergonomics), as well as improved working conditions, efficiency, productivity, and space utilization. When the relevant factors are added to the ROI equation, the result must be compared to the financial situation, priorities, and policies of the company. Due to the difficulty of comparing offers from suppliers, this can prove useful (Čech et al., 2020). The vendor relationship can also play a role when selecting solutions. Do they offer 24/7 customer support, do they have representatives in our geographical location, do they rely on third party implementers and what is their service like, what is the financial situation of the supplier, and can we expect to be using them in the future? These types of questions in addition to dealing with the suppliers, structuring tendering processes, negotiating, and the likes are an important part of the AMR procurement process but further discussions on this are out of scope for this thesis. In short, the cost always plays a role in the design decision but can be difficult to measure and compare between vendor offers, and is also lacking a basis in the scientific literature (Winkelhaus and Grosse, 2020).

5.6 Overview of Characteristics for Intralogistics System Design based on AMRs

The shortcomings in the literature regarding the lack of an overview of the characteristics and considerations that guide the practical design process of AMR systems highlights the relevance and importance of work on this topic. This is the motivation for RQ1:

RQ 1: *What are the characteristics to consider when designing intralogistics systems based on AMRs?*

By addressing RQ1 the established procedures for intralogistics design can be synthesized with the AMR capabilities, prior research, and vendor solutions to create an overview that can support practitioners in the process of designing intralogistics systems based on AMRs. The proposed overview is presented in Figure 5.9.

The basic structure of the overview is based on the material handling equation, and each of the characteristics relate to the previously discussed topics. For instance, the product can range from computer hardware to automobiles, the manufacturing environment can range from production lines to cellular manufacturing (following the scope of this thesis), and the AMR top module can range from no attachment to manipulators (following the scope of this thesis). It includes a separation between qualitative and quantitative characteristics. Some qualitative characteristics can be considered quantitative for other purposes, or vice versa, but not necessarily relevant to the intralogistics system design process, or out of scope for this thesis. Some examples are ergonomic ratings, orders and customers, and accuracy of the vehicle. It is important to note that the overview is focused on AMRs as the MH equipment, effectively excluding other MH equipment types. The materials are linked with the moves and methods with an arrow because the moves and methods are directly impacted by the materials. For example, the product mix directly influences the configuration of the manufacturing environment. The reason is that the characteristics of the materials can be linked to the demand, which the manufacturer has little control over in today's competitive environment. Hence, the moves and methods will rarely have the possibility to impact the material. The moves and methods are linked with a loop: The intention is that in addition to the moves significantly impacting the methods, with AMRs the method can also impact the moves in various ways. New layout designs are an example of this, such as Matrix Production which was briefly introduced in Chapter 5.4. Simply viewing the decision in this way can stimulate practitioners to view the facility planning in a new way. Finally, considerations for the evaluation of the proposed alternatives are provided and provides input to the selection process.

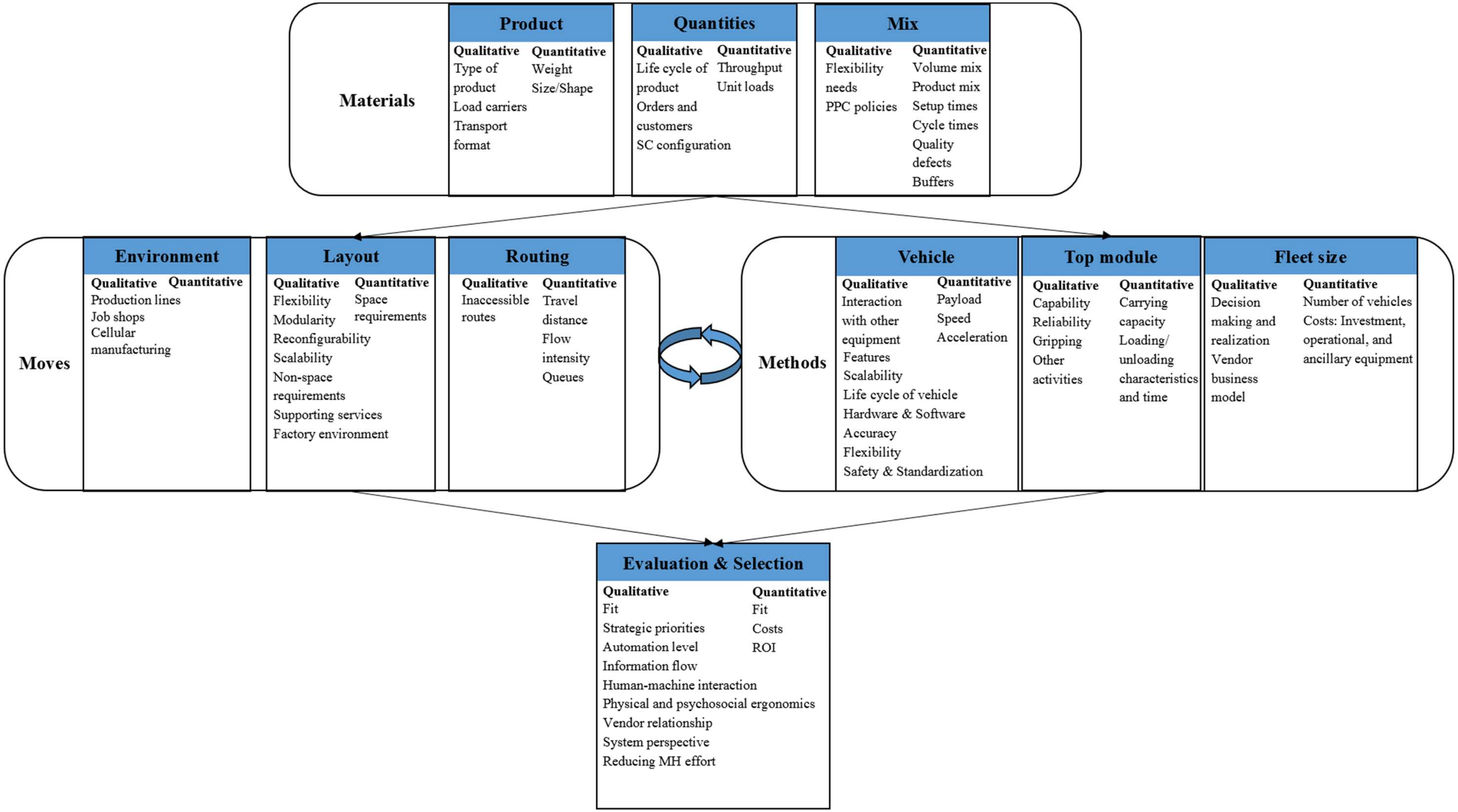

Figure 5.9 – Overview of characteristics for intralogistics system design based on AMRs

6 Decision Support System for Intralogistics System Design based on AMRs

To address RQ2, a DSS is developed to link the most suited AMR type to the manufacturing environment's characteristics. This chapter starts with the development of the DSS, following the four steps described in Chapter 3.2: Shortlisting the characteristics from the overview that affect the choice of AMR type, grading characteristics towards the manufacturing environment by a Delphi study, grading the AMR performance on the characteristics, and determining the recommended AMR types in the DSS. Then, the process of validating the DSS is performed by comparing the results from the DSS with those of the parametric analysis on the mathematical models.

6.1 Characteristics and Grading for the Decision Support System

To address RQ2, the DSS must identify the most suitable vehicle type or types. This is based on the characteristics from the overview that would influence the choice of vehicle. First, the process of excluding irrelevant characteristics is explained, and then the included ones are defined and described.

6.1.1 Inclusion and Exclusion of Characteristics

None of the qualitative characteristics were included. The main reason is that they would not influence the choice of one of the three AMR types significantly compared to the quantitative ones. For example, scalability and inaccessible routes are highly relevant when designing the system, but they have little importance for which AMR is chosen. Some of the characteristics are also linked to a quantitative characteristic. For example, the type of product and load carrier can relate to the weight & size/shape of the product to simplify the DSS. In addition, the validation of the DSS was only possible for quantitative characteristics, as it is done through mathematical modeling. Briefly summarized, the qualitative characteristics do support the design of the system, but they would not influence the type of AMR, as the differences in these characteristics does not reflect the differences between the AMRs.

The selection of quantitative characteristics is guided by the same principle. What is relevant are their impacts on determining the type of AMR. The excluded ones from the materials category are volume mix, setup times, cycle times, quality defects, and buffers. Volume mix could be included for a large-scale system where vehicles could be exchanged between departments; however, here it is considered that the system must satisfy the highest throughput encountered. The same reasoning follows the exclusion of setup times, where in large scale systems this could reduce the fleet size if some machines/workstations were always unavailable. Cycle times are disregarded from the choice of vehicle because it does not influence which vehicle is more suited. It would serve as input to the flow intensity, the frequency of deliveries, and ultimately the fleet size. Quality defects and buffers are excluded because they also only contribute to the fleet size calculation. As a measure for the number of transportation missions, the throughput is considered most important, and the contribution of transporting quality defects are considered small in comparison. To keep the DSS simple, these overlapping characteristics were removed, and some are considered to be included in another characteristic, as the next characteristic is an example of. From the moves category, flow intensity is not considered. To simplify the DSS, it is considered that this characteristic is properly covered in the space requirements characteristic. The space requirements therefore also build on the flow intensity and queues arising from this. The purpose of the characteristics from the methods category is to evaluate how the vehicles performs on the various characteristics from the materials and moves. Hence, this does not impact the selection of the characteristics, but is included to determine the performance of each AMR type on each characteristic. The characteristics speed, acceleration, and carrying capacity are excluded because it can be assumed that all three AMR types can operate with the same speed and acceleration and can be adapted to have the same carrying capacity.

The remaining characteristics are weight & size/shape of the product, the production throughput, the space requirements, travel distances, unit loading considerations, and product mix, listed in Table 6.1. These are included in the DSS, and following is a presentation of each of them, what they entail, and why they are included. Further it is described what is considered to give a high or low score and what influences the AMR performance on the specific characteristic.

Table 6.1 – Shortlist of characteristics

Characteristics
Weight & Size/Shape
Throughput
Space Requirements
Travel Distance
Unit Loads
Product Mix

Weight & Size/Shape: The weight of the product or products in terms of kilograms, the size in terms of area or volume, and the shape in terms of geometrical properties. In manufacturing, a product can range from small nuts and bolts to full size automobiles. The simplest way to classify this is by judging their weight & size/shape. The weight has a significant impact on the payload capacity of the AMR, and the size and shape must directly relate to the size of the AMR and how it can be transported on the AMR (Chebab et al., 2015). A high score in this characteristic can mean products are heavy, large, difficult to handle, or similar. A product must not be especially heavy to score high, it could be difficult to handle due to its large size. For a low score, the product should not be especially heavy, large, or difficult to handle. An option is to transport the items in a suited load carrier, reducing the impact of challenging geometrical properties.

Payload capacity and top module design is the determining AMR characteristic that separates the vehicles on this characteristic. For example, low-payload AMRs or manipulator AMRs struggle with products that are heavy, large sized, or difficult to handle. Good performance here relies on the ability to handle these types of products.

Throughput: The required throughput of the system in terms of pieces per hour or similar. This is a key property for determining the fleet size, as higher throughputs mean more transportation and more AMRs. This is not considering the impact of unit loading, which is included as a separate characteristic. Several other studies for similar purposes also incorporate throughput as an important characteristic, such as Fragapane et al. (2020b) and Peron et al. (2020). When the fleet size increases, the cost of the AMR type has an increasing impact on the decision, as well as queues. At L/U stations, if the AMR cannot perform the operation themselves, operators or machinery might be occupied with other deliveries making the AMR wait in a queue, and the equipment takes up space (Alizon et al., 2009). As previously explained, the throughput is a good measure for eventually determining the fleet size. The impact of some excluded characteristics such as transportation of quality defects can be considered covered by this characteristic. A high score in this characteristic would normally indicate that a large fleet size is needed due to the high throughput and possibility for queues, while a low score indicates the opposite.

The number of AMRs required, relying on the time used to perform a mission and L/U performance, separates the AMRs based on this characteristic. The AMR types with probabilities for queues at L/U stations will have a disadvantage for high throughput volumes. Good performance here relies on having autonomous L/U for several AMRs simultaneously, that can help reduce the fleet size and investment cost. If several AMR types can ensure queue-less L/U without ancillary equipment, the cost is the decisive factor.

Space requirements: The required space for ancillary equipment, space for buffers, and possibility of queues at routes with high flow intensity. Buffer space to temporarily store goods can be critical for some environments, and Čech et al. (2020) argued that space saving solutions can be preferred especially in assembly lines. Highly saturated routes can cause congestion for AMRs, reducing their capacity for delivery (Urru et al., 2017). A high score here means that space is pressured, and the AMR system must seek to reduce the needed space and probability for queues, while a low score allows for more space to be consumed by the AMR system.

The L/U design is the important consideration for the AMR here. The L/U design will impact how much ancillary equipment is needed to support the AMR system, such as manipulators on the workstation performing L/U. The L/U can be performed by the AMR for the manipulator and some special top modules, but not for the basic AMR. It can also determine the space needed for buffers at L/U stations. Good performance relies on reducing the need for ancillary equipment and space consumption of buffers, and fast L/U that can reduce the fleet size.

Travel distance: The average or expected travelling distance of the transports in terms of meters. This has a significant impact on the fleet size and is especially important in job shops where a lot of transportation is needed back and forth between departments. In environments with less flexible routing, such as production lines, this has less impact as the layout design usually results in a sequential routing, ensuring the shortest distance possible. A high score here is given for long distances, while a low score is given for short distances.

The cost of the AMR type is at the center. Since the fleet size increases with longer distances, a low-cost AMR will achieve better performance, and considering the speed is the same, costs are the only decisive factor.

Unit loads: *"A single item, a number of items or bulk material which is arranged and restrained so that the load can be stored and picked up and moved between two locations as a single mass"* (Tompkins et al., 2010). The unit load design can have a significant impact on the payload capacity of the vehicle and the number of transports. The larger a unit load is, the heavier and bulkier it becomes. The smaller a unit load is, the higher number of transports is needed. This characteristic is highly relevant in production lines if bulk material is moved from point A to B in large quantities. A high score indicates large unit loads reducing the number of transports but increasing the weight, and a low score indicates the opposite.

The unit load is influenced by the payload capacity and cost of the AMR. Bigger unit loads mean a higher required payload and a more expensive AMR. Smaller unit loads reduce the payload requirement but results in more AMRs. On this particular characteristic, good performance relies on concurrently designing the unit loads and MH system (Tompkins et al., 2010), and the AMR performance can be measured in its payload per Euro ratio.

Product mix: The variation in weight & size/shape of the products. Under some definitions, a high product mix can imply for instance different colors and customization options not relevant to the weight & size/shape and must not be confused with the product mix as defined here. The increasing customization and personalization trends of products means ever increasing product mixes, and this is especially the case in assembly lines (Kousi et al., 2019). This has a high impact on the choice of AMR, especially manipulator AMRs or special top module AMRs that actively interact with the goods. The end effectors on the manipulator have limitations in terms of what it can handle, and more complex manipulators covering a broader range can be more expensive. A high score indicates a wide range of different weights, sizes, and shapes the system must handle. A low score indicates more uniform physical properties of the range of products.

The L/U characteristic plays the central role for the AMR type here. When handling large product mixes, the L/U equipment must be more general and can increase time spent L/U. The price of the AMR can also increase as a result of this. Good performance here relies on being able to handle wide product mixes without increasing the cost of the AMR.

Table 6.2 summarizes the characteristics, their impact on the intralogistics system, and AMR performance evaluations.

Table 6.2 – Summary of characteristic grading requirements

Characteristic	Low grade	High grade	AMR performance
Weight & Size/Shape	Easy to handle Low weight Suited load carrier	Difficult to handle High weight	Gripping capability Payload capacity Suited transportation platform
Throughput	Low number of transports No queues Small fleet size	High number of transports Potential for queues Large fleet size	Cost of vehicle L/U performance
Space Requirements	Not pressured space availability Low queue potential	Pressured space availability High queue potential	Ancillary equipment for L/U L/U station and buffer space
Travel Distance	Short distances	Long distances	Cost of vehicle
Unit Loads	Small unit loads High number of transports	Large unit loads Low number of transports	Payload capacity Cost of vehicle Payload/Euro ratio
Product Mix	Uniform physical properties	Wide range of weights, sizes, and shapes	L/U capabilities Cost of vehicle

To propose the DSS, both the manufacturing environments and vehicle types are graded on the characteristics based on their importance and performance. The grading for manufacturing environments is done on a Likert scale of one to five. One means it has little to no importance or is not a common problem/characteristic for the manufacturing environment, while five is highest, meaning this characteristic has high importance, is a common problem/characteristic, and therefore will have a high impact on the choice of vehicle for this manufacturing environment. The vehicles are graded relative to each other, so that three points are given to the highest performer for the characteristic, two points for the type in the middle, and one point for the worst performer in that category. The grading for the manufacturing environments is now presented, based on the results from the Delphi study.

6.1.2 Grading for Production Lines

The biggest contender to AMRs in production lines are connection-based systems such as conveyors. The decision of using AMRs or not is considered a vital decision for this manufacturing environment. Although this decision is not a part of this thesis, strong emphasis is put on thoroughly considering whether AMRs are financially justifiable or not. An example of how this decision can be made is found in the work by Fragapane et al. (2020b), which compared conveyor systems to AMR loops.

Production lines can potentially experience the full range of item weights, sizes, and shapes. They can be big and heavy, transported in bulk, have challenging geometrical properties, or be small discrete items. Throughput is likely to be the highest of the three manufacturing environments, which strongly influences the required fleet size. In general, the facilities are large in size due to e.g., large sized equipment, where space is not highly limited. The layout planning process should ensure enough space to reduce the concern of cramped space in such a facility, making the impact of space less important in production lines. For the travelling distance, the SLP procedure heavily relies on the flow intensity between the machines. The objective is to reduce MH effort between machines as much as possible. As product routings are similar due to the limited size of the product mix, the layout design is bound to be sequential ensuring short travel distances. Choosing AMRs as the MH equipment, new and innovative designs might appear due to the many benefits of AMRs. This could allow for connecting several production lines together as a production network, since AMRs do not block routes contrary to conveyors, and have flexible pathing. Unit loads are linked to the choice of AMR type in this scenario, as material normally is moved in high quantities, and the options of designing the unit loads are many. It should therefore be considered the vehicle payload and cost against the number of transports needed between the stations. The number of transports will increase with smaller unit loads and vice versa. Furthermore, vehicles with higher payloads will have a higher cost. A cost optimum is present in the relation between the cost of the vehicle and the fleet size required to satisfy the number of transports. The product mix produced on each line is likely to be limited. The products can be challenging to transport but adapting the equipment to the products could ensure more effective AMR operation.

The results from the Delphi study reflect the main considerations presented above. Grades are generally low for all the characteristics except throughput, which has received the highest grade. This also reflects the important decision of whether AMRs are suitable or not in these environments since high throughput might not reflect the strengths of the AMR.

Table 6.3 presents the grades given for the importance of the characteristics for the production line environment resulting from the Delphi study.

Table 6.3 – Grades for production lines

Characteristic	Grade
Weight & Size/Shape	2
Throughput	5
Space Requirements	2
Travel Distance	2
Unit Loads	2
Product Mix	2

6.1.3 Grading for Job Shops

To accommodate the wide product mix found in job shops, a standardized set of load carriers can be a challenge, requiring the products to be transported without a load carrier. Hence, the size and shape can be difficult for the intralogistics system to handle. The system is generally not handling bulk items or small components, but the weight and geometrical properties of products being made can be challenging. Job shops are likely to have the lowest throughput among the three manufacturing environments, but since there is a lot of transportation back and forth between departments, fleet sizes can be large depending on the travel distances. Reducing the size of each department helps to ensure short travel distances, which will affect the fleet size, making space an important characteristic. Flexible routing to different departments reduces queues on routes, combined with the potentially lower utilization of each machine means more time available for L/U and reduced queues. The unit loads are usually related to the production batch size, which can be challenging if not designed to fit the intralogistics system. A high product mix with variety in weight, size, and shape is highly likely to be present, since the range of products that can be produced is large.

In the results from the Delphi study, the overall importance of the characteristics is high. Throughput received a low score, which was expected. All the others have high scores which essentially means that job shops deal with complex products to handle, high variety, high unit loads, and restricted space. Travelling distances are naturally highly important due to the frequent transportation of items between departments.

Table 6.4 presents the grades given for the importance of the characteristics for the job shop environment resulting from the Delphi study.

Table 6.4 – Grades for job shops

Characteristic	Grade
Weight & Size/Shape	4
Throughput	2
Space Requirements	4
Travel Distance	5
Unit Loads	5
Product Mix	5

6.1.4 Grading for Cellular Manufacturing

The intralogistics in cellular manufacturing can be divided between the activities of feeding the cells with material and components from the RMI or supermarket and moving the products within the cells.

The materials and components delivered to the cells are usually smaller and lighter compared to the other two environments. If the components are easily handled by affordable end effectors on manipulators, a manipulator AMR might be a good choice. For feeding small items and kits of items, SLCs can be utilized, standardizing the load carrier, and combined with either manipulator AMRs or conveyor AMRs, allow for deliveries to a small L/U station by the cell entrance. Within the cells, the AMR type is more connected to the product characteristics. If the products are small and transported in SLCs, basic AMRs can rely on operators for L/U. If the product is large or heavy, the AMR might follow the product through all the processes. However, items are usually easier to handle than both production lines and job shops. The throughput is usually high, since the benefit of cellular manufacturing is to be efficient for given product families. Especially if throughput is high, the number of deliveries to the cells can become high, causing queues to form. Space is deliberately restricted in cellular manufacturing to achieve many of its benefits including flexible workers, easier communication and coordination, and so on (Nicholas, 2011). Due to this, and with centralized inventories, queues can form both on the routes and at L/U stations. If space is limited, then L/U equipment installed on the workstations might be challenging, and less space consuming solutions can be preferred (Čech et al., 2020). The operators can also handle the L/U, which can conserve space but be a bottleneck and add to the cycle time of each workstation.

The layout and centralization level of components to feed play a large role in the travelling distance of the vehicles. Decentralized inventories are an alternative to the centralized inventories, which can help reduce the travelling distance but can also increase the complexity in the operation between inbound goods and the inventories. Within the cells, distances are kept short and are less of a concern. The unit loads have two considerations in cellular manufacturing. For delivery to the cells, ideally, kitting is performed before the AMR reaches the inventory and allows for better capacity utilization of the AMR. Kitting, or also kanban systems, reduces the impact of the unit load designs, as the AMR capacity can be adapted to the kits and kanban delivery sizes and vice versa. Within the cells, the unit load is related to the production batch size similar to job shops.

For the feeding operation, the product mix is relevant. High product mixes require smaller and more frequent deliveries and is in fact one of the common problems now facing assembly operations (Kousi et al., 2019). Within the cells, the product mix is likely to be low due to the creation of product families. However, it can still have an impact as the families are usually based on similarity in processing requirements and not physical properties of the items - meaning products in a family are not necessarily uniform in the weight, size, or shape.

In the results from the Delphi study, almost all grades are in the middle of the scale. This reflects that cellular manufacturing draws on the concepts and reaps the benefits of both job shops and production lines, and hence the low grades from production lines are influenced by the high grades from job shops. The aim is to efficiently produce a given product family, which is highly reflected in these grades, showing medium variety, complexity in handling, travel distances, and the likes. Throughput is slightly higher precisely due to the aim of efficient production of a given family.

Table 6.5 presents the grades given for the importance of the characteristics for the cellular manufacturing environment resulting from the Delphi study.

Table 6.5 – Grades for cellular manufacturing

Characteristic	Grade
Weight & Size/Shape	3
Throughput	4
Space Requirements	3
Travel Distance	3
Unit Loads	3
Product Mix	3

6.1.5 Grading of AMR Type Performance

The AMRs are graded relative to each other depending on who is the top and bottom performer for each characteristic. Three points are given to the top performer, two for the one in the middle, and one point for the bottom performer. The difficulty of determining an exact grade value due to the ability to customize AMRs made a relative grading scale appropriate, and in addition there are only three types to distinguish among. The three types are separated on distinct characteristics in terms of costs, payload capacity, and L/U performance and requirements. The AMR performance on each characteristic is now explained.

Weight & Size/Shape: The ability to handle goods which are heavy, large, or with shapes that are difficult to handle will give a high score. The basic AMR has a clear advantage since it can transport the item as long as it fits on top of the vehicle and within the payload capacity, where payload capacities can reach up to 1000 kg (Mobile Industrial Robots A/S, 2021c), and possibly higher for customized vehicles such as the RB Volcano with 1750kg (Robotnik Automation S.L.L., 2021b). This requires the L/U equipment paired with the AMR to be able to handle the same products. The worst is the manipulator AMR, because the end effector of the manipulator is limited to what it can handle, and payloads are usually much lower than for the other AMR types. The special top module type is then left in the middle, but with a performance closer to the basic AMR because of the wide range of products it can support. Worth noting is the large variation of special top module AMRs, but the top module must be specialized towards a certain group of products, making the basic AMR a more versatile option.

Throughput: The consequences of high throughput levels is an increased fleet size and possibly a bottleneck arising at the L/U stations. The bottleneck at L/U stations can increase fleet sizes because the system needs more vehicles only to stand in the queue. Due to this, the top performer is the special top module AMR. It can be adapted to the type of products and L/U stations, spending less time L/U, performing it autonomously, ultimately reducing the fleet size. The cost is also generally lower than manipulator AMRs. Following the same reasoning, especially the possibility for L/U several vehicles simultaneously, the manipulator AMR occupies the middle score on this characteristic. The basic AMR is the worst, because L/U is restricted by the capacity of the installed ancillary equipment and thus creating the highest possibility for queues, negatively impacting the fleet size. Paradoxical as it may sound, the lowest cost vehicle performs the worst where fleet size is of the essence. The reason lies with the interaction between the cost of vehicles and ancillary equipment, and the increased fleet size from L/U queues. This will favor autonomous L/U by the vehicle. This effect is further demonstrated in the parametric analysis performed in Chapter 6.3.

Space requirements: The space related to ancillary equipment and buffers are usually high for the basic and special top module AMR. Hence, the manipulator AMR is the top performer because it can deliver material without the use of ancillary equipment, directly at the point of use. It can also autonomously perform L/U, which reduces the potential for queues significantly. Buffers might be utilized but are not required. The basic AMR is the worst performer because it is reliant on ancillary equipment and larger L/U stations, requiring space and creates a potential for queues. The special top module can be adapted so that the L/U station size is limited, and the potential for queues can be limited if the top module can autonomously perform L/U.

Travel distance: The cheapest AMR is the basic AMR and is also the top performer here since travel distances are directly related to the fleet size. The manipulator AMR is the most expensive and thus becomes the worst performer. The special top module AMR is in between the cost of these two vehicles.

Unit loads: The payload per euro ratio is the important criteria considering unit loads. Hence, unit load considerations follow the same logic as the travel distance. The basic AMR is the top performer because it is the cheapest, and manipulator AMR is the lowest performer because it is most expensive. There is also a challenge with heavy payloads for the manipulators, as was found in Chapter 5.3. The special top module AMR is in between the basic and manipulator AMR.

Product mix: The ability to handle products of different weights, sizes, and shapes is highest with the special top module AMR, as they can transport anything that fits on top of it, or the installed equipment. They can also be adapted to certain product groups. The basic AMR has a slightly narrower range because it is reliant on the equipment that performs the L/U. The lowest is the manipulator AMR due to the limitations of the end effector both in terms of payload capacity and gripping capability.

Table 6.6 provides a summary of the AMR grades on the shortlisted characteristics.

Table 6.6 – Grades for AMR types

Characteristic	Basic AMR	Manipulator AMR	Special top module AMR
Weight & Size/Shape	3	1	2
Throughput	1	2	3
Space requirements	1	3	2
Travel distance	3	1	2
Unit loads	3	1	2
Product mix	2	1	3

6.2 Decision Support System for Identifying the Most Suitable Type of AMR

Addressing RQ2, a DSS is now proposed using the shortlisted characteristics and the grades of both their importance in the manufacturing environments and AMR performance on them.

RQ 2: *What is(are) the most suitable AMR type(s) in different manufacturing environments?*

This RQ is answered by providing decision trees for the three manufacturing environments production lines, job shops, and cellular manufacturing. Figure 6.1, Figure 6.2, and Figure 6.3 present the decision trees which make up the DSS. The recommended AMR type is considered the most suited because the higher the importance of the characteristic is for the manufacturing environment, and the better the AMR performs on this characteristic, the higher the score it receives. The scores are determined by Equation (3.1). The ratio between scored points and the highest scorer is calculated, and the AMR type is either excluded or included as a recommended solution based on if the ratio is above or below a given threshold. The threshold value is determined by Equation (3.2) and is therefore not equal for all scenarios. The average threshold for production lines, job shops, and cellular manufacturing was calculated as 86%, 84%, and 85%, respectively, giving an overall average of 85%. The reasoning behind using a ratio and threshold is partly due to the subjectivity and uncertainty in the grades, as well as the dynamic threshold having several benefits for recommending solutions, as discussed in Chapter 3.2.

An overview of the considered scenarios are shown in Appendix 3, and the full results that the decision trees are based on are found in Appendix 4, Appendix 5, and Appendix 6. The first scenario on the right-hand side in the decision trees shows when all characteristics are high, meaning that all AMR grades are multiplied with all the characteristic’s grades, and can be considered an overall recommendation for the manufacturing environment. The first scenario on the left-hand side in the decision trees will always give a zero score for all options, thus resulting in all three types being recommended. Every scenario in between these is a different configuration of the characteristics, as each manufacturing environment is different. The intended use is for practitioners to follow the branches that best reflect their environment and processes, arriving at the recommended type of AMR that best suits their environment.

6.2.1 Decision Tree for Production Lines

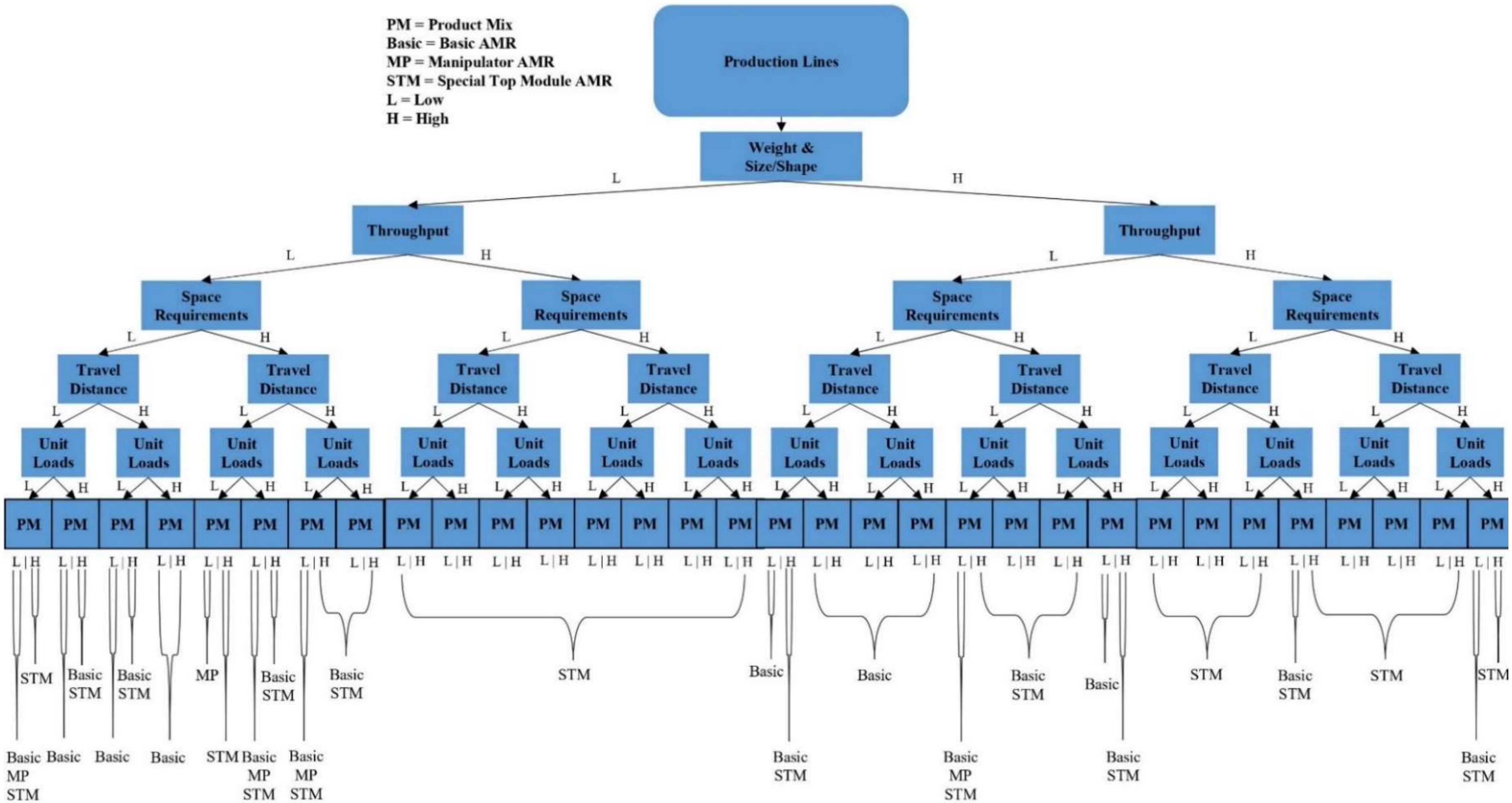

Figure 6.1 – Decision tree for production lines

Figure 6.1 shows the decision tree for production lines. The first scenario on the right-hand side, which can be considered an overall recommendation, shows that the special top module AMR is the preferred solution. This can partly be explained by the high importance of throughput, and that the special top module AMR has the highest grade on throughput. In fact, when throughput is high, the special top module AMR is always one of the recommended options. When throughput is low, it also appears in about 60% of the scenarios. This makes it the overall most recommended solution in production lines, with being recommended in 80% of the total scenarios. The basic AMR is recommended in almost all scenarios where throughput is low, but often together with the special top module AMR. It is the only recommended solution in the scenarios where the special top module AMR performance is low, due to the basic AMR's high performance on unit loads and travelling distances. The total number of recommendations are in 48% of the scenarios. The manipulator AMR is rarely recommended and can be found in only 8% of the scenarios for this manufacturing environment. However, when it is recommended, it is always the top performer, or equal with the others.

The results show that the special top module AMR can be a generally good choice in production lines. It is also worth noting that the special top module AMR occupies several long stretches of scenarios where no other solution is recommended. Again, this is attributed to the high importance of throughput. Although it has the highest number of recommendations, practitioners should only study the branches that represent their environment and processes, which could lead to a different answer than the special top module AMR. However, when looking at the generally most recommended, and the highly important first scenario on the right-hand side, the special top module AMR is the most recommended.

6.2.2 Decision Tree for Job Shops

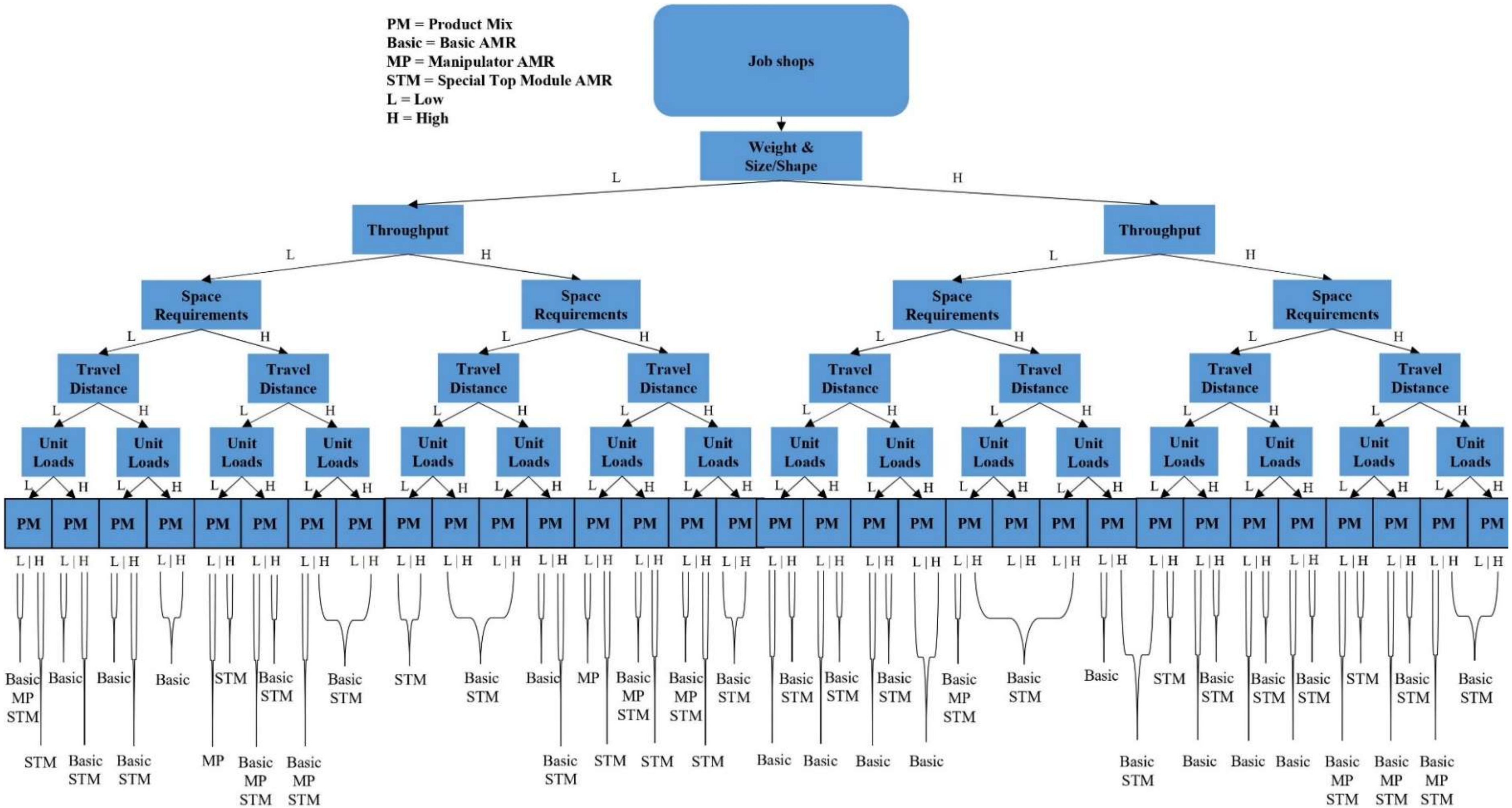

Figure 6.2 – Decision tree for job shops

Figure 6.2 shows the decision tree for job shops. The immediate difference from production lines is that no single vehicle occupies longer stretches of scenarios. The basic and special top module AMR are recommended in 83% and 75% of the scenarios, respectively. The sum of the importance of characteristics is the highest for the job shop environment, and with these two AMR types receiving high performance on the most characteristics, this explains the high representation. Throughput is the lowest in job shops, and this explains the basic AMR slightly outperforming the special top module AMR. The first scenario on the right-hand side includes both the basic and special top module AMR, and as previously stated, this scenario can be considered highly representative for a general job shop environment. The manipulator AMR has its highest representation in this manufacturing environment with 17%. Considering the low grades it received on performance, this is not negligible. The high importance of reducing space consumed by the AMR system makes the manipulator AMR more competitive in this manufacturing environment than the others.

When the recommended types are fragmented, and two types are recommended a high number of times, following the specific branch that represents the environment and process becomes additionally important. For example, the first scenario on the right-hand side does not include the manipulator AMR which is the best for conserving space consumption. Since space is most important in job shops, one could consider how to reduce the impact of other characteristics to accommodate this type. A visual inspection of the decision tree can allow practitioners to see where this effort can be applied. In general, the basic AMR and special top module AMR are the most recommended solutions, with a slight edge going to the basic AMR. This also reflects the first scenario on the right-hand side. However, the manipulator AMR can see more applications if practitioners can adapt the system to reduce the impact of its weaknesses.

6.2.3 Decision Tree for Cellular Manufacturing

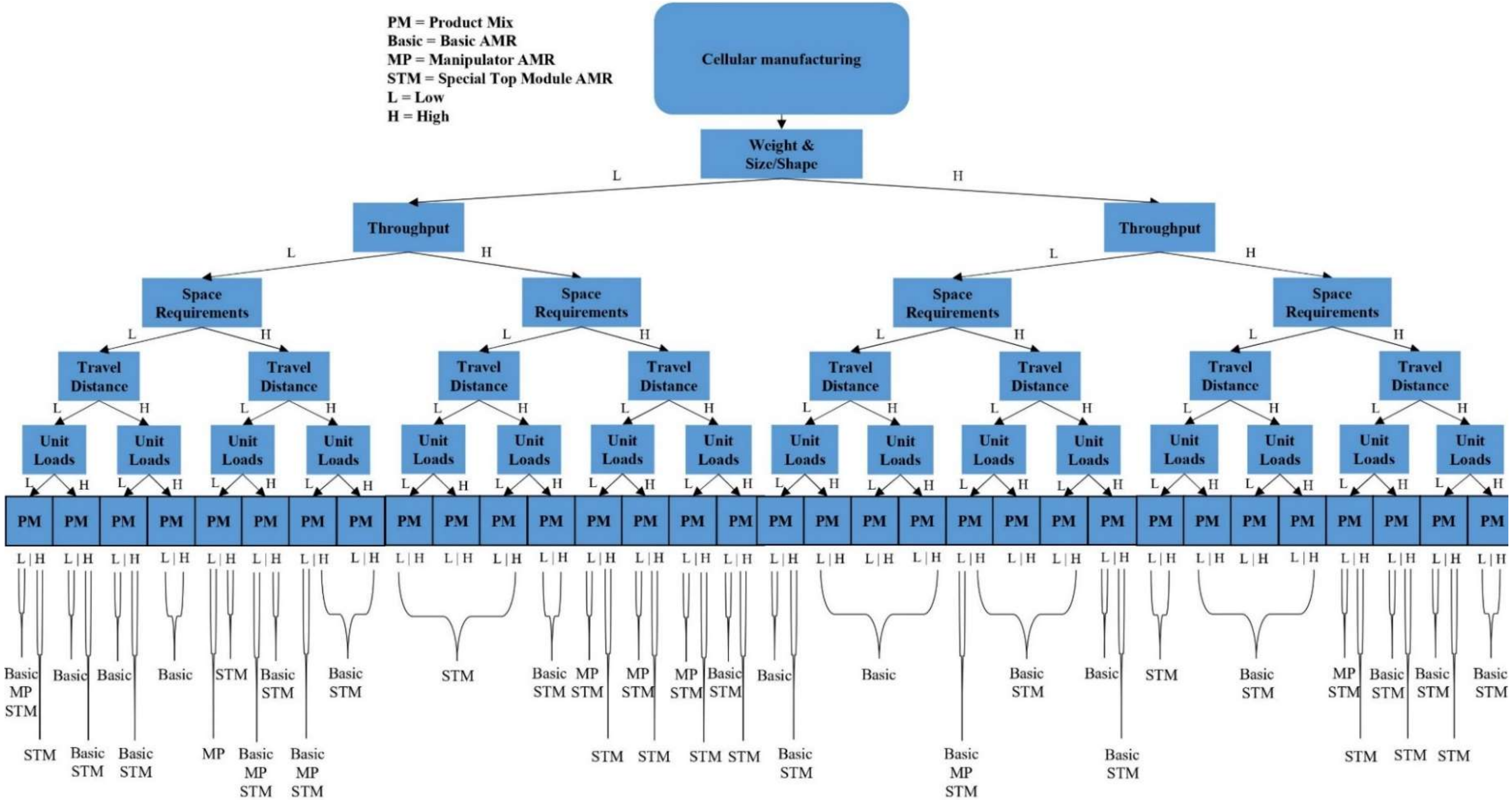

Figure 6.3 – Decision tree for cellular manufacturing

Figure 6.3 shows the decision tree for cellular manufacturing. In the cellular manufacturing environment, it is observed that some longer stretches of scenarios are occupied by one or two AMR types, more alike production lines. However, a lot of fragmented recommendations are also visible. This reflects that cellular manufacturing is a combination of the production line and job shop environment. The characteristics received the grade three, in the middle of the scale, for all except throughput which received four. This is reflected in the recommended solutions: 80% of the scenarios have the special top module AMR recommended, which has the best all-round performance on the characteristics. The basic AMR is recommended in 66% of the scenarios, higher than for production lines. The manipulator AMR is recommended in 14% of the scenarios, which is closer to the job shop than production lines performance. Again, the ability of the special top module AMR to handle high throughput gives it an edge when throughput is high, as it also has the highest grade among the characteristics in the cellular manufacturing environment. The basic AMR is highly represented when throughput is low. The manipulator AMR receives less attention and is essentially only recommended when space requirements are high and other characteristics are low.

For this manufacturing environment, again the basic AMR and the special top module AMR are both frequently recommended. The first scenario on the right-hand side also recommends these two. The manipulator AMR receives some more attention than for production lines. It should be noted that within a production cell, a scenario can be seen where space is more important and thus making the manipulator AMR more competitive. Since this decision tree also includes the transportation to and from the cells, this reduces the presence of the manipulator AMR in the recommended solutions.

6.3 Validation of the Decision Support System

Validating the proposed DSS is done through a parametric analysis on the mathematical models presented in Chapter 4. First, the fleet sizes for each scenario are determined through the fleet sizing models. The characteristics of throughput, travel distance, and unit loads are the ones to impact the fleet size, and they are given specific values for low and high depending on the grade they received in the Delphi study. When the fleet sizes are obtained, the characteristics weight & size/shape, space requirements, and product mix are included to determine the AMR and L/U station cost. Under the definitions given in this thesis, these three does not impact the fleet size, but they will have an impact on the costs. Therefore, when the characteristic is considered high, additional costs will incur on either the AMR or L/U station depending on the characteristic and the type of AMR. The total cost is then determined for each scenario, based on the fleet size, cost of the AMR, number of L/U stations, and cost of L/U station. The recommended AMR type from the mathematical model is the one with the lowest cost. However, a threshold is also used here to include recommendations that are close in performance. The threshold value is the same that was obtained from the DSS for each scenario since there are no theoretical minimum or maximum in the cost calculations. With the obtained results, they are compared to the results from the DSS to evaluate the matching recommendations between them.

The parametric analysis uses input data according to the values in Table 6.7, Table 6.8, Table 6.9, and Table 6.10. The input data for the manufacturing environments are inspired by values from similar theoretical studies performed by Fragapane et al. (2020b), Zou et al. (2018), and Ilić (1994) and the case study by Hvilshøj et al. (2012b). These values represent a baseline, which is used to represent the values for when the variable/characteristic is set to low. The values for high equals the baseline multiplied with the grade given to the characteristic for the manufacturing environment from the Delphi study. The input values for the AMR are equal for all manufacturing environments and AMR types and are inspired by similar values tested in the theoretical study performed by Fragapane et al. (2020b) and case study by Melo and Corneal (2020).

Table 6.7 – Input data for production line

Characteristics input	Delphi Study Grade	Low (Baseline)	High
Throughput	5	500 pcs/hr	2500 pcs/hr
Travel Distance	2	10 m	20 m
Unit Loads	2	10 pcs/load	20 pcs/load

System input	Value	Unit
Number of L/U Stations	5	
q	0.9	
Distance machines to repair shop	3*Travel distance	m
Distance RMI-Machine 1 and Machine 3-FGI	Travel distance	m

Table 6.8 – Input data for job shop

Characteristics input	Delphi Study Grade	Low (Baseline)	High
Throughput	2	500 pcs/hr	1000 pcs/hr
Travel Distance	5	10 m	50 m
Unit Loads	5	10 pcs/load	50 pcs/load

System input	Value	Unit
Number of L/U Stations	6	
q	0.9	
Distance departments to repair shop	3*Travel distance	m
Distance RMI-Departments and Departments-FGI	Travel distance	m

Product routing and mix	Department Routing	Product mix
Product 1	1 – 2 – 3 – FGI*	30%
Product 2	2 – 3 – 4 – FGI*	10%
Product 3	1 – 4 – 3 – FGI*	25%
Product 4	2 – 3 – 2 – FGI*	35%

**FGI must be included as a department in the mathematical model*

Table 6.9 – Input data for cellular manufacturing

Characteristics input	Delphi Study Grade	Low (Baseline)	High
Throughput	4	500 pcs/hr	2000 pcs/hr
Travel Distance	3	10 m	30 m
Unit Loads	3	10 pcs/load	30 pcs/load

System input	Value	Unit
Number of L/U stations	7	
q	0.9	
Distance cell to repair shop	3*Travel distance	m
Distance RMI-Cell and Cell-FGI	2*Travel distance	m

Table 6.10 – Input data for AMRs

AMR input	Value	Unit
$\boldsymbol{v}$	1	m/s
$\boldsymbol{a}$	1	m/s^2
$\boldsymbol{T_{L/U}}$	20	s
$\boldsymbol{C_v}$	1	load/trip
$\boldsymbol{T_a}$	3600	s
$\boldsymbol{A_{amr}}$	0.85	

The total cost is used to compare the different AMR types, and the costs used are presented in Table 6.11 and Table 6.12. In addition to having a baseline cost, the costs are variable depending on the characteristics of weight & size/shape, space requirements, and product mix. The baseline costs of the different AMR types are based on the price of a basic AMR, which has a cost of approximately €25 000 (Mobile Industrial Robots A/S, 2016). From this cost, the manipulator AMR is considered to cost twice what the basic AMR does, due to the addition of a manipulator, which results in a cost of €50 000. The special top module AMR is considered to cost 1.5 times the cost of a basic AMR, due to the addition of the top module, being cheaper than a manipulator, making a cost of €37 500 considered appropriate. The L/U station cost entails the space they require, equipment and manual operators if needed, new standardized load carriers, adjustments to existing equipment, and the likes. To simplify, the three types are assumed to have the same cost for load carriers, adjustments, and the likes. Manual operators are not considered an option. Hence, the equipment required for L/U and the space it occupies is what separates the types. The corresponding L/U station to a basic AMR includes a manipulator - and the considered cost is €25 000 since this is also the difference in cost between the basic and manipulator AMR. For the manipulator AMR, when the cost of load carriers and the likes are considered the same, there is no additional cost for L/U equipment. The special top module AMR then must have a cost for its L/U station equipment and space, and half of the manipulator cost is used, €12 500. In effect, these costs give equal values for AMR plus L/U station costs, but this measure is not useful as the number of L/U stations and the fleet size is not directly related.

When the characteristic weight & size/shape is high, an additional 15% is added to the vehicle cost due to additional payload capacity or equipment needed to handle the items. When the characteristic space requirements is high, an additional 15% is added on the L/U station cost to penalize the options with expensive (and thereby considered large) L/U stations. This is not an actual cost per se, but it penalizes the options that requires a L/U station. When the characteristic product mix is high, the basic AMR is given an additional 15% on the L/U station cost, since the equipment for L/U must accommodate the high variety, but the AMR can handle this as it is just a transportation platform. For the manipulator AMR, a 15% increase in AMR cost is added because the manipulator must handle the variety, and there is no equipment at the L/U station. For the special top module AMR, the additional cost is split in half between AMR and L/U station, being a 7.5% increase in both, as both the AMR and L/U station have equipment that must handle the increased variety. Combined with the differences in fleet sizes, this results in different options having different costs for different scenarios and provides an approximation to which AMR is more suited from a fleet sizing and cost perspective.

Table 6.11 – AMR costs

AMR costs	**Baseline**	**Weight & Size/Shape**	**Space Requirements**	**Product mix**
	Low	High	High	High
Basic AMR	€25 000	+15%	+0%	+0%
Manipulator AMR	€50 000	+15%	+0%	+15%
Special Top Module AMR	€37 500	+15%	+0%	+7.5%

Table 6.12 – L/U station costs

L/U station costs	**Baseline**	**Weight & Size/Shape**	**Space Requirements**	**Product mix**
	Low	High	High	High
Basic AMR	€25 000	+0%	+15%	+15%
Manipulator AMR	€0	+0%	+15%	+0%
Special Top Module AMR	€12 500	+0%	+15%	+7.5%

The comparison of the results from the DSS and the parametric analysis was conducted by looking at the scenarios and determining where they have the same recommendation for AMR type. Figure 6.4, Figure 6.5, and Figure 6.6 shows the decision trees from the DSS, where the scenarios and recommendations highlighted is where the mathematical model has the same recommendation. The results from the mathematical model where a common recommendation is not present or where the mathematical model has additional recommendations is not included in the figure, but these are found in Appendix 9, Appendix 12, and Appendix 15. The number of scenarios where a common recommendation is found is divided by the total number of scenarios. This results in the percentage of match between the DSS and the mathematical model. The next sections present the comparison of the recommendations from the DSS and the mathematical models for each manufacturing environment. The numerical results from the parametric analysis are found in Appendix 7, Appendix 8, Appendix 10, Appendix 11, Appendix 13, and Appendix 14.

6.3.1 Comparison of Mathematical Model and DSS Results for Production Lines

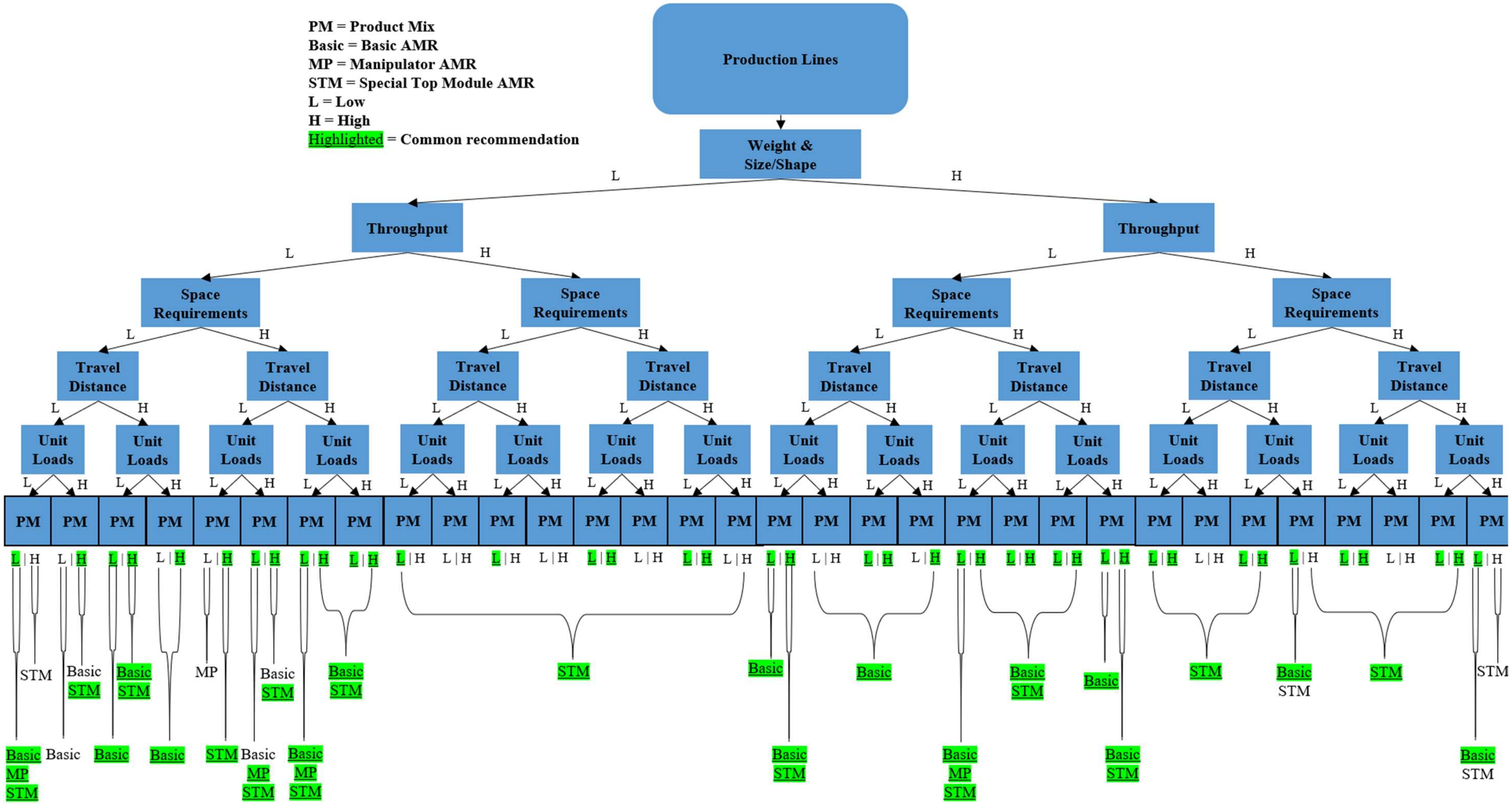

Figure 6.4 – Comparison of mathematical model and DSS results for production lines

6.3.2 Comparison of Mathematical Model and DSS Results for Job Shops

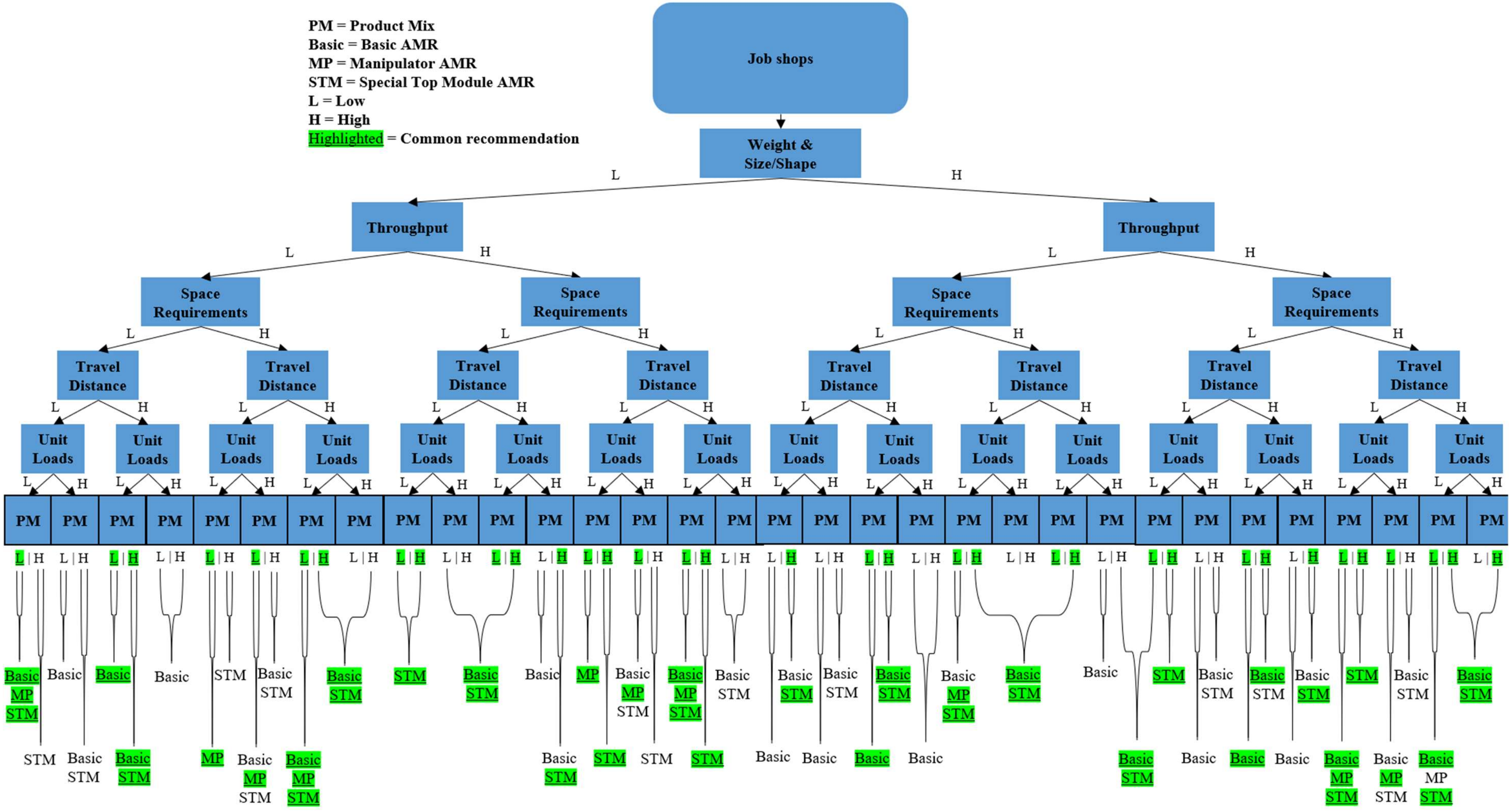

Figure 6.5 – Comparison of mathematical model and DSS results for job shops

6.3.3 Comparison of Mathematical Model and DSS Results for Cellular Manufacturing

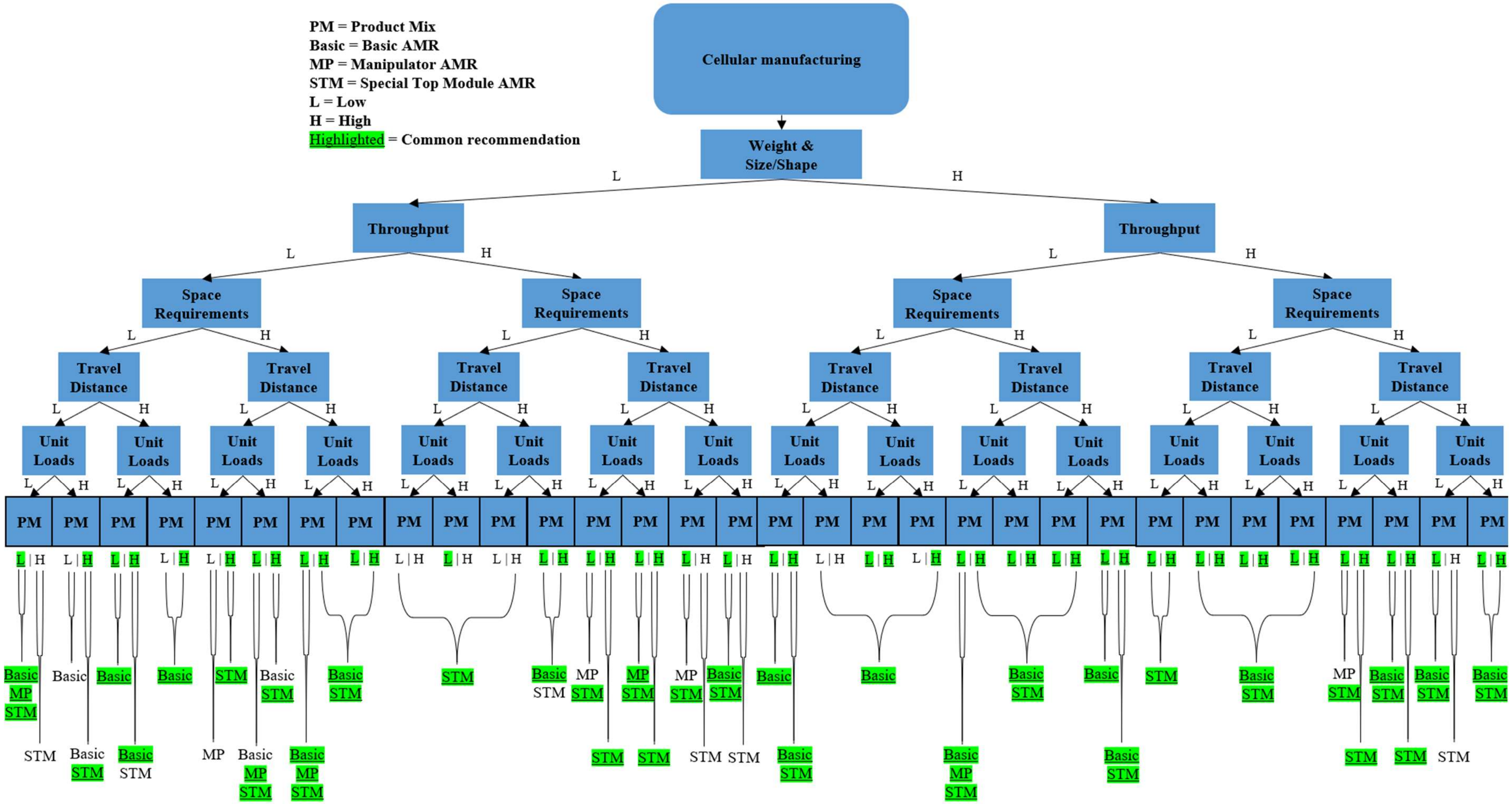

Figure 6.6 – Comparison of mathematical model and DSS results for cellular manufacturing

6.3.4 Summary of Validation Results

For production lines, the basic AMR is recommended in 83% of the scenarios in the mathematical model, compared to 48% in the DSS. However, the special top module AMR is recommended in 56% of the scenarios in the mathematical model, and 80% in the DSS. The manipulator AMR is recommended in 33% and 8% in the mathematical model and DSS, respectively. From these results, it appears that the basic and special top module AMR have switched places in respect to the number of recommendations, while the manipulator AMR is preferred more frequently by the mathematical model. The common recommendations are mainly found for the basic and special top module AMR, while only a few is common for the manipulator AMR. There is a common recommendation found in 64% of the scenarios. The mathematical model mostly recommends either the basic or manipulator AMR where no common recommendation is found. It also includes the basic AMR a lot as an additional recommendation where common recommendations are found not including the basic AMR. In general, the manipulator AMR is often recommended by the mathematical model when the fleet sizes are small, and the basic and special top module AMR is recommended for larger fleet sizes. In fact, the manipulator AMR is never recommended with a fleet size larger than eight AMRs. As for the first scenario on the right-hand side, the mathematical model disagrees with the DSS and recommends the basic AMR instead of the special top module AMR, being well outside the threshold of 18% for this scenario with a cost 34% higher.

For job shops, the basic AMR is recommended in 39% of the scenarios in the mathematical model, compared to 83% in the DSS. The special top module AMR in the mathematical model is recommended in 42% of the scenarios, while for the DSS this number is 75%. The manipulator AMR is recommended in 83% of the scenarios in the mathematical model, and 17% in the DSS. It appears that the manipulator AMR is highly preferred by the mathematical model in this manufacturing environment. The performance of both the basic and special top module AMR is similar and low in comparison. The common recommendations are at or above ten for all three AMR types, with the special top module AMR being the highest. There is a common recommendation found in 55% of the scenarios, the lowest among the three manufacturing environments. This is mainly explained by the apparent dominance of the manipulator AMR in the mathematical model. The manipulator AMR is recommended as an additional recommendation by the mathematical model in almost every scenario, while the basic or special top module AMR is rarely additionally recommended by the mathematical model. The fleet size exceeds eight AMRs in only eight scenarios, and here the manipulator AMR is only recommended in one scenario. The first scenario on the right-hand side from the DSS recommends the basic and special top module AMR, and the mathematical model recommends the manipulator and special top module AMR, resulting in one AMR type that matches.

For cellular manufacturing, the basic AMR is recommended in 84% of the scenarios in the mathematical model, compared to 66% in the DSS. The special top module is recommended in 59% of the scenarios in the mathematical model and 80% in the DSS. The manipulator AMR is recommended in 36% and 14% in the mathematical model and DSS, respectively. Again, the representation of the manipulator AMR is much higher in the mathematical model than that of the DSS. The most recommended solution by the mathematical model is the basic AMR, while in the DSS this is the special top module AMR, again appearing to have switched places. The common recommendations are mainly for the basic and special top module AMR, and a few with the manipulator AMR. There is a common recommendation found in 77% of the scenarios, which is the highest for all three manufacturing environments. This amounts to an average match of 65% across all three manufacturing environments. The mathematical model mainly recommends the basic and manipulator AMR where no common recommendations is found, as well as when having common recommendations. The range of fleet sizes are the biggest for cellular manufacturing, where both the highest and some of the lowest fleet sizes are present. The first scenario on the right-hand side has the basic and special top module AMR as recommendations from the DSS, and the mathematical models has the basic AMR, making this scenario match as well.

Comparing the results from the DSS and the mathematical model, some tendencies are evident. The basic AMR and special top module AMR appear to have switched places when it comes to the number of recommendations. In addition to this, the manipulator AMR is recommended more frequently by the mathematical model than by the DSS. This occurs mainly when the fleet size is at or below eight AMRs. Although the number of recommendations for the AMR types in the mathematical model and DSS seem very different, the average match for all three manufacturing environments is 65%, or close to two-thirds of the scenarios. This is also the case for the important first scenario on the right-hand side where all characteristics are set to high, where job shops and cellular manufacturing has a matching AMR type recommended, but not production lines, resulting in a match for two-thirds of the scenarios also there. Common recommendations are found for all three AMR types in all three manufacturing environments, meaning there is no best AMR type that rules them all.

7 Discussion

This thesis has so far proposed an overview of characteristics, a DSS, along with a validation procedure of the DSS. This chapter discusses these results obtained in light of the research objective and questions, the limitations of the proposed tools, introduce viewpoints on the future of intralogistics system design, and finally discusses the contributions and general limitations of the thesis. Within the limitations and insights gained from the thesis, future research possibilities are identified and suggested.

7.1 Overview of Characteristics, Decision Support System, and Validation Procedure

First, the results from the overview of characteristics, DSS, and validation procedure are discussed in light of the research objective and questions. The discussions offer insight into the content and design of the tools, the most important findings, limitations of the specific tools, and an evaluation of whether the RQs are appropriately answered.

7.1.1 Overview of Characteristics

In practice, the AMR market consists of a wide range of vehicles with different top module designs and capabilities. Practitioners are faced with the challenge of knowing how to effectively utilize this new technology to achieve desired productivity and flexibility improvements. As identified in the scientific literature, a gap is present between the development of hardware and software for the AMRs, and the practical design of intralogistics systems. Few researchers have focused on linking the two together. In fact, clear definitions and overviews in both intralogistics design and AMRs are either fragmented or lacking in the current literature. Hence, reviewing the scientific literature on relevant topics under the intralogistics domain and the state of the art in AMR research, including reviewing AMR vendor solutions, was conducted to create an overview of the characteristics that influence the design process, combining the two topics.

Relating the overview to the material handling equation was considered appropriate as their objectives align: Identifying and analyzing the pieces that make up the manufacturing environment and the alternatives for MH equipment should guide practitioners to the most suitable solutions. The overview does; however, include more specific characteristics, especially in the methods section, than the original material handling equation. This was done to tailor the process to the use of AMRs. The loop connecting the characteristics for moves and methods is a deliberate effort to make practitioners view the process of designing the intralogistics system not as a step-by-step model. This should inspire practitioners to review how the autonomous and flexible nature of the AMR can increase productivity and flexibility for the production system. This could be the key to reach a competitive advantage in today's fierce market competition. An example of this is the concept of matrix production, which was briefly discussed in Chapter 5.4. The characteristics were separated between qualitative and quantitative to structure the visual presentation, but it is recognized that some qualitative could be considered quantitative for other purposes, and vice versa.

The development of the overview of characteristics was necessary before the development of the DSS could commence. The overview contains characteristics that are commonly addressed in the scientific literature for selection of MH equipment, AMRs, and intralogistics system design. Furthermore, it is supplied with information from AMR vendor solutions, case studies, and decisions both at the strategic and tactical decision level. Hence, the overview is considered to appropriately answer RQ1: *What are the characteristics to consider when designing intralogistics systems based on AMRs?* It provides practitioners with a good overview of what is important to consider, which characteristics that can influence the choice of AMR type, and how this can be used to further make the final decision. For researchers, it can be a good starting point for selecting further characteristics to provide decision support on and investigating the interaction between characteristics. Further discussions regarding the characteristics that are not included in the DSS is provided in Chapter 7.2, and contributes with insight from previous research on these characteristics.

The overview and included characteristics can be considered incomplete. For instance, this thesis focused on the material flow and not the information flow. Although it is listed in the overview, this thesis does not offer specific insights into how the information flow is supported by AMRs, nor what information to collect and share, how to share it, when to share it, and what it should be used for. The term information flow must be decomposed into appropriate characteristics on the same level of detail as the material flow. This is left as an opportunity for future research to address. Including all characteristics that could be relevant for this decision is not realistic to achieve, nor is it likely to improve the support to the practitioner. Certainly, some characteristics might be defined differently than what the practitioner uses, or comprise a wide range of more detailed characteristics, which might impact how practitioners perceive it. However, when going through the overview, other important characteristics for a specific scenario can emerge despite not stated explicitly in the overview.

7.1.2 Decision Support System

RQ2 sought to address: *What is(are) the most suitable AMR type(s) in different manufacturing environments?* The results from the DSS shows that this is in fact highly dependent on the manufacturing environment and the configuration of the characteristics. The answer to RQ is found in Figure 6.1, Figure 6.2, and Figure 6.3, which shows the recommended AMR type for each configuration scenario in each manufacturing environment.

One general result that must be addressed is that the manipulator AMR has by far the lowest presence in the recommended solutions across the board. However, this is an expected result due to the low grades it received in the grading process. The DSS is based on the shortlisted characteristics, and in these the manipulator AMR is not competitive enough due to its shortcomings. However, the manipulator AMR has potential to perform well on some of the other characteristics, such as the possibility to perform additional activities while transporting. Hence, the performance of the manipulator AMR in the DSS might be artificially low due to the selection of the characteristics. For the two other types, the special top module AMR has the highest percentage recommendations overall, with the basic AMR being slightly better for job shops, close in performance for cellular manufacturing, and further behind in production lines. This behavior is expected as the special top module AMR has slightly higher average grades than the basic AMR. The high variation in recommended solutions clearly shows the impact of the dynamic threshold and can be interpreted as a clear result that the procedure behind developing the DSS is working as intended. In fact, the recommended AMR type in each of the scenarios is easily explained by looking at the grade of importance and performance of the AMR.

A difficult decision to make for practitioners using the proposed DSS is how to determine whether their products and environment characteristics are considered low or high in the eyes of the DSS. A reference for throughput, travel distance, and unit loads can be found in the input for the parametric analysis on the mathematical models. For the other three, it is recommended to evaluate it in the light of offered solutions from the AMR vendors. For instance, knowing that an increased product mix will require the vehicles to handle a wide range of geometrical properties, this must be assessed regarding how dynamic the process of L/U these items is. The manipulator AMR illustrates this point clearly, as it must be considered if the end effectors can handle the relevant range of products. If it does not, the product mix can be considered high. The DSS offers general recommendations but reviewing the process that it is based on can be of great support to these decisions. Therefore, Chapter 6.1 should be closely examined.

The DSS can also allow for it to be used in reverse. This can be done by looking at the AMR type which seem most promising first, and then evaluating whether some of the characteristics could be adapted to suit this AMR type. The manipulator AMR is a great example of this. The manipulator can for instance perform quality inspections or sorting of the items while transporting. If this is highly beneficial for the company, practitioners can look at the branches that lead to a recommendation for the manipulator AMR and try to best accommodate it according to the branch. This could lead to an even better fit between the materials, moves, and methods.

The development of the DSS and the results it provides is affected by a certain degree of subjectivity. Through the Delphi study, the degree of subjectivity is reduced, but not eliminated, as consensus does not necessarily equal a correct answer. Validity is a challenge in Delphi studies, but using participants invested and knowledgeable in the topic, and performing two iterations, the validity is increased (Hasson et al., 2000). However, the reliability of the study, under which the results can be reproduced with a new set of participants, is not guaranteed. Selecting the characteristics which make up the DSS are largely based on findings in the literature, but grading the AMRs are further affected by subjectivity and affects the validity of the results. The use of a threshold for the recommendations is also a limitation, as it does not provide an exact answer in all scenarios, but rather recommends several options.

Despite its limitations, the DSS offers direct input towards the most suitable AMR type in a quick and easy-to-grasp manner, and its novelty enables interesting opportunities for future research. Consequently, RQ2 can be considered appropriately answered by the results presented in the DSS.

7.1.3 Mathematical Models and Validation of the Decision Support System

The intended use of the mathematical models was to provide estimates of fleet sizes and costs to compare it to the DSS, and not to accurately determine fleet sizes of real-world systems. The use for validation of the DSS was made possible through using approaches building on the reviewed scientific literature and incorporating different elements that would allow fleet sizes and costs to be differentiated based on different types of AMRs. In fact, no mathematical models for AMR systems are found in the scientific literature which distinguish between AMR types, to the best of the author's knowledge. The mathematical models also allow for expansions, where more lines, departments, or cells could be added to allow for fleet sizing of bigger systems, without much effort. If this is to be done, the service area for each AMR must be closely determined to obtain the correct fleet sizes, e.g., grouping AMRs that is dedicated to one cell or one production line. The input data used for the parametric analysis was gathered from various theoretical and practical case studies, allowing the validation procedure to build on other similar studies conducted.

The mathematical models have several assumptions that limit their ability to accurately determine the fleet size and costs. The determination of the fleet size is done through expanding on the basic equation considering required and available time. Although many variables are accounted for, some assumptions are made for the sake of simplifying the models. One such example is the assumption of unlimited buffers which allows the use of net flow calculations. Determining unloaded travel times should not be based on deterministic net flows, especially with the autonomy of travelling paths found in AMRs. The proposed fleet sizing models therefore model a stochastic reality to be deterministic, which is a clear limitation. In addition to this, the costs are loosely based on actual prices from AMR vendors, as exact costs are not available to the author. The additional costs from some of the characteristics also work as a penalty rather than a reflection of the actual cost of the system.

The validation of the DSS had some interesting findings. In general, for small fleet sizes, the manipulator AMR is highly represented in the recommended solutions from the mathematical model. This is true if the fleet size stays at or below eight AMRs. The reasoning for this is found in the cost structure of the manipulator AMR. When fleet sizes are small, and especially when the fleet size is lower than the number of L/U stations, the proportion of the vehicle cost in the total cost is smaller than the proportion of the L/U station cost for the two other types. Since the L/U station cost is considered to be €0 for the manipulator AMR, this favors it when fleet sizes are low despite its high vehicle cost. This also means the opposite is true, that when fleet sizes become large it is never recommended because the vehicle cost is the highest, despite it avoiding the L/U station queue consideration. This is one of the factors that limited the number of matches in the validation procedure, which were especially relevant for the job shop environment, as the fleet sizes are low in almost all scenarios. Although the manipulator AMR has its highest number of recommendations for job shops in the DSS, the number of recommendations is low compared to the others. However, as discussed in the previous section, the number of recommendations the manipulator AMR received in the DSS can be considered artificially low.

As identified when comparing the results of the DSS and the mathematical models, the basic and special top module AMR appears to have switched places in terms of the number of recommendations they receive. The basic AMR is the most recommended by the mathematical model, while the special top module AMR is the most recommended by the DSS. The percentage of recommendations are similar, only they have switched who receives the higher percentage. The reason for this is twofold. The special top module AMR received a slightly higher average grade on performance on the various characteristics than the basic AMR, 2.33 vs. 2.17, which determines the score they receive in the DSS. In addition to the importance of the characteristics in the different manufacturing environments, this is part of why it outperforms the basic AMR in the DSS. In the mathematical models, the basic AMR has a lower vehicle cost than the special top module AMR, and in most scenarios the fleet size is larger than the number of L/U stations. This results in a lower total cost for the basic AMR. For the largest fleet sizes, the additional cost for the special top module AMR is balanced off with the increased fleet sizes of the basic AMR due to the L/U station queue when the utilization of this exceeds 100%. In addition to this, the advantage the special top module AMR has for lower fleet sizes due to its cost structure is reduced by the advantage for the manipulator AMR at low fleet sizes. In effect, this explains that the DSS leans more towards the special top module AMR, while the mathematical models lean more towards the basic AMR.

These discussions indicate that low fleet sizes favor the manipulator AMR, medium fleet sizes favor the basic AMR, and high fleet sizes favor both the basic and special top module AMR in the mathematical model. This is not directly transferable to the DSS because the fleet size is not directly considered, along with the cost structures. However, a possible conclusion that can be drawn from this is that the AMR grading does not reflect the costs of the various AMR types well enough. This is one of the limiting factors in terms of the number of common recommendations. Another limitation of the validation procedure is how the different characteristics are modelled. The throughput, travel distance, and unit loads are considered in the fleet size as they can be directly applicable in a fleet sizing model. The weight & size/shape, space requirements, and product mix is considered to impact the cost of the AMR and the corresponding L/U station. As previously stated, these are not necessarily actual costs that incur, but are a way of modeling the differences between the AMR types and to penalize solutions that e.g., is more expensive when the weight is high and increases the required payload capacity.

The impact of the characteristics on the recommended AMR types are different in the DSS and the mathematical models. In the DSS, the grades given towards the importance of the characteristic in the manufacturing environment governs which characteristics will have the biggest impact on the AMR type. In the mathematical models, it is evident that the fleet size has a bigger impact on the recommended AMR type than the additional costs from the other characteristics. This is supported by the pattern described above regarding that a general recommendation can be made based on the fleet size. Hence, the throughput, travel distance, and unit loads that impact the fleet size are more influential than the weight & size/shape, space requirements, and product mix that influences the cost of the AMR and L/U station.

Although there are specific reasons for why the scenarios match, or do not match, most important of all is to recognize that there is uncertainty and limitations to both the DSS and the mathematical models. Although measures are taken to increase the validity and reliability, this does not replace practical case studies. Due to a lack of suitable case studies available in the scientific literature, and the limited time frame of this thesis, no such studies were conducted. Therefore, the results of the DSS, mathematical models, and the interactions between them must be seen in the light of these limitations.

The question of whether the validity of the DSS is strengthened or not by the results from the parametric analysis on the mathematical models is now addressed. The recommendations shown in the DSS are a result of reviewing the scientific literature and AMR vendor solutions, grading of the characteristics based on consensus among experts through a Delphi study, and the process of determining the scores and thresholds. It can evaluate the impact of the characteristics in a more nuanced way than what the mathematical models does, as it is not necessary to translate every characteristic to the fleet size and cost. Due to this approach, it has fewer assumptions and limitations than the mathematical models. The value of each grade is the biggest source of uncertainty; however, different values can be used by practitioners and researchers in future work if deemed appropriate. The high percentage of matching scenarios between the DSS and the mathematical model further strengthens its validity, and the evident impact of the fleet size on the results in the mathematical models is a weakness of the validation procedure and not the DSS itself. Furthermore, as they are based on two different approaches, a match in almost two-thirds of the scenarios can be considered satisfactory. Instead of questioning whether the percentage match should have been higher, the limitations of the mathematical models are more relevant to address. The mathematical models have a limited ability to accurately determine both the fleet size and the costs, as they are influenced by assumptions and simplifications. The models must translate the impact of every characteristic to a cost in the end and are not able to consider what cannot be translated into a cost. The question of what AMR type is most suitable is not a question of choosing the lowest cost option, it is rather about achieving the best fit among the materials, moves, and methods. Such a recommendation is better suited by the procedure used for developing the DSS.

To summarize, the mathematical models can model the various properties that separate the AMR types and, in many cases, result in recommendations that align with those of the DSS. The comparisons show a 65% match across all manufacturing environments that result in a common recommendation. This number is highest for cellular manufacturing, slightly lower for production lines, and the lowest in the job shop environment, being 77%, 64%, and 55%, respectively. The validity of the DSS is considered strengthened by the results from the mathematical models when accounting for the limitations facing the mathematical models; however, indicating that the manipulator AMR can be suited in more scenarios than what is presented in the DSS.

7.2 Discussion of the Qualitative Characteristics

With the prior analysis on the shortlisted quantitative characteristics and how they impact the most suitable AMR type, a discussion on the qualitative characteristics in the overview from RQ1 is now presented. As previously stated, the classification of the characteristics in this thesis regarding qualitative and quantitative must not be considered strict and can be different for other purposes.

The material handling equation with the elements of materials, moves, and methods are the foundation for vehicle selection (Tompkins et al., 2010). As seen in the proposed overview, the materials are strongly connected to the demand, but the moves and methods are up to the manufacturer to design. Hence, no further discussion is made towards the material characteristics, as they are essentially now input to the design process. Although design for manufacturing and similar initiatives can support intralogistics, this belongs to the domain of product development and similar activities. For the remainder of this thesis, it is considered that these characteristics are either properly covered by the quantitative characteristics and the prior analysis on these, or that they are too specific to add any value in the scope of this thesis. The characteristics of inaccessible routes, capability, and gripping of the AMR is also excluded from further discussions, as they are properly covered in either the analysis of travel distances and flow intensity or the L/U discussion regarding the choice of vehicle.

The interaction between moves and methods is highlighted in the overview. Their connection is represented by a loop, which indicates that the AMR should influence how the layout should be configured and vice versa. This interaction can be hard to evaluate or address without performing a satisfying amount of case studies to gain practical experience, and this interaction is lacking research. Among the few case studies available on this issue, especially a concurrent design process of both layout and AMR system, there is the study by Melo and Corneal (2020). The study conducted at an automotive parts supplier had the goals of reducing manual MH, improving floor space utilization, and optimizing the material flow. In addition, operators should be focused on value adding work, and traceability of parts should be increased. Hence, a system with AMRs was considered. Evaluating different alternatives based on the KPIs throughput, response time, manual labor, buffers, avoidance of starvation, blocking, and deadlocks, disruptions, and capital cost, a new layout proposal with a corresponding plan for the AMR system was developed. The new layout proposal has its roots in the SLP with a focus on proximity between points with high flow intensity between them, while the suggested AMR system was based on tandem loops with multiple vehicles as suggested by Ventura and Lee (2001). Concerns were raised towards sharing lanes with forklifts and having one or more AMRs covering certain sections of the shop floor. AMRs sharing lanes with forklifts were avoided for safety reasons and risk of damage. In addition, a tradeoff was identified between having more vehicles serving larger areas, or a single vehicle serving a smaller area. The latter is susceptible to breakdowns of the AMR, while the former creates more challenges regarding deadlocks and blocking.

The insights from Melo and Corneal (2020) spurs a discussion regarding the interaction between AMRs and layout planning. The modularity, reconfigurability, and scalability of a layout is important for added flexibility and is part of what AMRs can contribute to. Using a system like tandem loops, assigning specific vehicles to specific areas of the shop floor, allows for equipping and configuring AMRs according to the tasks within the area. Furthermore, AMRs can be rapidly reassigned L/U points due to their autonomous navigation. This allows the AMR to highly accommodate a modular shop floor, which can be regularly reconfigured. In addition, scalability is a core focus for some AMR vendors (Mobile Industrial Robots A/S, 2021d). If manual MH is disregarded as an option, as there is a growing trend towards, no other MH equipment can accommodate these properties in the way the AMR does. The advantage of having more modular and reconfigurable layout setups is that it can change according to demand. With the increasing range of products and decreasing life cycle of products, this is exactly what manufacturers need. This is not only about developing new layout types, but also to be able to reconfigure the more traditional structures presented in this thesis, namely production lines, job shops, and cellular manufacturing. However, there are still challenges to address, especially related to safety, availability/reliability of the vehicles, and solving navigation problems such as deadlocks and blocking, as seen in Melo and Corneal (2020).

As suggested in the overview, non-space requirements, supporting services, and the factory environment influences the layout design. Non-space requirements such as clean zones or hazardous environments can either be supported or restricted by AMRs. Clean zones are perfect environments where AMRs can be deployed, because it removes the need for human presence. However, hazardous environments can cause trouble, such as high temperatures not supported by the vehicle batteries, or electromagnetic fields interfering with sensors and navigating equipment.

Supporting services are needed for the AMR in terms of a space to park, charge, and possibly for maintenance. This can create a need for additional space, and especially valuable space close to the production area, due to the frequent need for charging and parking during idle time. Manual forklifts can more easily be driven and parked further away from the production area when not in use.

The impact on the factory environment can be regarded as an impact towards psychosocial ergonomics. Working alongside robots, and especially mobile robots, is relatively new and few have experience with it. Important for practitioners is to not lose focus on the well-being of their workforce when considering new technologies. This is especially important when considering both the aging workforce and the fear of job loss. Studying the psychosocial impact of deploying AMRs in an order picking warehouse, Berx et al. (2021) reached the following conclusions: *"... Based on this research, there is no reason to conclude that working with an AMR leads to an increased psychosocial load"*. They attributed this to the agreement among participants to the statements of less monotonous work and more enthusiasm for the work, and less cognitive load and time pressure. In addition to this, they found that: *"... There is a generally positive to very positive perception and attitude towards working with an AMR"*. This indicated that AMRs were not seen as the enemy threatening their job security or wellbeing at the workplace. They did; however, not study the impact the AMRs had on physical ergonomics, nor did they provide long term effects on the psychosocial impacts. In collaboration with the participants of the study, safety was identified as a key area for further research. This is emphasized in this thesis, and also plays a role in the human-machine interaction. The generalizability of the study by Berx et al. (2021) can be questioned, as it considers a picking operation in a warehouse and not a manufacturing shop floor, but it is among the only studies performed on this topic. Using AMRs in a picking operation should lead to more comfortable everyday tasks for the operators, as the average walking distance is significantly reduced. However, other aspects can be relevant on manufacturing shop floors.

As for the qualitative characteristics in the overview related to methods, the three categories of vehicle, top module, and fleet size have some impactful characteristics not yet discussed. The interaction with other types of MH equipment is in some cases crucial. This can be collecting products from AS/RS systems, flexible manufacturing systems, or conveyor belts. Handovers between such systems require additional floor space and can quickly become bottlenecks but are often necessary to the operation. Emphasis should be put on what can create a smooth flow of material and reduce the time for L/U for the handovers. A simple example would be to pair a conveyor top AMR with an existing conveyor system, reducing the need for any extra space or equipment. If there is a mismatch, a fixed manipulator or sorting zones with manual operators might be required for L/U of the AMRs. The accuracy of the vehicles and the required accuracy of the corresponding equipment also becomes a factor here (Vosniakos and Mamalis, 1990). Precise parking in the designated L/U spots can be ensured not only through sensors, but also additional guiding and referencing systems such as QR codes (Pedersen et al., 2016), or physical barriers.

When it comes to the features, hardware, and software of the vehicles, the technical knowledge and experience from the AMR vendor is a useful resource. Some sensors are better at detecting certain obstacles than others, and the challenges related to the specific environment must be accounted for. Often the AMR is equipped with several sensors and safety systems to cover all such obstacles, but each shop floor is different and can have unexpected results for not only the safety but also the efficient operation of the AMR. Another point to make is the flexibility and standardization of the AMR, its operating procedures, and interfaces. Operator's interaction with the vehicles should be intuitive and standardized. This way, the operation of the AMR system can be more flexible because every operator knows how to interact with the vehicle. This is also part of the human-machine interaction, and this is important to consider because the efficient operation of the AMR system relies on operators that understand how it works and are able to use it to their advantage (Gorecky et al., 2014).

As previously mentioned, the AMR can be equipped to perform other tasks while L/U or transporting the items. This all depends on how the tasks are designed and the equipment on the AMR. For instance, a QR-code reader can be added if the items are fitted with QR codes to correct inventory status. Outfitting other types of equipment and designing tasks in similar ways to the QR codes can allow for creative ways of performing other non-value-added or value-added tasks while transporting. Especially where throughput volumes and utilization levels are high, saving time by letting the AMR sort the items or perform simple quality inspections can be highly beneficial. Cost-benefit analysis should be used when evaluating whether this is justifiable or not, as it adds costs but can reduce time spent for operators. A related study in this regard is the work by Fager et al. (2020), which addressed collaborative robots for item sorting in picking systems, showing that collaborative robots can be financially beneficial for more extensive sorting tasks by relieving the operator of the task.

As for the fleet size considerations, there are two components to look at. The fleet size first plays a role in the decision-making process. Estimated fleet sizes based on the vehicle characteristics in relation to the manufacturing environment will determine a high percentage of the cost of the solution. The cost entails the vehicles, ancillary equipment, and operational costs. Each AMR type has a different cost structure, depending on the required equipment and the vendor's business model. Hence, a life cycle cost approach should be considered. The second component is that the fleet sizing must be accurately performed when realizing the AMR system. Having too few or too many vehicles both have a negative impact on the financial performance of the company. Too few vehicles will starve the production system, while too many become wasteful. Detailed simulations, studying comparable systems, and the vendor's experience are useful tools for accurately determining this.

The characteristics and considerations made towards the evaluation and selection was presented in Chapter 5.5 to develop the overview of characteristics. Hence, only a brief summary of the most important are presented here. First and foremost, the fit of the materials, moves, and methods is the overall aim. Choosing an AMR type because of its innovative technology and capability is not guaranteed a good result if it neglects the requirements of the intralogistics system. Neither is not adapting the shop floor to harvest the potential benefits AMRs bring and ensure efficient operation. This can be summarized by a quote from Fottner et al. (2021) on autonomous intralogistics, who stated that *"Once again, it is clear that it is not only a question of developing new technologies, but above all of forming technology and process into a well-functioning unit"*. This is also true for the strategic considerations a company might have, the desired automation level of the intralogistics system, and the material and information flow. Retaining the system perspective is key. In the end, the intralogistics system served by AMRs should help reduce the resources spent on MH, and potentially open for new and innovative solutions for the intralogistics design, such as the introduction of matrix production.

7.3 The Future of Intralogistics System Design

The widely recognized work by Tompkins et al. (2010) stated that MH decisions should be requirement driven and not solution driven. This implies that MH equipment is chosen based on the materials and moves, and not forcing the method and technology onto the materials and moves. Is this view challenged when AMRs are considered to be a candidate for all manufacturing environments and configurations? Do they hold the key to all our intralogistics challenges? The answer to both questions is no. The first question is explained by looking at the future requirements for intralogistics. AMRs are capable of all discussed factors such as modularization, provided they are designed and supplied with the correct hardware and software. The number and variety of tasks they can perform is wide; however, versatile, multi-purpose, high payload capacity AMRs are expensive. In short, choosing AMRs can be seen as requirement driven because they suit the current market requirements, and can be customized to perform the specific tasks. For the second question, AMRs is not the answer to all intralogistics challenges. The explanation for this lies with the CODP. Although market trends imply an upstream CODP shift, manufacturers of consumer goods, cars, and the likes cannot remain competitive without standardizing some stage in the production process. Strictly project-based products such as buildings and ships have this property. Therefore, AMRs are suited after the CODP in the SC. In specific scenarios, applications prior to the CODP might be viable. However, AMRs cannot compete with the cost and efficiency of conveyors if the task is to move high, constant volumes of bulk products between static points. This is not implied in this thesis either, because it requires the AMR to be deemed a viable solution prior to selecting the most suitable type of AMR.

AMRs challenge traditional layout design procedures. The layout is normally heavily influenced by flow intensity, manufacturing environment, and the likes but in addition a high number of minor details for every single scenario. With the flexibility of AMRs, intralogistics will become more adaptable to these details. The proposed overview of characteristics is a tool that can prove useful for such analysis. The AMR versatility will to some degree let the creativity of facility designers put them to the best possible use. Minimizing the need for MH, thus reducing the fleet size, should play the most crucial role. This facilitates a reduction in the investment cost of MH equipment, higher efficiency in operation, and improvements on KPIs such as productivity and flexibility. An added benefit which is often forgotten is also that AMRs require a certain level of standardization of transportation, goods, palletizing, tidiness, and cleanliness on the shop floor. This can force improvement and added focus on these areas compared to traditional MH solutions.

AMRs contribute to a lot of the factors that manufacturers seek improvement on, such as productivity, flexibility, and increased value-added work for operators. However, the vendors need to guarantee for both the specifications and the range of applications for their solutions to justify their high cost (Schneier and Bostelman, 2015). As any other business decision, the cost and ROI always play a key role. AMR vendors seemingly make the selling point of payback periods of approximately two years (Mobile Industrial Robots A/S, 2020), and this might not be far off in some instances. Especially in warehousing, where the cost of an order picker can be directly compared to the cost of the AMR, a payback period of two years might be highly realistic. However, as we have seen through this thesis, manufacturing has a range of other characteristics which plays into this equation. The technology has come a long way, but the cost of the solutions is still too high for AMRs to dominate the MH equipment selection. This is evident when we see the results from case studies that small fleets of two-three vehicles are deployed, which might or might not be scaled up in the future. Despite this, the increasing demand for AMRs and competition in the vendor market, combined with better and more affordable technologies, can change the equation we are looking at today.

7.3.1 New Emerging Intralogistics Solutions: A look at Matrix Production

Briefly introduced in Chapter 5.4, matrix production is a new type of layout and intralogistics interaction. The idea is that identical production cells are supplied tools and products depending on allocated orders. Matrix production relies on a decoupling of logistics and production, and all parts needed in the manufacturing process are stored in a centralized warehouse. The production cells are modular in the sense that they are product and cycle time neutral. They do not need to adhere to strict takt times, which accommodates flexibility. The importance of cycle time neutrality is stressed, because it is the enabler for increased flexibility, as unbalanced flows are avoided, which relieves the system for blocking or starving issues commonly found in e.g., assembly lines (Greschke et al., 2014). The production cells are customer order specific only when equipped with the tools and materials required for the production order. Tools are stored in a tool warehouse shared among all production cells. The modularity and decoupling require the system to be integrated by software solutions. Sensors and IoT devices, connected production cells, and connected MH systems can create a digital twin of the shop floor, so managers can control the shop floor, review performance, and keep track of parts, WIP, and tools, or other resources (Bányai et al., 2019). Together with the advanced equipment, digital twin, and data collection, such production systems can improve themselves over time.

Matrix production is highly scalable. More cells can be added in times of sustained growth, and cells can be shut down in periods of low demand. Breakdowns, setups, and maintenance can easily be accommodated due to the modular structure. Scalability is also achieved in terms of production output, and it allows for ease of changes in layout and process configurations, due to the cycle time neutrality and flexible routing (Schönemann et al., 2015). This makes it possible to react fast to changes in market demands, introduce new products, and produce more variants of the products (Schönemann et al., 2015). This makes matrix production suitable for e.g., spare parts production or other scenarios when demand is highly uncertain, but also other applications where the investment costs can be justified with a satisfying productivity level.

Matrix production is not ideal in every scenario, and this is where differentiation once again proves its power in manufacturing management. Layout design should always follow the manufacturing environment - and the manufacturing environment can be traced back to the demand and CODP. Efficient processes are generally preferred for general, high volume products and vice versa. Therefore, a matrix production setup is best suited after the CODP in the SC, where the product variety increases, such as T-points. This process can be supported by creating modularity in the product structure through design for manufacturing initiatives. Processes prior to the CODP should be performed on efficient and standardized lines either in the same facility, at another facility, or the products can be purchased from a supplier (outsourcing). This depends on a range of factors, including but not limited to the level of factory focus, size of the manufacturing enterprise and its economical capabilities, and supplier market competence and competitiveness. As suggested by Hu et al. (2011), three categories of differentiation can be defined: The common, customized, and personalized category. Common parts should be manufactured with dedicated equipment, customized parts can make use of reconfigurable equipment and the personalized parts should be handled by truly flexible systems. Following this logic, matrix production occupies the last manufacturing steps in the

SC, before shipping to distribution centers, retailers, customers, and the likes. Figure 7.1 shows a conceptual model of how this can be done. Additional simple product differentiation could be further delayed and customized according to local specifications, such as the addition of documentation, instructions, and packaging.

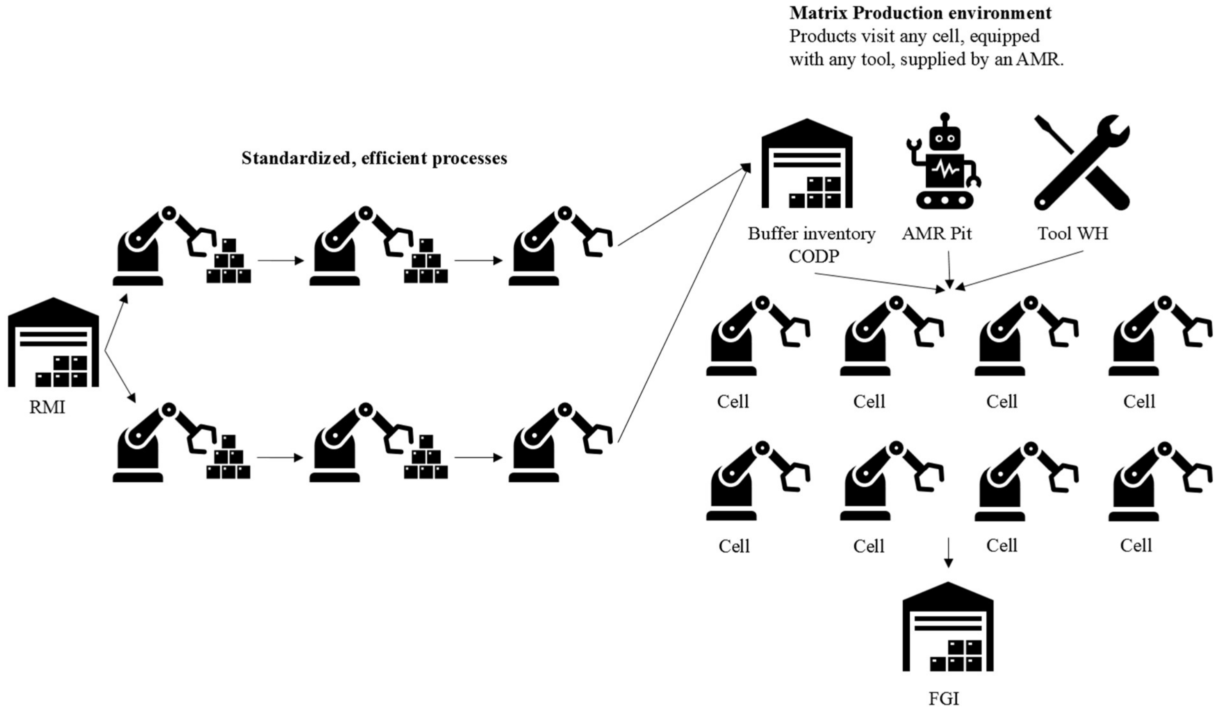

Figure 7.1 – Conceptual model of matrix production environment and efficient processes

This layout fundamentally changes the way of transporting items within the production facility (Fries et al., 2020) and puts pressure on intralogistics systems; in terms of e.g., transport volume, accuracy, control, and monitoring; due to the decoupling of production and logistics. The intralogistics system must accommodate the dynamically changing demand posed by the matrix production system (Bányai et al., 2019). This is achieved only by integrated, efficient and economically competitive MH solutions. Therefore, AMRs are the prime candidate for this position, as they have the possibility to be integrated, efficient, accurate, scalable, and economically competitive. They also occupy the characteristics of the modern role of intralogistics, which is flexibility, responsiveness, and IoT connectivity (Bányai et al., 2019). Traditional intralogistics reach their limits when faced with the requirements from matrix production, and thus the flexibility gains cannot be achieved (Fries et al., 2020).

Cross training of workers, much like what is seen in the lean manufacturing U-cells, becomes important in matrix production. Workers should be able to perform work at the different cells depending on the demand, and equipment should be independent of locations to increase resource utilization (Fries et al., 2020). As previously stated, the production and intralogistics must be connected via software solutions. Production planning becomes complex in this dynamic environment, and proper tools must be provided to operate and predict how the system behaves (Schönemann et al., 2015). Production sequencing can be based on e.g., achieving the lowest lead times, lowest transportation distances, or highest utilization (Schönemann et al., 2015). For assembly lines, the assignment of tasks to workstations becomes much more dynamic, which can help improve utilization. As suggested by Küpper et al. (2018), looking at the automotive industry, the dynamic task assignment ensures that the car is waiting for available workers instead of workers waiting for the car such as in conveyor belt assembly. Buffers between cells function as waiting areas. The dark side of this strategy could be increased throughput times and increasing WIP, which are critical KPI's for many companies (Küpper et al., 2018). Another consideration to make is also the possibility that matrix production has more equipment, higher investment costs, and space requirements compared to traditional production lines (Schönemann et al., 2015). However, the additional equipment functions as reserve capacity, and can reduce the need for buffers between production cells, as suggested by Freiheit et al. (2004). This can in some cases produce a better cost/productivity optimum, as well as support both scalability and flexibility (Freiheit et al., 2004).

7.4 Contributions, Limitations, and Future Research Possibilities

Before presenting the main contributions from the thesis, the general limitations under which the proposed tools are developed, and possibilities for future research, a brief discussion on the choice of manufacturing environments is presented. AMRs are not widely applied and established in industrial manufacturing yet, and this made relating the DSS to three common and established manufacturing environments more appropriate than suggesting both new environments and AMR type recommendations. The idea is that flexibility can be increased within these established environments with little effort using AMRs, such as increased reconfigurability, or more flexible routing of products, as seen in Fragapane et al. (2020b). The exception is the concept of matrix production, which is not included in the DSS but is introduced and discussed because it is in many ways the epitome of what the AMRs can facilitate. The overview of characteristics also highlights the interaction between methods and moves to facilitate new ways of looking at the intralogistics design. As seen in matrix production, the dark side is that performance on some critical KPI's today, such as WIP levels, may worsen (Küpper et al., 2018). This shows that the configuration of manufacturing environments and AMR type selection is part of a bigger picture. Together with the limited scope of this thesis, it made relating the DSS to common and established manufacturing environments the most appropriate.

7.4.1 Contributions and Managerial Impact

The shortcomings in the present scientific literature on this topic can be summarized as the lack of procedures, frameworks, and models that provide an overview of the characteristics and considerations that guide the practical design process of AMR systems, including the link between suitable AMR vehicle types and the specific configuration of the manufacturing environment. To expand the literature in the field of intralogistics system design with the use of AMRs, the main contribution is a DSS for practitioners directly addressing this literature gap. This thesis appears to be the first study to link specific AMR types to different configurations of manufacturing environments. The intended use is to follow the branches of the decision tree that best resemble the specific scenario for the practitioner, which provides a quick and general recommendation that they can further analyze. This visual representation of the DSS resembling decision trees makes it easy-to-grasp for practitioners. The DSS does not seek to recommend the best solution in all scenarios but indicates which solutions must be further analyzed to find the best solution. The included characteristics are all variables and input data that should be either known a priori or is easily accessible to practitioners, which reduces the amount of resources required to start the process of designing the intralogistics system based on AMRs. In addition to this, the procedure of creating it can be replicated with other characteristics and grades. Hence, the procedure itself can be of value to practitioners.

The DSS' high level of generality and the division into three common manufacturing environments found in industry allow for a wide range of applications. It includes a recommendation for the type of AMR in a total of 192 different configuration scenarios, which can suit a wide range of industries and businesses. An overview of the characteristics to consider was also developed to further build into the DSS. This overview can be of value to both practitioners and researchers because it synthesizes and unifies the findings from the two topics of intralogistics system design and AMRs, an issue which, to this date, has received little attention in the scientific literature.

With these results on RQ1 and RQ2, the research objective of addressing the gap in the literature regarding the lack of procedures, frameworks, and models that provide an overview of the characteristics and considerations that guide the practical design process of AMR systems, including the link between suitable AMR vehicle types and the specific configuration of the manufacturing environment, is considered reached.

7.4.2 Limitations

In addition to the limitations previously addressed on the tools used to address the RQs, the most significant limitation to this thesis is the lack of input, testing, and validation from industrial applications. It is based on theoretical input, and the proposed DSS is not applied in a real-world scenario. Measures have been taken to reduce the impact of this, such as mathematical modeling; however, it does not replace practical experience and testing. This can limit how the problem is solved and neglect the actual needs in industry; thus, such decision support as proposed here should not be an abstract academic exercise but should seek input and validation from industrial case studies (Nilsen, 2020). Hence, the results presented in this thesis should be seen in light of this limitation, and further development of the DSS should be conducted through case study applications. Furthermore, distinctions can be made within the three considered manufacturing environments, as well as exploring other environments. For instance, assembly lines and project-based products are excluded, limiting the applicability of the DSS.

Since this study appears to be the first to link various AMR types available on the market to different configurations of manufacturing environments, no discussions connecting the results of the DSS towards prior findings in the scientific literature were possible. Researchers have mainly focused on designing the AMR system and assessed the applicability of the AMR as a concept without differentiating the AMR into types. Due to this novelty of the DSS, a limitation that arises is this lack of comparable studies that are relevant to discuss up against the results and insights gained from this thesis.

7.4.3 Future Research Possibilities

Based on the limitations and findings in this thesis, future research can be conducted to extend the list of characteristics, validate or revise the DSS, and further develop the mathematical models focusing on the differences between AMR types. Although this thesis comprises what is available in the current literature as of the time of writing, new and improved AMRs emerge rapidly along with relevant research. Additional studies directed towards the practical planning and implementation process, including case studies for relevant manufacturing companies and AMR vendors, are suggested to develop a complete picture of the intralogistics system design based on AMRs. From the overview of characteristics, only a selected few are studied in detail and taken a step further towards decision support. On this new and growing topic, the results from the overview can undergo analysis, mathematical modeling, simulations, and case studies to every characteristic to evaluate their impact. This would allow for improved and expanded decision support for the entire intralogistics system, and not only the choice of AMR type. In such studies, the relationship between various characteristics can also be investigated. In short, applying and testing the proposed DSS through practical applications allows for validation and further development. Both the DSS and the overview of characteristics provide a basis for further work in the field of intralogistics system design with AMRs, for practitioners and researchers alike.

8 Conclusion

This thesis set out to address the literature gap in the practical design process of using AMRs for intralogistics in industrial manufacturing environments; thus, providing decision support to practitioners. The main contributions from the thesis were an overview of the characteristics that play a role in the design of intralogistics systems based on AMRs, and a DSS that links the specific design configuration of the manufacturing environment to the most suitable type of AMR. The DSS was validated through the means of mathematical modeling of AMR fleet sizes and costs. By answering the two RQ's of the thesis through the development of these tools, the research objective is considered reached.

The results show that the configuration of the characteristics guides what AMR type is the most suitable in the manufacturing environment. The special top module AMR was recommended in the highest number of scenarios, followed by the basic AMR, while the manipulator AMR received little attention. By following the branches that best represent the considered manufacturing environment, practitioners arrive at the correct recommendations. The mathematical models mainly strengthen the validity of the DSS; however, indicating that the manipulator AMR could have been considered a viable option in more scenarios. Also, limitations regarding the selected characteristics, the development of the DSS, and the mathematical models limit the validity of the results. Furthermore, the scope of this thesis was limited in terms of solely focusing on the material flow part of the intralogistics system. The lack of application and validation through practical case studies limits the results further. Hence, two main areas for future research should seek to address the design of the information flow and validation of the DSS through industrial applications. Other possibilities include further investigations into the characteristics that were not taken the step towards decision support.

The findings in this thesis have important implications for determining the most suitable AMR type in the design of intralogistics systems based on AMRs. Among the findings, it provides practitioners with a quick and easy-to-grasp recommendation of which AMR suits their environment for a total of 192 different scenarios. The findings are of interest to practitioners either considering or are currently designing intralogistics systems based on AMRs, which is becoming increasingly common in the Industry 4.0 era. The broad range of scenarios explored in the DSS can suit a wide range of industries and businesses. Furthermore, it unifies the scientific literature regarding intralogistics design and AMRs, an issue that has received little attention to this date. The thesis contributes to our understanding of how the new and emerging AMR technology can be applied in industrial manufacturing for the purpose of increasing flexibility to meet the trends and requirements that characterize competing in today's markets.

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Appendices

Abbreviations used in the appendices: Basic = Basic AMR, MP = Manipulator AMR, STM = Special Top Module AMR, MM = Mathematical Model.

Appendix 1 - Delphi study round 1 result

Round 1 - Participant 1	Manufacturing environment		
Characteristic	**Production Lines**	**Job Shops**	**Cellular Manufacturing**
Weight & Size/Shape	4	5	2
Throughput	5	3	4
Space Requirements	2	2	5
Travel Distance	2	5	2
Unit Loads	2	4	3
Product Mix	2	5	3

Round 1 - Participant 2	Manufacturing environment		
Characteristic	**Production Lines**	**Job Shops**	**Cellular Manufacturing**
Weight & Size/Shape	4	3	2
Throughput	5	1	3
Space Requirements	1	4	3
Travel Distance	1	5	3
Unit Loads	2	4	3
Product Mix	2	5	4

Round 1 - Participant 3	Manufacturing environment		
Characteristic	**Production Lines**	**Job Shops**	**Cellular Manufacturing**
Weight & Size/Shape	1	4	3
Throughput	5	3	4
Space Requirements	3	3	3
Travel Distance	2	5	3
Unit Loads	1	5	3
Product Mix	1	5	3

Round 1 - Participant 4	Manufacturing environment		
Characteristic	**Production Lines**	**Job Shops**	**Cellular Manufacturing**
Weight & Size/Shape	4	5	2
Throughput	5	2	4
Space Requirements	3	2	4
Travel Distance	2	4	3
Unit Loads	4	5	4
Product Mix	4	5	3

Round 1 Average grades	Manufacturing environment		
Characteristic	**Production lines**	**Job shops**	**Cellular manufacturing**
Weight & Size/Shape	3	4	2
Throughput	5	2	4
Space Requirements	2	3	4
Travel Distance	2	5	3
Unit Loads	2	5	3
Product Mix	2	5	3

Appendix 2 - Delphi study round 2 results and final grades

Round 2 Final Grading Matrix	Manufacturing environment		
Characteristic	**Production Lines**	**Job Shops**	**Cellular Manufacturing**
Weight & Size/Shape	2	4	3
Throughput	5	2	4
Space Requirements	2	4	3
Travel Distance	2	5	3
Unit Loads	2	5	3
Product Mix	2	5	3

Production Lines	High	Low
Weight & Size/Shape	2	0
Throughput	5	0
Space Requirements	2	0
Travel Distance	2	0
Unit Loads	2	0
Product Mix	2	0

Job Shops	High	Low
Weight & Size/Shape	4	0
Throughput	2	0
Space Requirements	4	0
Travel Distance	5	0
Unit Loads	5	0
Product Mix	5	0

Cellular Manufacturing	High	Low
Weight & Size/Shape	3	0
Throughput	4	0
Space Requirements	3	0
Travel Distance	3	0
Unit Loads	3	0
Product Mix	3	0

Grading AMR	Basic AMR	Manipulator AMR	Special Top Module AMR
Weight & Size/Shape	3	1	2
Throughput	1	2	3
Space Requirements	1	3	2
Travel Distance	3	1	2
Unit Loads	3	1	2
Product Mix	2	1	3

Appendix 3 - Scenario overview for the DSS and mathematical models

Scenario	Weight & Size/Shape	Throughput	Space Requirements	Travel Distance	Unit Loads	Product Mix
1	High	High	High	High	High	High
2	High	High	High	High	High	Low
3	High	High	High	High	Low	High
4	High	High	High	High	Low	Low
5	High	High	High	Low	High	High
6	High	High	High	Low	High	Low
7	High	High	High	Low	Low	High
8	High	High	High	Low	Low	Low
9	High	High	Low	High	High	High
10	High	High	Low	High	High	Low
11	High	High	Low	High	Low	High
12	High	High	Low	High	Low	Low
13	High	High	Low	Low	High	High
14	High	High	Low	Low	High	Low
15	High	High	Low	Low	Low	High
16	High	High	Low	Low	Low	Low
17	High	Low	High	High	High	High
18	High	Low	High	High	High	Low
19	High	Low	High	High	Low	High
20	High	Low	High	High	Low	Low
21	High	Low	High	Low	High	High
22	High	Low	High	Low	High	Low
23	High	Low	High	Low	Low	High
24	High	Low	High	Low	Low	Low
25	High	Low	Low	High	High	High
26	High	Low	Low	High	High	Low
27	High	Low	Low	High	Low	High
28	High	Low	Low	High	Low	Low
29	High	Low	Low	Low	High	High
30	High	Low	Low	Low	High	Low
31	High	Low	Low	Low	Low	High
32	High	Low	Low	Low	Low	Low
33	Low	High	High	High	High	High
34	Low	High	High	High	High	Low
35	Low	High	High	High	Low	High
36	Low	High	High	High	Low	Low
37	Low	High	High	Low	High	High
38	Low	High	High	Low	High	Low
39	Low	High	High	Low	Low	High
40	Low	High	High	Low	Low	Low
41	Low	High	Low	High	High	High
42	Low	High	Low	High	High	Low
43	Low	High	Low	High	Low	High
44	Low	High	Low	High	Low	Low
45	Low	High	Low	Low	High	High
46	Low	High	Low	Low	High	Low
47	Low	High	Low	Low	Low	High
48	Low	High	Low	Low	Low	Low
49	Low	Low	High	High	High	High
50	Low	Low	High	High	High	Low
51	Low	Low	High	High	Low	High
52	Low	Low	High	High	Low	Low
53	Low	Low	High	Low	High	High
54	Low	Low	High	Low	High	Low
55	Low	Low	High	Low	Low	High
56	Low	Low	High	Low	Low	Low
57	Low	Low	Low	High	High	High
58	Low	Low	Low	High	High	Low
59	Low	Low	Low	High	Low	High
60	Low	Low	Low	High	Low	Low
61	Low	Low	Low	Low	High	High
62	Low	Low	Low	Low	High	Low
63	Low	Low	Low	Low	Low	High
64	Low	Low	Low	Low	Low	Low

Appendix 4 – DSS for production lines results

Production lines							Ratio to top scorer, above threshold highlighted		
	Score			Threshold calculation					
Scenario	Basic	MP	STM	Theoretical max	Top performer	Threshold	Basic	MP	STM
1	29	24	37	45	37	0,82	0,78	0,65	1,00
2	25	22	31	39	31	0,79	0,81	0,71	1,00
3	23	22	33	39	33	0,85	0,70	0,67	1,00
4	19	20	27	33	27	0,82	0,70	0,74	1,00
5	23	22	33	39	33	0,85	0,70	0,67	1,00
6	19	20	27	33	27	0,82	0,70	0,74	1,00
7	17	20	29	33	29	0,88	0,59	0,69	1,00
8	13	18	23	27	23	0,85	0,57	0,78	1,00
9	27	18	33	39	33	0,85	0,82	0,55	1,00
10	23	16	27	33	27	0,82	0,85	0,59	1,00
11	21	16	29	33	29	0,88	0,72	0,55	1,00
12	17	14	23	27	23	0,85	0,74	0,61	1,00
13	21	16	29	33	29	0,88	0,72	0,55	1,00
14	17	14	23	27	23	0,85	0,74	0,61	1,00
15	15	14	25	27	25	0,93	0,60	0,56	1,00
16	11	12	19	21	19	0,90	0,58	0,63	1,00
17	24	14	22	30	24	0,80	1,00	0,58	0,92
18	20	12	16	24	20	0,83	1,00	0,60	0,80
19	18	12	18	24	18	0,75	1,00	0,67	1,00
20	14	10	12	18	14	0,78	1,00	0,71	0,86
21	18	12	18	24	18	0,75	1,00	0,67	1,00
22	14	10	12	18	14	0,78	1,00	0,71	0,86
23	12	10	14	18	14	0,78	0,86	0,71	1,00
24	8	8	8	12	8	0,67	1,00	1,00	1,00
25	22	8	18	24	22	0,92	1,00	0,36	0,82
26	18	6	12	18	18	1,00	1,00	0,33	0,67
27	16	6	14	18	16	0,89	1,00	0,38	0,88
28	12	4	8	12	12	1,00	1,00	0,33	0,67
29	16	6	14	18	16	0,89	1,00	0,38	0,88
30	12	4	8	12	12	1,00	1,00	0,33	0,67
31	10	4	10	12	10	0,83	1,00	0,40	1,00
32	6	2	4	6	6	1,00	1,00	0,33	0,67
33	23	22	33	39	33	0,85	0,70	0,67	1,00
34	19	20	27	33	27	0,82	0,70	0,74	1,00
35	17	20	29	33	29	0,88	0,59	0,69	1,00
36	13	18	23	27	23	0,85	0,57	0,78	1,00
37	17	20	29	33	29	0,88	0,59	0,69	1,00
38	13	18	23	27	23	0,85	0,57	0,78	1,00
39	11	18	25	27	25	0,93	0,44	0,72	1,00
40	7	16	19	21	19	0,90	0,37	0,84	1,00
41	21	16	29	33	29	0,88	0,72	0,55	1,00
42	17	14	23	27	23	0,85	0,74	0,61	1,00
43	15	14	25	27	25	0,93	0,60	0,56	1,00
44	11	12	19	21	19	0,90	0,58	0,63	1,00
45	15	14	25	27	25	0,93	0,60	0,56	1,00
46	11	12	19	21	19	0,90	0,58	0,63	1,00
47	9	12	21	21	21	1,00	0,43	0,57	1,00
48	5	10	15	15	15	1,00	0,33	0,67	1,00
49	18	12	18	24	18	0,75	1,00	0,67	1,00
50	14	10	12	18	14	0,78	1,00	0,71	0,86
51	12	10	14	18	14	0,78	0,86	0,71	1,00
52	8	8	8	12	8	0,67	1,00	1,00	1,00
53	12	10	14	18	14	0,78	0,86	0,71	1,00
54	8	8	8	12	8	0,67	1,00	1,00	1,00
55	6	8	10	12	10	0,83	0,60	0,80	1,00
56	2	6	4	6	6	1,00	0,33	1,00	0,67
57	16	6	14	18	16	0,89	1,00	0,38	0,88
58	12	4	8	12	12	1,00	1,00	0,33	0,67
59	10	4	10	12	10	0,83	1,00	0,40	1,00
60	6	2	4	6	6	1,00	1,00	0,33	0,67
61	10	4	10	12	10	0,83	1,00	0,40	1,00
62	6	2	4	6	6	1,00	1,00	0,33	0,67
63	4	2	6	6	6	1,00	0,67	0,33	1,00
64	0	0	0	0	0	0,00	0,00	0,00	0,00

Appendix 5 – DSS for job shops results

Job shop							Ratio to top scorer, above threshold highlighted		
	Score			Threshold calculation					
Scenario	Basic	MP	STM	Theoretical max	Top performer	Threshold	Basic	MP	STM
1	58	35	57	75	58	0,77	1,00	0,60	0,98
2	48	30	42	60	48	0,80	1,00	0,63	0,88
3	43	30	47	60	47	0,78	0,91	0,64	1,00
4	33	25	32	45	33	0,73	1,00	0,76	0,97
5	43	30	47	60	47	0,78	0,91	0,64	1,00
6	33	25	32	45	33	0,73	1,00	0,76	0,97
7	28	25	37	45	37	0,82	0,76	0,68	1,00
8	18	20	22	30	22	0,73	0,82	0,91	1,00
9	54	23	49	63	54	0,86	1,00	0,43	0,91
10	44	18	34	48	44	0,92	1,00	0,41	0,77
11	39	18	39	48	39	0,81	1,00	0,46	1,00
12	29	13	24	33	29	0,88	1,00	0,45	0,83
13	39	18	39	48	39	0,81	1,00	0,46	1,00
14	29	13	24	33	29	0,88	1,00	0,45	0,83
15	24	13	29	33	29	0,88	0,83	0,45	1,00
16	14	8	14	18	14	0,78	1,00	0,57	1,00
17	56	31	51	69	56	0,81	1,00	0,55	0,91
18	46	26	36	54	46	0,85	1,00	0,57	0,78
19	41	26	41	54	41	0,76	1,00	0,63	1,00
20	31	21	26	39	31	0,79	1,00	0,68	0,84
21	41	26	41	54	41	0,76	1,00	0,63	1,00
22	31	21	26	39	31	0,79	1,00	0,68	0,84
23	26	21	31	39	31	0,79	0,84	0,68	1,00
24	16	16	16	24	16	0,67	1,00	1,00	1,00
25	52	19	43	57	52	0,91	1,00	0,37	0,83
26	42	14	28	42	42	1,00	1,00	0,33	0,67
27	37	14	33	42	37	0,88	1,00	0,38	0,89
28	27	9	18	27	27	1,00	1,00	0,33	0,67
29	37	14	33	42	37	0,88	1,00	0,38	0,89
30	27	9	18	27	27	1,00	1,00	0,33	0,67
31	22	9	23	27	23	0,85	0,96	0,39	1,00
32	12	4	8	12	12	1,00	1,00	0,33	0,67
33	46	31	49	63	49	0,78	0,94	0,63	1,00
34	36	26	34	48	36	0,75	1,00	0,72	0,94
35	31	26	39	48	39	0,81	0,79	0,67	1,00
36	21	21	24	33	24	0,73	0,88	0,88	1,00
37	31	26	39	48	39	0,81	0,79	0,67	1,00
38	21	21	24	33	24	0,73	0,88	0,88	1,00
39	16	21	29	33	29	0,88	0,55	0,72	1,00
40	6	16	14	18	16	0,89	0,38	1,00	0,88
41	42	19	41	51	42	0,82	1,00	0,45	0,98
42	32	14	26	36	32	0,89	1,00	0,44	0,81
43	27	14	31	36	31	0,86	0,87	0,45	1,00
44	17	9	16	21	17	0,81	1,00	0,53	0,94
45	27	14	31	36	31	0,86	0,87	0,45	1,00
46	17	9	16	21	17	0,81	1,00	0,53	0,94
47	12	9	21	21	21	1,00	0,57	0,43	1,00
48	2	4	6	6	6	1,00	0,33	0,67	1,00
49	44	27	43	57	44	0,77	1,00	0,61	0,98
50	34	22	28	42	34	0,81	1,00	0,65	0,82
51	29	22	33	42	33	0,79	0,88	0,67	1,00
52	19	17	18	27	19	0,70	1,00	0,89	0,95
53	29	22	33	42	33	0,79	0,88	0,67	1,00
54	19	17	18	27	19	0,70	1,00	0,89	0,95
55	14	17	23	27	23	0,85	0,61	0,74	1,00
56	4	12	8	12	12	1,00	0,33	1,00	0,67
57	40	15	35	45	40	0,89	1,00	0,38	0,88
58	30	10	20	30	30	1,00	1,00	0,33	0,67
59	25	10	25	30	25	0,83	1,00	0,40	1,00
60	15	5	10	15	15	1,00	1,00	0,33	0,67
61	25	10	25	30	25	0,83	1,00	0,40	1,00
62	15	5	10	15	15	1,00	1,00	0,33	0,67
63	10	5	15	15	15	1,00	0,67	0,33	1,00
64	0	0	0	0	0	0	0	0	0

Appendix 6 – DSS for cellular manufacturing results

Cellular manufacturing							Ratio to top scorer, above threshold highlighted		
	Score			Threshold calculation					
Scenario	Basic	MP	STM	Theoretical max	Top performer	Threshold	Basic	MP	STM
1	40	29	45	57	45	0,79	0,89	0,64	1,00
2	34	26	36	48	36	0,75	0,94	0,72	1,00
3	31	26	39	48	39	0,81	0,79	0,67	1,00
4	25	23	30	39	30	0,77	0,83	0,77	1,00
5	31	26	39	48	39	0,81	0,79	0,67	1,00
6	25	23	30	39	30	0,77	0,83	0,77	1,00
7	22	23	33	39	33	0,85	0,67	0,70	1,00
8	16	20	24	30	24	0,80	0,67	0,83	1,00
9	37	20	39	48	39	0,81	0,95	0,51	1,00
10	31	17	30	39	31	0,79	1,00	0,55	0,97
11	28	17	33	39	33	0,85	0,85	0,52	1,00
12	22	14	24	30	24	0,80	0,92	0,58	1,00
13	28	17	33	39	33	0,85	0,85	0,52	1,00
14	22	14	24	30	24	0,80	0,92	0,58	1,00
15	19	14	27	30	27	0,90	0,70	0,52	1,00
16	13	11	18	21	18	0,86	0,72	0,61	1,00
17	36	21	33	45	36	0,80	1,00	0,58	0,92
18	30	18	24	36	30	0,83	1,00	0,60	0,80
19	27	18	27	36	27	0,75	1,00	0,67	1,00
20	21	15	18	27	21	0,78	1,00	0,71	0,86
21	27	18	27	36	27	0,75	1,00	0,67	1,00
22	21	15	18	27	21	0,78	1,00	0,71	0,86
23	18	15	21	27	21	0,78	0,86	0,71	1,00
24	12	12	12	18	12	0,67	1,00	1,00	1,00
25	33	12	27	36	33	0,92	1,00	0,36	0,82
26	27	9	18	27	27	1,00	1,00	0,33	0,67
27	24	9	21	27	24	0,89	1,00	0,38	0,88
28	18	6	12	18	18	1,00	1,00	0,33	0,67
29	24	9	21	27	24	0,89	1,00	0,38	0,88
30	18	6	12	18	18	1,00	1,00	0,33	0,67
31	15	6	15	18	15	0,83	1,00	0,40	1,00
32	9	3	6	9	9	1,00	1,00	0,33	0,67
33	31	26	39	48	39	0,81	0,79	0,67	1,00
34	25	23	30	39	30	0,77	0,83	0,77	1,00
35	22	23	33	39	33	0,85	0,67	0,70	1,00
36	16	20	24	30	24	0,80	0,67	0,83	1,00
37	22	23	33	39	33	0,85	0,67	0,70	1,00
38	16	20	24	30	24	0,80	0,67	0,83	1,00
39	13	20	27	30	27	0,90	0,48	0,74	1,00
40	7	17	18	21	18	0,86	0,39	0,94	1,00
41	28	17	33	39	33	0,85	0,85	0,52	1,00
42	22	14	24	30	24	0,80	0,92	0,58	1,00
43	19	14	27	30	27	0,90	0,70	0,52	1,00
44	13	11	18	21	18	0,86	0,72	0,61	1,00
45	19	14	27	30	27	0,90	0,70	0,52	1,00
46	13	11	18	21	18	0,86	0,72	0,61	1,00
47	10	11	21	21	21	1,00	0,48	0,52	1,00
48	4	8	12	12	12	1,00	0,33	0,67	1,00
49	27	18	27	36	27	0,75	1,00	0,67	1,00
50	21	15	18	27	21	0,78	1,00	0,71	0,86
51	18	15	21	27	21	0,78	0,86	0,71	1,00
52	12	12	12	18	12	0,67	1,00	1,00	1,00
53	18	15	21	27	21	0,78	0,86	0,71	1,00
54	12	12	12	18	12	0,67	1,00	1,00	1,00
55	9	12	15	18	15	0,83	0,60	0,80	1,00
56	3	9	6	9	9	1,00	0,33	1,00	0,67
57	24	9	21	27	24	0,89	1,00	0,38	0,88
58	18	6	12	18	18	1,00	1,00	0,33	0,67
59	15	6	15	18	15	0,83	1,00	0,40	1,00
60	9	3	6	9	9	1,00	1,00	0,33	0,67
61	15	6	15	18	15	0,83	1,00	0,40	1,00
62	9	3	6	9	9	1,00	1,00	0,33	0,67
63	6	3	9	9	9	1,00	0,67	0,33	1,00
64	0	0	0	0	0	0,00	0,00	0,00	0,00

Appendix 7 – Fleet size and costs for production lines

Production lines									
	Fleet size			Vehicle cost			L/U station cost		
Scenario	Basic	MP	STM	Basic	MP	STM	Basic	MP	STM
1	19	19	19	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 32 500,00	€ -	€ 15 312,50
2	19	19	19	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 28 750,00	€ -	€ 14 375,00
3	51	37	37	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 32 500,00	€ -	€ 15 312,50
4	51	37	37	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 28 750,00	€ -	€ 14 375,00
5	14	14	14	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 32 500,00	€ -	€ 15 312,50
6	14	14	14	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 28 750,00	€ -	€ 14 375,00
7	42	28	28	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 32 500,00	€ -	€ 15 312,50
8	42	28	28	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 28 750,00	€ -	€ 14 375,00
9	19	19	19	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 28 750,00	€ -	€ 13 437,50
10	19	19	19	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 25 000,00	€ -	€ 12 500,00
11	51	37	37	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 28 750,00	€ -	€ 13 437,50
12	51	37	37	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 25 000,00	€ -	€ 12 500,00
13	14	14	14	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 28 750,00	€ -	€ 13 437,50
14	14	14	14	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 25 000,00	€ -	€ 12 500,00
15	42	28	28	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 28 750,00	€ -	€ 13 437,50
16	42	28	28	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 25 000,00	€ -	€ 12 500,00
17	4	4	4	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 32 500,00	€ -	€ 15 312,50
18	4	4	4	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 28 750,00	€ -	€ 14 375,00
19	8	8	8	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 32 500,00	€ -	€ 15 312,50
20	8	8	8	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 28 750,00	€ -	€ 14 375,00
21	3	3	3	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 32 500,00	€ -	€ 15 312,50
22	3	3	3	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 28 750,00	€ -	€ 14 375,00
23	6	6	6	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 32 500,00	€ -	€ 15 312,50
24	6	6	6	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 28 750,00	€ -	€ 14 375,00
25	4	4	4	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 28 750,00	€ -	€ 13 437,50
26	4	4	4	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 25 000,00	€ -	€ 12 500,00
27	8	8	8	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 28 750,00	€ -	€ 13 437,50
28	8	8	8	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 25 000,00	€ -	€ 12 500,00
29	3	3	3	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 28 750,00	€ -	€ 13 437,50
30	3	3	3	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 25 000,00	€ -	€ 12 500,00
31	6	6	6	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 28 750,00	€ -	€ 13 437,50
32	6	6	6	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 25 000,00	€ -	€ 12 500,00
33	19	19	19	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 32 500,00	€ -	€ 15 312,50
34	19	19	19	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 28 750,00	€ -	€ 14 375,00
35	51	37	37	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 32 500,00	€ -	€ 15 312,50
36	51	37	37	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 28 750,00	€ -	€ 14 375,00
37	14	14	14	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 32 500,00	€ -	€ 15 312,50
38	14	14	14	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 28 750,00	€ -	€ 14 375,00
39	42	28	28	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 32 500,00	€ -	€ 15 312,50
40	42	28	28	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 28 750,00	€ -	€ 14 375,00
41	19	19	19	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 28 750,00	€ -	€ 13 437,50
42	19	19	19	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 25 000,00	€ -	€ 12 500,00
43	51	37	37	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 28 750,00	€ -	€ 13 437,50
44	51	37	37	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 25 000,00	€ -	€ 12 500,00
45	14	14	14	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 28 750,00	€ -	€ 13 437,50
46	14	14	14	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 25 000,00	€ -	€ 12 500,00
47	42	28	28	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 28 750,00	€ -	€ 13 437,50
48	42	28	28	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 25 000,00	€ -	€ 12 500,00
49	4	4	4	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 32 500,00	€ -	€ 15 312,50
50	4	4	4	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 28 750,00	€ -	€ 14 375,00
51	8	8	8	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 32 500,00	€ -	€ 15 312,50
52	8	8	8	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 28 750,00	€ -	€ 14 375,00
53	3	3	3	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 32 500,00	€ -	€ 15 312,50
54	3	3	3	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 28 750,00	€ -	€ 14 375,00
55	6	6	6	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 32 500,00	€ -	€ 15 312,50
56	6	6	6	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 28 750,00	€ -	€ 14 375,00
57	4	4	4	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 28 750,00	€ -	€ 13 437,50
58	4	4	4	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 25 000,00	€ -	€ 12 500,00
59	8	8	8	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 28 750,00	€ -	€ 13 437,50
60	8	8	8	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 25 000,00	€ -	€ 12 500,00
61	3	3	3	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 28 750,00	€ -	€ 13 437,50
62	3	3	3	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 25 000,00	€ -	€ 12 500,00
63	6	6	6	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 28 750,00	€ -	€ 13 437,50
64	6	6	6	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 25 000,00	€ -	€ 12 500,00

Appendix 8 - Total costs and ratio for production lines

	Production lines						
		Total cost, within threshold highlighted			Ratio		
Scenario	Threshold	Basic	MP	STM	Basic	MP	STM
1	1,18	€ 708 750	€ 1 235 000	€ 949 375	1,00	1,74	1,34
2	1,21	€ 690 000	€ 1 092 500	€ 891 250	1,00	1,58	1,29
3	1,15	€ 1 628 750	€ 2 405 000	€ 1 776 250	1,00	1,48	1,09
4	1,18	€ 1 610 000	€ 2 127 500	€ 1 667 500	1,00	1,32	1,04
5	1,15	€ 565 000	€ 910 000	€ 719 688	1,00	1,61	1,27
6	1,18	€ 546 250	€ 805 000	€ 675 625	1,00	1,47	1,24
7	1,12	€ 1 370 000	€ 1 820 000	€ 1 362 813	1,01	1,34	1,00
8	1,15	€ 1 351 250	€ 1 610 000	€ 1 279 375	1,06	1,26	1,00
9	1,15	€ 690 000	€ 1 235 000	€ 940 000	1,00	1,79	1,36
10	1,18	€ 671 250	€ 1 092 500	€ 881 875	1,00	1,63	1,31
11	1,12	€ 1 610 000	€ 2 405 000	€ 1 766 875	1,00	1,49	1,10
12	1,15	€ 1 591 250	€ 2 127 500	€ 1 658 125	1,00	1,34	1,04
13	1,12	€ 546 250	€ 910 000	€ 710 313	1,00	1,67	1,30
14	1,15	€ 527 500	€ 805 000	€ 666 250	1,00	1,53	1,26
15	1,07	€ 1 351 250	€ 1 820 000	€ 1 353 438	1,00	1,35	1,00
16	1,10	€ 1 332 500	€ 1 610 000	€ 1 270 000	1,05	1,27	1,00
17	1,20	€ 277 500	€ 260 000	€ 260 313	1,07	1,00	1,00
18	1,17	€ 258 750	€ 230 000	€ 244 375	1,13	1,00	1,06
19	1,25	€ 392 500	€ 520 000	€ 444 063	1,00	1,32	1,13
20	1,22	€ 373 750	€ 460 000	€ 416 875	1,00	1,23	1,12
21	1,25	€ 248 750	€ 195 000	€ 214 375	1,28	1,00	1,10
22	1,22	€ 230 000	€ 172 500	€ 201 250	1,33	1,00	1,17
23	1,22	€ 335 000	€ 390 000	€ 352 188	1,00	1,16	1,05
24	1,33	€ 316 250	€ 345 000	€ 330 625	1,00	1,09	1,05
25	1,08	€ 258 750	€ 260 000	€ 250 938	1,03	1,04	1,00
26	1,00	€ 240 000	€ 230 000	€ 235 000	1,04	1,00	1,02
27	1,11	€ 373 750	€ 520 000	€ 434 688	1,00	1,39	1,16
28	1,00	€ 355 000	€ 460 000	€ 407 500	1,00	1,30	1,15
29	1,11	€ 230 000	€ 195 000	€ 205 000	1,18	1,00	1,05
30	1,00	€ 211 250	€ 172 500	€ 191 875	1,22	1,00	1,11
31	1,17	€ 316 250	€ 390 000	€ 342 813	1,00	1,23	1,08
32	1,00	€ 297 500	€ 345 000	€ 321 250	1,00	1,16	1,08
33	1,15	€ 637 500	€ 1 092 500	€ 842 500	1,00	1,71	1,32
34	1,18	€ 618 750	€ 950 000	€ 784 375	1,00	1,54	1,27
35	1,12	€ 1 437 500	€ 2 127 500	€ 1 568 125	1,00	1,48	1,09
36	1,15	€ 1 418 750	€ 1 850 000	€ 1 459 375	1,00	1,30	1,03
37	1,12	€ 512 500	€ 805 000	€ 640 938	1,00	1,57	1,25
38	1,15	€ 493 750	€ 700 000	€ 596 875	1,00	1,42	1,21
39	1,07	€ 1 212 500	€ 1 610 000	€ 1 205 313	1,01	1,34	1,00
40	1,10	€ 1 193 750	€ 1 400 000	€ 1 121 875	1,06	1,25	1,00
41	1,12	€ 618 750	€ 1 092 500	€ 833 125	1,00	1,77	1,35
42	1,15	€ 600 000	€ 950 000	€ 775 000	1,00	1,58	1,29
43	1,07	€ 1 418 750	€ 2 127 500	€ 1 558 750	1,00	1,50	1,10
44	1,10	€ 1 400 000	€ 1 850 000	€ 1 450 000	1,00	1,32	1,04
45	1,07	€ 493 750	€ 805 000	€ 631 563	1,00	1,63	1,28
46	1,10	€ 475 000	€ 700 000	€ 587 500	1,00	1,47	1,24
47	1,00	€ 1 193 750	€ 1 610 000	€ 1 195 938	1,00	1,35	1,00
48	1,00	€ 1 175 000	€ 1 400 000	€ 1 112 500	1,06	1,26	1,00
49	1,25	€ 262 500	€ 230 000	€ 237 813	1,14	1,00	1,03
50	1,22	€ 243 750	€ 200 000	€ 221 875	1,22	1,00	1,11
51	1,22	€ 362 500	€ 460 000	€ 399 063	1,00	1,27	1,10
52	1,33	€ 343 750	€ 400 000	€ 371 875	1,00	1,16	1,08
53	1,22	€ 237 500	€ 172 500	€ 197 500	1,38	1,00	1,14
54	1,33	€ 218 750	€ 150 000	€ 184 375	1,46	1,00	1,23
55	1,17	€ 312 500	€ 345 000	€ 318 438	1,00	1,10	1,02
56	1,00	€ 293 750	€ 300 000	€ 296 875	1,00	1,02	1,01
57	1,11	€ 243 750	€ 230 000	€ 228 438	1,07	1,01	1,00
58	1,00	€ 225 000	€ 200 000	€ 212 500	1,13	1,00	1,06
59	1,17	€ 343 750	€ 460 000	€ 389 688	1,00	1,34	1,13
60	1,00	€ 325 000	€ 400 000	€ 362 500	1,00	1,23	1,12
61	1,17	€ 218 750	€ 172 500	€ 188 125	1,27	1,00	1,09
62	1,00	€ 200 000	€ 150 000	€ 175 000	1,33	1,00	1,17
63	1,00	€ 293 750	€ 345 000	€ 309 063	1,00	1,17	1,05
64	2,00	€ 275 000	€ 300 000	€ 287 500	1,00	1,09	1,05

Appendix 9 – DSS and mathematical model recommendations comparison production lines

Production lines												
Scenario	**DSS recommendation**			**MM recommendation**			**Common recommendation**			**Additional from MM**		
1			STM	Basic						Basic		
2	Basic		STM	Basic			Basic					
3			STM	Basic		STM			STM	Basic		
4			STM	Basic		STM			STM	Basic		
5			STM	Basic						Basic		
6			STM	Basic						Basic		
7			STM	Basic		STM			STM	Basic		
8			STM	Basic		STM			STM	Basic		
9			STM	Basic						Basic		
10	Basic		STM	Basic			Basic					
11			STM	Basic		STM			STM	Basic		
12			STM	Basic		STM			STM	Basic		
13			STM	Basic						Basic		
14			STM	Basic						Basic		
15			STM	Basic		STM			STM	Basic		
16			STM	Basic		STM			STM	Basic		
17	Basic		STM	Basic	MP	STM	Basic		STM		MP	
18	Basic			Basic	MP	STM	Basic				MP	STM
19	Basic		STM	Basic		STM	Basic		STM			
20	Basic		STM	Basic		STM	Basic		STM			
21	Basic		STM		MP	STM			STM		MP	
22	Basic		STM		MP	STM			STM		MP	
23	Basic		STM	Basic	MP	STM	Basic		STM		MP	
24	Basic	MP	STM	Basic	MP	STM	Basic	MP	STM			
25	Basic			Basic	MP	STM	Basic				MP	STM
26	Basic				MP						MP	
27	Basic			Basic			Basic					
28	Basic			Basic			Basic					
29	Basic				MP	STM					MP	STM
30	Basic				MP						MP	
31	Basic		STM	Basic		STM	Basic		STM			
32	Basic			Basic			Basic					
33			STM	Basic						Basic		
34			STM	Basic						Basic		
35			STM	Basic		STM			STM	Basic		
36			STM	Basic		STM			STM	Basic		
37			STM	Basic						Basic		
38			STM	Basic						Basic		
39			STM	Basic		STM			STM	Basic		
40			STM	Basic		STM			STM	Basic		
41			STM	Basic						Basic		
42			STM	Basic						Basic		
43			STM	Basic						Basic		
44			STM	Basic		STM			STM	Basic		
45			STM	Basic						Basic		
46			STM	Basic						Basic		
47			STM	Basic						Basic		
48			STM			STM			STM			
49	Basic		STM	Basic	MP	STM	Basic		STM		MP	
50	Basic		STM	Basic	MP	STM	Basic		STM		MP	
51	Basic		STM	Basic		STM	Basic		STM			
52	Basic	MP	STM	Basic	MP	STM	Basic	MP	STM			
53	Basic		STM		MP	STM			STM		MP	
54	Basic	MP	STM		MP	STM		MP	STM			
55			STM	Basic	MP	STM			STM	Basic	MP	
56		MP		Basic						Basic		
57	Basic			Basic	MP	STM	Basic				MP	STM
58	Basic				MP						MP	
59	Basic		STM	Basic		STM	Basic		STM			
60	Basic			Basic			Basic					
61	Basic		STM		MP	STM			STM		MP	
62	Basic				MP						MP	
63			STM	Basic						Basic		
64	Basic	MP	STM	Basic	MP	STM	Basic	MP	STM			

Appendix 10 - Fleet size and costs for job shops

Job shops									
	Fleet size			Vehicle cost			L/U station cost		
Scenario	Basic	MP	STM	Basic	MP	STM	Basic	MP	STM
1	3	3	3	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 32 500,00	€ -	€ 15 312,50
2	3	3	3	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 28 750,00	€ -	€ 14 375,00
3	11	11	11	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 32 500,00	€ -	€ 15 312,50
4	11	11	11	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 28 750,00	€ -	€ 14 375,00
5	2	2	2	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 32 500,00	€ -	€ 15 312,50
6	2	2	2	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 28 750,00	€ -	€ 14 375,00
7	6	6	6	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 32 500,00	€ -	€ 15 312,50
8	6	6	6	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 28 750,00	€ -	€ 14 375,00
9	3	3	3	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 28 750,00	€ -	€ 13 437,50
10	3	3	3	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 25 000,00	€ -	€ 12 500,00
11	11	11	11	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 28 750,00	€ -	€ 13 437,50
12	11	11	11	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 25 000,00	€ -	€ 12 500,00
13	2	2	2	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 28 750,00	€ -	€ 13 437,50
14	2	2	2	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 25 000,00	€ -	€ 12 500,00
15	6	6	6	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 28 750,00	€ -	€ 13 437,50
16	6	6	6	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 25 000,00	€ -	€ 12 500,00
17	2	2	2	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 32 500,00	€ -	€ 15 312,50
18	2	2	2	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 28 750,00	€ -	€ 14 375,00
19	6	6	6	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 32 500,00	€ -	€ 15 312,50
20	6	6	6	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 28 750,00	€ -	€ 14 375,00
21	1	1	1	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 32 500,00	€ -	€ 15 312,50
22	1	1	1	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 28 750,00	€ -	€ 14 375,00
23	3	3	3	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 32 500,00	€ -	€ 15 312,50
24	3	3	3	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 28 750,00	€ -	€ 14 375,00
25	2	2	2	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 28 750,00	€ -	€ 13 437,50
26	2	2	2	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 25 000,00	€ -	€ 12 500,00
27	6	6	6	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 28 750,00	€ -	€ 13 437,50
28	6	6	6	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 25 000,00	€ -	€ 12 500,00
29	1	1	1	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 28 750,00	€ -	€ 13 437,50
30	1	1	1	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 25 000,00	€ -	€ 12 500,00
31	3	3	3	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 28 750,00	€ -	€ 13 437,50
32	3	3	3	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 25 000,00	€ -	€ 12 500,00
33	3	3	3	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 32 500,00	€ -	€ 15 312,50
34	3	3	3	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 28 750,00	€ -	€ 14 375,00
35	11	11	11	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 32 500,00	€ -	€ 15 312,50
36	11	11	11	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 28 750,00	€ -	€ 14 375,00
37	2	2	2	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 32 500,00	€ -	€ 15 312,50
38	2	2	2	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 28 750,00	€ -	€ 14 375,00
39	6	6	6	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 32 500,00	€ -	€ 15 312,50
40	6	6	6	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 28 750,00	€ -	€ 14 375,00
41	3	3	3	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 28 750,00	€ -	€ 13 437,50
42	3	3	3	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 25 000,00	€ -	€ 12 500,00
43	11	11	11	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 28 750,00	€ -	€ 13 437,50
44	11	11	11	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 25 000,00	€ -	€ 12 500,00
45	2	2	2	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 28 750,00	€ -	€ 13 437,50
46	2	2	2	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 25 000,00	€ -	€ 12 500,00
47	6	6	6	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 28 750,00	€ -	€ 13 437,50
48	6	6	6	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 25 000,00	€ -	€ 12 500,00
49	2	2	2	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 32 500,00	€ -	€ 15 312,50
50	2	2	2	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 28 750,00	€ -	€ 14 375,00
51	6	6	6	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 32 500,00	€ -	€ 15 312,50
52	6	6	6	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 28 750,00	€ -	€ 14 375,00
53	1	1	1	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 32 500,00	€ -	€ 15 312,50
54	1	1	1	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 28 750,00	€ -	€ 14 375,00
55	3	3	3	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 32 500,00	€ -	€ 15 312,50
56	3	3	3	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 28 750,00	€ -	€ 14 375,00
57	2	2	2	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 28 750,00	€ -	€ 13 437,50
58	2	2	2	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 25 000,00	€ -	€ 12 500,00
59	6	6	6	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 28 750,00	€ -	€ 13 437,50
60	6	6	6	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 25 000,00	€ -	€ 12 500,00
61	1	1	1	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 28 750,00	€ -	€ 13 437,50
62	1	1	1	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 25 000,00	€ -	€ 12 500,00
63	3	3	3	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 28 750,00	€ -	€ 13 437,50
64	3	3	3	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 25 000,00	€ -	€ 12 500,00

Appendix 11 - Total costs and ratio for job shops

Job shops							
		Total cost, within threshold highlighted			Ratio		
Scenario	Threshold	Basic	MP	STM	Basic	MP	STM
1	1,23	€ 281 250	€ 195 000	€ 229 688	1,44	1,00	1,18
2	1,20	€ 258 750	€ 172 500	€ 215 625	1,50	1,00	1,25
3	1,22	€ 511 250	€ 715 000	€ 597 188	1,00	1,40	1,17
4	1,27	€ 488 750	€ 632 500	€ 560 625	1,00	1,29	1,15
5	1,22	€ 252 500	€ 130 000	€ 183 750	1,94	1,00	1,41
6	1,27	€ 230 000	€ 115 000	€ 172 500	2,00	1,00	1,50
7	1,18	€ 367 500	€ 390 000	€ 367 500	1,00	1,06	1,00
8	1,27	€ 345 000	€ 345 000	€ 345 000	1,00	1,00	1,00
9	1,14	€ 258 750	€ 195 000	€ 218 438	1,33	1,00	1,12
10	1,08	€ 236 250	€ 172 500	€ 204 375	1,37	1,00	1,18
11	1,19	€ 488 750	€ 715 000	€ 585 938	1,00	1,46	1,20
12	1,12	€ 466 250	€ 632 500	€ 549 375	1,00	1,36	1,18
13	1,19	€ 230 000	€ 130 000	€ 172 500	1,77	1,00	1,33
14	1,12	€ 207 500	€ 115 000	€ 161 250	1,80	1,00	1,40
15	1,12	€ 345 000	€ 390 000	€ 356 250	1,00	1,13	1,03
16	1,22	€ 322 500	€ 345 000	€ 333 750	1,00	1,07	1,03
17	1,19	€ 252 500	€ 130 000	€ 183 750	1,94	1,00	1,41
18	1,15	€ 230 000	€ 115 000	€ 172 500	2,00	1,00	1,50
19	1,24	€ 367 500	€ 390 000	€ 367 500	1,00	1,06	1,00
20	1,21	€ 345 000	€ 345 000	€ 345 000	1,00	1,00	1,00
21	1,24	€ 223 750	€ 65 000	€ 137 813	3,44	1,00	2,12
22	1,21	€ 201 250	€ 57 500	€ 129 375	3,50	1,00	2,25
23	1,21	€ 281 250	€ 195 000	€ 229 688	1,44	1,00	1,18
24	1,33	€ 258 750	€ 172 500	€ 215 625	1,50	1,00	1,25
25	1,09	€ 230 000	€ 130 000	€ 172 500	1,77	1,00	1,33
26	1,00	€ 207 500	€ 115 000	€ 161 250	1,80	1,00	1,40
27	1,12	€ 345 000	€ 390 000	€ 356 250	1,00	1,13	1,03
28	1,00	€ 322 500	€ 345 000	€ 333 750	1,00	1,07	1,03
29	1,12	€ 201 250	€ 65 000	€ 126 563	3,10	1,00	1,95
30	1,00	€ 178 750	€ 57 500	€ 118 125	3,11	1,00	2,05
31	1,15	€ 258 750	€ 195 000	€ 218 438	1,33	1,00	1,12
32	1,00	€ 236 250	€ 172 500	€ 204 375	1,37	1,00	1,18
33	1,22	€ 270 000	€ 172 500	€ 212 813	1,57	1,00	1,23
34	1,25	€ 247 500	€ 150 000	€ 198 750	1,65	1,00	1,33
35	1,19	€ 470 000	€ 632 500	€ 535 313	1,00	1,35	1,14
36	1,27	€ 447 500	€ 550 000	€ 498 750	1,00	1,23	1,11
37	1,19	€ 245 000	€ 115 000	€ 172 500	2,13	1,00	1,50
38	1,27	€ 222 500	€ 100 000	€ 161 250	2,23	1,00	1,61
39	1,12	€ 345 000	€ 345 000	€ 333 750	1,03	1,03	1,00
40	1,11	€ 322 500	€ 300 000	€ 311 250	1,08	1,00	1,04
41	1,18	€ 247 500	€ 172 500	€ 201 563	1,43	1,00	1,17
42	1,11	€ 225 000	€ 150 000	€ 187 500	1,50	1,00	1,25
43	1,14	€ 447 500	€ 632 500	€ 524 063	1,00	1,41	1,17
44	1,19	€ 425 000	€ 550 000	€ 487 500	1,00	1,29	1,15
45	1,14	€ 222 500	€ 115 000	€ 161 250	1,93	1,00	1,40
46	1,19	€ 200 000	€ 100 000	€ 150 000	2,00	1,00	1,50
47	1,00	€ 322 500	€ 345 000	€ 322 500	1,00	1,07	1,00
48	1,00	€ 300 000	€ 300 000	€ 300 000	1,00	1,00	1,00
49	1,23	€ 245 000	€ 115 000	€ 172 500	2,13	1,00	1,50
50	1,19	€ 222 500	€ 100 000	€ 161 250	2,23	1,00	1,61
51	1,21	€ 345 000	€ 345 000	€ 333 750	1,03	1,03	1,00
52	1,30	€ 322 500	€ 300 000	€ 311 250	1,08	1,00	1,04
53	1,21	€ 220 000	€ 57 500	€ 132 188	3,83	1,00	2,30
54	1,30	€ 197 500	€ 50 000	€ 123 750	3,95	1,00	2,48
55	1,15	€ 270 000	€ 172 500	€ 212 813	1,57	1,00	1,23
56	1,00	€ 247 500	€ 150 000	€ 198 750	1,65	1,00	1,33
57	1,11	€ 222 500	€ 115 000	€ 161 250	1,93	1,00	1,40
58	1,00	€ 200 000	€ 100 000	€ 150 000	2,00	1,00	1,50
59	1,17	€ 322 500	€ 345 000	€ 322 500	1,00	1,07	1,00
60	1,00	€ 300 000	€ 300 000	€ 300 000	1,00	1,00	1,00
61	1,17	€ 197 500	€ 57 500	€ 120 938	3,43	1,00	2,10
62	1,00	€ 175 000	€ 50 000	€ 112 500	3,50	1,00	2,25
63	1,00	€ 247 500	€ 172 500	€ 201 563	1,43	1,00	1,17
64	2,00	€ 225 000	€ 150 000	€ 187 500	1,50	1,00	1,25

Appendix 12 - DSS and mathematical model recommendations comparison job shops

Job shops												
Scenario	DSS recommendation			MM recommendation			Common recommendation			Additional from MM		
1	Basic		STM		MP	STM			STM		MP	
2	Basic		STM		MP						MP	
3	Basic		STM	Basic		STM	Basic		STM			
4	Basic	MP	STM	Basic		STM	Basic		STM			
5	Basic		STM		MP						MP	
6	Basic	MP	STM		MP			MP				
7			STM	Basic	MP	STM			STM	Basic	MP	
8	Basic	MP	STM	Basic	MP	STM	Basic	MP	STM			
9	Basic		STM		MP	STM			STM		MP	
10	Basic				MP						MP	
11	Basic		STM	Basic			Basic					
12	Basic			Basic			Basic					
13	Basic		STM		MP						MP	
14	Basic				MP						MP	
15			STM	Basic		STM			STM	Basic		
16	Basic		STM	Basic	MP	STM	Basic		STM		MP	
17	Basic		STM		MP						MP	
18	Basic				MP						MP	
19	Basic		STM	Basic	MP	STM	Basic		STM		MP	
20	Basic		STM	Basic	MP	STM	Basic		STM		MP	
21	Basic		STM		MP						MP	
22	Basic		STM		MP						MP	
23	Basic		STM		MP	STM			STM		MP	
24	Basic	MP	STM		MP	STM		MP	STM			
25	Basic				MP						MP	
26	Basic				MP						MP	
27	Basic		STM	Basic		STM	Basic		STM			
28	Basic			Basic			Basic					
29	Basic		STM		MP						MP	
30	Basic				MP						MP	
31	Basic		STM		MP	STM			STM		MP	
32	Basic				MP						MP	
33	Basic		STM		MP						MP	
34	Basic		STM		MP						MP	
35			STM	Basic		STM			STM	Basic		
36	Basic	MP	STM	Basic	MP	STM	Basic	MP	STM			
37			STM		MP						MP	
38	Basic	MP	STM		MP			MP				
39			STM	Basic	MP	STM			STM	Basic	MP	
40		MP		Basic	MP	STM		MP		Basic		STM
41	Basic		STM		MP	STM			STM		MP	
42	Basic				MP						MP	
43	Basic		STM	Basic			Basic					
44	Basic		STM	Basic		STM	Basic		STM			
45	Basic		STM		MP						MP	
46	Basic		STM		MP						MP	
47			STM	Basic		STM			STM	Basic		
48			STM	Basic	MP	STM			STM	Basic	MP	
49	Basic		STM		MP						MP	
50	Basic		STM		MP						MP	
51	Basic		STM	Basic	MP	STM	Basic		STM		MP	
52	Basic	MP	STM	Basic	MP	STM	Basic	MP	STM			
53	Basic		STM		MP						MP	
54	Basic	MP	STM		MP			MP				
55			STM		MP						MP	
56		MP			MP			MP				
57	Basic				MP						MP	
58	Basic				MP						MP	
59	Basic		STM	Basic	MP	STM	Basic		STM		MP	
60	Basic			Basic	MP	STM	Basic				MP	STM
61	Basic		STM		MP						MP	
62	Basic				MP						MP	
63			STM		MP						MP	
64	Basic	MP	STM	Basic	MP	STM	Basic	MP	STM			

Appendix 13 - Fleet size and costs for cellular manufacturing

Cellular manufacturing									
	Fleet size			Vehicle cost			L/U station cost		
Scenario	Basic	MP	STM	Basic	MP	STM	Basic	MP	STM
1	19	19	19	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 32 500,00	€ -	€ 15 312,50
2	19	19	19	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 28 750,00	€ -	€ 14 375,00
3	63	52	52	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 32 500,00	€ -	€ 15 312,50
4	63	52	52	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 28 750,00	€ -	€ 14 375,00
5	11	11	11	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 32 500,00	€ -	€ 15 312,50
6	11	11	11	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 28 750,00	€ -	€ 14 375,00
7	40	30	30	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 32 500,00	€ -	€ 15 312,50
8	40	30	30	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 28 750,00	€ -	€ 14 375,00
9	19	19	19	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 28 750,00	€ -	€ 13 437,50
10	19	19	19	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 25 000,00	€ -	€ 12 500,00
11	63	52	52	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 28 750,00	€ -	€ 13 437,50
12	63	52	52	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 25 000,00	€ -	€ 12 500,00
13	11	11	11	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 28 750,00	€ -	€ 13 437,50
14	11	11	11	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 25 000,00	€ -	€ 12 500,00
15	40	30	30	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 28 750,00	€ -	€ 13 437,50
16	40	30	30	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 25 000,00	€ -	€ 12 500,00
17	6	6	6	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 32 500,00	€ -	€ 15 312,50
18	6	6	6	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 28 750,00	€ -	€ 14 375,00
19	14	14	14	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 32 500,00	€ -	€ 15 312,50
20	14	14	14	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 28 750,00	€ -	€ 14 375,00
21	4	4	4	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 32 500,00	€ -	€ 15 312,50
22	4	4	4	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 28 750,00	€ -	€ 14 375,00
23	9	9	9	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 32 500,00	€ -	€ 15 312,50
24	9	9	9	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 28 750,00	€ -	€ 14 375,00
25	6	6	6	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 28 750,00	€ -	€ 13 437,50
26	6	6	6	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 25 000,00	€ -	€ 12 500,00
27	14	14	14	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 28 750,00	€ -	€ 13 437,50
28	14	14	14	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 25 000,00	€ -	€ 12 500,00
29	4	4	4	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 28 750,00	€ -	€ 13 437,50
30	4	4	4	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 25 000,00	€ -	€ 12 500,00
31	9	9	9	€ 28 750,00	€ 65 000,00	€ 45 937,50	€ 28 750,00	€ -	€ 13 437,50
32	9	9	9	€ 28 750,00	€ 57 500,00	€ 43 125,00	€ 25 000,00	€ -	€ 12 500,00
33	19	19	19	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 32 500,00	€ -	€ 15 312,50
34	19	19	19	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 28 750,00	€ -	€ 14 375,00
35	63	52	52	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 32 500,00	€ -	€ 15 312,50
36	63	52	52	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 28 750,00	€ -	€ 14 375,00
37	11	11	11	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 32 500,00	€ -	€ 15 312,50
38	11	11	11	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 28 750,00	€ -	€ 14 375,00
39	40	30	30	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 32 500,00	€ -	€ 15 312,50
40	40	30	30	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 28 750,00	€ -	€ 14 375,00
41	19	19	19	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 28 750,00	€ -	€ 13 437,50
42	19	19	19	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 25 000,00	€ -	€ 12 500,00
43	63	52	52	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 28 750,00	€ -	€ 13 437,50
44	63	52	52	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 25 000,00	€ -	€ 12 500,00
45	11	11	11	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 28 750,00	€ -	€ 13 437,50
46	11	11	11	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 25 000,00	€ -	€ 12 500,00
47	40	30	30	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 28 750,00	€ -	€ 13 437,50
48	40	30	30	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 25 000,00	€ -	€ 12 500,00
49	6	6	6	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 32 500,00	€ -	€ 15 312,50
50	6	6	6	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 28 750,00	€ -	€ 14 375,00
51	14	14	14	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 32 500,00	€ -	€ 15 312,50
52	14	14	14	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 28 750,00	€ -	€ 14 375,00
53	4	4	4	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 32 500,00	€ -	€ 15 312,50
54	4	4	4	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 28 750,00	€ -	€ 14 375,00
55	9	9	9	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 32 500,00	€ -	€ 15 312,50
56	9	9	9	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 28 750,00	€ -	€ 14 375,00
57	6	6	6	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 28 750,00	€ -	€ 13 437,50
58	6	6	6	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 25 000,00	€ -	€ 12 500,00
59	14	14	14	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 28 750,00	€ -	€ 13 437,50
60	14	14	14	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 25 000,00	€ -	€ 12 500,00
61	4	4	4	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 28 750,00	€ -	€ 13 437,50
62	4	4	4	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 25 000,00	€ -	€ 12 500,00
63	9	9	9	€ 25 000,00	€ 57 500,00	€ 40 312,50	€ 28 750,00	€ -	€ 13 437,50
64	9	9	9	€ 25 000,00	€ 50 000,00	€ 37 500,00	€ 25 000,00	€ -	€ 12 500,00

Appendix 14 - Total costs and ratio for cellular manufacturing

Cellular manufacturing							
		Total cost, within threshold highlighted			Ratio		
Scenario	Threshold	Basic	MP	STM	Basic	MP	STM
1	1,21	€ 773 750	€ 1 235 000	€ 980 000	1,00	1,60	1,27
2	1,25	€ 747 500	€ 1 092 500	€ 920 000	1,00	1,46	1,23
3	1,19	€ 2 038 750	€ 3 380 000	€ 2 495 938	1,00	1,66	1,22
4	1,23	€ 2 012 500	€ 2 990 000	€ 2 343 125	1,00	1,49	1,16
5	1,19	€ 543 750	€ 715 000	€ 612 500	1,00	1,31	1,13
6	1,23	€ 517 500	€ 632 500	€ 575 000	1,00	1,22	1,11
7	1,15	€ 1 377 500	€ 1 950 000	€ 1 485 313	1,00	1,42	1,08
8	1,20	€ 1 351 250	€ 1 725 000	€ 1 394 375	1,00	1,28	1,03
9	1,19	€ 747 500	€ 1 235 000	€ 966 875	1,00	1,65	1,29
10	1,21	€ 721 250	€ 1 092 500	€ 906 875	1,00	1,51	1,26
11	1,15	€ 2 012 500	€ 3 380 000	€ 2 482 813	1,00	1,68	1,23
12	1,20	€ 1 986 250	€ 2 990 000	€ 2 330 000	1,00	1,51	1,17
13	1,15	€ 517 500	€ 715 000	€ 599 375	1,00	1,38	1,16
14	1,20	€ 491 250	€ 632 500	€ 561 875	1,00	1,29	1,14
15	1,10	€ 1 351 250	€ 1 950 000	€ 1 472 188	1,00	1,44	1,09
16	1,14	€ 1 325 000	€ 1 725 000	€ 1 381 250	1,00	1,30	1,04
17	1,20	€ 400 000	€ 390 000	€ 382 813	1,04	1,02	1,00
18	1,17	€ 373 750	€ 345 000	€ 359 375	1,08	1,00	1,04
19	1,25	€ 630 000	€ 910 000	€ 750 313	1,00	1,44	1,19
20	1,22	€ 603 750	€ 805 000	€ 704 375	1,00	1,33	1,17
21	1,25	€ 342 500	€ 260 000	€ 290 938	1,32	1,00	1,12
22	1,22	€ 316 250	€ 230 000	€ 273 125	1,38	1,00	1,19
23	1,22	€ 486 250	€ 585 000	€ 520 625	1,00	1,20	1,07
24	1,33	€ 460 000	€ 517 500	€ 488 750	1,00	1,13	1,06
25	1,08	€ 373 750	€ 390 000	€ 369 688	1,01	1,05	1,00
26	1,00	€ 347 500	€ 345 000	€ 346 250	1,01	1,00	1,00
27	1,11	€ 603 750	€ 910 000	€ 737 188	1,00	1,51	1,22
28	1,00	€ 577 500	€ 805 000	€ 691 250	1,00	1,39	1,20
29	1,11	€ 316 250	€ 260 000	€ 277 813	1,22	1,00	1,07
30	1,00	€ 290 000	€ 230 000	€ 260 000	1,26	1,00	1,13
31	1,17	€ 460 000	€ 585 000	€ 507 500	1,00	1,27	1,10
32	1,00	€ 433 750	€ 517 500	€ 475 625	1,00	1,19	1,10
33	1,19	€ 702 500	€ 1 092 500	€ 873 125	1,00	1,56	1,24
34	1,23	€ 676 250	€ 950 000	€ 813 125	1,00	1,40	1,20
35	1,15	€ 1 802 500	€ 2 990 000	€ 2 203 438	1,00	1,66	1,22
36	1,20	€ 1 776 250	€ 2 600 000	€ 2 050 625	1,00	1,46	1,15
37	1,15	€ 502 500	€ 632 500	€ 550 625	1,00	1,26	1,10
38	1,20	€ 476 250	€ 550 000	€ 513 125	1,00	1,15	1,08
39	1,10	€ 1 227 500	€ 1 725 000	€ 1 316 563	1,00	1,41	1,07
40	1,14	€ 1 201 250	€ 1 500 000	€ 1 225 625	1,00	1,25	1,02
41	1,15	€ 676 250	€ 1 092 500	€ 860 000	1,00	1,62	1,27
42	1,20	€ 650 000	€ 950 000	€ 800 000	1,00	1,46	1,23
43	1,10	€ 1 776 250	€ 2 990 000	€ 2 190 313	1,00	1,68	1,23
44	1,14	€ 1 750 000	€ 2 600 000	€ 2 037 500	1,00	1,49	1,16
45	1,10	€ 476 250	€ 632 500	€ 537 500	1,00	1,33	1,13
46	1,14	€ 450 000	€ 550 000	€ 500 000	1,00	1,22	1,11
47	1,00	€ 1 201 250	€ 1 725 000	€ 1 303 438	1,00	1,44	1,09
48	1,00	€ 1 175 000	€ 1 500 000	€ 1 212 500	1,00	1,28	1,03
49	1,25	€ 377 500	€ 345 000	€ 349 063	1,09	1,00	1,01
50	1,22	€ 351 250	€ 300 000	€ 325 625	1,17	1,00	1,09
51	1,22	€ 577 500	€ 805 000	€ 671 563	1,00	1,39	1,16
52	1,33	€ 551 250	€ 700 000	€ 625 625	1,00	1,27	1,13
53	1,22	€ 327 500	€ 230 000	€ 268 438	1,42	1,00	1,17
54	1,33	€ 301 250	€ 200 000	€ 250 625	1,51	1,00	1,25
55	1,17	€ 452 500	€ 517 500	€ 470 000	1,00	1,14	1,04
56	1,00	€ 426 250	€ 450 000	€ 438 125	1,00	1,06	1,03
57	1,11	€ 351 250	€ 345 000	€ 335 938	1,05	1,03	1,00
58	1,00	€ 325 000	€ 300 000	€ 312 500	1,08	1,00	1,04
59	1,17	€ 551 250	€ 805 000	€ 658 438	1,00	1,46	1,19
60	1,00	€ 525 000	€ 700 000	€ 612 500	1,00	1,33	1,17
61	1,17	€ 301 250	€ 230 000	€ 255 313	1,31	1,00	1,11
62	1,00	€ 275 000	€ 200 000	€ 237 500	1,38	1,00	1,19
63	1,00	€ 426 250	€ 517 500	€ 456 875	1,00	1,21	1,07
64	2,00	€ 400 000	€ 450 000	€ 425 000	1,00	1,13	1,06

Appendix 15 - DSS and mathematical model recommendations comparison cellular manufacturing

Cellular manufacturing												
Scenario	DSS recommendation			MM recommendation			Common recommendation			Additional from MM		
1	Basic		STM	Basic			Basic					
2	Basic		STM	Basic		STM	Basic		STM			
3			STM	Basic						Basic		
4	Basic		STM	Basic		STM	Basic		STM			
5			STM	Basic		STM			STM	Basic		
6	Basic		STM	Basic	MP	STM	Basic		STM		MP	
7			STM	Basic		STM			STM	Basic		
8		MP	STM	Basic		STM			STM	Basic		
9	Basic		STM	Basic			Basic					
10	Basic		STM	Basic			Basic					
11	Basic		STM	Basic			Basic					
12	Basic		STM	Basic		STM	Basic		STM			
13	Basic		STM	Basic			Basic					
14	Basic		STM	Basic		STM	Basic		STM			
15			STM	Basic		STM			STM	Basic		
16			STM	Basic		STM			STM	Basic		
17	Basic		STM	Basic	MP	STM	Basic		STM		MP	
18	Basic			Basic	MP	STM	Basic				MP	STM
19	Basic		STM	Basic		STM	Basic		STM			
20	Basic		STM	Basic		STM	Basic		STM			
21	Basic		STM		MP	STM			STM		MP	
22	Basic		STM		MP	STM			STM		MP	
23	Basic		STM	Basic	MP	STM	Basic		STM		MP	
24	Basic	MP	STM	Basic	MP	STM	Basic	MP	STM			
25	Basic			Basic	MP	STM	Basic				MP	STM
26	Basic				MP						MP	
27	Basic			Basic			Basic					
28	Basic			Basic			Basic					
29	Basic				MP	STM					MP	STM
30	Basic				MP						MP	
31	Basic		STM	Basic		STM	Basic		STM			
32	Basic			Basic			Basic					
33			STM	Basic						Basic		
34	Basic		STM	Basic		STM	Basic		STM			
35			STM	Basic						Basic		
36		MP	STM	Basic		STM			STM	Basic		
37			STM	Basic		STM			STM	Basic		
38		MP	STM	Basic	MP	STM		MP	STM	Basic		
39			STM	Basic		STM			STM	Basic		
40		MP	STM	Basic		STM			STM	Basic		
41	Basic		STM	Basic			Basic					
42	Basic		STM	Basic			Basic					
43			STM	Basic						Basic		
44			STM	Basic						Basic		
45			STM	Basic						Basic		
46			STM	Basic		STM			STM	Basic		
47			STM	Basic						Basic		
48			STM	Basic						Basic		
49	Basic		STM	Basic	MP	STM	Basic		STM		MP	
50	Basic		STM	Basic	MP	STM	Basic		STM		MP	
51	Basic		STM	Basic		STM	Basic		STM			
52	Basic	MP	STM	Basic	MP	STM	Basic	MP	STM			
53	Basic		STM		MP	STM			STM		MP	
54	Basic	MP	STM		MP	STM		MP	STM			
55			STM	Basic	MP	STM			STM	Basic	MP	
56		MP		Basic						Basic		
57	Basic			Basic	MP	STM	Basic				MP	STM
58	Basic				MP						MP	
59	Basic		STM	Basic			Basic					
60	Basic			Basic			Basic					
61	Basic		STM		MP	STM			STM		MP	
62	Basic				MP						MP	
63			STM	Basic						Basic		
64	Basic	MP	STM	Basic	MP	STM	Basic	MP	STM			

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