Juan Carlos Ayala Zavaleta

Assessment of Order Picking Technologies in Picker-to-parts Order Picking Systems: An MCDM Approach

Master's thesis in Global Manufacturing Management
Supervisor: Fabio Sgarbossa
Co-supervisor: Vivek Vijayakumar
August 2022

Master's thesis

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Acknowledgments

Fast forward 2+1 years at NTNU in Trondheim, time has come to finally finish this cycle. After more than 8700kms skiing, more than 1400hrs of training, 26kg lost, many interesting lectures, trips, adventures, and experiences; the time has come.

First, I would like to thank Vivek Vijayakumar sincerely and infinitely, the co-supervisor for this thesis, for his undoubted help, encouragement, and deep understanding of the topic. Much of this happened from your guidance. Marco Semini for your patience in the process. Fabio Sgarbossa, the supervisor for this thesis, you were key to achieve this delivery; your understanding of the extra-academic situation and your knowledge and inspiration in the topic made it possible.

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An incredibly special thanks goes to my family, for supporting me in ways I did not think I would need to be supported. Physically far from you but always close in soul. Thanks for asking always how the thesis is going rather than how the skiing going to remind me what was important.

After deciding to live the life of athlete for two seasons and put in pause the engineering academic side it feels wrong not to mention the team that helped me to be the skier and person I am now. Virginia, Erik, Geske, Angélica, Clarissa, Ella, and Mihailo. Thanks for including me in your group and for teaching me so much about sport science, only then I was reading papers. Engineering and sports are not as separate as we might think.

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This thesis marks the joint contribution of effort, time, knowledge, energy, of many people along this academic and sportful journey. It has been a long way but and none of this would have been possible without any of you. Once again: Thank you. Tusen takk. Gracias.

"Sin miedo al éxito"

Summary

This thesis evaluates the available order picking technologies and their level of automation based on performance criteria in picker-to-parts order picking systems. To evaluate these technologies a group MCDM approach was used to include experts knowledge and to deliver a ranked list.
The research was guided and based through research questions:

1) What are the main performance criteria of the order picking system in a picker-to-parts warehouse?
2) What are the most suitable order picking technologies for a warehouse that operates with a picker-to-parts method?
3) What should managers be aware when implementing an order-picking technology in a warehouse?

The research methodology of the present thesis is based in a combination of literature reviews, MCDM through group AHP and a sensitivity analysis of the results. The literature study was performed to find the performance criteria in a picker-to-parts OP system and to find the order picking technologies available. The MCDM was performed with a panel of operational experts from different countries and industries with experience in order picking, and an academic expert in warehousing and logistics using the criteria and technologies found in the literature studies.

Little literature in multi-criteria decision-making was found in the field of order-picking, thus the relevance of this study and the value it provides to both the academy, and the industry is based in the support for taking decisions backed up in relevant data when assessing OP technologies in a picker-to-parts OPS. A holistic approach, considering economic performance, quality, and wellbeing of the operators was considered to assess the different technologies. Furthermore, three different system settings, independent from industry or type of warehouse, were defined and analyzed with the aim to find the most suitable OP technology for each scenario. Results show that technologies with a higher level of automation are preferred over manual solutions because they provide better quality and wellbeing, however DMs have a strong preference for considering the economic performance of the OP system, where manual technologies score better. Future research should focus in using fuzzy theory to account for uncertainty, and comparing more combinations of different technologies in the same analysis.

Keywords: MCDM, order picking, picker-to-parts, warehouse, group AHP.

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Abbreviations

Abbreviation	Meaning
AGV	Automated Guided Vehicle
AHP	Analytic Hierarchy Process
AIJ	Aggregation of Individual Judgements
AMR	Autonomous Mobile Robot
AS/RS	Automated Storage & Retrieval System
DM	Decision Maker
GMM	Geometric Mean Method
HF	Human Factors
HMD	Head Mounted Devices
KPI	Key Performance Indicator
LOA	Level of Automation
MCDM	Multiple-Criteria Decision-Making
MH	Material Handing
OP	Order-Picking
OPS	Order Picking System
PTR	Pick and Transport Robot
RQ	Research Question
SA	Sensitivity Analysis
SC	Supply Chain
SKU	Stock Keeping Unit
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution

1. Introduction

The first chapter has the purpose to describe the overall research topic presenting the theoretical and practical motivation for the work. Then, the guiding research questions and objectives of the thesis are presented. Followed by a definition and explanation of the scope. Finishing with the thesis outline and structure.

1.1 Background

Warehouses are a basic component of any supply chain since they are the link that, among other tasks, stores the inventory and distribute the product further down to the chain. The essential objective of a warehouse is to serve the customer demand while using resources in an efficient manner; in other words, to deliver the right amount to the right customer when it is requested. With an increasingly globalized and competitive environment, where customers are more demanding and better informed, and tighter supply chains looking to take advantage of any margin, it makes sense that warehouses are required and expected to execute more transactions of smaller volumes, to manage a bigger product catalogue, to provide a wider service customization, and to process more returns (Frazelle, 2002). From this starting point, warehouses play a strategic role in businesses, and they should not be only seen as cost centers because they can add value to the customer by customization, availability, shorter delivery times than the competition and increasing the service level.

Through the years the function of a warehouse has evolved from only storing goods to assemble orders, add value to products through services and even to assembly products to fulfill a required customization (Frazelle, 2016) Independently from the industry, type of product, or sub-processes performed, a warehouse or distribution center, as it is often called, employs a form of the traditional which is composed of receiving, put-away, storage, order picking and shipping (Frazelle, 2016). This thesis will focus on the order picking process, and it will be referred as order picking system as it is composed of several parts forming the whole unit and it creates value.

The order picking activity is often the most resource and time consuming within a warehouse (Frazelle, 2016) as it typically accounts for 55% of the warehouse operating costs (Bartholdi and Hackman, 2019). It can be defined as the process of retrieving products from storage in response to a specific customer request (de Koster et al., 2007). This activity has been subject of extensive research with the objective to make its processes more efficient, reduce costs, and even develop innovative technologies. It is important to recall that many of the decision-support systems and projects in warehousing are in order picking (Frazelle, 2016), and this thesis adds up to this point. Moreover, according to Frazelle (2016) most of the errors in a warehouse operation occur in order picking and shipping, which indicates the necessity to put attention and further develop frameworks to make the order picking system error-proof. Since developing and operating an order picking system is a demanding and expensive task, then it is logical to analyze it in detail.

OP systems can be classified by the employment (or not) of humans, and in a more specific level, by how picker and parts interact to fulfill the order, according to de Koster et al. (2007). When the operator goes into the storage area to fetch and retrieve the specific stock keeping unit, it is called a picker-to-parts method; this method is the most common, usually for its high flexibility and lower cost than other methods (De Koster, 2012). When the operator is standing in an area and the SKUs are made available to them, then it is a parts-to-picker method; this method involves advanced automation since usually an automated storage and retrieval system (AS/RS) or a vertical lift module (VLM) is used. It is important to mention that most of the research in OP has focused on the parts-to-picker method. The present thesis will focus on the different technologies for a picker-to-parts method because nearly 90% of the warehouses operates within this scheme costs (Bartholdi and Hackman, 2019).

A central part of the OP system is the technology used to achieve a certain level of performance. Automation within the picker-to-parts method has been used with the intent to increase the overall performance of the system in order to minimize loss of productivity, quality errors and to improve the working conditions of the operators. However, it is the human factors that can deviate the actual performance of the technology from the planned performance. Research has been done on automation in picker-to-parts (Azadeh et al. (2019), Boysen et al. (2019), Fottner et al. (2021), Glock et al. (2020), and Jaghbeer et al. (2020)) but these don’t consider the HF aspects, therefore it is valid to assume that practitioners in the warehouse industry also neglect these factors. This work then takes relevance since it would be the first of its kind to assess OP technologies within the picker-to-parts method including the HF.

Selecting the correct OP technology is a significant task that decision makers need to address to have the best possible OP system within their constraints and work environment. This decision has direct implications for the operational ground because the technology interacts directly with the OP tasks (setup, search, travel, and pick) as well as for the strategic level since these implementations require capital expenditure and depend directly on the design characteristics of the OP system (batching, zoning, layout design, and storage assignment). Hence, such decision does not have only one dimension but several as well as various alternatives, increasing the complexity of taking the decision. For these reasons, a multi-criteria decision-making method, such as the analytical hierarchy process, is employed in this thesis because the DM has to consider all the dimensions of the problem at hand and find a solution from a system perspective.

The OP technology selection problem considering the human factors has not been explored before in literature. Therefore, it is relevant for both the academic and practical perspectives to understand more in the topic. This thesis compares not only manual OP technologies but all the automation range, from manual to completely automated considering assisted solutions. For this purpose, AHP is selected as the MCDM method because it has been used before in similar studies, the following are examples: selection of material handling technologies (Horňáková et al., 2021), selection of warehouse location (Singh et al., 2018), (Bingqing and Liting, 2020),(Ratih Dyah Kusumastuti, 2018), framework for logistics operations in distribution centers (Vidal Vieira et al., 2017), selection and ranking technologies for mining (Namin et al., 2022), underground mining method selection (Gupta and Kumar, 2012), photovoltaic technology selection (van de Kaa et al., 2014), material selection for optimal design (Emovon and Oghenenyerovwho, 2020), technology selection to support energy management (Ferreira et al., 2019), and assessment of green technologies in buildings (Si et al., 2016). With the proposed methodology, resources, and objectives, this work is addressing a relevant real-life problem that can serve as a reference for future and current practitioners and researchers.

1.2 Problem Description

Up to today, there is no other academic research that has considered productivity, quality, and wellbeing criteria to select an order picking technology within the picker-to-parts method, much less a study that considers the different system settings in an OP system. This literature gap should be studied so that practitioners take decisions based on a methodology backed up by data.

Managers are usually challenged with decisions where the criteria may contradict each other. Order Picking is the most resource consuming process in a warehouse and it is vital for achieving high service level in a warehouse. Therefore, selecting the right order picking technology is no simple task since it directly impacts many performance indicators.

Currently managers depend on technology vendors and external consulting companies to assess and decide what type of technology to use in their OP system. For the organizations that take the decision internally, the process is based on a combination of experience, capital available, and willingness to change. Consequently, practitioners need a structured and methodologic decision-making process that considers academically approved criteria to reach a valid and logic answer.

Addressing the literature gap in the topic and the practical need for warehouse managers to select an OP technology in a picker-to-parts OP system, this thesis tries to provide insight in the field and be of utility to decision makers.

1.3 Research Objective and Research Questions

The present works parts from the understanding in literature that OP in warehousing operations is critical to achieve an optimal service level in the overall supply chain but also from the perspective that OP systems are the most resource consuming within a warehouse. From these perspectives, the technology selection for the OP system is an important tactical decision where not only the economic factor should be considered but also how the technology fits within a given environment and how it impacts the performance indicators.

Focusing on the picker-to-parts method, five different system settings are the most common ones: multilevel picking (case/pallet) and floor level (pallet). Since warehouses can have different system settings therefore one technology might not fit all the different scenarios. In other words, the most appropriate technology varies depending on how the warehouse is set.

The main goal is to construct a framework that helps decision makers to understand the implications of order picking technologies in the different scenarios. From this premise, the first specific objective is to find the most appropriate picker-to-parts order picking technology for each of these scenarios. In order to find and rank the technology suggestion, criteria need to be defined based on three relevant areas: productivity metrics, quality metrics and wellbeing metrics. In turn, each criterion is composed of relevant subcriteria. A secondary objective is to find the weight of the criteria and subcriteria for each of the three scenarios

A subgoal of this study is to work with high quality data in order to produce valid and reliable results. Hence, knowledgeable experts in the operational field and recognized experts in the academic field will be contacted to collect data.

Through the selected methodologies it is possible to assemble a framework which results will be criteria weights and a technology ranking. This framework can help managers with clear information about what they should consider when implementing a technology in the OP system depending on their type of warehouse.

In order to reach the objectives, the following research questions have been formulated:

4) What are the main performance criteria of the order picking system in a picker-to-parts warehouse?
5) What are the most suitable order picking technologies for a warehouse that operates with a picker-to-parts method?
6) What should managers be aware when implementing an order-picking technology in a warehouse?

In chapter 2, the methodology followed to answer these questions is explained in detail.

Research question	Objectives	Methodology	Deliverable for practitioners
What are the main performance criteria of the order picking system in a picker-to-parts warehouse?	- To find the performance criteria and subcriteria for the OP system scenarios.	- Literature review	Relative weights of performance criteria
What are the most suitable order picking technologies for a warehouse that operates with a picker-to-parts method?	- To find the state-of-the-art OP technologies for a picker-to-parts method. - To find the most suitable picker-to-parts OP technology for each of the three OP system scenarios.	- Literature review - Group MCDM - Based on RQ1	A ranked suggestion of the OP technology for each scenario
What should managers be aware when implementing an order-picking technology in a warehouse?	- To validate the MCDM model - To construct a framework that helps DMs to understand the implications of OP technologies in the different scenarios	- Sensitivity analysis of the MCDM model - Based on RQ1 & RQ2	Sensitivity analysis varying the weight of criteria. A rational framework for assessing OP technologies against OP criteria.

Table 1 – Research questions, objectives, methodology, and deliverables for practitioners

1.4 Research Scope and Structure

This thesis is concerned to the technology selection for an OP system in warehousing. Since warehouse operations is such a broad field, it is reasonable to focus on only one aspect, but at the same time it is important to mention that a system perspective on the overall operation is needed to understand the relevance of the topic at hand. To address the interaction of the OP system with other warehouse processes, operational experts with practical experience in managing such systems were interviewed to collect relevant data. Focusing on the order picking system is relevant because it is well documented in literature about how resource consuming and important the activity is.

The industry of the warehouses is an independent variable since all the warehouses can be characterized by their OP method. Therefore, as long as there are order picking activities in the method of picker-to-parts, the study is relevant, regardless of the type of goods handed. This work will focus on the picker-to-parts method where the following three different system settings are the most common ones according to the way the tasks are performed:

1. Multilevel – Case (items are stored in different levels and picker retrieve a case of product at a time)
2. Multilevel – Pallet (items are stored in different levels and picker retrieves a full pallet at a time)
3. Floor level – Pallet (items are not stacked therefore are stored in the floor and picker retrieves a full pallet at a time)

These three system settings are also referred as scenarios in the thesis to make it easier for the reader to follow up the different models set up. A more detailed explanation of the three system settings can be found in section 2.1.4.

Given that the scope of the thesis corresponds to the order picking system in warehouses, it will not address other parts of the material handing process in the warehousing. Likewise, it will not consider the logistic position, in the physical and strategic dimensions, of the warehouse in the overall supply chain system.

Within OP systems, there are different methods, technology characterizations and levels of automation. The present thesis is concerned with the picker-to-parts method. As for the level of automation in the order picking technologies, all the range is considered, from paper and paperless picking to completely automated picking.

Regarding to the literature review, the search was restricted to relevant topics such as order picking, performance criteria in order picking, performance criteria in warehousing, and order picking technologies. The rationale for this is that the focus of the thesis is directed towards selecting the most appropriate technology for OP and finding the criteria to performance criteria to select such technologies. Therefore, the purpose of this work is not to create a new OP method, or develop new OP technologies, or change how practitioners measure and benchmark an OP system, but to develop a framework to select an OP technology for a warehouse with given system settings, based on common and understood criteria. The illustration bellow depicts where this thesis will be focusing in the overall topic of warehousing.

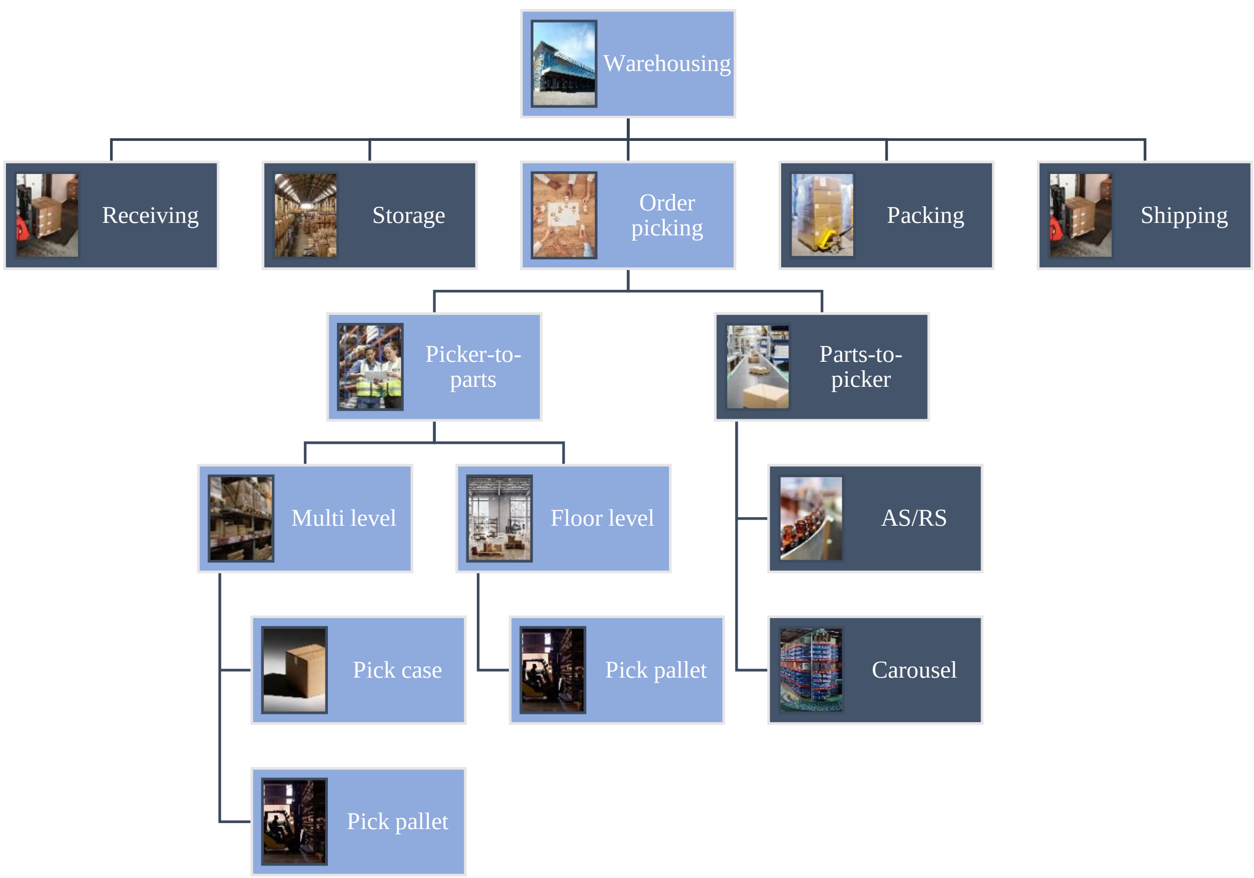


Figure 1 – Thesis topic localization, adapted from Tompkins et al. (2010) and de Koster et al. (2007)

The structure of the thesis at hand follows a logic flow using a funneling strategy where the generalities, motivation and overall problem is described at the beginning of the work and each chapter becomes more specific to answer the RQs and achieve the research objectives. In the next figure the research outline and its correlation to the thesis chapter structure can be found.

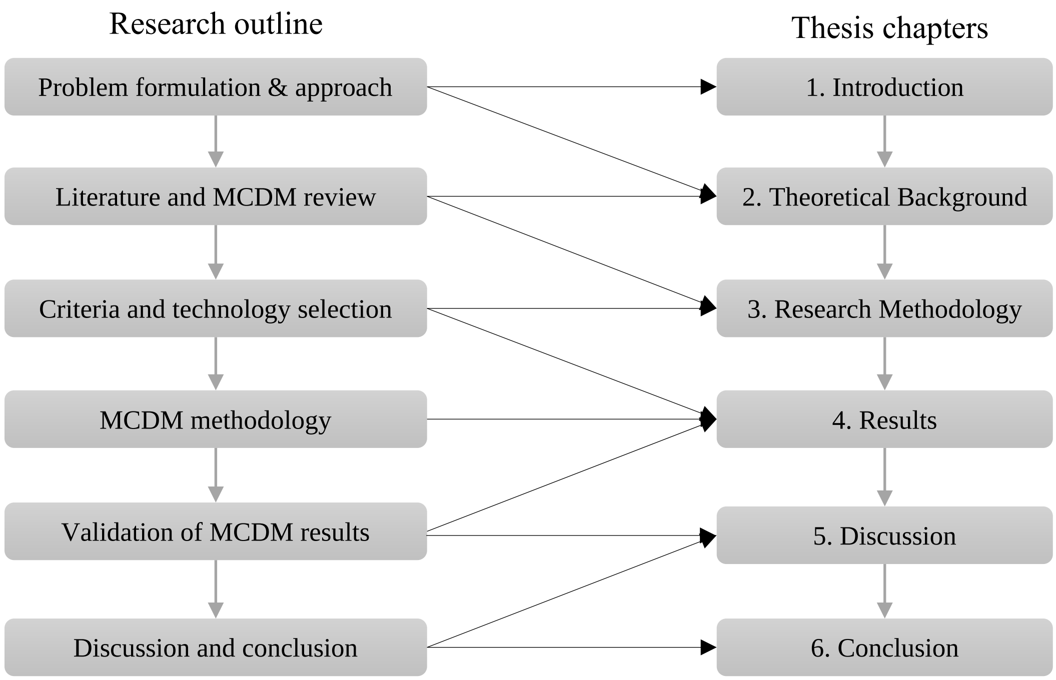


Figure 2 - Research outline and thesis chapters

2. Theoretical Background

This chapter serves as a general introduction to the order picking topic where other relevant aspects out of the scope of this thesis are explained to have a full understanding and overview of the topic. For this thesis, order picking is the backbone of the whole work, therefore it is relevant to establish a starting ground. The chapter begins with general definitions and the different OP tasks and goes in depth to the design characteristics and OP system settings.

2.1 Order picking

From the perspective that warehouses are inventory buffers in the supply chain, OP would be the link in the chain between specific order customers and the overall demand. With this in mind, order picking can be defined as the process of collecting products from the general inventory to fulfill a personalized customer orders (de Koster et al., 2007). For this reason, order picking systems are typically always found within any warehouse operation. Since OP has the purpose to comply with customers needs, it has often been analyzed and presented as the most resource and time consuming process in a warehouse (Frazelle, 2016) as well as the determinant for the service level with downstream customers (Bartholdi and Hackman, 2019).

Order picking systems can be divided into two depending on how the picker, independently of robotized solution or human, interacts with the parts namely: picker-to-parts or parts-to-picker (de Koster et al., 2007). When the parts are moved into the station of the picker, it is a parts-to-picker OP system, this type of systems are usually dependent on high level of automation because the different activities happen automatically. When the picker is the one traveling through and searching in the warehouse for the parts, it is a picker-to-parts OP system, this is the most common type of system found because it provides a high degree of flexibility and lower costs. (De Koster, 2012).

2.1.1 Order picking policies

Characterizing the complexity of an OP system can be done by assessing the five order picking policies, also called order picking planning problems (van Gils et al., 2018). Which are: routing, storage, batching, zoning and order release mode (de Koster et al., 2007). The routing policies have the objective of optimizing the sequence of the items in the picking list so the picker spends the least time possible in the warehouse, according to de Koster et al. (2007) this can be understood as a development of the classic travelling salesman problem. The storage assignment policies are concerned with how the products are located within the warehouse and the prerequisite for a successful policy is to decide which activities will take place where in the system (de Koster et al., 2007). Batching policies attend the principle of optimizing picking tours by grouping orders (de Koster et al., 2007), where the decision depends on two criterias: the proximity and the delivery time window (Sharp et al., 1991). Zoning policies act as a division of the picking area where a picker is responsible for an assigned zone and potentially decreasing the traveling and congestions in the area (de Koster et al., 2007). Lastly, the order release mode policy is used in conjunction with batching and/or zoning policies to further split the batch and consolidate the orders therefore making a wave-picking or a continuous picking method system (de Koster et al., 2007). These policies should work towards the same goal of maximizing the service level however advanced policies increase the complexity of the OP system as they require more control. In this thesis these policies are not subject of study and fall out of the scope because the technologies should adapt to the existing policies in the warehouse.

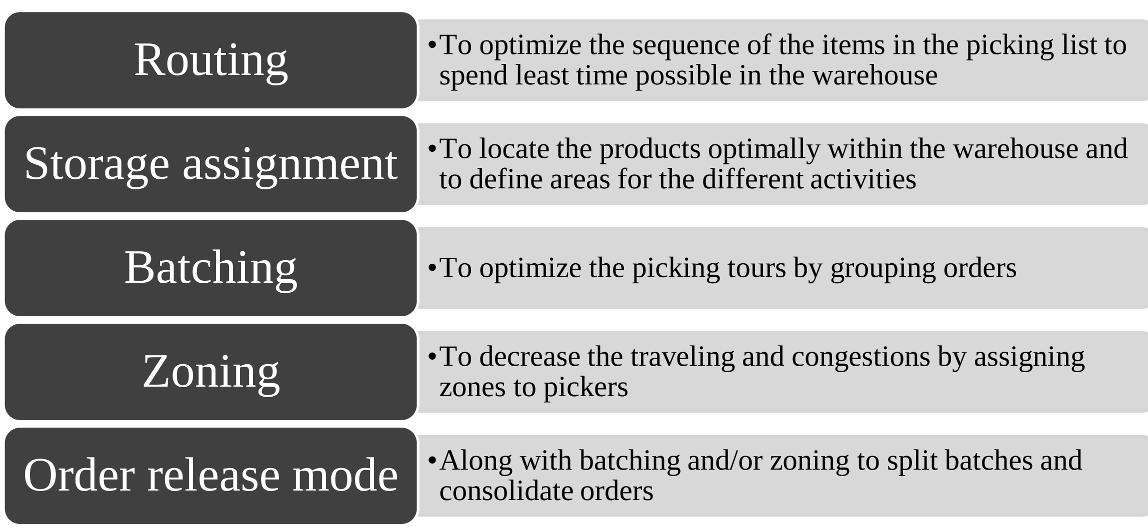


Figure 3 – Order picking policies, adapted from de Koster et al. (2007)

2.1.2 Order picking tasks

A picker-to-parts OP system has four tasks that are performed in a sequential manner by the picker: setup consisting of the preparation of the order, travel consisting of physically moving to the needed location, search defined as identifying the item in the location, and pick which is grabbing the item in the right quantity (Gu et al., 2007). These tasks can be used to characterize the level of automation of the different OP technologies. The level of automation achieved depends on the degree that the technology automates or assist the specific task.

Vijayakumar and Sgarbossa (2021) divided the technologies in four possible categories: manual, paperless picking, AGV/AMR assisted picking and pick and transport robot. This technology classification is relevant to this thesis because it helps to order and understand the characteristics of the OP technologies that will be assessed and suggested. The figure below is a merger of the OP tasks and the LOA of the OP technologies in a picker-to-parts environment.

OP Tasks	Solutions for picker-to-parts OP			
	Manual	Paperless picking	AGV assisted picking	Pick and transport robot
Setup	M	A/M	A/M	A
Travel	M	M	A	A
Search	M	A/M	M	A
Pick	M	M	M	A

Figure 4 – LOA and OP tasks, collected from Vijayakumar and Sgarbossa (2021)

2.1.3 Order picking productivity factors

OP was defined previously as the point where specific customer orders get assembled from the overall available inventory and it is critical to achieving a desired service level, moreover it is accountable for 50% of the staff in a warehouse (Rushton et al., 2017) therefore it is also needed to define what influences an OP system productivity. According to Rushton et al. (2017) the OP productivity depends on the operational requirements, such as the size, scale, catalogue range, and number of items to pick. Equipment such as use of racks and assisted trolleys or trucks. Management such as the work processes, the workload balancing, stock accuracy, and motivation. IT such as technological aids. It is worth to mention that even though Rushton et al. (2017) talk about motivation and technological aids the overall human factors of the operators are not considered even though an OP system still uses a considerable percentage of human resources.

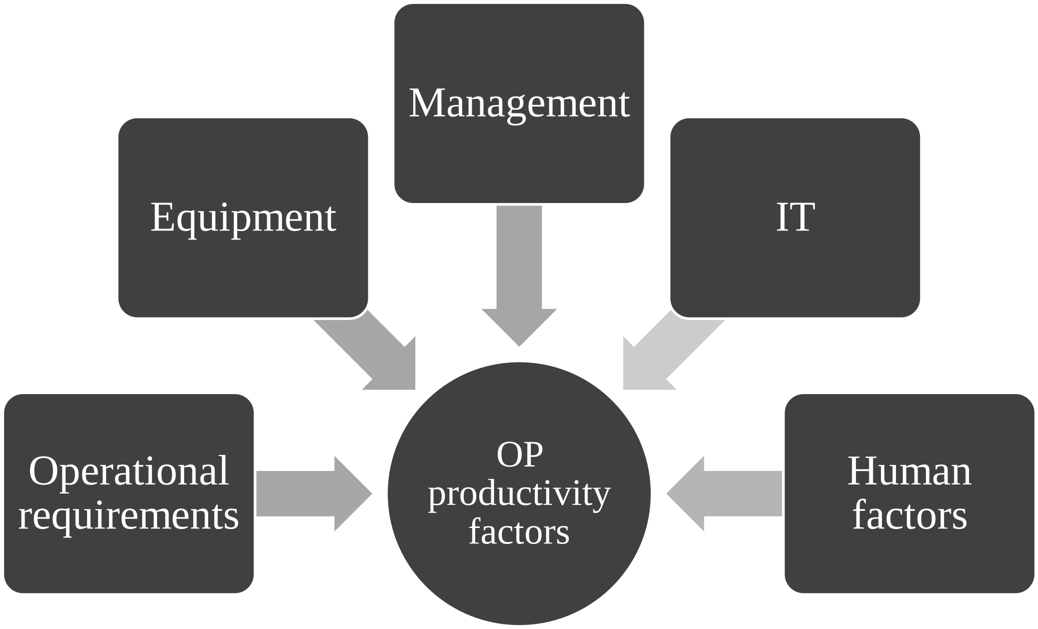


Figure 5 – OP productivity factors, adapted from Rushton et al. (2017)

2.1.4 Order picking system settings - scenarios

The following OP system settings are valid independently of the industry and nature of the products stored and picked in a warehouse, furthermore the OP tasks and policies described previously will still apply. The first division in the system settings correspond by how the products are stored in the warehouse, multilevel or floor level. Multilevel picking stands for items that are stacked in more than one level, usually it is with a help of a rack, but package or pallet stacking is also possible. Floor level stands for the case where the items are not stacked into different levels and typically, they are in the ground, this setting is commonly used for bulky goods that does not fit in racks or the handling is special, or the pallet is too heavy for the rack. The second division in the system settings corresponds to the unit picked: case, or pallet. In a multilevel scenario the two different units could be picked, whereas in a floor level scenario pallets could be picked. The three different OP system settings are relevant to the study because even though the OP tasks are the same, the implications and technologies used are different, therefore it is worth to analyze each of these scenarios.

Type of item / Stacking level	Case	Pallet
Multilevel	X	X
Floor level		X

Table 2 – Type of item considered per type of stacking

Scenario	Scenario ID
Multilevel Case	Mul-Cs
Multilevel Pallet	Mul-Pl
Floor level Pallet	Flo-Pl

Table 3 – Scenario IDs

The three system settings were converted into generic operational scenarios with the aim to provide a context for the OP technology assessment. The data to conform the context was provided by managers of warehouses where an OP system is already in place and it was generalized so as other operations can also be benefited from the results. The contexts are divided according to the three system settings, and it can be said that the size of the operation corresponds to a medium to large warehouse. The number of aisles was calculated using a simplified equation developed by Caron et al. (1998) with the aim to match the picking area, furthermore, to simplify the model no cross aisles were selected as this is a factor that directly impacts the traveling distance. The length of the aisles can be considered as long and the width is typical for forklifts to operate and be able to turn. A specification about the conditions of the warehouse is needed as outdoor warehouses have different implications than indoor warehouses but the majority of warehouses store dry items at ambient temperatures, specialized warehouses can have different temperatures, but this work is scoped to the most typical type of operation. The order volume is based on the assumption that a case-based OP operation has a bigger volume since in the sorting area a pallet can contain many orders. For a pallet-based operation, one pallet can only be either one order or part of an order, moreover in a bulky goods one order could also be divided into different pallets due to space reasons. Regarding the working hours of the scenarios, a 3 shifts operation with Sunday as day off was standardized for the three scenarios. See table below for the specifications used in the data collection for the ranking of OP technologies.

Scenario / Characteristics	Multilevel Case	Multilevel Pallet	Floor level Pallet
Aisles	40 to 60 aisles (no cross aisle)		
Aisle length	40m-50m		
Aisle width	4m-5m		
Picking area	Multilevel racks (up to 5 levels)		Ground level – no stacking
Products picked	Cases (all sizes but possible for operators to carry)	Pallets	Pallets – Bulky goods
SKU catalogue	Over 500 SKUs		
Storage characteristics	Ambient temperature - indoor		
Volume (per day)	In average 4000 orders	In average 1500 orders	In average 1300 orders
Shifts	3 shifts (Sunday is off)		

Table 4 – Scenario characteristics

3. Research Methodology

This chapter defines the research methodology used to address the RQs and accomplish the research objectives. In general terms, RQ1 is answered with a literature review described in section 2.2, RQ2 is answered with the group MCDM via AHP described in section 2.3, and RQ3 is answered with the findings of RQ1 and RQ2 mixed with a sensitivity analysis of the AHP model. The following illustration summarizes the overall research methodology of this thesis.

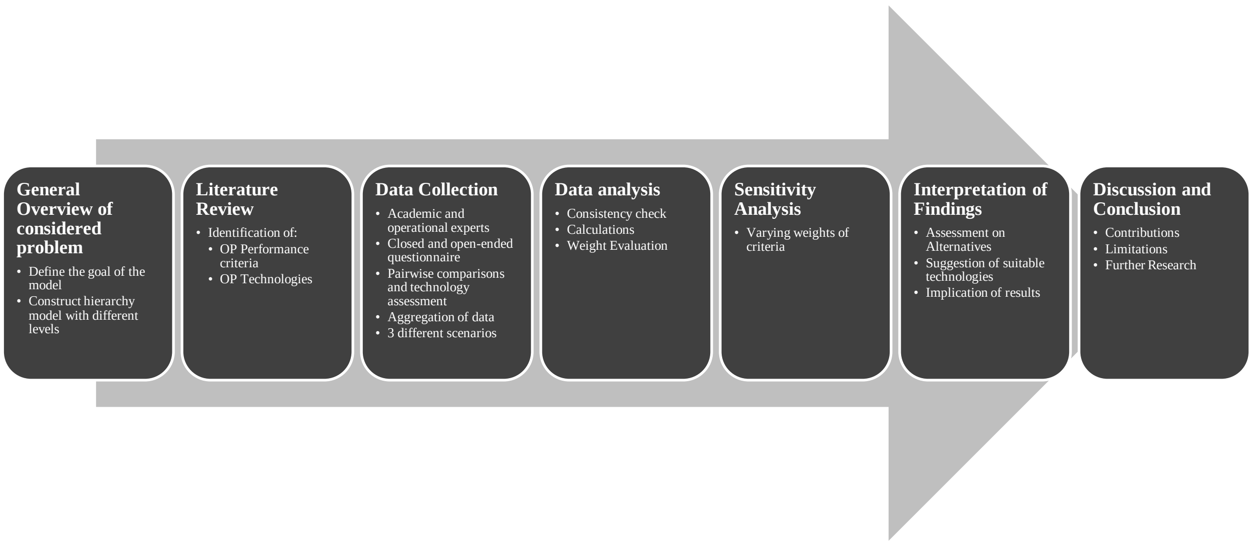


Figure 6 – Summary of research methodology

3.1 Research workflow

In order to accomplish the stated goals, a valid research methodology has been developed. Starting from defining the problem and goals. Followed by a literature review performed on the relevant topics such as warehouse operations and order picking systems in order to find the available technologies for order picking and the criteria for selecting them. Afterwards, the data collection will take place; with the specifics explained further in this document. Followed the implementation of AHP with the software SuperDecisions (Creative Decisions Foundation) to calculate the criteria weight and technology ranking. After that, a sensitivity analysis varying the weights of criteria for each scenario will be performed. Next, an interpretation of the findings and results will be written which will include an assessment of the alternatives and suggestion of the most appropriate technology. Finally, a discussion and conclusion of the research will be presented.

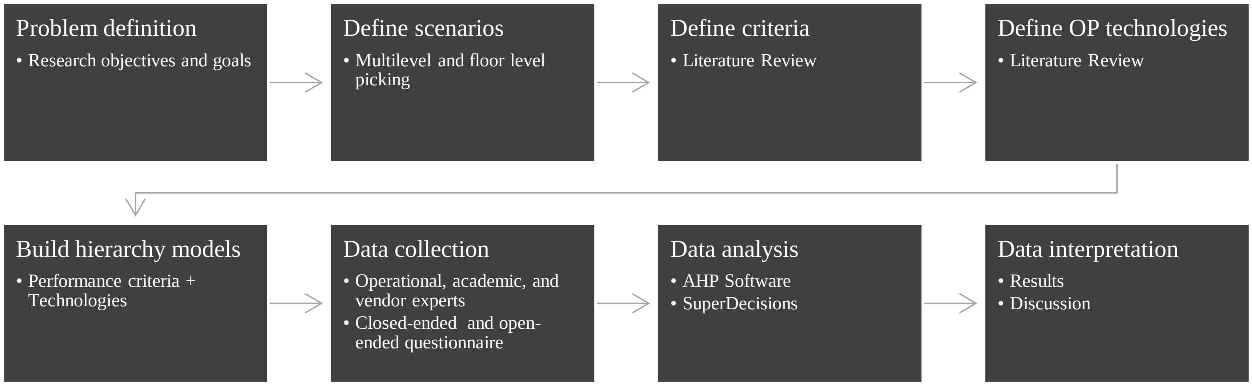


Figure 7 – Thesis workflow in relation to the research methodology

3.2 Literature Review

For the purpose of finding the performance criteria of an OP system a scientific literature study was carried out. Through the studies found and analyzed, it was clear that the performance criteria of an OP system had more than one dimension, but it is not clear how they interact with themselves as that depends on the priorities of the organization. Relevant articles from this literature review were used and mentioned in the introduction as well as in the theoretical background.

The general objective of the literature review is to search and establish a starting ground on the field of warehouse operation but focusing especially, and most importantly, in order picking, warehouse performance indicators, and order picking performance indicators. The general field of warehousing and OP is not new in the academic research hence, the idea is to gather existing knowledge and to try to unify it for RQ1 and also to provide ground for RQ3.

With the intention of merging the existent knowledge to create a new and logic model, the literature review was done from an integrative approach. As Russell (2005) explains, the benefits of an integrative literature review lay in identifying gaps in the current research, bridge between related work areas, and identifying a conceptual framework where the output could be a contribution to a particular field in practice and research. Since the problem addressed by this thesis has not been researched before but there is enough knowledge and literature on the underlying fields, an integrative review serves the purpose to identify the performance criteria of an OP system.

It is important to mention that an integrative literature review is composed of 5 stages: 1. Problem formulation, 2. Literature search, 3. Evaluation of data, 4. Data analysis and 5. Interpretation and presentation of results. Such stages are also relevant for this thesis. Since the validity of a literature study resides on its structure on which it was conducted and, on its replicability, the process of the present literature review is described as follows. Scopus and Oria databases were used for a first search of relevant scientific literature. However, only the papers accessible via the NTNU licenses were used. The main and only search language was English to have the best possible quality of papers because that is the principal language on which the leading order picking and warehousing research is published. The timeframe for the literature review was frozen up to April 2022, which means that relevant papers, books, and publications were considered up to the freeze date. When seemed appropriate for the thesis, relevant articles were also obtained from the citation and references using a snowball method.

The search strategy used Boolean operators to gather as many relevant hits as possible. Different levels and combinations in the search were used. Within the levels the operator OR was used and to connect the distinct levels the operator AND was used. The first level is composed of variations of the most generic search term; warehouse, warehousing and distribution center were also used as certain literature use distribution center as synonym and because in other languages that’s the right word for this type of building, this level is the starting ground. Level 2 helps the search aiming to find the KPIs and several forms of the performance indicator were used. Level 3 supports the search to specify the warehouse activity and delimit the search into order picking terms.

Level 1	Level 2	Level 3
Warehouse	Key Performance Indicator(s), KPI(s)	Order picking (system)
Distribution Center	Indicator	Picking
Warehousing	Criteria	

Table 5 – Search terms for literature review 1

After getting results from the search a screening was performed. The first criteria were the title and abstracts, in case the abstract was not concluding then a full text read was conducted to validate or not the relevance of that paper. For the papers where the abstract was already relevant a full text read was performed for its inclusion.

The second literature review had the goal of identifying and characterizing the existing OP technologies. For this, the same method for searching and screening, and same databases were used than previously described. This search was comprised of three levels. Level 1 was intended to set the generic environment of the search within warehouse or distribution centers. Level 2 was more specific within the warehouse environment focusing on OP and its variations. Level 3 concentrated on finding the different technologies for the topic at hand, synonyms like solution and alternatives were also used to increase the chances of finding relevant hits.

Level 1	Level 2	Level 3
Warehouse	Order picking (system)	Technology(ies)
Distribution Center	Picking	Solution(s)
		Alternative(s)

Table 6 – Search terms for literature review 2

Because the OP technology is not a field where only academics publish relevant literature, non-academic media like vendor information, industrial magazines and interviews were included in this step. However, such sources weren't considered for drawing conclusions because they lack validity, but the OP technology field and the automation is in constant development.

It is of the interest of the reader to know that another literature research was also performed in the preliminary problem stage with the aim to search for relevant resources on the application of MCDM techniques in OP technology selection. Such search was performed also in Oria and Scopus, accessing to the studies available by the NTNU license. The search included three levels. Level 1 was the most general with the topic of MCDM or MCDA. Level 1a had the goal to support the first level with specific techniques of MCDM "AHP, ANP, TOPSIS, ELECTRE, PROMETHEE", because some authors might not identify them as MCDM. Level 2 was focused in OP and its variations. Finally, Level 3 delimited the search to warehouse or distribution center. The results of this preliminary search were very limited and that increased the motivation for this thesis.

3.3 MCDM

With the purpose to answer RQ2 and to provide a suggestion for the most appropriate OP technology, a multi-criteria decision-making method is implemented in the form of analytic hierarchy process to obtain the criteria weight and technology ranks. This methodology is relevant for this question because the criteria identified by the literature review will be multiple, therefore a suggestion needs to be made considering all the dimensions. Likewise, there are more than one possible technology for the case at hand.

Decision analysis is a hot area in operation research and management science, where AHP and TOPSIS are preferred methods (Liao et al., 2019). MCDM has its origins in operation research where decision problems have different criteria and where these selection criteria might appear as conflicting. The general form of MCDM is composed of three basic steps (Triantaphyllou et al., 1998):

1. Determine relevant criteria and alternatives,
2. Determine measures to the relative importance of criteria and its relationship to the alternatives
3. Compute the values to determine a ranking for the alternatives

One of the many applications of MCDM methodology is to solve problems where it is of interest to find the best alternative while at the same time there is an interest of finding the relative importance of all the alternatives and criteria selection under consideration. Moreover, there might be different configurations available which increases the complexity of the decision model. For these reasons and possibilities, MCDM plays a critical role in real life problems, both in the public and private sectors, independently of the industry and activities involved (Triantaphyllou et al., 1998).

Problems in supply chain and logistics often are concerned with several inputs to produce an outcome, where many criteria need to be considered as they are highly interrelated, and they influence each other (Zandieh and Aslani, 2019). Traditional optimization approaches can deal with one criterion but logistic systems, like an OP system, requires a multi-factor approach. Furthermore, some of these factors, or criteria, have different relative importance for the DM or for the business in question. The analytical hierarchy process is a methodology within MCDM that can deal with different factors and different alternatives in order to reach the goal.

Crisp logic parts from the classic set theory where elements have a binary condition, in other words, either the element belongs or not to the set. The implications and meanings of crisp numbers in MCDM and AHP are that the information is precise and complete. On the other hand, fuzzy numbers are an extension of the classic set, and its elements can have a degree of membership to the set. Fuzzy numbers or fuzzy logic is also known as uncertain sets because it can account for the uncertainty decision making systems (Kuzmin, 1982). Crisp numbers will be used for this thesis as it simplifies the calculation, and it is a valid approach to make a technology assessment and suggestion.

Beyond the academic need to answer RQ2 and to provide ground for RQ3, the practical motivation to choose an MCDM method is helping DMs to solve complex problems in a simple and transparent way. Simple language and a precise methodology that reduces possible interpretation problems is a factor in making DMs comfortable with the process (Hernandez et al., 2020). AHP methodology combines various conflicting objectives into the process where some cannot be expressed in monetary units, such as the wellbeing of the operators. Furthermore, the model and process need to take the rationality and preferences of the DMs since they are the ones who represent the organization and the environment in which the model will (Hernandez et al., 2020).

3.3.1 AHP

The Analytic Hierarchy Process methodology was developed by Thomas L. Saaty in 1971 -1975 with the aim to derive scales from discrete and continuous paired comparisons (Saaty, 1987). The AHP is an MCDM methodology that structures, measure, and synthesize problem situations where it is needed to select and rank alternatives within a multi-objective environment, in other words, its principal use lies in resolving choice problems where the complexity is high (Forman and Gass, 2001). With the help of the AHP method, facts and interrelationships within the criteria selection can be discovered because the premise of AHP is that the user’s conception of reality is crucial instead of the conventional representation; like statistics (Saaty, 1988). From this approach, AHP allows the user to convert abstract concepts or preferences into numerical values to use a structured framework.

When using the AHP methodology, the problem needs to be simplified and modeled as a hierarchy where the highest, or first level, is the overall objective. The second level is the criteria. The third level could be composed of subcriteria, which are understood as further divisions that depends directly on the criteria. Finally, the last level will be possible alternatives. The figure below exemplifies the hierarchical model for this thesis, it is important to mention that subcriteria will be used to increase the level of detail. For the hierarchical structure of an AHP model to work the complexity needs high enough to capture the situation but small enough to still be sensitive to changes (Saaty, 1987).

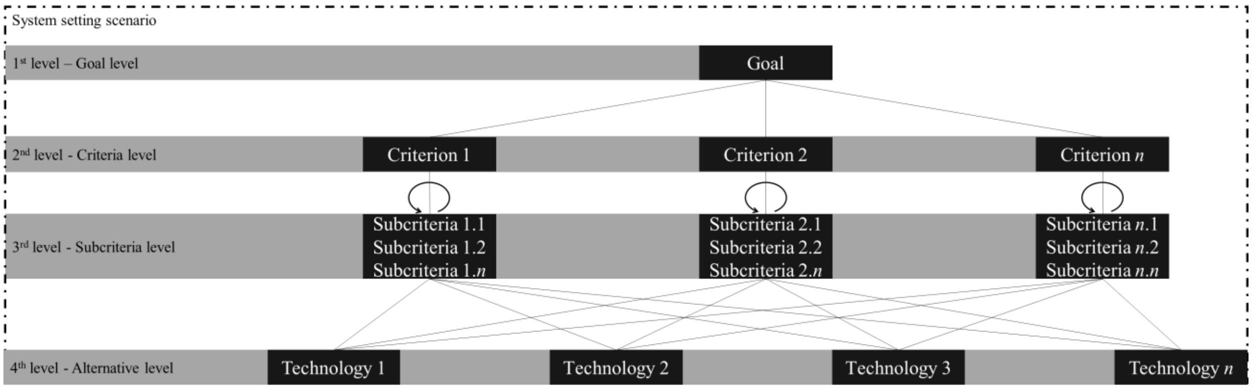


Figure 8 – Hierarchical outline for the thesis

Once the structure is defined and by having the right complexity in the model, the overall problem is broken down into simpler and more specific problems that are assessed with the pairwise comparisons. These comparisons follow the fundamental 9-point scale developed by Saaty (1980) that uses crisp logic. In the scale the number 1 represent equal importance, where both options contribute equally to the objective. On the other hand, the number 9 represent extreme importance, where one option is ranked as high as possible vs the other. Numbers 2, 4, 6, and 8 are immediate values and they are recommended when a compromise is needed between the priorities It is important to mention that each pairwise comparison has a reciprocal comparison, and the value is the reciprocal number. The table below shows the 9-point scale, definition, and explanation.

Intensity	Definition	Explanation
1	Equal Importance	Both options contribute equally to the objective
3	Moderate Importance	The judgment slightly favors one option
5	Strong Importance	The judgment strongly favors one option
7	Very Strong Importance	One option is strongly favored over the other
9	Absolute/Extreme Importance	There is evidence of one option being favored over the other. Highest level of affirmation
2, 4, 6, 8	Intermediate values	Compromise is required for the scale
Reciprocals of the above	If element i has a non-zero number assigned when compared to j. Then j has the reciprocal value when compared to i.	

Table 7 – 9-point scale, collected from Saaty (1980)

The AHP method has been widely used in over 20 countries (Akaa et al., 2016), in private and public sectors in a variety of decision-making scenarios such like: choice of an alternative out of a set, prioritization of an alternative out of a set, resource allocation for a set of alternatives with a variety of constraints, benchmark processes or systems and quality management (Rajput et al., 2018). AHP uses range from conflict resolution, healthcare research, flexible manufacturing systems, machine selections, project selections, software quality evaluations, technology selection, supplier selection and has been used in 6835 publications being the most used method in multi criteria decision problems (Creative Decisions Foundation), (Forman and Gass, 2001), (Basílio et al., 2022). Within supply chain, AHP has been used for selecting material handling equipment (Horňáková et al., 2021), selecting manual OP technologies (Villarreal-Zapata et al., 2020), and selecting a warehouse location ((Singh et al., 2018), (Ratih Dyah Kusumastuti, 2018) and (Bingqing and Liting, 2020)). Therefore, the method has been proved to be valid for selecting alternatives in a given scenario which, in this case, is all the OP technologies spectrum within a picker-to-parts OP system.

As any methodology, AHP is not perfect, and it has strengths and weaknesses. AHP has been proved to be subject of rank reversal issues; an example is when introducing a worse alternative, the ordering of the previous alternatives can change (Triantaphyllou, 2000). Moreover, AHP is also bound to the decision-making paradox that comes from determining the reliability of MCDM methods. When feeding the same data for the same problem, AHP gave a different result from the wighted product model, ELECTRE and TOPSIS methods (Triantaphyllou and Mann, 1989). However, AHP's simplicity and easiness to understand and apply in group settings is what has made AHP the leading methodology in decision-making (Srdjevic and Srdjevic, 2013). As the calculations are straightforward the methodology has outnumbered any other methodology in the MCDM field (Wallenius et al., 2008). Another strength of AHP is the consistency check for the pairwise comparisons. Since humans might be inconsistent in judgements, AHP methodology require that the consistency ratio value does not exceed 0.10, otherwise the pairwise comparison has to be performed again (Saaty, 1980).

For the AHP calculation, SuperDecisions software will be used. SuperDecisions was developed by the researchers team that worked with the method creator. Currently, the software, along with its development and maintenance, is sponsored by the Creative Decisions Foundations which is an organization that focuses on the development of advanced methods of decision-making to solve societal issues, conflict resolutions and optimization of resources in both private and public organizations. SuperDecisions follows the AHP method and its conventions; its use has been validated with several application on research papers, therefore it is safe to retrieve valid and reliable results.

The mathematic steps and the governing equations of the method are well established, researched, and explained in the available literature, therefore it is out of the scope of this thesis to explain the matrixes obtained; the data analysis will rather be focused on the results. However, the steps and main matrixes from SuperDecisions will be available in the appendix II. Nevertheless, this thesis follows the AHP approach following the steps of the figure 9.

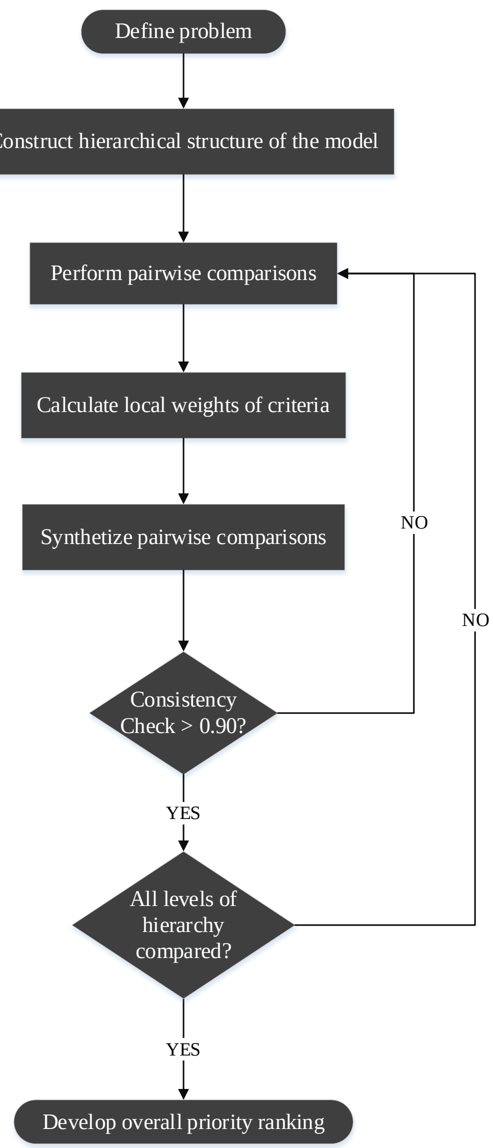


Figure 9 – AHP methodology steps, adapted from Saaty (2012)

3.3.2 Group MCDM

In order to increase the validity of the process and results for this thesis a group MCDM will be executed. AHP was originally developed as a single MCDM method where the input of one expert is valid to achieve the goal. However, to be able to generalize results, a panel of experts can also be considered and then aggregated to comply with the input form of AHP (Saaty, 1989). For the aggregation of data there are two main approaches: aggregation of individual judgements (AIJ) and aggregation of individual priorities (AIP) (Forman and Peniwati, 1998). AIJ is optimal when the group is considered to function as a unit, whereas AIP is optimal when the group is considered as separate individuals. For this thesis, AIJ was selected for the previous consideration because this work seeks to generalize the results.

To aggregate the individual judgements and be able to have one input, the arithmetic mean method (AMM) or the geometric mean method (GMM) can be used. Both methods have had criticism in regard to the way to achieve consensus, ideally the consensus would take place in one meeting room (Akaa et al., 2016). Mathematically the GMM represent the average ratio of decision while the AMM represents the average interval of the same DMs judgements (Akaa et al., 2016). For this thesis, the GMM will be used because this method keeps the matrix consistent and reciprocal (Mu and Pereyra-Rojas, 2018), and because the thesis is founded on the assumption that all experts hold the same importance. Moreover, getting all the experts in one room to achieve consensus is not practical since they are established in different countries.

A critical factor when working with a group MCDM methodology is the type of coordination of the group experts. Leyva Lopez et al. (2017) developed a model depending on how the group was coupled: sequential or parallel. When the group is loosely connected, and the members perform all the steps without interacting with others until reaching a consensus solution it is a parallel coordination mode. On the other hand, sequential coordination mode is when the group works together to reach consensus in the different stages. This thesis employs a hybrid coordination mode in the sense that the group of experts will work parallel, but the agreed criteria and alternatives are given beforehand based on the literature review, therefore they don't need to reach consensus on these stages. Figure 10 shows the coordination method for this thesis.

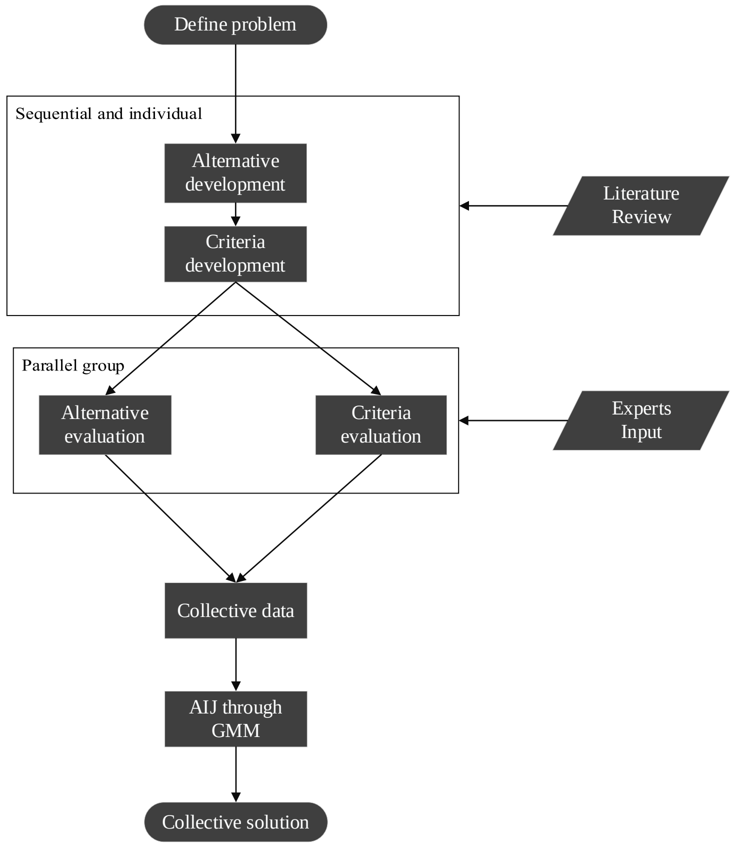


Figure 10 – Coordination method for group MCDM

3.3.3 Data collection

As described previously, linguistic, quantitative, and qualitative data can be used in for the AHP technique. Such data will be divided into two:

1. Pairwise comparisons of criteria and subcriteria: With the aim to find the relative weight.
    a. Questions that compare which criteria is more important.
2. Technology evaluation: With the aim to assess each technology vs each subcriterion.
    a. Matrix that compares each technology to a relevant scale for each subcriterion.

The technique to collect the data is described as follows. The pairwise comparisons will employ a commonly used 9-point scale where the validity of the results is confirmed by an inconsistency value lower than 0.10. Since the number of pairwise comparisons directly increases with the possible combinations of technologies vs criteria, it makes more sense to use the ranking method to assess the technologies. The ranking method uses a custom defined scale that should be relevant for the intensity of each subcriterion and should also be validated with an inconsistency index value than 0.10. Each possibility of the ranking is translated into a numerical value for the calculation. Examples of such scales could be:

- High, medium, low
- Excellent, above average, average, below average, poor
- Extreme, great, significant, moderate, tad
- Very dangerous, dangerous, safe
- Cost ranks
- Segment percentiles

With the scale defined, the issue of characterizing the values into the scale is left. To address this concern, the data collection of the technologies will be carried out as follows. First, the academic and vendor exports will order the technologies from more to less (depending on the criteria). Once all the answers are gathered the geometric mean method will be applied to unify the answers into one. For the pairwise comparisons, the 9-point scale will be used while for the ranking of technology a relevant scale depending on the subcriterion will be used.

With the aim to have as valid results as possible a combination of experts will be used. Since the pairwise comparisons are delimited to the performance indicators of the warehouse an operational expert –an executive– will answer these questions. This is based on the ground that a manager with experience knows the criteria in practice as it is their duty to deliver results based on the performance indicators. Such operational expert should have at least 5 years in a position that requires taking managerial decisions in a warehouse. Four managers work in the fourth largest postal and logistic solution provider in the Nordic region. Another manager is responsible for a 3PL who handles lifestyle products and consumer electronics for all Europe with operations in the Netherlands. A sixth manager is responsible for the logistics at the biggest regional glass vendor in mid Norway. A seventh manager is the responsible of a warehouse from the world's biggest beverage bottler in Mexico. An eighth manager is responsible for logistics operations of a tooling manufacturing company in the USA. A ninth manager is the logistics responsible from an OEM automotive company in Mexico. An academic expert will validate these criteria weights. The technology evaluation, on the other hand, will be done by an academic expert in an independent manner. Academic experts are the ones leading the research of innovative technologies therefore they are familiar with the different technologies and their capabilities where an operational expert might be only familiar with the technologies at hand.

For the AHP model to work, the experts' results need to be aggregated and for that purpose the aggregation of individual judgements with geometric mean method will be employed since it keeps the matrix reciprocal, as explained before.

The following table summarizes the data collection for the thesis.

Data collection method	Close-ended questionnaire	
Type of expert	Operational expert	Academic and vendor expert
Type of questionnaire	Pairwise comparisons of criteria and subcriteria	Technology assessment
Experience	Practical experience with performance indicators	Research experience within OP technologies and their capabilities
Goal	Find criteria and subcriteria weight	Find the technology ranking
Scale	9-point scale	Relevant scale for the subcriterion
Number of experts	At least 4	At least 1
Aggregation method	Aggregation of Individual Judgments by Geometric Mean Method	Aggregation of Individual Judgments by Geometric Mean Method

Table 8 – Data collection specifications

3.4 Sensitivity Analysis

With the main objective to answer RQ3 but also to increase the validity and soundness of the MCDM model, a sensitivity analysis will be performed because it an important part of developing a model (Razavi and Gupta, 2015). However, SA vary on theoretical definitions, philosophies, methods and goals (Razavi and Gupta, 2015), therefore it is important to establish a common definition that fits the purpose. With this type of analysis, the robustness of the model can be tested because it gives information on which criteria is more important towards a given alternative and by how much. Rank reversals of the alternatives can be found through a sensitivity analysis. A reversal in the alternatives means that the weight of the selected criteria is enough to make another alternative better ranked. In other words, performing this analysis can show how stable the overall model is and how the top ranked alternative changes in function of the subcriterion or criterion.

When performing a valid SA three questions needs to be answered: What is the objective of performing a SA? What is the intended definition of SA in the current context? What is the computational budget available for the SA? (Razavi and Gupta, 2015). To answer the first question, the purpose of the SA in this thesis is to find the implications of the OP technologies in different situations, to serve as *what if* assessments to further understand the relationship of criteria and technologies. To answer the second question, in this thesis it is defined as an evaluation of how the ranking of the alternatives change as a function of the relative weight of a criterion or subcriterion. For the third question, in this case it is not relevant since the model in question does not involve heavy processing due to the nature of AHP and can be done cheaply and simply with SuperDecisions software. The table 9 shows the three questions with the respective answers.

Fundamental question	Answer
What is the objective of performing a SA?	To find the implications of the OP technologies in different situations, to serve as what if assessments to further understand the relationship of criteria and technologies.
What is the intended definition of SA in the current context?	An evaluation of how the ranking of the alternatives change as a function of the relative weight of a criterion or subcriterion.
What is the computational budget available for the SA?	In this case it is not relevant since the model in question does not involve heavy processing and can be done cheaply with SuperDecisions software.

Table 9 – Fundamental questions of performing a sensitivity analysis

The method of this SA will be a One-Factor-At-a-Time method which is also called monothethic analysis within design of experiments. This method test the inputs one at a time to calculate the resulting output of the model (Ruano et al., 2012). What the One-Factor-At-a-Time method implies for this work is that only one criterion or subcriterion will be selected at a time with the aim to obtain results in the technology rankings. What this means in practical terms is that the DM can position themselves in different perspectives blocking or stimulating a specific criterion or subcriterion, which serves as *what-if* assessments. In case of analyzing a subcriterion, the relationship between and weights of the other dimensions is untouched as they are independent from the selected parent.

4. Results

The fourth chapter shows the result of the different research methodologies described in the previous chapter. As the findings encompass different goals, and they assemble different parts of the research, it is relevant to show the pure results before discussing them. This chapter starts with the findings of the literature review focused in finding performance criteria. Following the findings of the literature review on the OP technologies. Thirdly, the MCDM model, its inputs, specifications and results are described. In the last section of the chapter, the representation and values of the sensitivity analysis performed are shown.

4.1 Literature review on OP performance criteria

To the best of the author's knowledge, there is still no general agreement in which performance criteria the warehouses should follow, much less when it comes for the criteria related to an OP system. Possible explanations for this are because these criteria are business dependent or manager dependent. Nevertheless, this study aims to identify and structure these KPIs, below the literature findings are explained.

As a starting point, the KPIs should follow the SMART criteria (Drucker, 2012). SMART refers to: Specific (what to measure should be clear), Measurable (what to measure should be quantifiable and as direct as possible), Achievable (it should be feasible to achieve), Realistic (the planned level should be possible to obtain), and Timely (time sensitive as time goes by). Following this guideline, if a KPI is missing one of these characteristics, then its validity is hindered.

The characteristics and importance of KPIs are studied by Marziali et al. (2021) but focusing on a case study at a warehouse. This paper became relevant because it highlights the importance of following and defining the right type of KPIs as they form part of the control function of a company. There is information that managers that operate in the supply chain dedicate more than half of their time to manage uncertainties and risks (Ivanov et al., 2018). From this perspective, KPIs are a main component of decision support tools because they allow DMs to have an overview and state of the situation, systems, and processes. In a warehouse, the KPIs are an effective method to improve the performance in terms of sustainability, use of resources or economic benefits. KPIs can and will vary between organizations due to the different business strategies and strategic priorities of the businesses but even then, the indicators are related to measure and ultimately improve performance in four dimensions: Efficacy (degree of compliance with the objectives, without reference to cost), Efficiency (evaluation of the cost per good), Economy (ability to adequately mobilize financial resources), Quality (technical characteristics of the service vs requirements of the customer), and Ecology (degree of pollution released). This study on KPI in warehousing is important but still lacks the human factor dimension.

A study to determine the KPIs in a construction material warehouse was done by Kusrini et al. (2018) using AHP to find the most important criteria. The Frazelle model was also used. Frazelle (2016) proposes a 5-dimension performance model where financial, productivity, utilization, quality, and cycle time are considered. The KPIs for an OP system are as follows: Picking cost per order line (Financial), Order lines per person-hour (Productivity), % Utilization of picking labor and equipment (Utilization), % Perfect picking lines (Quality), and OP cycle time per order (Cycle Time). However, Frazelle does not consider the human dimension which is relevant to the real world because technologies still need human interaction and the performance. It is relevant to remark the point that none of these KPIs have a relative weight which explains the reason for Kusrini et al. (2018) to use AHP to find the priorities of the case study.

Order picking objectives are defined by de Koster et al. (2007), where the most important is maximizing the service level because the faster the order is ready the faster it can be shipped to the customer. From the perspective of supporting the service level the secondary main objective is to minimize the total travel distance of the picker which is identified as the first candidate for improvement in order picking systems. Complementary objectives are related to minimizing cost, minimize throughput time of orders, maximize use of space, maximize use of equipment, maximize use of labour, and maximize accessibility to items.

Grosse et al. (2017) talks about order picking objectives and human factor aspects in the order picking process. Such objectives have the aim of maximizing or minimizing a set of variables like travel distance, costs, throughput time, use of space, pick error, risks, safety and working conditions. These objectives are what managers in warehouses work to improve, therefore it makes sense that these are transformed into key indicators. Most of the objectives found in this paper correlate directly to the ones defined by de Koster et al. (2007), therefore increasing the validity and applicability of them. The study of human factors in warehouse operations, and specifically, order picking process, is relevant because humans still play an important role in such processes, therefore neglecting these factors can jeopardize the safety, the reliability, and the intended improvement of any technology implemented. Moreover, since human workers are still a central part of logistic and OP systems, not considering human factors can result in unexpected loss of performance across the system (Sgarbossa et al., 2020).

KPIs in automatic warehouse systems are analyzed by Faveto et al. (2021). This approach is relevant for the current study because they present a framework on indicators through a systematic quantitative literature review resulting in a ranking based on the frequency of the indicator in publications. They classify the different indicators in three domains being, economic (generic performances, time related performances, cost performances, information system performances and warehouse measure), social and environmental. Since the present work is scoped specifically to the order picking process in warehouse, not all of the indicators in their paper are applicable. In this case, environmental performance indicators are not considered relevant because that measure is intended for the whole operation of a warehouse and not only for a subsystem like OP.

Soft metrics such as manager's perception of customer satisfaction and loyalty, and the alikes are not considered because these are based on a subjective ground. Moreover, these indicators are not replicable or valid across different organizations because they each manager, or organization in the best case, can define in different ways and with different time frames, therefore making it unpractical to generalize and standardize.

In the table below, the reviewed papers and the objectives, indicators or dimensions are presented as a summary for the reader.

Author – Reference	**Objective [a]/Indicator [b]/Dimension [c]**
Marziali et al. (2021)	Efficacy [c]
	Efficiency [c]
	Economy [c]
	Quality [c]
	Ecology [c]
Frazelle (2016)	Picking cost per order line [b] (Financial [c])
	Order lines per person-hour [b] (Productivity [c])
	% Utilization of picking labor and equipment [b] (Utilization [c])

	% Perfect picking lines [b] (Quality [c])
	OP cycle time per order [b] (Cycle Time [c])
de Koster et al. (2007)	Maximize the service level [a]
	Minimize the total travel distance [a]
	Minimize total cost [a]
	Minimize the throughput time of orders [a]
	Maximize use of space [a]
	Maximize use of equipment [a]
	Maximize use of labour [a]
	Maximize accessibility to items [a]
Grosse et al. (2017)	Minimize travel distance [a]
	Minimize costs [a]
	Minimize throughput time [a]
	Maximize use of space [a]
	Minimize pick error [a]
	Minimize risk of injury [a]
	Maximize occupational safety [a]
	Improve working conditions [a]
	Perceptual workload [b]
	Mental workload [b]
	Physical workload [b]
	Psychosocial workload [b]
	Work environment workload [b]
Faveto et al. (2021)	Generic performances [c]
	Time related performances [c]
	Costs performances [c]
	Information system performances [c]
	Warehouse measures [c]
	Social KPIs [c]
	Environmental KPIs [c]

Table 10 – Summary of objectives, indicators or dimensions found

As it is visible in the previous table, most of the objectives, measures, and dimensions correlate with themselves. In order to organize them into the relevant criteria they will be divided into three dimensions. In this thesis the financial, productivity, utilization and cycle time aspects are considered into one dimension called Economic performance of the OP system. This dimension encompass the use of resources following the definition of economics by Robbins (1945). Aspects regarding the degree of excellence of the process are included within the dimension of Quality in the OP system. Aspects regarding the human factors of operators are contemplated in the Wellbeing of operators working in the OP system. The latter is of particular interest in this thesis because there are technologies that directly interact with the humans performing the tasks via visual, touch, auditive, or voice interfaces. The figure below is a diagram of the dimensions with the respective indicators that will be used.

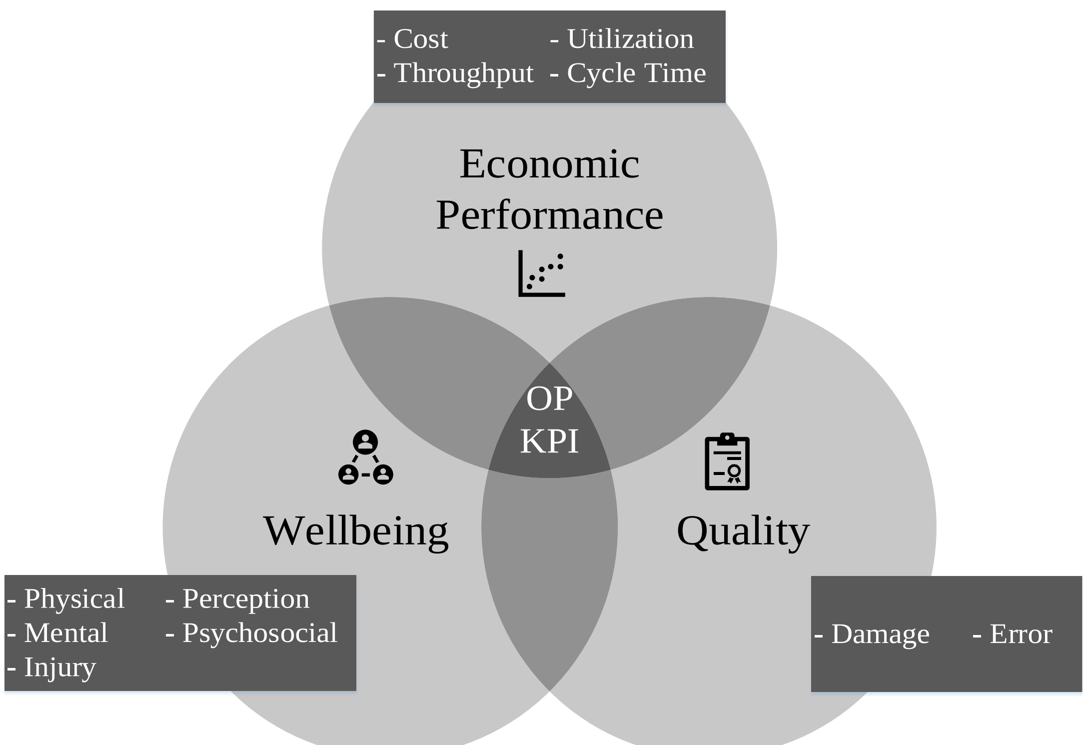


Figure 11 – Order picking KPIs

With the criteria and subcriteria selected and listed, it is needed to define what does each point mean. This is of special relevance for both the academic and practitioners because even though both sides have experience in their respective fields, they are subject to bias or misunderstanding. Moreover, the experts consulted are not in the same region therefore it is imperative to establish a standard understanding based on definitions to be able to assess the task at hand from the same perspective. The scheme below was designed to have a clear understanding of each subcriterion.

Economic Performance

- **Cost**: All the financial expenses incurring operating the technology. (Grosse et al., 2017)
- **Throughput**: Quantity of items passing through the system in a time frame (Faveto et al., 2021)
- **Utilization**: Degree of effective use of the system based on the OP tasks (Faveto et al., 2021)
- **Cycle Time**: : Time spent from the start of the first OP task until the fulfillment of the last OP task (Frazelle, 2016)

Quality

- **Damage**: Any type of harm to the product during its retreival and handling that converts it into noncompliant. (Frazelle, 2016)
- **Error**: All the possible failure modes in OP. For example: selecting the wrong item, wrong amount, not fullfilling the order, traveling to the wrong location (Grosse et al., 2017)

Wellbeing

- **Physical workload**: Amount of phsysical work the operator needs to do within the OP system. For example: walking, moving, lifting, carrying, etc. (Grosse et al., 2015)
- **Mental workload**: Amount of mental work the operator needs to do within the OP system. For example: thinking, calculating, remembering, etc. (Grosse et al., 2015)
- **Perceptual workload**: Amount of attention that an operator needs to put into receiving and understanding the task within the OP system. For example: reading, seeing, hearing, etc. (Grosse et al., 2015)
- **Psychosocial load**: Level of psychologic wellbeing of the operator in the OP system. Consisting of motivation, stress, workload, boredom, structure and work assignment (Grosse et. al., 2015)
- **Injury** (risk of): Probability of injury for the operator wthin the OP system, including accidents or fatigue related injuries (Grosse et. al., 2015)

Figure 12 – OP subcriteria definitions

As explained in the section 3.3.3, the methodology to assess the different technologies will be based on the ranking method with the SuperDecisions software, therefore a scale for each criterion is needed. For applicability purposes the scale is described with words but for calculation purposes each point of the scale has a mathematical value where, in the ideal weight, a value of "1.0" is the one with the heaviest weight, as shown in table 11.

- Cost: Very expensive, expensive, average, cheap, very cheap
    1. Where the lower the better.
    2. Five steps give enough clarity in the rank for the different technologies because the price tends to be exponential with the level of automation.
- Throughput: High, above average, average, below average, low
    1. Where higher is the better
    2. Five steps give enough clarity for the throughput of the different technologies
- Utilization: High, medium, low
    1. Where higher is the better
    2. Three steps give enough clarity for the amount of time the technology is in actual use, 33% increases where high is almost all the time.
- Cycle Time: Very short, short, average, long, very long
    1. Where shorter is the better
    2. Five steps give enough clarity in the speed of each technology
- Damage: High, medium, low
    1. Where lower is the better
    2. Three steps give enough clarity in how much each technology can damage the product picked.
- Error: High, above average, average, below average, low
    1. Where lower is the better
    2. Five steps give enough clarity in the ranking and average is used since experts know which technology can give a reference value.
- Injury (risk of): High, medium, low
    1. Where lower is the better
    2. Three steps give enough clarity in the ranking of risk of injuries
- Physical workload: Extreme, big, significant, moderate, low

1. Where lower is the better
2. Five steps give enough clarity for a workload perspective, 25% increases where extreme is 100% busy, no time to rest.

- Mental workload: Extreme, big, significant, moderate, low
  1. Where lower is the better
  2. Five steps give enough clarity for a workload perspective, 25% increases where extreme is 100% busy, no time to rest.
- Perception workload: Extreme, big, significant, moderate, low
  1. Where lower is the better
  2. Five steps give enough clarity for a workload perspective, 25% increases where extreme is 100% busy, no time to rest.
- Psychosocial workload: Extreme, big, significant, moderate, low
  1. Where lower is the better
  2. Five steps give enough clarity for a workload perspective, 25% increases where extreme is 100% busy, no time to rest.

In the following table the subcriteria scales and the different linguistic names and category values are condensed.

Criteria	Subcriteria	ID	Scale used	# of options	Category names	Category values (0-1.0)
Economic Performance (C1)	Cost	*C11*	Lower is better	5	Very expensive, expensive, average, cheap, very cheap	0.0520, 0.1062, 0.1884, 0.4107, 1.0
	Throughput	*C12*	Higher is better	5	High, above average, average, below average, low	1.0, 0.4107, 0.1884, 0.1062, 0.0520
	Utilization	*C13*	Higher is better	3	High, medium, low	1.0, 0.3467, 0.0801
	Cycle Time	*C14*	Shorter is better	5	Very short, short, average, long, very long	1.0, 0.4107, 0.1884, 0.1062, 0.0520
Quality (C2)	Damage	*C21*	Lower is better	3	High, medium, low	0.0801, 0.3467, 1.0
	Error	*C22*	Lower is better	5	High, above average, average, below average, low	0.0520, 0.1062, 0.1884, 0.4107, 1.0
Wellbeing (C3)	Physical workload	*C31*	Lower is better	5	Extreme, big, significant, moderate, low	0.0520, 0.1062, 0.1884, 0.4107, 1.0
	Mental workload	*C32*	Lower is better	5	Extreme, big, significant, moderate, low	0.0520, 0.1062, 0.1884, 0.4107, 1.0
	Perception workload	*C33*	Lower is better	5	Extreme, big, significant, moderate, low	0.0520, 0.1062, 0.1884, 0.4107, 1.0
	Psychosocial load	*C34*	Lower is better	5	Extreme, big, significant, moderate, low	0.0520, 0.1062, 0.1884, 0.4107, 1.0
	Injury	*C35*	Lower is better	3	High, medium, low	0.0801, 0.3467, 1.0

Table 11 – Criteria and subcriteria scale specifications

4.2 Literature review on OP technologies

Focusing on the picker-to-parts method, this section aims to list the different technologies available for an OP system where the picker, could be a robot or a human, travels within the warehouse to retrieve the desired item.

With the aim to organize the spectrum of different technologies, (Vijayakumar and Sgarbossa, 2021) performed a literature review on the level of automation and categorized the existing technologies into four possible groups ranging from the lowest to the highest level of automation: manual, paperless picking, AGV/AMR assisted picking, and pick and transport robot.

The manual level of automation is the most implemented in warehouses (Gajšek et al., 2020), in this level all the OP tasks are performed by the picker. This level only considers the basic picking list. The use of pallet jacks, forklifts and similar tools are not considered as OP technologies because they are regarded as means of transportation that support an operator (Gajšek et al., 2020) in traveling within the picking area or moving the desired items but the relevant OP tasks like setup, search and pick are still done by the operator (Vijayakumar and Sgarbossa, 2021).

Paperless picking is a development where specific technology aids the operator with the purpose to reduce errors with tasks like gathering information, finding the product, and guiding the operator through the warehouse (Battini et al., 2015). This level includes handheld scanners, pick to light, pick to voice, and head mounted devices. In practice, companies and vendors could implement a combination of such technologies, however for research purposes they are kept separated as they are fundamentally different.

AGV/AMR assisted picking is the third level of automation where the travel, usually considered an unproductive task, is reduced (He et al., 2018) because the picker can stay in the storage area waiting for the next AGV/AMR to fulfill the next picking list. This level consist of two types of robots that vary in their capabilities, AGVs are robots that only move from A to B without sorting out potential blocks or traffic issues in their way unless there is a central unit dispatching the vehicles (Fragapane et al., 2021) while AMRs are more advanced and are able to dynamically navigate the warehouse in an independent manner (Fragapane et al., 2021). Nonetheless, AGVs and AMRs are not considered as OP technologies because they are, at the most basic level, a development of forklifts or manual jacks. Following their capabilities, these two types of solutions should be considered as material handling tools rather than OP technologies, hence they are excluded from this research.

The most advanced level of automation is the pick and transport robot, where the robot autonomously performs all the OP tasks from creating the picking list, fetch the product and bring it to the picking area (Lee and Murray, 2019). A special consideration in this level of automation, because of its novelty, is that it is not possible to pick all size range of items. This level is divided into two different types of robots depending on how the picking task is performed: pick to bin or pick to pallet, although both are .

The following tables summarizes the findings on the OP technologies including a brief description of each, the relation of technologies with the OP tasks, and their level of automation.

Technology	ID	Level of Automation	Description
Picking list	*T1*	Manual picking	Traditional paper based
Handheld Scanner	*T2*	Paperless picking	Operator uses a scanner to scan barcodes
Pick by Light	*T3*		Operator is guided by light signals and small digital displays - free hands
Pick by Voice	*T4*		Operator is guided by voice - free hands
HMD	*T5*		Also called Pick by Vision. Operator uses googles with Augmented Reality - free hands
PTR (Pick to Bin)	*T6*	Pick and transport robot	Robot performs all the OP task to a bin
PTR (Pick to Pallet)	*T7*		Robot performs all the OP task to a pallet

Table 12 – OP technology summary

OP Tasks / Technologies	T1	T2	T3	T4	T5	T6	T7
Level of Automation	Manual picking	Paperless picking				Pick and transport robot	
Setup	M	AS	M	AS	AS	AT	AT
Travel	M	M	M	M	AS	AT	AT
Search	M	M	AS	AS	AS	AT	AT
Pick	M	M	M	M	M	AT	AT

Where: **M:** Manual, **AS:** Assisted, **AT:** Automated

Table 13 – OP technologies and the OP tasks, adapted from collected from Vijayakumar and Sgarbossa (2021)

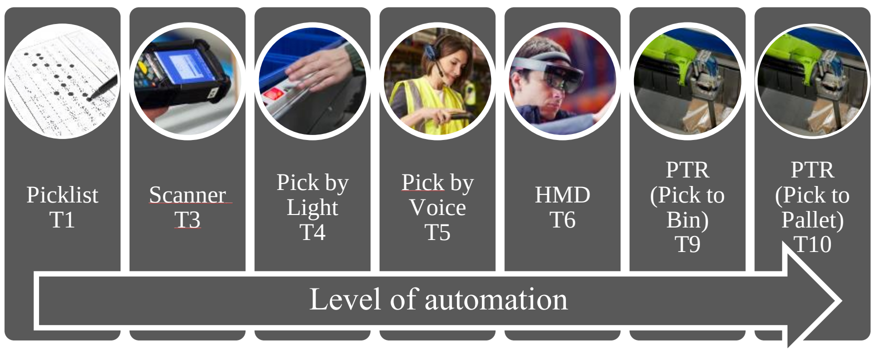


Figure 13 – OP technologies by level of automation

To summarize the literature reviews, there has been research efforts in the OP topic however these efforts have not been focused in selecting and rating performance criteria or ranking the different technologies. Consequently, the integrative approach of the literature review becomes relevant as these findings will serve as input for the MCDM model and the sensitivity analysis.

4.3 MCDM

For this thesis it is not of interest to describe and prove the AHP methodology formulation or mathematical foundation since it has been academically researched and applied in numerous other works. The interest, however, resides in its application and the outcome to deliver a criterion ranking and technology suggestion that is both useful to practitioners and academically valid. Hence, this section shows the results of the group AHP performed for each of the scenarios with SuperDecisions software.

4.3.1 Hierarchy model

The hierarchical structure of the model results from merging the results of the literature reviews. The AHP of this thesis is based upon the OP performance criteria that act as level 2 and 3, and the OP technologies that act as level 4 model. At this point of the AHP there are still no rankings or priorities, but all the possible combinations are listed and ready to be assessed and ranked. Figure 14 shows the hierarchy model that is valid for all the three scenarios.

4.3.2 Aggregated judgments

AHP method only allows one input and since multiple operational experts and multiple academic experts were consulted to have valid and reliable answers, the individual judgments from the pairwise comparisons and technology assessment were aggregated using the geometric mean method. Individual answers can be found in the appendix I-A. Table 26 shows the aggregated technology assessment. In the tables 14 to 25 the aggregated judgments for each of the scenarios are presented. These aggregated results create the input needed to solve the AHP problem

Mul-Case	C1	C2	C3
C1	1	0.693361274	1.44224957
C2	1.44224957	1	1.817120593
C3	0.693361274	0.550321208	1
Inconsistency:	0.054767		

Table 14 – Aggregated pairwise comparisons for Mul-Cas scenario criteria

Mul-Case	C11	C12	C13	C14
C11	1	4.71769398	2.466212074	2.758924176
C12	0.211967967	1	1.185631101	1.709975947
C13	0.405480133	0.843432665	1	0.793700526
C14	0.362460124	0.584803548	1.25992105	1
Inconsistency	0.05467			

Table 15 – Aggregated pairwise comparisons of economic performance subcriteria for Mul-Cas scenario

Mul-Case	C21	C22
C21	1	1
C22	1	1
Inconsistency	0	

Table 16 – Aggregated pairwise comparisons of quality subcriteria for Mul-Cas scenario

Mul-Case	C31	C32	C33	C34	C35
C31	1	1.912931183	1.775808003	2.758924176	0.480749857
C32	0.522757959	1	2.466212074	1.44224957	0.292401774
C33	0.56312394	0.405480133	1	2.080083823	0.281144222
C34	0.362460124	0.693361274	0.480749857	1	0.194934516
C35	2.080083823	3.419951893	3.556893304	5.12992784	1
Inconsistency	0.03304				

Table 17 – Aggregated pairwise comparisons of wellbeing subcriteria for Mul-Cas scenario

Mul-Pallet	C1	C2	C3
C1	1	0.686589048	0.914691219
C2	1.456475315	1	1.10668192
C3	1.093265114	0.903602004	1
Inconsistency:	0.00369		

Table 18 – Aggregated pairwise comparisons for Mul-Pal scenario criteria

Mul-Pallet	C11	C12	C13	C14
C11	1	0.614788153	0.759835686	0.854574013
C12	1.626576562	1	0.803428419	2.645751311
C13	1.316074013	1.244665955	1	1.626576562
C14	1.17017366	0.377964473	0.614788153	1
Inconsistency:	0.05574			

Table 19 – Aggregated pairwise comparisons of economic performance subcriteria for Mul-Pal scenario

Mul-Pallet	C21	C22
C21	1	2.279507057
C22	0.438691338	1
Inconsistency:	0	

Table 20 – Aggregated pairwise comparisons of quality subcriteria for Mul-Pal scenario

Mul-Pallet	C31	C32	C33	C34	C35
C31	C31	C32	C33	C34	C35
C32	1	3.343701525	4.090623489	3.201085873	0.467137978
C33	0.299069756	1	0.880111737	0.668740305	0.23570226
C34	0.244461511	1.136219366	1	0.577350269	0.386097395
C35	0.312393994	1.495348781	1.732050808	1	0.386097395
Inconsistency:	0.0326				

Table 21 – Aggregated pairwise comparisons of wellbeing subcriteria for Mul-Pal scenario

Floor level Pallet	C1	C2	C3
C1	1	0.480749857	0.480749857
C2	2.080083823	1	1
C3	2.080083823	1	1
Inconsistency:	0		

Table 22 – Aggregated pairwise comparisons for Flo-Pal scenario criteria

Flo-Pallet	C11	C12	C13	C14
C11	1	1.709975947	1	1.709975947
C12	0.584803548	1	0.843432665	1.817120593
C13	1	1.185631101	1	1.25992105
C14	0.584803548	0.550321208	0.793700526	1
Inconsistency:	0.02052			

Table 23 – Aggregated pairwise comparisons of economic performance subcriteria for Flo-Pal scenario

Flo-Pallet	C21	C22
C21	1	1.44224957
C22	0.693361274	1
Inconsistency:	0	

Table 24 – Aggregated pairwise comparisons of quality subcriteria for Flo-Pal scenario

Flo-Pallet	C31	C32	C33	C34	C35
C31	1	0.693361274	0.693361274	0.480749857	0.194934516
C32	1.44224957	1	1.44224957	1.25992105	0.405480133
C33	1.44224957	0.693361274	1	0.693361274	0.381571414
C34	2.080083823	0.793700526	1.44224957	1	0.381571414
C35	5.12992784	2.466212074	2.620741394	2.620741394	1
Inconsistency:	0.00925				

Table 25 – Aggregated pairwise comparisons of wellbeing subcriteria for Flo-Pal scenario

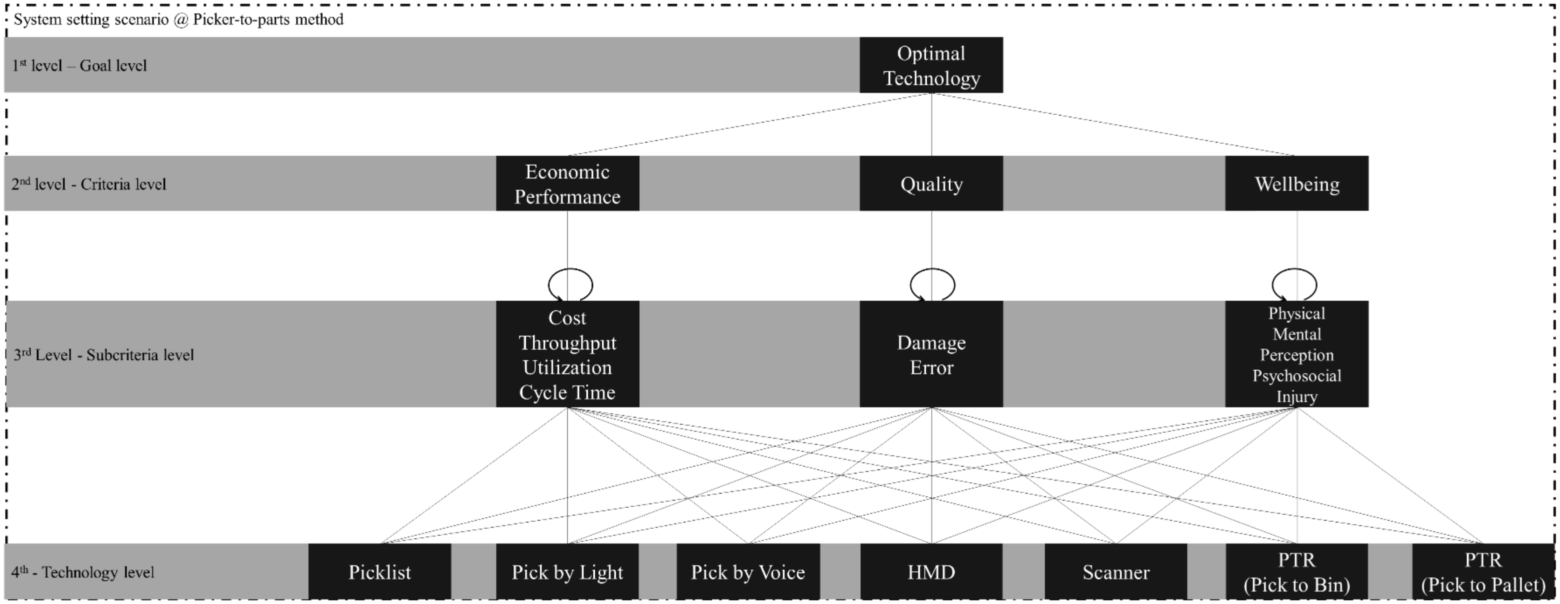


Figure 14 – Hierarchical model for the three scenarios

Alternatives / Criteria	C11	C12	C13	C14	C21	C22	C31	C32	C33	C34	C35
T1	1	0.052	0.3467	1	0.3467	0.052	0.052	0.052	0.052	0.052	0.3467
T2	0.4107	0.1062	0.3467	0.4107	0.3467	0.1062	0.1062	0.1062	0.1062	0.1062	0.3467
T3	0.1884	0.4107	0.3467	0.052	0.3467	0.1884	0.4107	0.1884	0.1884	0.1884	0.3467
T4	0.1884	1	0.3467	0.1884	0.3467	0.1884	0.4107	0.1884	0.1884	0.1884	0.3467
T5	0.1884	0.1884	0.3467	0.1884	0.3467	0.1884	0.4107	0.1884	0.1884	0.1884	0.3467
T6	0.1062	0.1884	0.3467	0.1884	0.3467	0.4107	0.4107	0.4107	0.4107	0.4107	0.3467
T7	0.052	0.1884	0.3467	0.1062	0.3467	1	1	1	1	1	0.3467

Table 26 – OP technology numeric assessment

4.3.3 AHP results

With SuperDecisions software the following criteria values were found for all the scenarios:

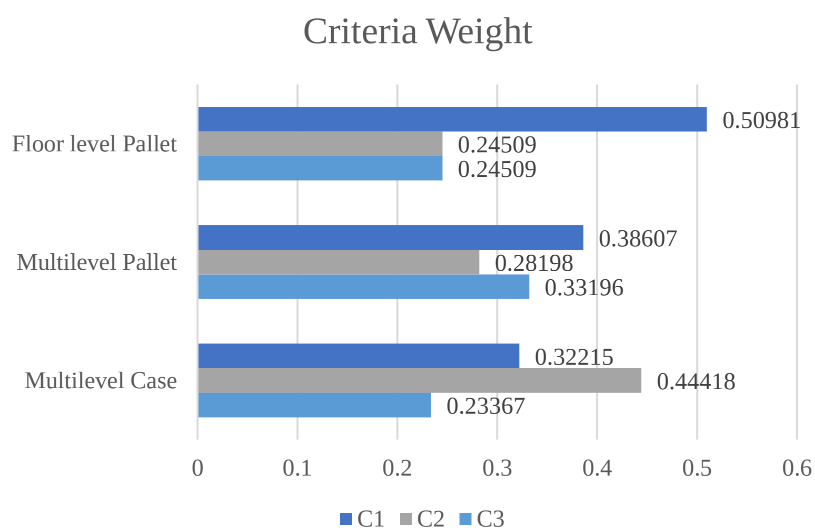


Figure 15 – OP criteria weight for the scenarios

With SuperDecisions software the following subcriteria values were found for all the scenarios:

Economic performance subcriteria

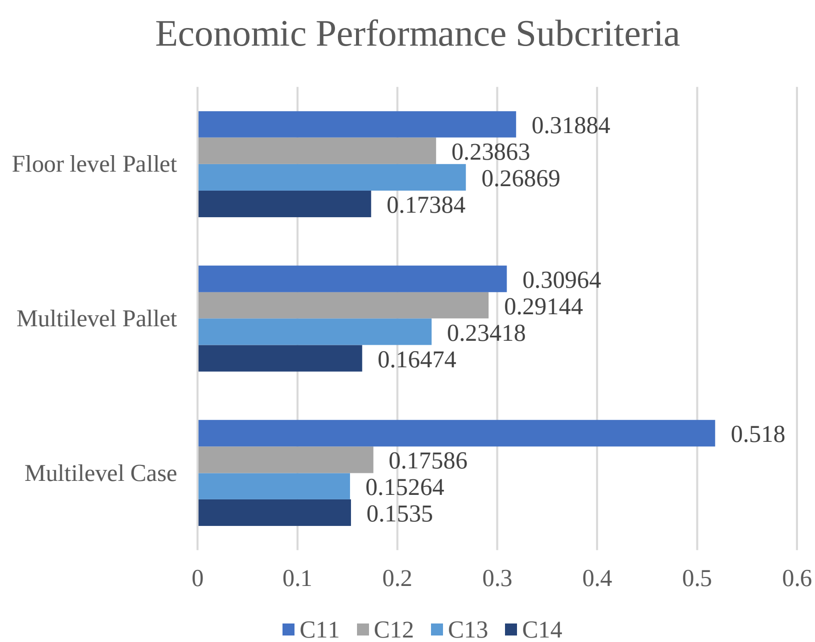


Figure 16 – Economic performance subcriteria weights for the scenarios

Quality subcriteria

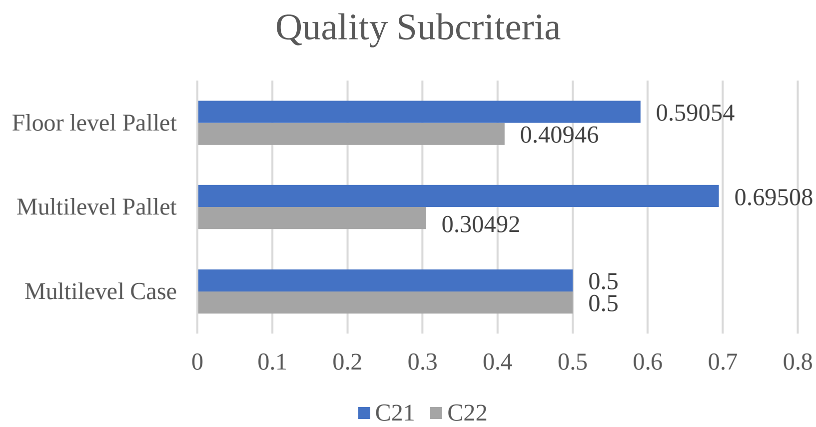


Figure 17 – Quality subcriteria weights for the scenarios

Wellbeing subcriteria

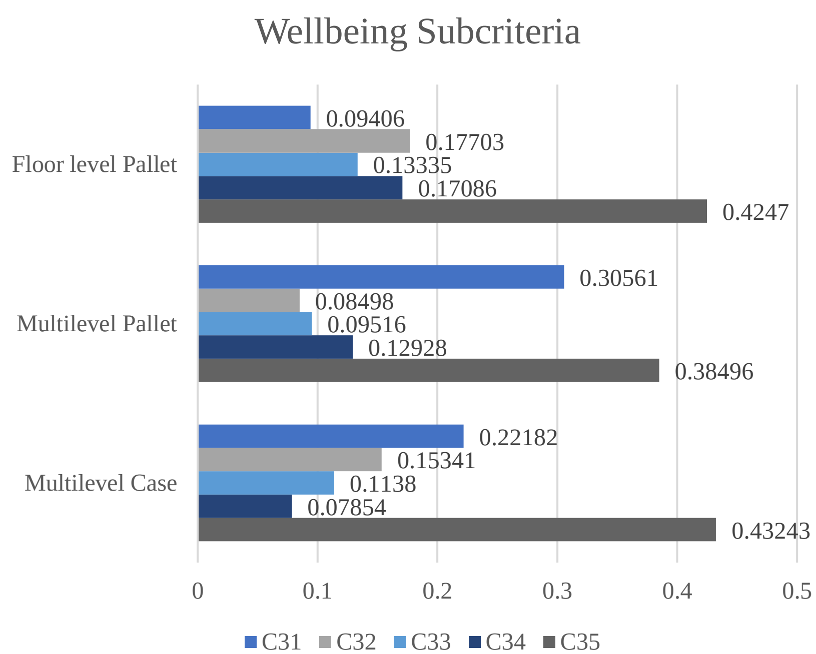
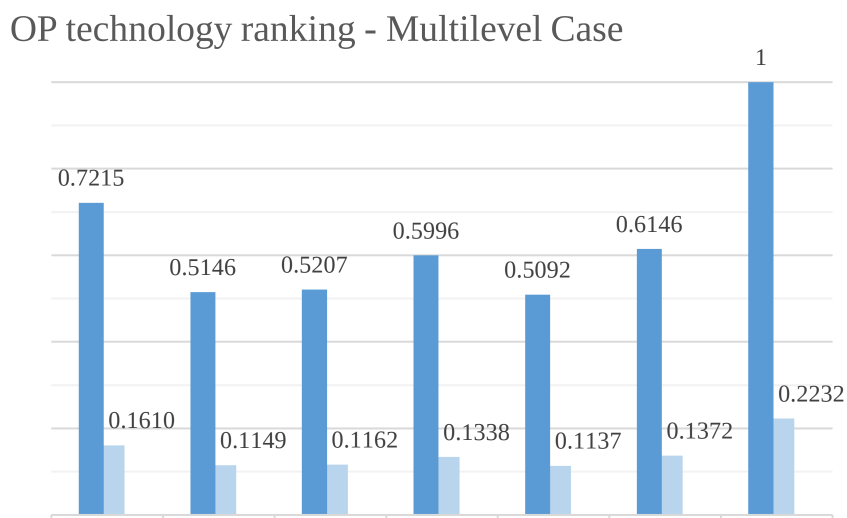


Figure 18 – Wellbeing subcriteria weights for the scenarios

With SuperDecisions and the merging of the input of both types of experts an overall technology ranking is achieved based on the criteria priorities.

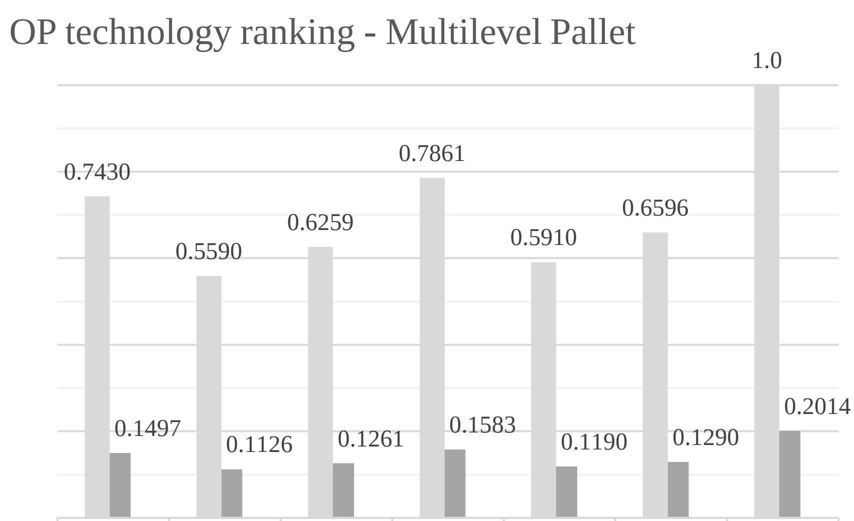
Multilevel Case



	T1	T2	T3	T4	T5	T6	T7
Raw (Normal) Value	0.1610	0.1149	0.1162	0.1338	0.1137	0.1372	0.2232
Ideal Value	0.7215	0.5146	0.5207	0.5996	0.5092	0.6146	1
Ranking	2	6	5	4	7	3	1

Figure 19 – OP technology ranking for multilevel case scenario

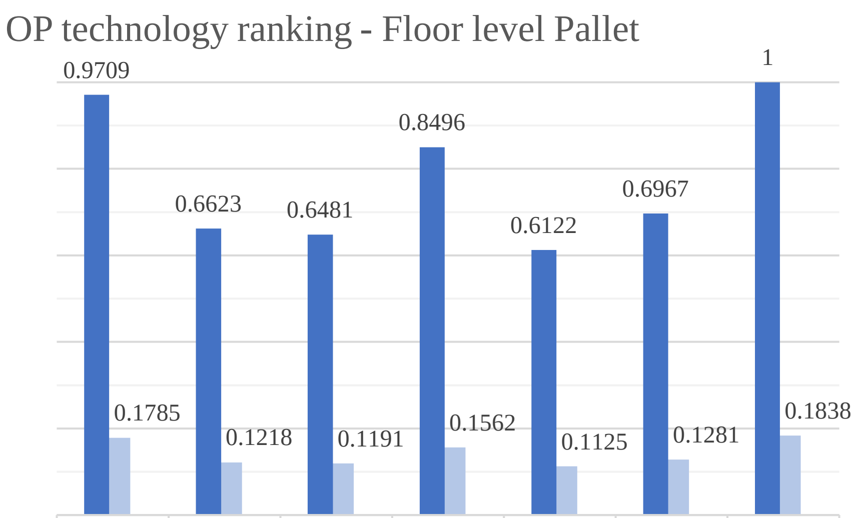
Multilevel Pallet



	T1	T2	T3	T4	T5	T6	T7
Raw (Normal) Value	0.1497	0.1126	0.1261	0.1583	0.1190	0.1290	0.2014
Ideal Value	0.7430	0.5590	0.6259	0.7861	0.5910	0.6596	1.0
Ranking	3	7	5	2	6	4	1

Figure 20 – OP technology ranking for multilevel pallet scenario

Floor level Pallet



	T1	T2	T3	T4	T5	T6	T7
Raw (Normal) Value	0.1785	0.1218	0.1191	0.1562	0.1125	0.1281	0.1838
Ideal Value	0.9709	0.6623	0.6481	0.8496	0.6122	0.6967	1
Ranking	2	5	6	3	7	4	1

Figure 21 – OP technology ranking for floor level pallet scenario

4.4 Sensitivity analysis

The sensitivity analysis is divided into the five scenarios. In each scenario the three main criteria were assessed. Furthermore, the subcriterion C11 (Cost), C31 (Physical workload), C32 (Mental workload), and C35 (Risk of injury) were also selected for the analysis. The results were obtained via the AHP sensitivity analysis module of the SuperDecisions software based on the obtained results from the AHP. The limits were set as follow: starting value of 0.00001 (0), ending value of 0.99999 (1) as to avoid the mathematical limits of absolute values. 10 steps were selected to observe the behavior of the technologies. The data tables from the software are available for consultation in the appendix II-C.

Multilevel case scenario

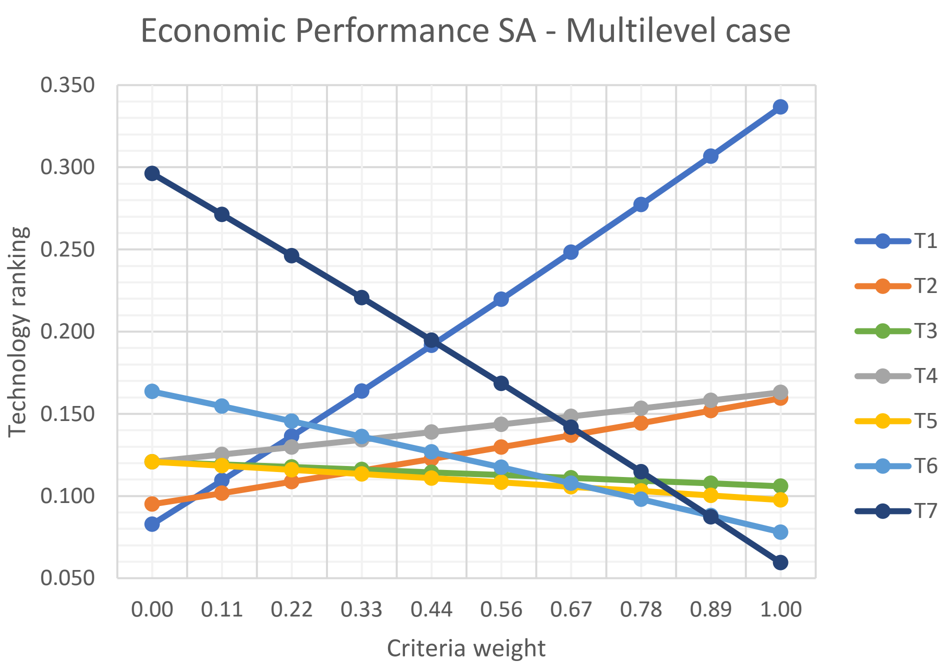


Figure 22 – Economic performance SA plot for multilevel case scenario

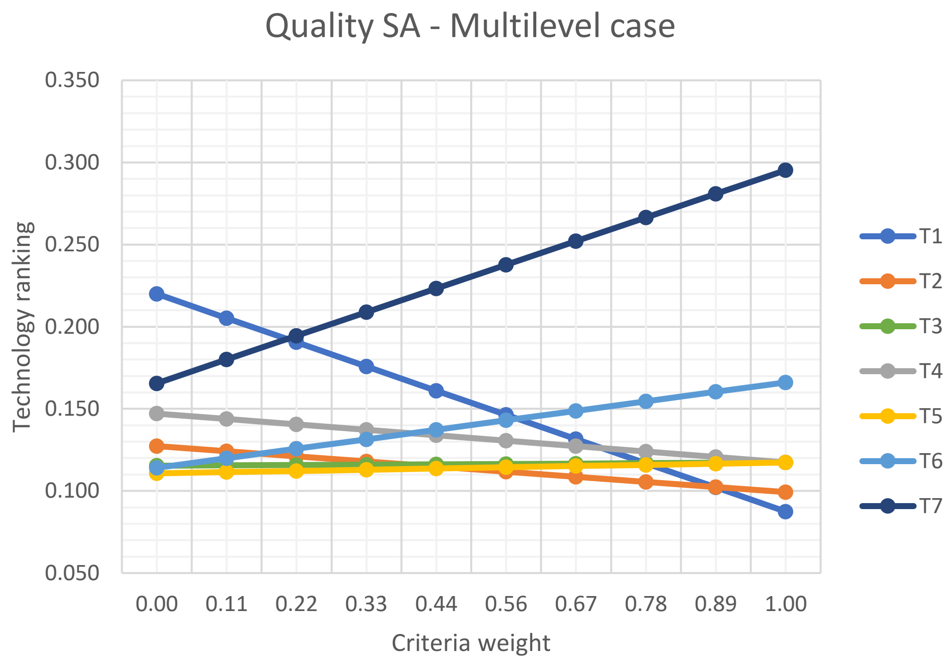


Figure 23 – Quality SA plot for multilevel case scenario

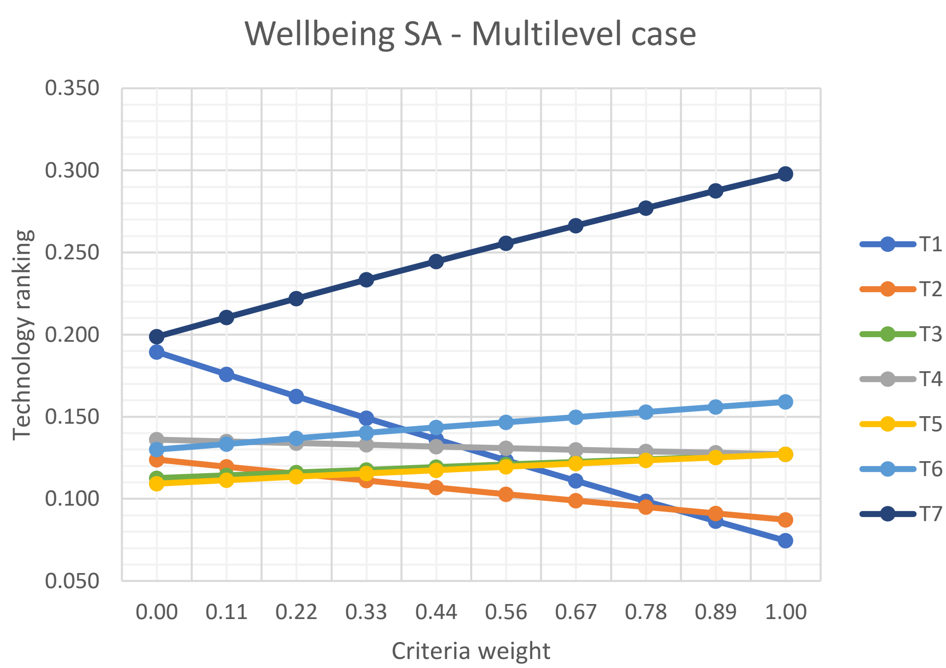


Figure 24 – Wellbeing SA plot for multilevel case scenario

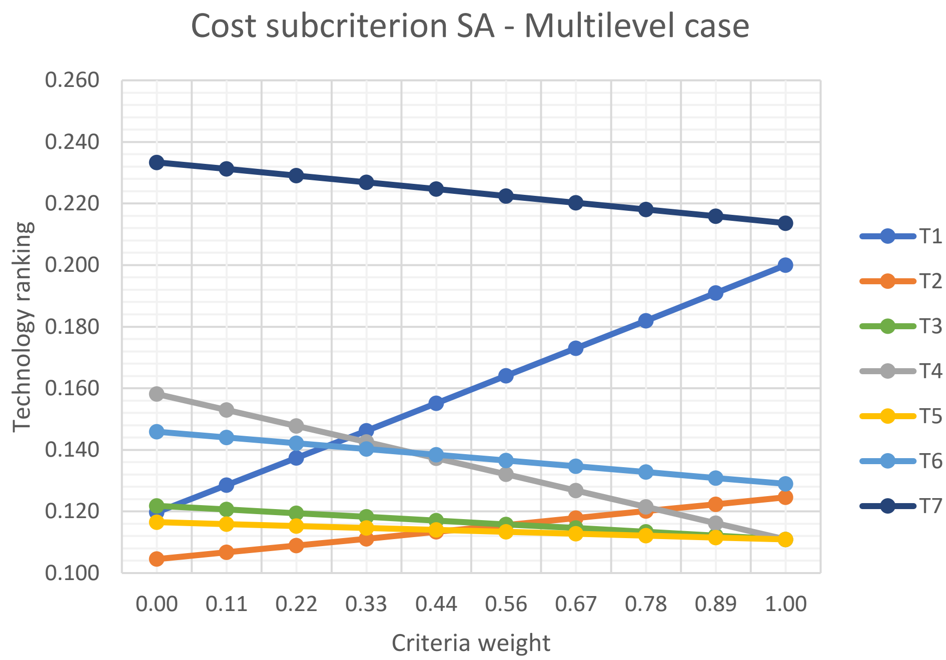


Figure 25 – Cost subcriterion SA plot for multilevel case scenario

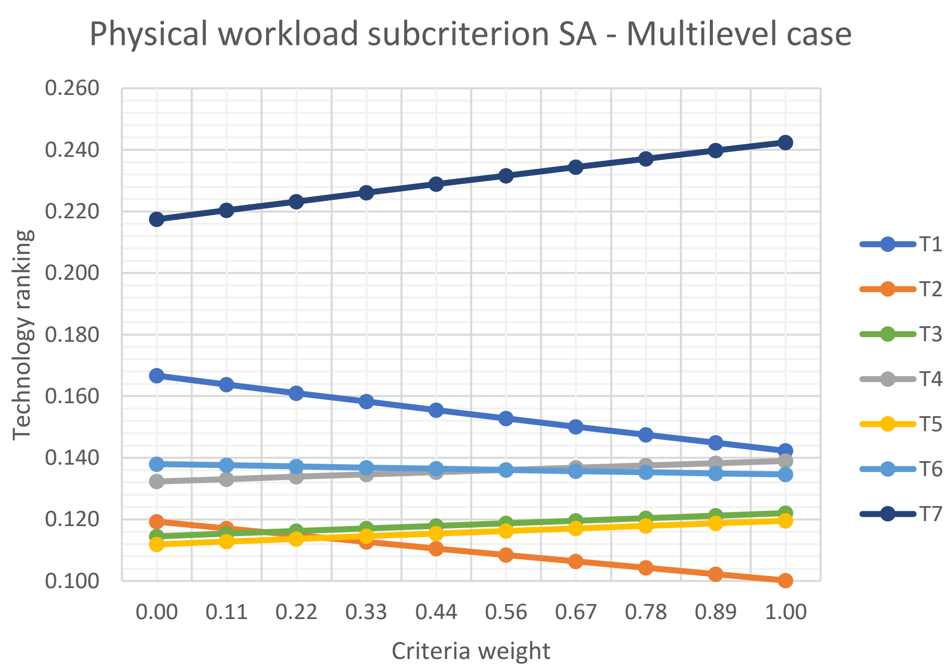


Figure 26 – Physical workload subcriterion SA plot for multilevel case scenario

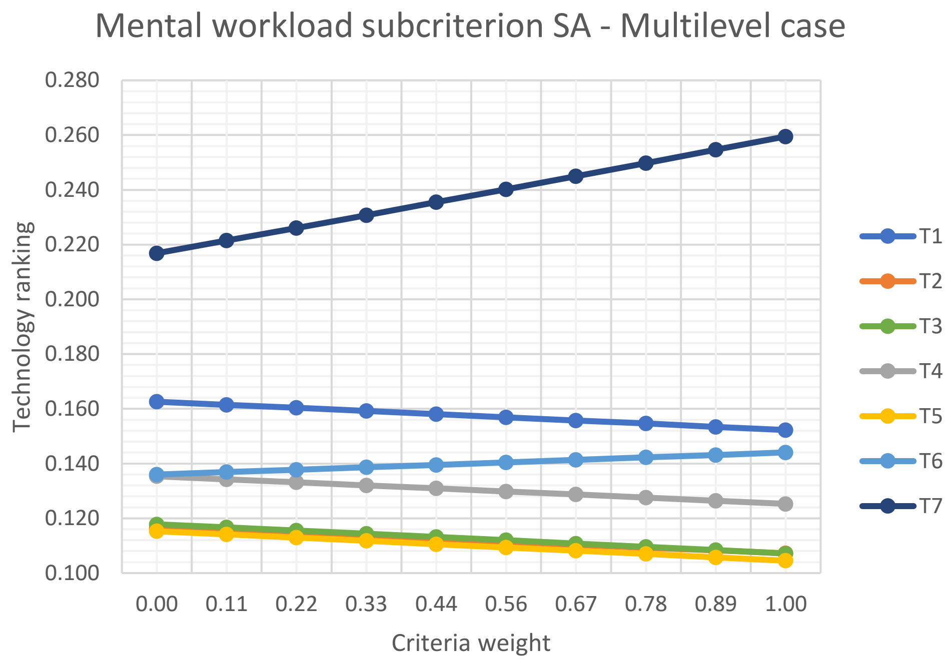


Figure 27 – Mental workload subcriterion SA plot for multilevel case scenario

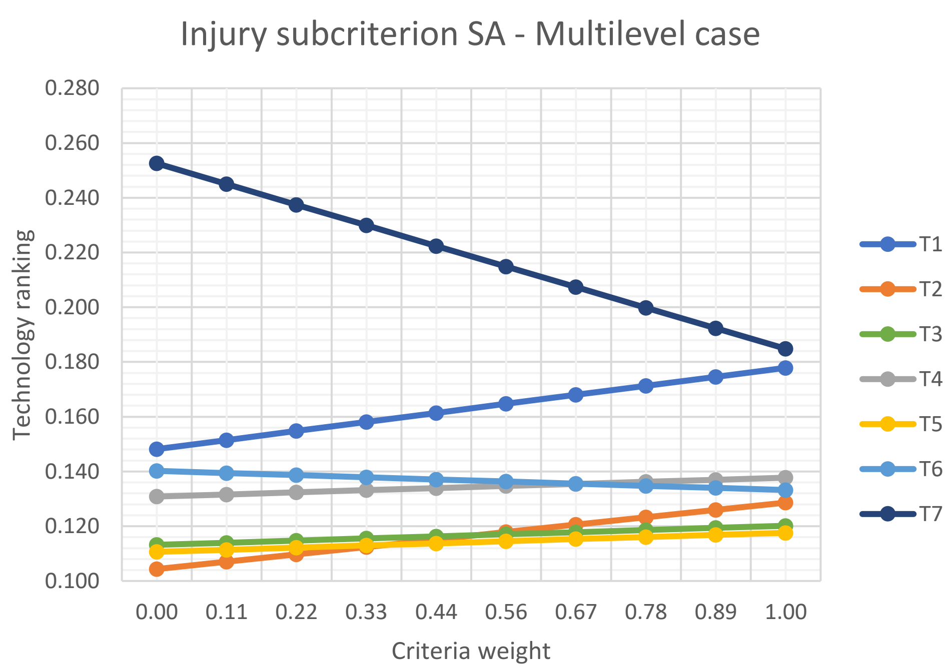


Figure 28 – Injury subcriterion SA plot for multilevel case scenario

Multilevel pallet scenario

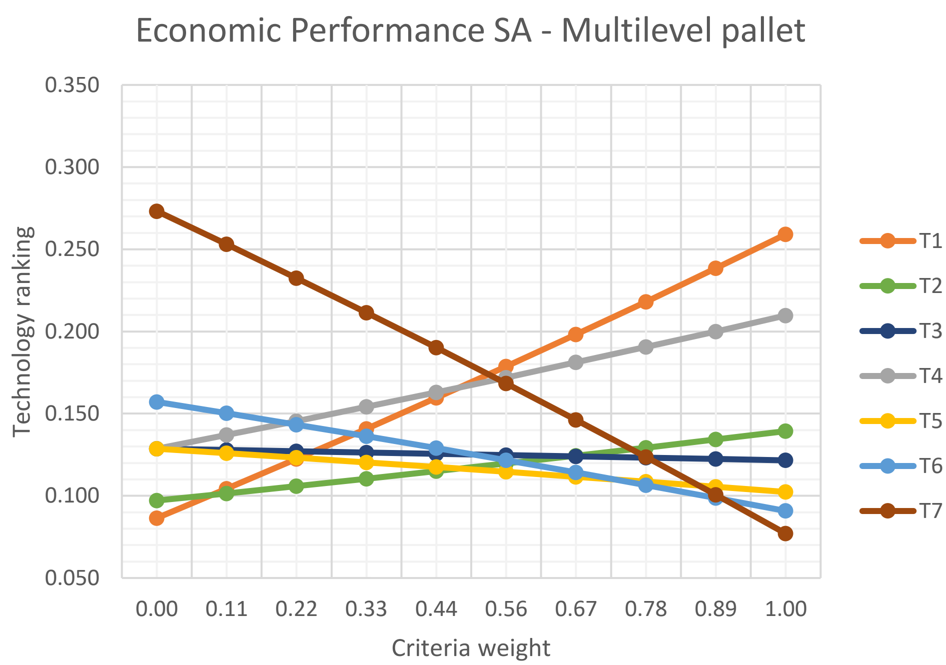


Figure 29 – Economic performance SA plot for multilevel pallet scenario

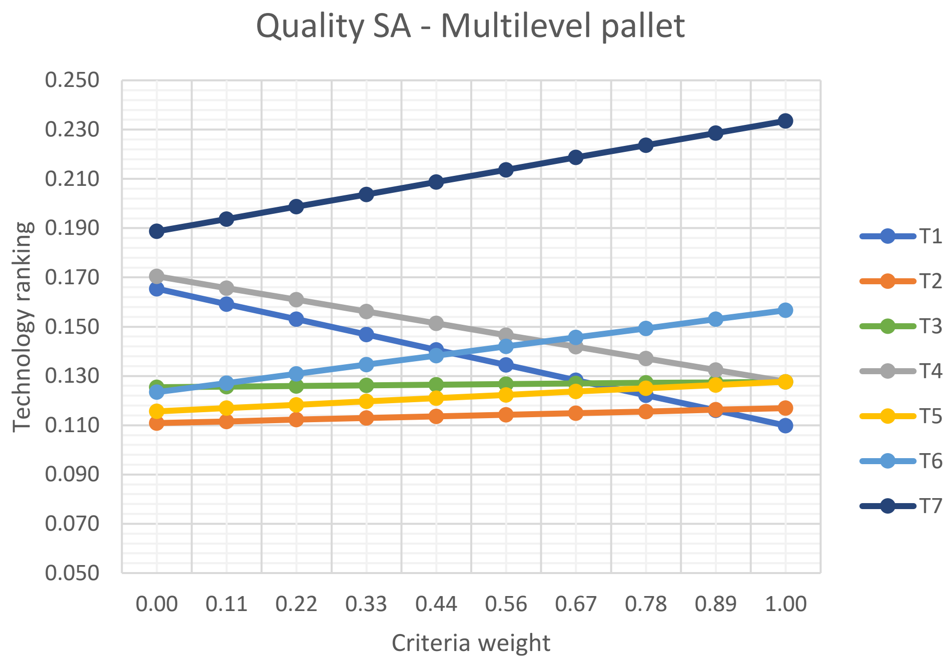


Figure 30 – Quality SA plot for multilevel pallet scenario

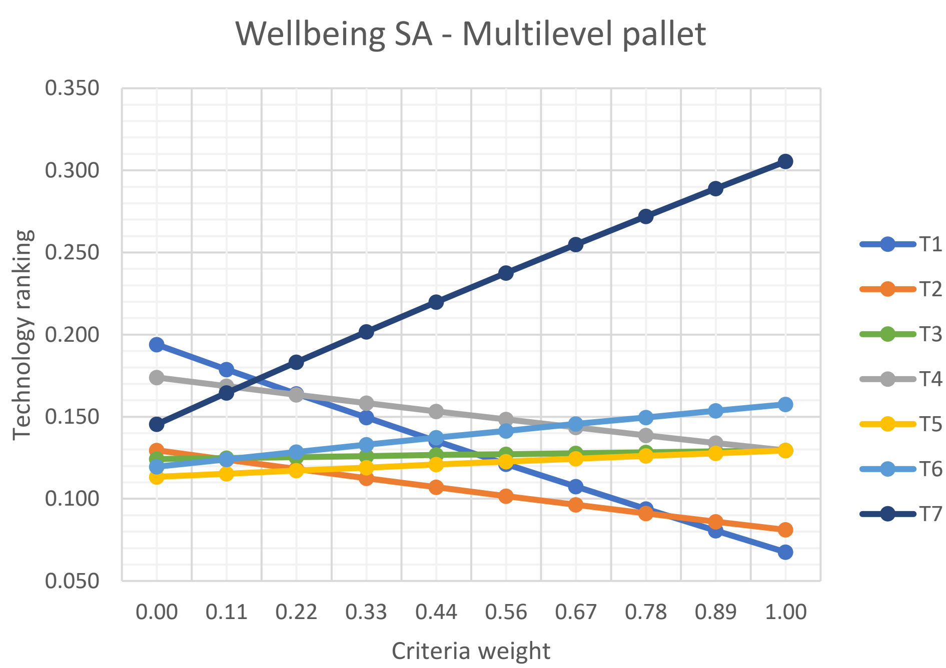


Figure 31 –Wellbeing SA plot for multilevel pallet scenario

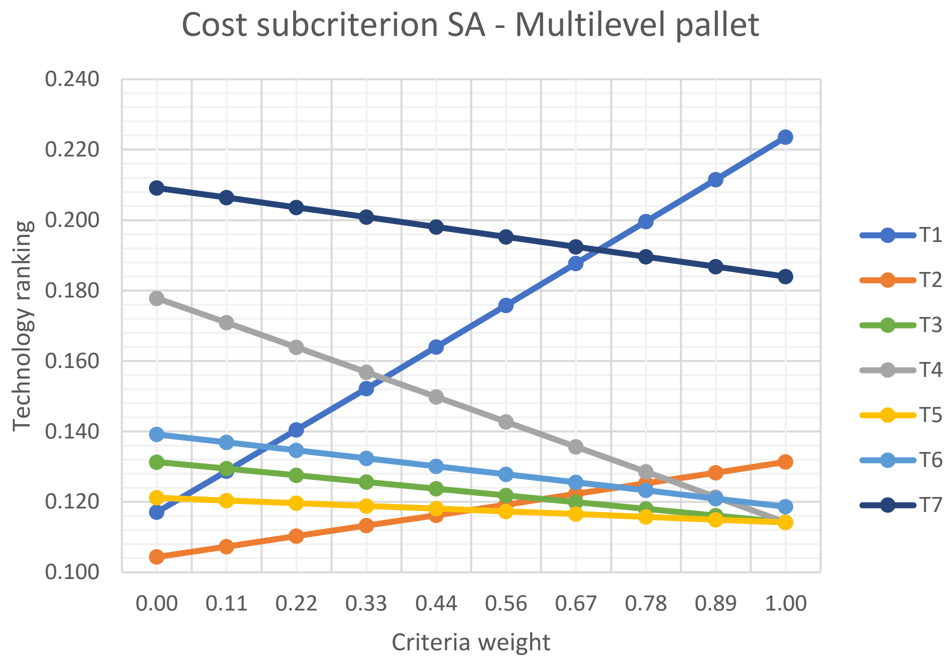


Figure 32 – Cost subcriterion SA plot for multilevel pallet scenario

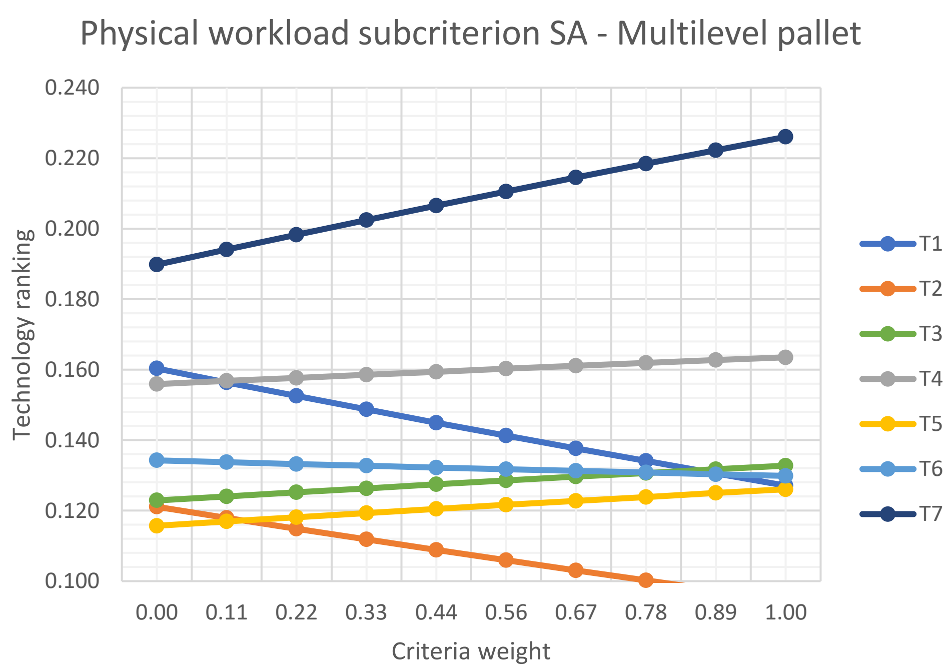


Figure 33 – Physical workload subcriterion SA plot for multilevel pallet scenario

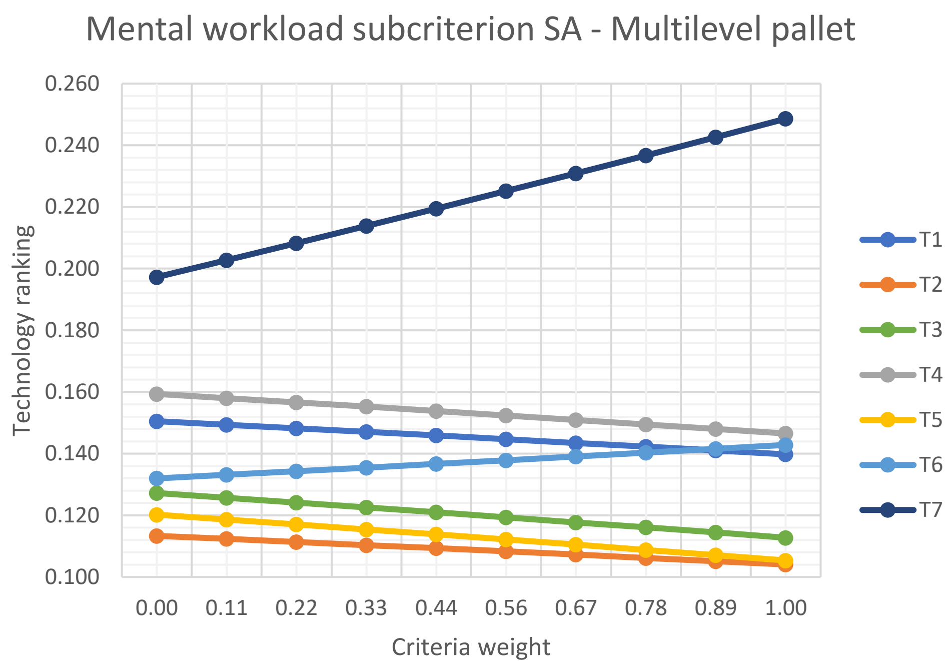


Figure 34 – Mental workload subcriterion SA plot for multilevel pallet scenario

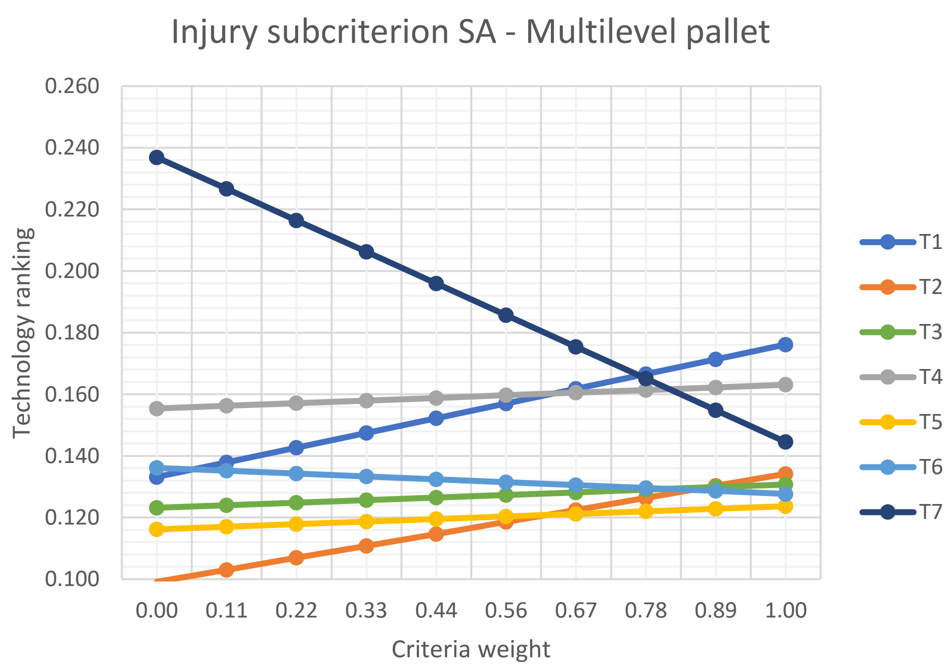


Figure 35 – Injury subcriterion SA plot for multilevel pallet scenario

Floor level pallet

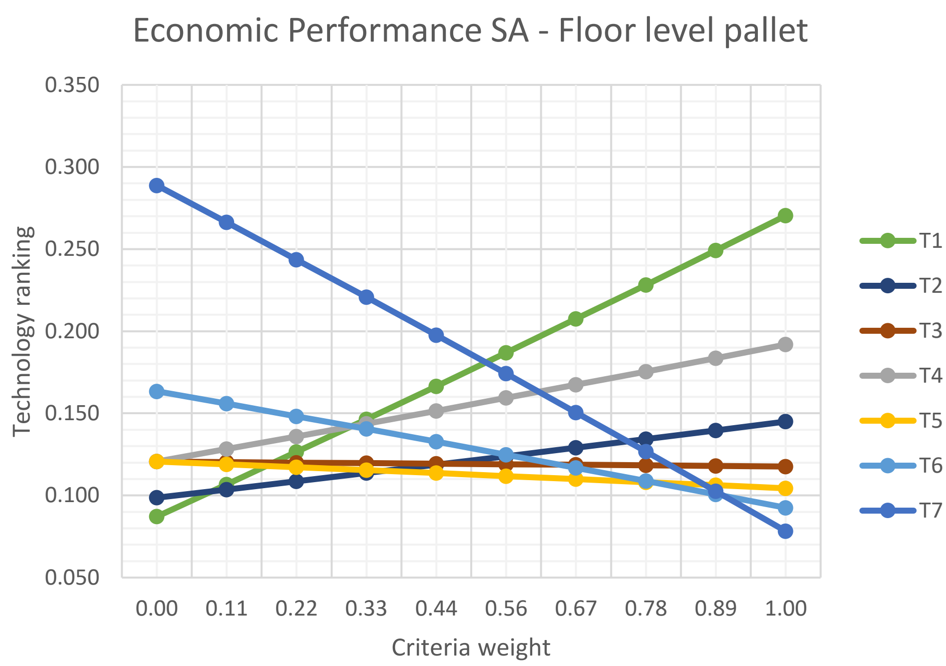


Figure 36 – Economic performance SA plot for floor level pallet scenario

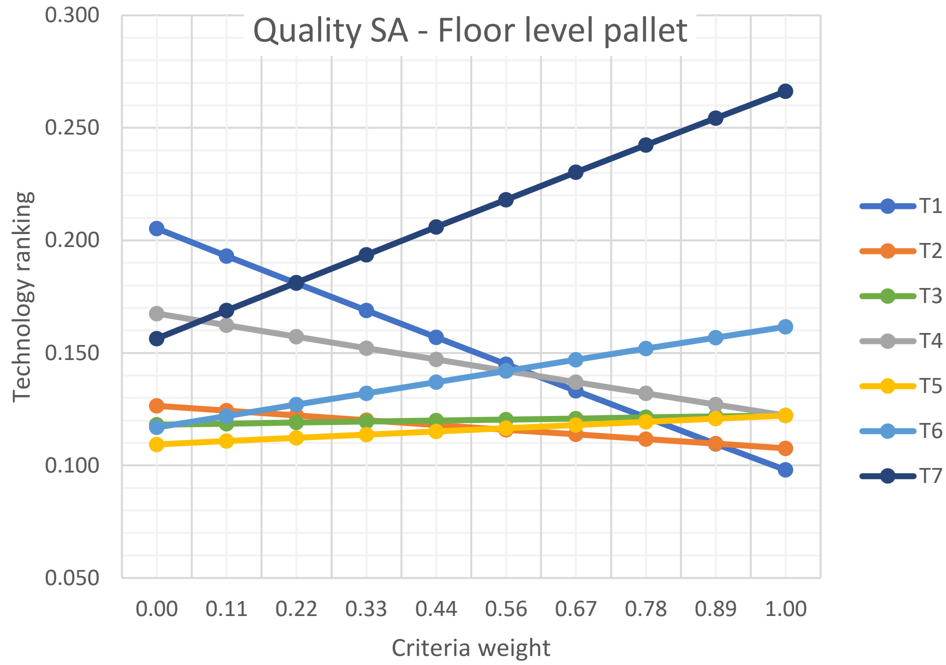


Figure 37 – Quality SA plot for floor level pallet scenario

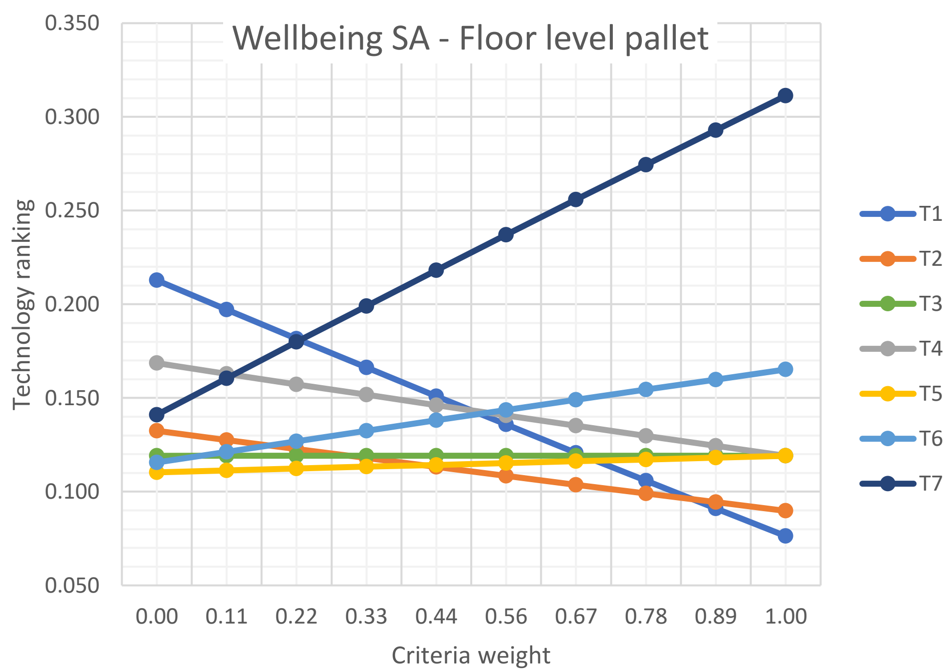


Figure 38 – Wellbeing SA plot for floor level pallet scenario

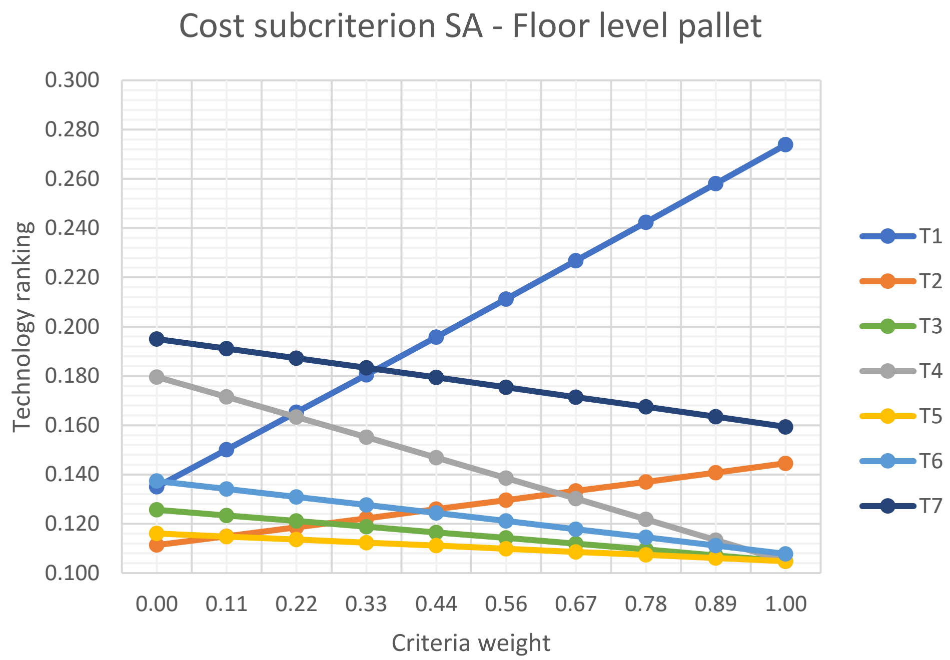


Figure 39 – Cost subcriterion SA plot for floor level pallet scenario

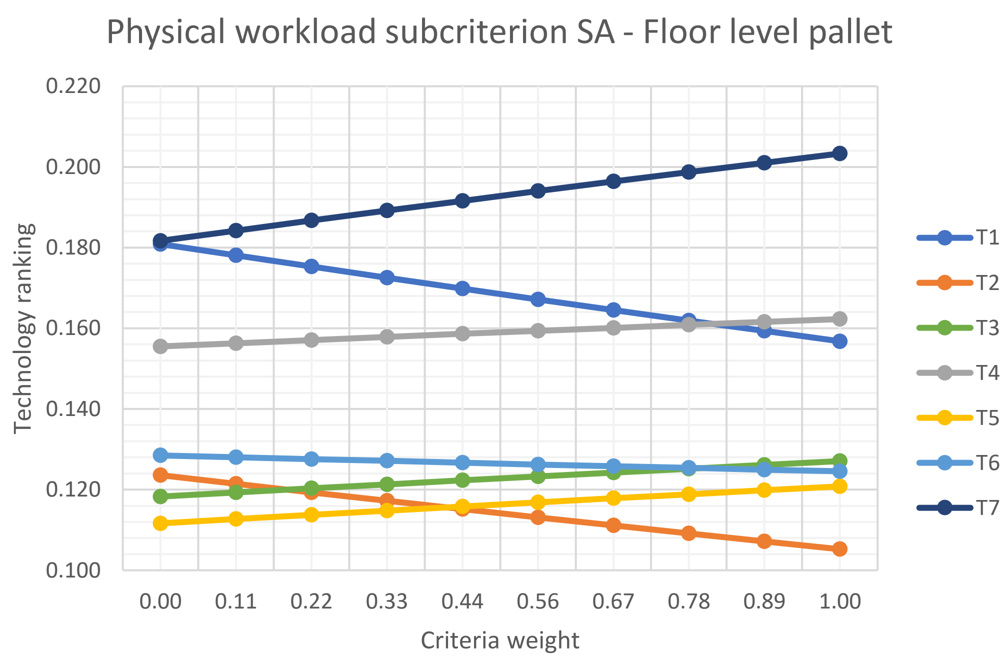


Figure 40 – Physical workload subcriterion SA plot for floor level pallet scenario

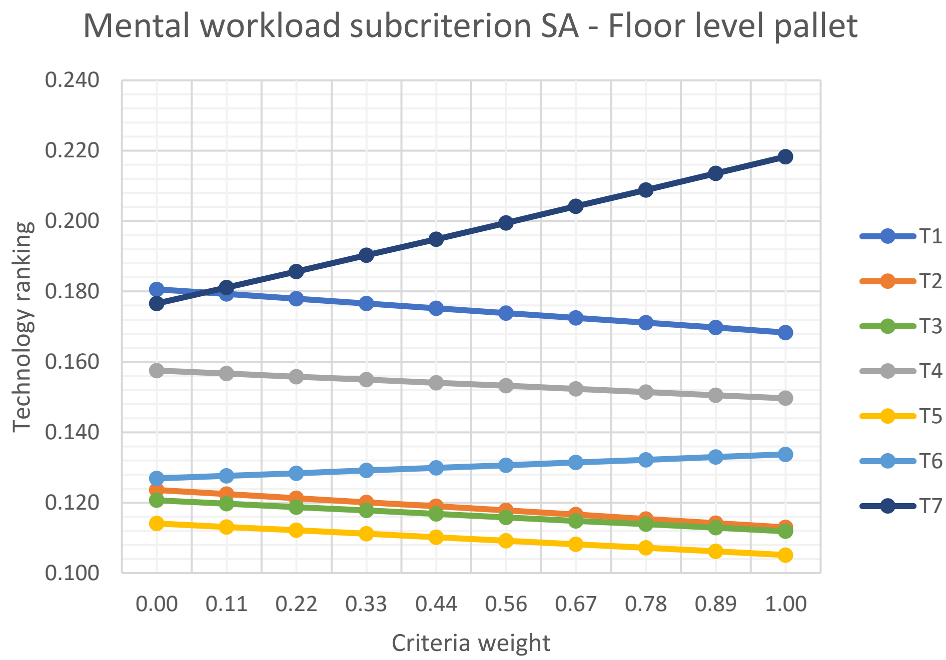


Figure 41 – Mental workload subcriterion SA plot for floor level pallet scenario

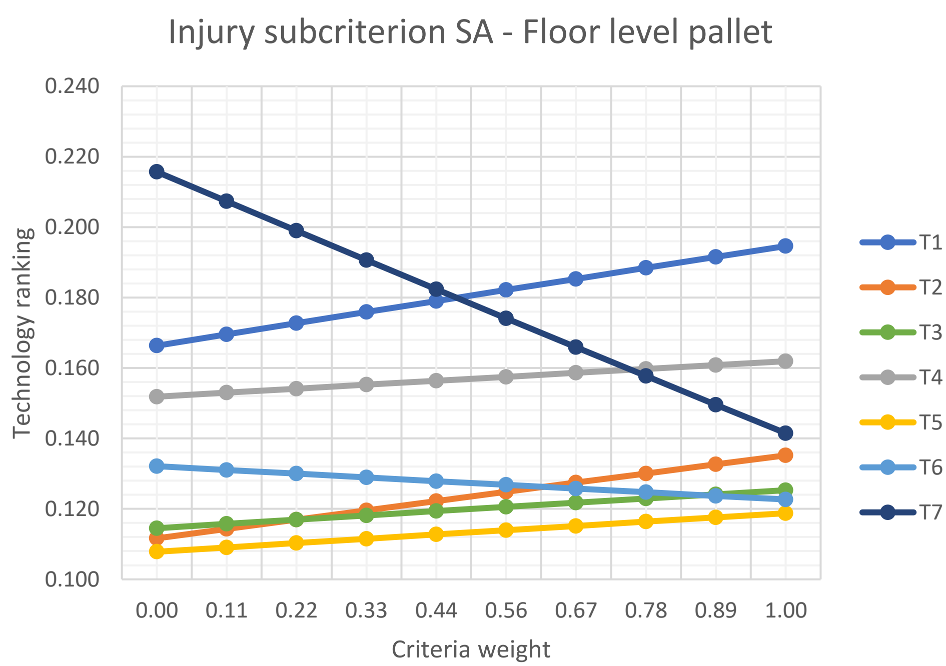


Figure 42 – Injury subcriterion SA plot for floor level pallet scenario

5. Discussion

The purpose of this chapter is to provide answers to the RQs of this thesis. So far, the results and findings for the different methodologies have been presented for the different scenarios however, they haven't been explained and connected to the research objectives. Below, the criteria and its weight is discussed to answer RQ1. Afterwards, a technology suggestion with a technology ranking is proposed for the different scenarios answering to RQ2. Further, the implications of different OP technologies relative to the criteria weights are discussed and built into a framework to assess RQ3. Finally, in the light of the research objectives and methodologies used, the limitations, contributions and further possibilities of research are suggested.

5.1 Performance criteria of an OP system

Through the literature review the OP performance criteria were found (table 11). The performance criteria are composed of 3 dimensions which in turn were further composed by 11 subcriterion. Specific definitions were provided to the decision makers, academic experts, and vendor experts in order to establish a common understanding. Even though the different type of experts consulted have knowledge in the area, providing a clear definition was important to decrease possible errors or bias due to misinterpretations. In fact, through the literature review it was identified that a unifying approach of the different dimensions is lacking as there are few references that consider more than one dimension in the same research.

Most of the literature regarding KPIs in OP systems was found to be in the economic dimension. A possible explanation is because these indicators rely on metrics that has been measured traditionally and are well understood for managers across different industries. Moreover, warehouses, in some cases, are still seen as cost centers therefore the financial aspect has the utmost importance in the different measures. Even though it is important to measure the OP system use of resources (money, time, use, and efficiency) it is also important to measure its efficacy, making the quality a relevant aspect. Within the quality dimensions aspects like the damage of products and errors in the OP are considered. These two criteria become relevant because they are related to the service level of the system and not considering them would defeat the overall purpose of OP. Lastly, the dimension that is least considered in the literature, and the most recent according to the findings, is the wellbeing of the operators. Considering the wellbeing of humans is particularly relevant because humans still play an important role in picker-to-parts OP systems, not considering these human factors would be neglecting the interaction between the operator and the technology. For this reason, many technologies are found to have a deviation from the planned performance to the actual performance.

Identifying the performance criteria have a dual objective for this research. First, to provide answer to RQ1 and secondly, to form part of the hierarchy model for providing ground to answer the further research questions. With the literature review, the criteria and subcriteria identified, the definitions given, and the AHP methodology to provide relative weights, it is considered to appropriately answer RQ1: *What are the main performance criteria of the order picking system in a warehouse?* Moreover, with the methodology selected the practitioners are provided valid input in dimensions beyond the traditional financial aspect, also what is important to consider when operating an OP system and what are their priorities in a quantitative manner. For academicians and research purposes, these findings can act as a unifying starting point for developing a practical backed-up-by-research holistic approach to measure OP systems.

5.1.1 Criteria Weight

Operational experts assessed the relative weight of the criteria and subcriteria. The comparisons were made at the second and third level of the hierarchical model to get the general and specific relative weights. From the values in the tables at section 4.3.2 and graphs at section 4.3.3 it is visible that managers generally tend to prefer the economic performance over quality and wellbeing, when referring to the general criteria. These results, even though are valid mathematically because they pass the consistency test needed in AHP, show the nature of decision-making where managers are confronted with dilemmas in their day-to-day operations. Next, the main criteria will be discussed in general terms to understand the general rankings. Further, the different scenarios will be explored and discussed in light of the different criteria and subcriteria.

In general terms, from figure 15 the economic performance dimension was ranked highest. Having the economic performance as the heaviest dimension means that DMs and organizations focus most of their time and priorities into being profitable and having a low-cost operation. This holds true the idea that businesses should be economically sustainable because a business that does not generate financial profit is likely to not last long because it is not productive. Furthermore, in general terms, quality was ranked as the second important dimension. Quality even though is only composed of two subcriteria has a direct impact on the economic performance of an operation because when a product is damaged it has to be replaced and if an order is incomplete then a lost sale was incurred. A high-quality OP system can be translated into an economic operation because the productivity losses are low. Lastly, it can be said that in general terms the wellbeing of the order pickers was ranked as the lowest from the three dimensions. These results bring to light that DMs leave this dimension behind the operative factors even when current literature is focusing on the wellbeing of the operators.

Dividing the criteria by the scenarios it is visible that the multilevel case setting is the only scenario where the quality dimension scores higher than the others, followed by the economic performance and wellbeing. The multilevel case scenario is characterized by having a high level of orders where the size of the item is less than a pallet and the number of SKUs is big which implies that a pallet could hold more than one order of different products. With these operational implications it makes sense that managers put resources into not harming the items and picking the right products, however the wellbeing of the operators is left last and mathematically, it is around the half of important than the quality dimension.

The multilevel pallet scenario is characterized by a high volume of orders of standard pallets, which implies that one order could consist of one or more pallets. With the operational implication of moving the highest number of pallets in the least amount of time, it is logical to have the economic performance ranked higher. Furthermore, in this scenario, the wellbeing of the operators has the second priority because this type of operation can generate a lot of traffic in the picking area therefore making the safety and awareness of the pickers of relevance. Lastly, the quality was ranked last, possibly due because picking the wrong pallet is harder than picking the wrong case based on size and location factors, however its mathematical value is not far from the second place.

At the floor level pallet system settings, the characterization is very similar to the multilevel with the difference that the pallets can't be stacked in levels because the pallets might not be standard size or could also be too heavy for a rack. This scenario has similar needs therefore the economic performance is also ranked as the first, interestingly its value is more than double than the other criteria, because the same need of picking many pallets is there. Nevertheless, the consensus of the managers was that quality and wellbeing had the same weight because in the individual level they were in exactly opposites. While this is mathematically possible and valid, the implication in this case is that DMs put, in general terms, the same amount of effort to quality measures than wellbeing measures. The previous explanation of the criteria ranking is summarized by the following table.

<table>
<tr><th>Scenario</th><th>Multilevel Case</th><th>Multilevel Pallet</th><th>Floor level Pallet</th></tr>
<tr><td>1st Priority</td><td>Quality</td><td>Economic performance</td><td>Economic performance</td></tr>
<tr><td>2nd Priority</td><td>Economic performance</td><td>Wellbeing</td><td rowspan="2">Quality & Wellbeing</td></tr>
<tr><td>3rd Priority</td><td>Wellbeing</td><td>Quality</td></tr>
</table>

Table 27 – Summary of criteria priorities for the scenarios

Discussing the subcriteria is only possible within the same dimension. In general terms, within the economic performance dimension and independently from the scenario analyzed, C1 (cost) was the most important followed by C12 (throughput), and finally C14 (cycle time). These results bring to light that C11 is still the most followed KPI for managers and it is understandable as warehouses should have accountability of all costs because the profit generated in these operations can only be calculated indirectly from the sales and service level, whereas the costs are straightforward to calculate through the resource use. On the other hand, having C14 as the least important subcriteria can be connected to the supposition that as long as the costs are within an acceptable limit and the service level is within target, the time it takes to fulfill the order correctly is not of the utmost importance. The most interesting outlier of the previous generalization is the ranking of rank reversal of C13 (utilization) where in the multilevel case scenario is the least priority while in the floor level pallet scenario it is the second most important. This ranking case could be based for the multilevel case scenario on the reason that as long as the cost is low, and throughput is high enough then the OPS is productive; whereas for the floor level pallet a high utilization of the technology means that the OPS is productive based on the different operative implications.

Economic performance	Multilevel Case	Multilevel Pallet	Floor level Pallet
1st priority	Cost	Cost	Cost
2nd priority	Throughput	Throughput	Utilization
3rd priority	Cycle time	Utilization	Throughput
4th priority	Utilization	Cycle time	Cycle time

Table 28 – Summary of the economic performance subcriteria priorities for the scenarios

The quality dimension is simpler in the sense that it encompasses only two options. Hence there was only one pairwise comparison and any result would be mathematically valid due to the inexistent possibility of inconsistency. In general terms, C21 (damage) was ranked as more important than C22 (error). DMs put more weight in damage because if the item is harmed in the process, then more resources need to be considered to replace the damaged item for a good one. This case is even more critical in industries where the stock is not owned by the warehouse such as 3PL, or when the products stored are chemicals or dangerous. It is important to say that some operational experts did not make a compromise in this dimension because any operation, including the OP system, should strive to be impeccable. Such is the case as the multilevel case scenario where the individual opinions where exactly opposite therefore the consensus was halfway.

<table>
<tr><th>Quality</th><th>Multilevel Case</th><th>Multilevel Pallet</th><th>Floor level Pallet</th></tr>
<tr><td>1st priority</td><td rowspan="2">Error & Damage</td><td>Damage</td><td>Damage</td></tr>
<tr><td>2nd priority</td><td>Error</td><td>Error</td></tr>
</table>

Table 29 – Summary of the quality subcriteria priorities for the scenarios

The wellbeing dimension is the most complex one with 5 subcriteria compared. As explained before, within wellbeing the human factors are considered, ranging from physical to psychosocial as well as the risk of injury. In general terms, C35 (risk of injury) was selected as the most important one, followed by C31 (physical workload), but no general conclusion can be drawn for the least important priority. Safety in the workplace is usually regarded as an imperative factor because all operations, regardless of if it is within the OP system or not, depend on continuity to be able to produce therefore, minimizing factors that put workers in danger in any aspect makes sense. Sources of injury risk come from the interface between a tool and the operator, such as a forklift crashing with a walking person but also from the repetition of the task like lifting or grabbing heavy items. Given that a picker-to-parts OP system requires a high share of physical labor, it is important that the risk of injuries, independently of the source, is as low as possible. For two cases C31 (physical workload) was the second priority. As explained before, OP requires physical labor, especially in a picker-to-parts environment where the operators perform a series of tasks routinely time after time, hence having a low as possible physical workload can be translated into productive operators as the accumulated fatigue is smaller. Consequently, technologies that automatize and decrease the physical aspect of the OP tasks can also score high. An interesting outlier is the floor level pallet scenario where the physical workload scored the last priority, this is based on the fact that given the characteristics of these items it is not possible for humans to move, push or carry. In such scenario the pickers always use a material handling tool that drastically decreases the physical workload.

Wellbeing	Multilevel Case	Multilevel Pallet	Floor level Pallet
1st priority	Injury	Injury	Injury
2nd priority	Physical workload	Physical workload	Mental workload
3rd priority	Mental workload	Psychosocial load	Psychosocial load
4th priority	Perception workload	Perception workload	Perception workload
5th priority	Psychosocial load	Mental workload	Physical workload

Table 30 – Summary of the wellbeing subcriteria priorities for the scenarios

The criteria identified and the assessed weights are valid independently of the industry the warehouse is operating in, as long as there is a picker-to-parts OP system in place. However, it can be arguable that the weights might differ depending on the specific priorities of the business. An argument against that statement is that the group AHP methodology followed consider judgments from operational experts whose knowledge is representative because they have enough experience and work in different type of warehouses and industries. In total, 9 operational experts from 9 warehouses, working in 6 different industries were consulted for this study.

5.2 OP technology ranking

Within a picker-to-parts OP system there are different technologies that could be used to accomplish the needs and goals of the activity. Such technologies can be seen in section 4.2 where the different solutions range from completely manual to completely automated. It is important to mention that in practice most warehouses have more than one technology in place or a combination in the way they are implemented, furthermore the way these technologies are used is not entirely standardized in the industry. This fact is important to consider as AHP works through direct comparisons therefore assumptions were needed to simplify the model while still making it relevant and applicable to reality. These assumptions and shortcomings are addressed deeper in the limitations further in the chapter.

It is valid to say that the manual technologies are the most basic solutions in the OP system because they depend entirely on the input of the operator. In this regard, a picking list does not tell the operator where to go or how to get to the destination, leaving room for inefficiencies and/or errors.

Moreover, a manual operation requires a high share of physical labor which in expensive countries that can be a big constraint as hiring labor is quite costly for all the direct and indirect cost it has; therefore, it is preferred to make operators as productive as possible. However, for operations where manual labor is not costly, manual labor might be preferred over more technologically advanced solutions. Paperless technologies support the operator in different levels and diminish the probability of errors and inefficiencies depending on their specific characteristics while still relying in humans. Finally, the PTR is able do all the process by themselves which would reduce the workload of the operator, or put in other terms, it would allow human operators to focus in other more productive or complicated tasks.

From the technology assessment performed by the academic expert, it becomes relevant to merge their level of automation and their characteristics, into the way they impact the different performance criteria. Given the three different scenarios and the results of the group MCDM, a suggestion for the most suitable OP technology is proposed in table 31. It is important to mention that three technologies are presented as suggestion because the first two values are the most coherent with the criteria weights, and the third could be a different approach, therefore these technologies fulfill the requirements the best. AHP results are to be interpreted in numerical terms, where the number is understood as the degree of compliance or alignment with the priorities. For all the cases the PTR technology is preferred because it scores well above the average in almost the half of subcriteria evaluated. Nevertheless, picklist is ranked high because it scores high in the most important criteria.

Ranking	Multilevel Case	Multilevel Pallet	Floor level Pallet
1	PTR (Pick to Bin)	Pick & Transport Robot	Pick & Transport Robot
2	Picklist	Pick by Voice	Picklist
3	PTR (Pick to Pallet)	Picklist	Pick by Voice

Table 31 – OP technology suggestion for each scenario

In the multilevel case scenario, a possible advantage of having a PTR (pick to bin or pick to pallet) is that, according to the level of automation of that solution, cases of items can be moved easier with a low effort from operators and with the lowest error possible, moreover that technology supports the goal because its rankings in quality and wellbeing criteria is the best from all the other technologies. On the other hand, picklist also provides a support to that scenario mainly because it is still the cheapest of all technologies, even when the ranking in quality and wellbeing is not good the operative cost is the lowest from all. It is important to recall the fact that a picklist technology can be paired up with a material handling tool like a forklift or an AGV to increase the volume it can handle. Furthermore, a picklist could also be digitalized into a screen that has the potential to decrease the amount of picking errors because it could require confirmation from the picker while still being considerably cheaper than a robotized solution. In the multilevel case scenario, the quality dimension is the most important followed by the economic performance and lastly the wellbeing of the operators.

Within the multilevel pallet and floor level pallet system settings, a fully automated solution was ranked as first priority. An advantage of having a pick and transport robot in a full pallet scenario is that usually the pallets are standard size therefore a robot can easily perform all the OP tasks by itself with a minimum strain for human operators, the lowest possible errors, and an average throughput. In the case of the multilevel pallet scenario, the economic performance is the most important criterion, and while the PTR has a high cost, it is compensated by the other criteria and subcriteria. While in the floor level scenario the quality and wellbeing dimensions have the same weight, the economic performance is also the most important, so the fully automated technology compensates its high operative cost with its advantages in quality and wellbeing. Interestingly, the second and third options for these two scenarios are reversed as seen on table 31. PbV and picklist are proposed as second and third option, respectively, for the multilevel pallet, and third and second, respectively, for the floor level pallet. Pick by voice form part of the paperless technologies where the picker is guided via voice commands towards the picking location and tells her how many items to grab, moreover, the picker has to confirm the task. PbV is ranked high because it has the highest throughput of all the technologies which is the second most important subcriterion in both scenarios.

Remarkably, even though picklist in gross terms is the most manual technology, and therefore simpler and the most prone to picking errors, it is generally ranked higher than many paperless technologies. The reasoning behind this result of picklist is based on the combination of cost ranking and wellbeing ranking. Picklist is the cheapest to operate which is the heaviest subcriteria but the technology with the most workload, however that does not matter too much, according to the experts. Regardless of these reasons, a consideration on the picklist requires the highest number of picking operators, which could be translated into costs and have low productivity against robots that their only downtime is while recharging battery.

The goal of performing a literature review on the available OP technologies that considers their level of automation and performing three different group AHP was to provide a valid ground to compare the different existing solutions against the different criteria and to answer RQ2. *What are the most suitable order picking technologies for a warehouse that operates with a picker-to-parts method?* The specific answer to RQ2 is in table 31 which shows the three most suitable technologies for the specific scenario. Besides addressing the research goal, having a technology ranking for the different system settings, is particularly useful information to practitioners who are in the process of implementing or evaluating an OP technology in their warehouse. For research purposes, this methodology can serve as a way to compare the suitability of technologies and investigate further applications and developments of these technologies.

5.3 Implications of implementing an Order Picking Technology

A sensitivity analysis varying the importance of the different performance criteria and subcriteria was performed for each scenario and for C1 (economic performance), C2 (quality), C3 (wellbeing), C11 (cost), C31 (physical workload), and C32 (mental workload). This is especially relevant because in a first approach the SA provides information on how the technologies relate to the performance criteria priorities but when analyzed deeper the sensitivity analysis provides information on what are the implications for implementing a specific technology based on the specific business priorities. Below the different sensitivity analysis available at section 4.4 will be discussed and will be rendered into operational situations depending on the variables.

When analyzing the economic performance SA, several rank reversals in the technologies are observed in the three scenarios. In general terms, the technologies with the highest LOA present a inversely proportional relation with the weight of C1, therefore the more important the economic performance is, the lower the more advanced technologies scores in all the scenarios. On the other hand, the manual technologies increase progressively in the ranking with the weight of C1. This relationship is backed up by two factors: the operation cost of the solution and the throughput. Cost is the most important subcriterion in the economic dimension, hence technologies that are cheap to operate, such like the manual ones, will score better. On the other hand, throughput was the second most important subcriterion for two scenarios and in floor level pallet was the third, where two out of four paperless technologies scored the best. As it has been found on the literature, picker-to-parts OPS are labor intensive and in countries where the human resources are expensive other factors should be considered when taking a decision. Having expensive OP technologies in the warehouse is translated into capital expenditure, which in turn is a way to increase the fixed costs, so from a purely economic and financial perspective, the cheapest OP technology, such as picklist, would be preferred for the three scenarios.

Within the analysis of the quality dimension, the behavior of the technologies is the opposite than the economic performance. The rank reversal in the ranking happens because the technologies with a high LOA are directly proportional related to the weight of C2. For multilevel case and floor level pallet, the picklist started as the best positioned technology and for all three scenarios the picklist ended in last followed by the scanner. It is important to recall that according to the academic expert, all the technologies scored the same in damage, hence the differentiation in quality terms is dependent on the error. Technologies with a higher LOA support the OPS by having a better and leaner process that decreases the different failure modes when performing any of the OP tasks. Technologies that do not automate any of the OP tasks are still dependent on the picker to perform them, hence the picker can walk to the wrong aisle or grab the wrong item, or grab the wrong amount, whereas a fully automated solution like the PTR will follow the requirements line by line. As it has been explained, the combination of technologies is out of scope of this work but having more than one in place could increase the quality in the tasks. For cases where the quality is the key factor to consider, such as the multilevel case scenario, technologies that automate the OP tasks provide a high level of quality, thus preferred over cheaper options that could provide a higher output.

The wellbeing is composed of the different loads and risk when the picker is performing the OP tasks. In the SA of this dimension the general trend in the three scenarios is similar as the previous criterion. There is a general correlation between the LOA and the wellbeing importance in a directly proportional way for the three scenarios. This connection is explained by the fact that advanced technologies perform more OP tasks thus freeing the picker of these loads. When a picklist is implemented, the picker is the one manually doing all the tasks, with paperless technologies the picker is assisted, and in a PTR is the robot performing the tasks. OP technologies that automate and perform tasks by themselves score better when analyzing the wellbeing of the operators and a consequence of this association is that the picker will be less tired which can be translated into a lower decline in the productivity. Manual and paperless technologies depend on the interaction and input from humans; even though paperless solutions support the picker the operator can still be tired, distracted or stressed therefore rendering the technology less productive. Wellbeing was not the most important dimension in any of the scenario, however in floor level pallet and multilevel pallet it ranked second. In the case managers or organizations have no compromise on the wellbeing of their operator, beyond the economic performance or the quality, an advanced technology, like a PTR, could be selected to diminish the workloads of the pickers.

Analyzing an individual subcriterion becomes relevant to reveal which technologies have a positive or negative correlation with that specific characteristic. As explained in the research methodology, when analyzing a subcriterion, all the other weights of the dimensions remain untouched as this SA is a monothethic analysis. When looking into the case of cost, picklist and scanner are the only two technologies for all the three scenarios where their ranking improves when the weight of cost increases. However, the rate at which picklist increase its ranking is higher than the rate of the scanner, to the point that in the multilevel pallet and floor level pallet it becomes the preferred technology. The rate of increase or decrease is given by how expensive the technology is, the more expensive or cheaper from the average, the rate will be higher. It is interesting to observe that in the multilevel case scenario, the picklist does not become the preferred solution, just under the PTR, this is due to the relationship between the other subcriteria in the other dimensions, where the quality dimension is more important than the economic performance dimension. When considering only the cost as the most relevant subcriterion within its dimension, picklist is preferred over PTR in the multilevel pallet and floor level pallet scenarios, but a PTR is preferred over the picklist in a multilevel case scenario for the benefits it provides to the operation in relation to the cost it represents. If cost is not a constraint, PTR and pick by voice are the most suitable solutions for the OPS for all the three scenarios.

Physical and mental workloads are subcriteria of the wellbeing dimension. Both subcriteria have the same ratings for all the technologies and the behavior of the sensitivity analysis is similar for all the scenarios, hence it makes sense to describe them together. When performing the OP tasks, is important that the picker is alert and active physically and mentally in order to complete the tasks. OP solutions that does not support the picker in these subcriteria, after time, will see a decline in the overall productivity. Considering the importance of these two subcriteria, the SA clearly identifies a relationship between technologies with a high LOA and their ranking. PTRs are the only technologies that have a directly proportional rate of preference when the mental and physical workload weight increases. This association is because the PTRs are a specific and advanced technology that can perform all the OP tasks by itself which dramatically decreases the workloads of the picker, freeing them to perform other tasks as the robot will fetch the desired product in the right quantities. Even when in general the wellbeing dimension was not ranked at the top, technologies with a high LOA are preferred because their attributes outperform those of the more basic technologies. In a situation where the mental and physical workload of the pickers are the most important factors, fully automated technologies like the PTRs should be considered as they free the human resources to perform more complex or advanced tasks than picking items.

5.4 Framework for OP technology selection for Decision Makers

This section presents the merger of the criteria with the technology ranking in order to create a visual framework for the practitioner to understand the implications of the OP technologies. Up to today, there is no technology that provides the best economic performance, with the highest quality, and the best wellbeing at the same time, therefore DMs need to have clear priorities when selecting an OP technology for their warehouse. Nevertheless, when all the different technologies are put together versus the three dimensions it becomes clear that there is a direct relation with the level of automation and the criteria performance. The higher the LOA the higher the quality of the OP technology; the higher the LOA the more expensive the technology becomes, and the higher the LOA the better wellbeing for the picker is afforded. However, as explained in the limitations section, this correlation is valid only when considering the direct application of the technology without modifying the environment, systems, the way workers interact with it, or the way it was implemented.

Figure 43 is a ternary representation that consists of the arithmetic mean of the individual subcriterion per dimension per technology with the values normalized so they can be represented in percentages. Integrating all the subcriteria, regardless of their weight becomes a different approach because the ternary plot lays out the primary dimensions while at the same time comparing the different technologies. This framework is of special utility to DMs when assessing the implementation of the available OP technologies in their picker-to-parts OPS, moreover, it is valid independently of the industry or type of items picked as long as the DM is interested in these three criteria and their subcriteria. To further interpret the ternary plot the manager should consider what is more important for them and how the overall OPS and warehouse adapt to the technology and viceversa. Therefore, the user of the framework should approach the OP technology from the perspective that a compromise should be made because there is still no solution that satisfies all the goals.

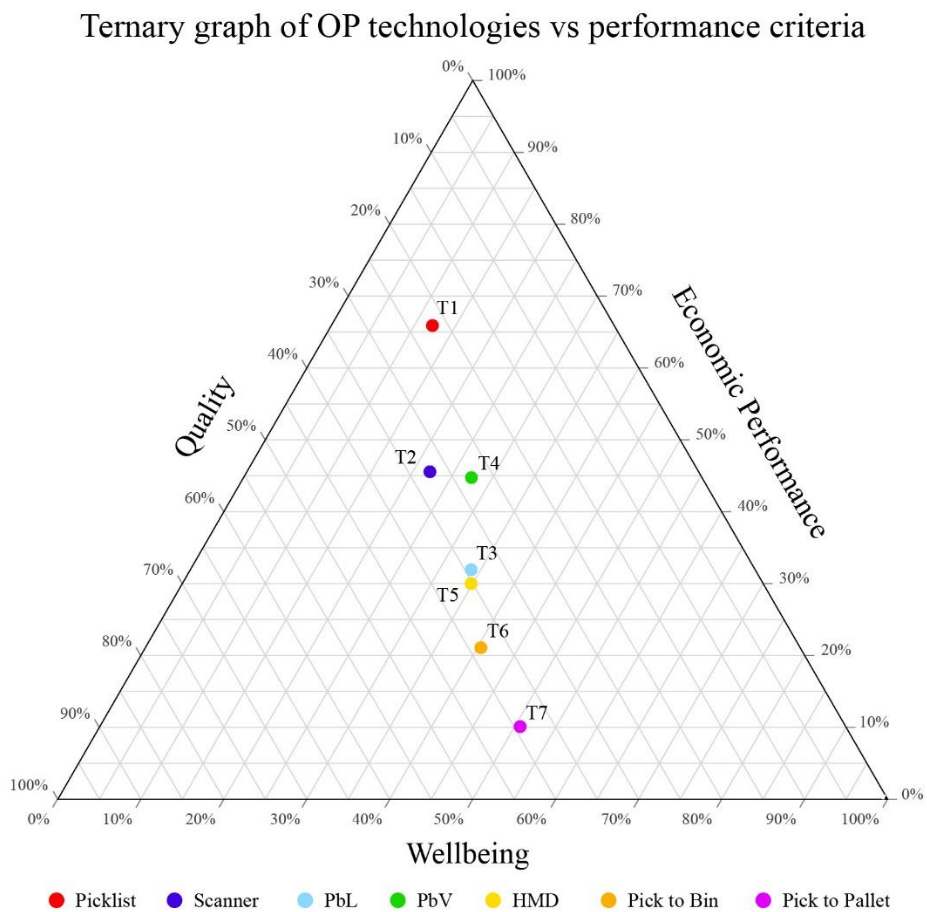


Figure 43 – Framework for OP technology selection

The possibility of visualizing and putting in a tridimensional space the location of the technologies is a simple, yet powerful, way for DMs to express and find their preferences when assessing the problem of selecting an OP technology. With this framework, the sensitivity analysis and the results of the AHP, a DM can better understand the relations and implications that influence a selected technology. Furthermore, the manager, when using these inputs, can decide which solution suits their operative environment with the help of their own experience, priorities and constraints. Section 5.3 and 5.4 provide the answer to RQ3 *What should managers be aware when implementing an order-picking technology in a warehouse?* The framework and the sensitivity analysis show the correlation between the LOA and the three performance criteria. Managers should be aware of this relationship between the dimension and the characteristics of the technology. To simplify the SA and the framework, advanced technologies provide better quality and lower workloads but at a higher cost and not a higher-than-average throughput.

5.5 Limitations, Contributions, and Further Research

To finalize the discussion chapter, a critical approach on the method used is presented where the capabilities and constraints of the AHP and overall model are discussed with the purpose of debating the characteristics upon which the thesis is built. Following, the contributions to both practice and academic are presented and discussed. As it has been acknowledged, the novelty of this work lays on the fact that no research so far has compared the three dimensions of performance criteria and tried to rank the full spectrum of OP technologies according to them. However, this thesis is just a step towards a better understanding of the interaction between different technologies and the performance criteria, therefore the research potential in the area is quite big and it is presented at the end. A brief discussion of OP topics and real-life implications is included in the three sections to criticize and support the findings and methodology. In general terms, considering the scope and the specific problem that the thesis is trying to address, the selected methodology and findings are relevant to practitioners and researchers although more work is needed.

5.5.1 Limitations

This thesis is mainly constructed around a group AHP where the results are main components of the study objectives and answers to the RQs. Therefore, it is important to mention the limitations of this work to further understand the implications and get the right understandings of the results. Using a group MCDM via AHP is a justified way (Karthikeyan et al., 2019) to assess a set of options and to getting the relative importance of a criteria set because it is backed up by a solid quantitative methodology, furthermore a number of studies have used this process and have had successful outcomes. Nevertheless, any model that uses AHP is bound to limitations which are derived from the methodology itself and the way the data has to be collected and processed.

The first, and main, limitation of a study that relies on AHP is the level of simplification needed to achieve a hierarchical model. In complex and real-world problems, such as selecting a suitable OP technology, the problems are not entirely hierarchical because there are relations between the different alternatives and criteria that a hierarchical model can't consider. In this sense, as AHP depends on pairwise comparisons to get numerical values, the questions asked only considers two aspects at a time when in reality the dependence is not that simple. Furthermore, alternative combinations, which are completely valid in real world (for example employing a scanner and an AGV), had to be left out because the potential combinations become too many to assess, rendering AHP unpractical. Therefore, a compromise had to be done to have standalone technologies to still be able to perform an AHP of quality. Simplifying a problem is not a drawback by itself if the resolution of the problem is still sophisticated and well posed, however in this case and considering the interconnectedness nature of an OP system, a pure AHP interpretation can be too basic.

The second limitation of this study is a result of the mathematical logic election. In the three AHP models performed, crisp numbers were used. In section 3.3 the characteristics of crisp sets were described and while numerous research has been performed following this method, the most advanced and complex AHP models use fuzzy numbers. Moreover, it has also been proven that the use of fuzzy sets provides a more real approach to situations where the information is very imprecise or when the nature of the numbers is not truly numerical (Sadovski, 2019). An OP system is, by definition, a conjunction of many constraints, resources, needs, variables, and goals, all working together to fulfill an order. Therefore, the use of a deterministic and clearly defined scale, such as crisp numbers, is not the best approach, because uncertainty is not considered under this mathematical logic.

A third limitation of this study is connected to the methodology selected and the scope within the OP system. The context of the OP technologies, how the technologies are used and possible combinations, are simplified. In real-life applications, the warehouses have a blend of scenarios, needs and technologies. In this study the different systems settings had to be compared in separate MCDM models because of the hierarchical nature of AHP, so what could be understood as three different and independent scenarios, most often will be happening inside the same walls and at the same time. Secondly, the technologies listed had to be compared and ranked individually. This compromise is based on the number of possible combinations, which is already high, including all the combination would deem AHP unpractical and weak, and collecting the necessary data becomes too complex. Lastly, technologies don't operate in isolation, so they are largely dependent on the way they are implemented and used. Considering the different ways of how technologies are deployed is not possible with an AHP because the lowest level of the hierarchy is the sole alternative and a change in the alternative would create another alternative. Therefore, the technologies listed in this study are scoped down and simplified to be able to establish a ground for comparison.

5.5.2 Contributions

The main contribution of this thesis is the proposition of a systematic method backed up by relevant literature with valid experience that assess performance criteria and technologies which is valid for warehouses with a picker-to-parts OP system under the scenarios modeled. This thesis supposes the first attempt to consider the three dimensions of performance: economic productivity, quality, and wellbeing factors to solve the problem regarding the selection of an OP technology in a picker-to-parts order picking system. Available literature and cases on the problem does not consider the three dimensions. Therefore, this thesis has relevance for practitioners that are in the process of assessing their OP capabilities and strategies, as well for academics because the OP technology selection problem could be approached from a MCDM perspective. Furthermore, for this study the diverse types of technologies available (manual, paperless picking, and pick and transport robot) were compared. In previous studies, only manual and paperless technologies were considered, therefore this study adds a better understanding of the available OP technology range.

The system settings used in this thesis are the main scenarios in which the hierarchy models are built, this means that for this thesis three different AHP models were performed. Having set up the scenarios based on the way the picking task is conducted is an alternative characterization from how the available literature approaches the picker-to-parts OP problems, which is a secondary contribution to the existing knowledge on OP systems. With this characterization it is possible to generalize the results to a broader set of warehouses where cases and pallets are picked. As a result, this study and its results are applicable to different warehouses independently of the industry where they operate however, the limitations previously explained should be always considered.

Using AHP as the backbone to evaluate the OP performance criteria and to rank the OP technologies is a clear, simple, and powerful way, to assess this challenging problem. Furthermore, this thesis contributes the operational field by having used valid input from the available literature and from experts consulted who works in different industries. The data collected encompass experts in the area of 3PL in B2B and B2C channels, logistics in automotive industry, logistics in manufacturing industry, and logistics in beverage industry; all across different countries such as Netherlands, Sweden, Mexico, and the USA. In this regard, the MCDM method selected is a suitable manner of collecting and converting linguistic, qualitative and quantitative data into a criteria weights and alternative rankings which is valuable for decision makers.

Lastly, this work contributes the field of OP research and application because through the results of the sensitivity analysis the relationship between the technologies and the performance criteria is explored. As it was explained in the background, the planned performance of OP technologies often deviates from the actual performance and the usual reason is because the different implications weren't considered. Including the wellbeing of the operators as part of the analysis is a step towards a more realistic decision model because in picker-to-parts OP systems the use of human operators is, and according to the trends, will keep being high. Therefore, to provide a holistic assessment of the technologies, not only the technology performance was compared but also the relative workloads of the technology with the human operator. This gives DMs a clearer picture of what does each technology imply if they were to implement it in the warehouse.

5.5.3 Further Research

Considering the results, limitations, and contributions of this thesis, the further steps within the OP technology selection problem are clear. Firstly, a different MCDM technique is proposed because this problem and its implications are not entirely hierarchical. Such MCDM technique could be the analytical network process where each of the elements of the network is not considered interdependent with all the others. In line with this, not only a most advanced technique could be implemented but also a hybrid methodology where two or more techniques are combined. Evaluating a set of criteria and alternatives with a hybrid methodology could potentially make the overall model bolder because each of the methodologies have distinctive characteristics, hence reducing the specific limitations of each and increasing the validity of the study. Moreover, by using a more realistic method and a hybrid approach, more technological alternatives and more criteria could be assessed at the same time.

This work set off from the system settings defined at the beginning nevertheless, more research should be performed in order to extend these scenarios. Furthermore, the possibility of merging these scenarios, for example picking a case and a piece in the same trip with the same equipment should be considered. This thesis was scoped down and limited to independent areas where the operations were executed in a separated manner, but practitioners might face more complex environments.

Finally, a fuzzy logic is suggested for further research because an OP system operates in a highly uncertain environment therefore, fuzzy sets are better at dealing with uncertainty. From this thesis it can be said that taking a MCDM approach is valid but both the practical and academic side would benefit from more precise and advanced results. In this regard, this thesis should be regarded as the first step in the field where a basic group MCDM methodology was used hence, more advanced and complex methodologies should be examined. The biggest benefit of including fuzzy logic into the processing of the data is that the results will be more realistic and less simplistic than the ones provided by a crisp logic.

6. Conclusions

This thesis aimed to contribute both the practical and the academic fields by using an MCDM approach to solve the resource-intensive and time-consuming problem of selecting an adequate OP technology for a picker-to-parts OPS. The main contribution of this thesis are the merger of three dimensions into the technology assessment to make an holistic suggestion, rankings of OP technologies for a specific scenario, and a framework that compares technologies versus the three dimensions. These contributions provide answers to the RQs of the thesis and therefore the research and practical objectives are achieved.

The results of this investigation showed that integrative and holistic efforts in the area of OP technology selection problem have not been done. This study considers the economic performance, quality, and operator wellbeing at the same time. A three-dimensional approach is not a novelty by itself, but the traditional literature only considers one aspect at a time. However, the results also showed that the operational experts prefer the economic performance, or the quality provided by the OP technology than the degree of wellbeing for the operators. The set of criteria used for this thesis, while backed up by a literature review, can depend on the business priorities however the ones used were understood by all the experts. Considering the characterization of the system settings and the experts who contributed, the results are valid and relevant across different industries as long as the case is within a picker-to-parts OPS.

The findings and research objectives aim to fill the literature gap of the OP technology selection problem with a group MCDM approach and contribute to practice by developing a functional framework for practitioners in the process to implement or assessing OP technologies in a picker-to-parts OPS. Among the relevant findings, the positive correlation between the LOA and quality and wellbeing is of particular interest since the operational experts showed a strong preference to the cost of operation over the other categories. Even though picker-to-parts OPS have been researched and studied from different perspectives, the system settings proposed in this thesis as the operational scenarios are accurate and simple enough to provide practitioners with a characterization so they can understand the implications of having certain OP technology. Lastly, this thesis considers that the economic performance, quality, and wellbeing dimensions should not be isolated elements when analyzing the OP technology selection problem.

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Appendices

I. Data Collected

A. Operational experts answers

Expert 1 – Multilevel case

Main Criteria			
Mul-Case	C1	C2	C3
C1	1	0.11111	0.5
C2	9	1	2
C3	2	0.5	1

Economic performance				
Mul-Case	C11	C12	C13	C14
C11	1	5	1	1
C12	0.2	1	0.33333	1
C13	1	3	1	1
C14	1	1	1	1

Wellbeing					
Mul-Case	C31	C32	C33	C34	C35
C31	1	7	7	7	1
C32	0.142857	1	5	1	0.2
C33	0.142857	0.2	1	1	0.2
C34	0.142857	1	1	1	0.2
C35	1	5	5	5	1

Quality		
Mul-Case	C21	C22
C21	1	5
C22	0.2	1

Expert 2 – Multilevel case

Main Criteria			
Mul-Case	C1	C2	C3
C1	1	3	2
C2	0.33333	1	1
C3	0.5	1	1

Economic performance				
Mul-Case	C11	C12	C13	C14
C11	1	3	5	7
C12	0.33333	1	5	5
C13	0.2	0.2	1	0.5
C14	0.14286	0.2	2	1

Wellbeing					
Mul-Case	C31	C32	C33	C34	C35
C31	1	1	0.2	1	0.111111
C32	1	1	1	1	0.25
C33	5	1	1	3	0.111111
C34	1	1	0.333333	1	0.111111
C35	9	4	9	9	1

Quality		
C21	1	1
C22	1	1

Expert 3 – Multilevel case

Main Criteria			
Mul-Case	C1	C2	C3
C1	1	1	3
C2	1	1	3
C3	0.33333	0.33333	1

Economic performance				
Mul-Case	C11	C12	C13	C14
C11	1	7	3	3
C12	0.14286	1	1	1
C13	0.33333	1	1	1
C14	0.33333	1	1	1

Wellbeing					
Mul-Case	C31	C32	C33	C34	C35
C31	1	1	4	3	1
C32	1	1	3	3	0.5
C33	0.25	0.333333	1	3	1
C34	0.333333	0.333333	0.333333	1	0.333333
C35	1	2	1	3	1

Quality		
Mul-Case	C21	C22
C21	1	0.2
C22	5	1

Expert 1 – Multilevel Pallet

Main Criteria			
Mul-Case	C1	C2	C3
C1	1	1	1
C2	1	1	1
C3	1	1	1

Economic performance				
Mul-Case	C11	C12	C13	C14
C11	1	0.33333	1	0.33333
C12	3	1	1	1
C13	1	1	1	1
C14	3	1	1	1

Quality		
Mul-Case	C21	C22
C21	1	1
C22	1	1

Wellbeing					
Mul-Case	C31	C32	C33	C34	C35
C31	1	1	1	1	0.333333
C32	1	1	1	1	0.333333
C33	1	1	1	1	1
C34	1	1	1	1	1
C35	3	3	1	1	1

Expert 2 – Multilevel Pallet

Main Criteria			
Mul-Case	C1	C2	C3
C1	1	0.11111	0.5
C2	9	1	2
C3	2	0.5	1

Economic performance				
Mul-Case	C11	C12	C13	C14
C11	1	3	1	1
C12	0.33333	1	0.33333	1
C13	1	3	1	1
C14	1	1	1	1

Quality		
Mul-Case	C21	C22
C21	1	3
C22	0.333333	1

Wellbeing					
Mul-Case	C31	C32	C33	C34	C35
C31	1	5	7	7	1
C32	0.2	1	1	1	0.333333
C33	0.142857	1	1	1	0.2
C34	0.142857	1	1	1	0.2
C35	1	3	5	5	1

Expert 3 – Multilevel Pallet

Main Criteria			
Mul-Case	C1	C2	C3
C1	1	2	0.2
C2	0.5	1	0.25
C3	5	4	1

Economic performance				
Mul-Case	C11	C12	C13	C14
C11	1	0.14286	0.33333	0.2
C12	7	1	5	7
C13	3	0.2	1	1
C14	5	0.14286	1	1

Quality		
Mul-Case	C21	C22
C21	1	1
C22	1	1

Wellbeing					
Mul-Case	C31	C32	C33	C34	C35
C31	1	5	5	3	1
C32	0.2	1	0.2	0.2	0.25
C33	0.2	5	1	0.333333	1
C34	0.333333	5	3	1	1
C35	1	4	1	1	1

Expert 4 – Multilevel Pallet

Main Criteria			
Mul-Case	C1	C2	C3
C1	1	1	7
C2	1	1	3
C3	0.14286	0.33333	1

Economic performance				
Mul-Case	C11	C12	C13	C14
C11	1	1	1	8
C12	1	1	0.25	7
C13	1	4	1	7
C14	0.125	0.14286	0.14286	1

Quality		
Mul-Case	C21	C22
C21	1	9
C22	0.111111	1

Wellbeing					
Mul-Case	C31	C32	C33	C34	C35
C31	1	5	8	5	0.142857
C32	0.2	1	3	1	0.111111
C33	0.125	0.333333	1	0.333333	0.111111
C34	0.2	1	3	1	0.111111
C35	7	9	9	9	1

Expert 1 – Floor level Pallet

Main Criteria			
Mul-Case	C1	C2	C3
C1	1	1	1
C2	1	1	1
C3	1	1	1

Economic performance				
Mul-Case	C11	C12	C13	C14
C11	1	1	0.2	1
C12	1	1	0.2	0.5
C13	5	5	1	1
C14	1	2	1	1

Quality		
Mul-Case	C21	C22
C21	1	1
C22	1	1

Wellbeing					
Mul-Case	C31	C32	C33	C34	C35
C31	1	0.333333	1	1	0.111111
C32	3	1	1	1	1
C33	1	1	1	1	0.5
C34	1	1	1	1	0.5
C35	9	1	2	2	1

Expert 2 – Floor level Pallet

Main Criteria			
Mul-Case	C1	C2	C3
C1	1	1	0.33333
C2	1	1	0.33333
C3	3	3	1

Economic performance				
Mul-Case	C11	C12	C13	C14
C11	1	1	1	1
C12	1	1	1	3
C13	1	1	1	1
C14	1	0.33333	1	1

Quality		
Mul-Case	C21	C22
C21	1	3
C22	0.333333	1

Wellbeing					
Mul-Case	C31	C32	C33	C34	C35
C31	1	3	1	0.333333	0.2
C32	0.333333	1	1	1	0.2
C33	1	1	1	1	0.333333
C34	3	1	1	1	0.333333
C35	5	5	3	3	1

Expert 3 – Floor level Pallet

Main Criteria			
Mul-Case	**C1**	**C2**	**C3**
C1	1	0.11111	0.33333
C2	9	1	3
C3	3	0.33333	1

Economic performance				
Mul-Case	**C11**	**C12**	**C13**	**C14**
C11	1	5	5	5
C12	0.2	1	3	4
C13	0.2	0.33333	1	2
C14	0.2	0.25	0.5	1

Quality		
Mul-Case	**C21**	**C22**
C21	1	1
C22	1	1

Wellbeing					
Mul-Case	**C31**	**C32**	**C33**	**C34**	**C35**
C31	1	0.333333	0.333333	0.333333	0.333333
C32	3	1	3	2	0.333333
C33	3	0.333333	1	0.333333	0.333333
C34	3	0.5	3	1	0.333333
C35	3	3	3	3	1

B. Academic expert answer

Expert 1

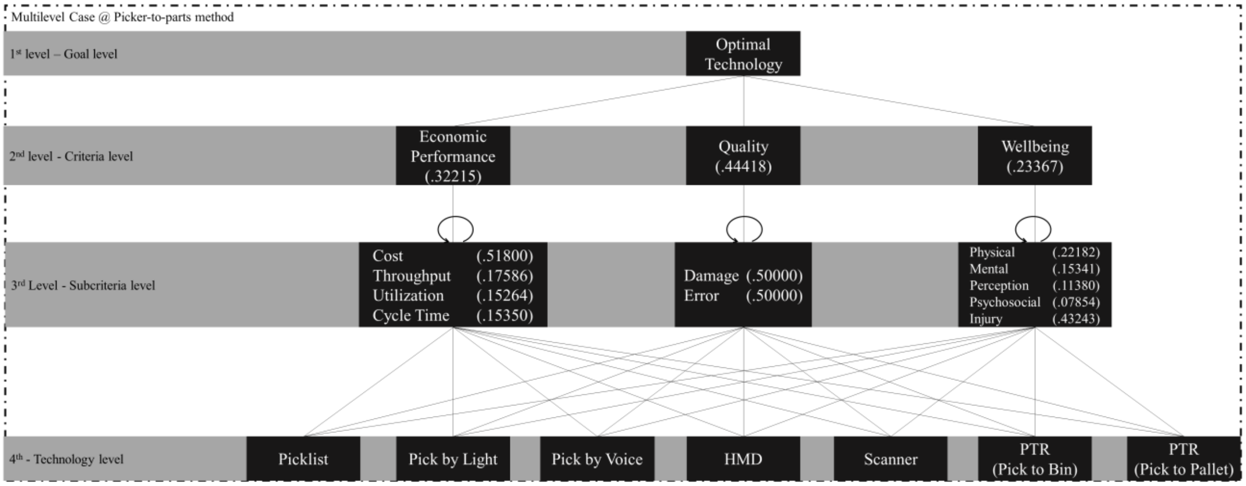
Economic Performance											
Cost			Throughput			Utilization			Cycle Time		
C11			C12			C13			C14		
Cheaper is better			Higher is better			Higher is better			Shorter is better		
Technology	Category Name	Category Value	Technology	Category Name	Category Value	Technology	Category Name	Category Value	Technology	Category Name	Category Value
T1	Very cheap	1	T1	Low	0.052	T1 & T2 & T3 & T4 & T5 & T6 & T7	Medium	0.3467	T1	Very short	1
T2	Cheap	0.4107	T2	Below average	0.1062				T2	Short	0.4107
T3	Average	0.1884	T3	Above average	0.4107				T3	Very long	0.052
T4	Average	0.1884	T4	High	1				T4	Average	0.1884
T5	Average	0.1884	T5	Average	0.1884				T5	Average	0.1884
T6	Expensive	0.1062	T6	Average	0.1884				T6	Average	0.1884
T7	Very expensive	0.052	T7	Average	0.1884				T7	Long	0.1062

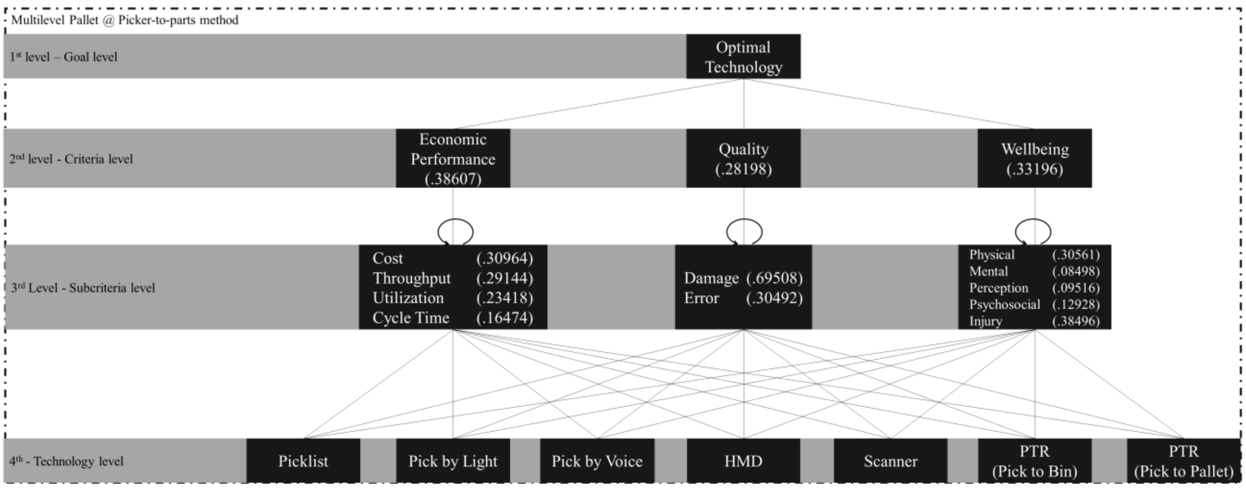
Quality					
Damage			Error		
C21			C22		
Lower is better			Lower is better		
Technology	Category Name	Category Value	Technology	Category Name	Category Value
T1 & T2 & T3 & T4 & T5 & T6 & T7	Medium	0.3467	T1	High	0.052
			T2	Above average	0.1062
			T3	Average	0.1884
			T4	Average	0.1884
			T5	Average	0.1884
			T6	Below average	0.4107
			T7	Low	1

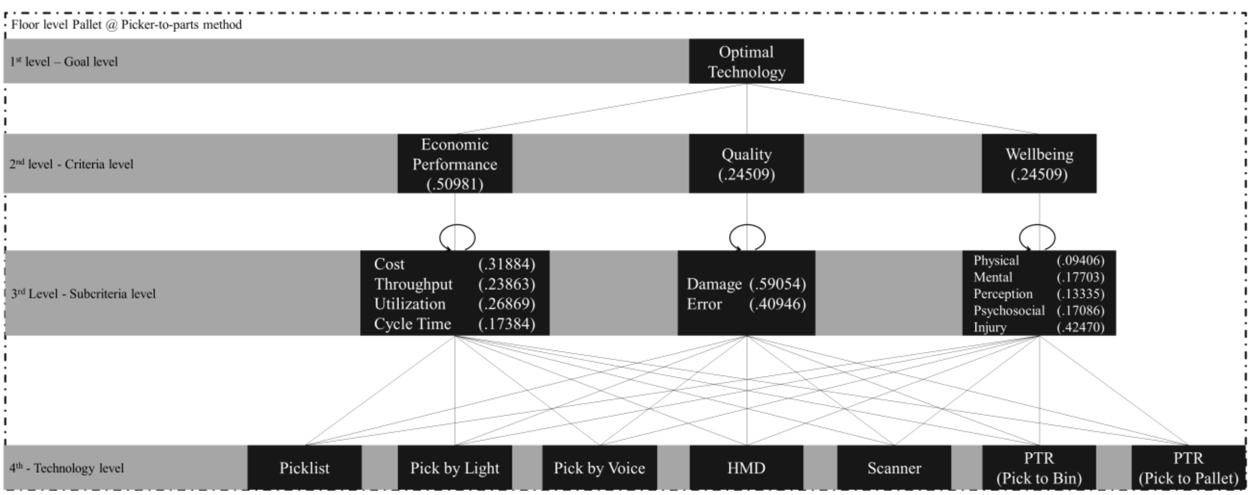
Wellbeing														
Physical			Mental			Perception			Psychosocial			Injury		
C31			C32			C33			C34			C35		
Lower is better			Lower is better			Lower is better			Lower is better			Lower is better		
Technology	Category Name	Category Value	Technology	Category Name	Category Value	Technology	Category Name	Category Value	Technology	Category Name	Category Value	Technology	Category Name	Category Value
T1	Extreme	0.052	T1	Extreme	0.052	T1	Extreme	0.052	T1	Extreme	0.052	T1 & T2 & T3 & T4 & T5 & T6 & T7	Medium	0.3467
T2	Big	0.1062	T2	Big	0.1062	T2	Big	0.1062	T2	Big	0.1062			
T3	Significant	0.1884	T3	Significant	0.1884	T3	Significant	0.1884	T3	Significant	0.1884			
T4	Significant	0.1884	T4	Significant	0.1884	T4	Significant	0.1884	T4	Significant	0.1884			
T5	Significant	0.1884	T5	Significant	0.1884	T5	Significant	0.1884	T5	Significant	0.1884			
T6	Moderate	0.4107	T6	Moderate	0.4107	T6	Moderate	0.4107	T6	Moderate	0.4107			
T7	Low	1	T7	Low	1	T7	Low	1	T7	Low	1			

II. MCDM Calculations

A. Hierarchical Representation with weights







B. AHP

Supermatrix Multilevel case scenario

Unweighted Supermatrix					
	Node	Goal Node	C1	C2	C3
Mul-Cas	C1	0.32215	0	0	0
	C2	0.44418	0	0	0
	C3	0.23367	0	0	0
	C11	0	0.518	0	0
	C12	0	0.17586	0	0
	C13	0	0.15264	0	0
	C14	0	0.1535	0	0
	C21	0	0	0.5	0
	C22	0	0	0.5	0
	C31	0	0	0	0.22182
	C32	0	0	0	0.15341
	C33	0	0	0	0.1138
	C34	0	0	0	0.07854
	C35	0	0	0	0.43243

Supermatrix Multilevel pallet scenario

Unweighted Supermatrix					
	Node	Goal Node	C1	C2	C3
Mul-Pal	C1	0.38607	0	0	0
	C2	0.28197	0	0	0
	C3	0.33196	0	0	0
	C11	0	0.30964	0	0
	C12	0	0.29144	0	0
	C13	0	0.23418	0	0
	C14	0	0.16474	0	0
	C21	0	0	0.69508	0
	C22	0	0	0.30492	0
	C31	0	0	0	0.30561
	C32	0	0	0	0.08498
	C33	0	0	0	0.09516
	C34	0	0	0	0.12928
	C35	0	0	0	0.38496

Supermatrix Floor level pallet scenario

Unweighted Supermatrix					
	Node	Goal Node	C1	C2	C3
Flo-Pal	C1	0.50981	0	0	0
	C2	0.24509	0	0	0
	C3	0.24509	0	0	0
	C11	0	0.31884	0	0
	C12	0	0.23863	0	0
	C13	0	0.26869	0	0
	C14	0	0.17384	0	0
	C21	0	0	0.59054	0
	C22	0	0	0.40946	0
	C31	0	0	0	0.09406
	C32	0	0	0	0.17703
	C33	0	0	0	0.13335
	C34	0	0	0	0.17086
	C35	0	0	0	0.42469

Limit matrix Multilevel case scenario

Limit Matrix					
	Node	Goal Node	C1	C2	C3
Mul-Cas	C1	0.16108	0	0	0
	C2	0.22209	0	0	0
	C3	0.11683	0	0	0
	C11	0.08344	0.518	0	0
	C12	0.02833	0.17586	0	0
	C13	0.02459	0.15264	0	0
	C14	0.02473	0.1535	0	0
	C21	0.11105	0	0.5	0
	C22	0.11105	0	0.5	0
	C31	0.02592	0	0	0.22182
	C32	0.01792	0	0	0.15341
	C33	0.0133	0	0	0.1138
	C34	0.00918	0	0	0.07854
	C35	0.05052	0	0	0.43243

Limit matrix Multilevel pallet scenario

Limit Matrix					
	Node	Goal Node	C1	C2	C3
Mul-Pal	C1	0.19303	0	0	0
	C2	0.14099	0	0	0
	C3	0.16598	0	0	0
	C11	0.05977	0.30964	0	0
	C12	0.05626	0.29144	0	0
	C13	0.0452	0.23418	0	0
	C14	0.0318	0.16474	0	0
	C21	0.098	0	0.69508	0
	C22	0.04299	0	0.30492	0
	C31	0.05072	0	0	0.30561
	C32	0.0141	0	0	0.08498
	C33	0.0158	0	0	0.09516
	C34	0.02146	0	0	0.12928
	C35	0.0639	0	0	0.38496

Limit matrix Floor level pallet scenario

Limit Matrix					
	Node	Goal Node	C1	C2	C3
Flo-Pal	C1	0.25491	0	0	0
	C2	0.12255	0	0	0
	C3	0.12255	0	0	0
	C11	0.08128	0.31884	0	0
	C12	0.06083	0.23863	0	0
	C13	0.06849	0.26869	0	0
	C14	0.04431	0.17384	0	0
	C21	0.07237	0	0.59054	0
	C22	0.05018	0	0.40946	0
	C31	0.01153	0	0	0.09406
	C32	0.02169	0	0	0.17703
	C33	0.01634	0	0	0.13335
	C34	0.02094	0	0	0.17086
	C35	0.05205	0	0	0.42469

C. Sensitivity Analysis data

C1 – Economic performance criteria

	Input Value	T1	T2	T3	T4	T5	T6	T7
MUL-CAS	0.00001	0.0828	0.0950	0.1208	0.1208	0.1208	0.1635	0.2962
	0.1111	0.1094	0.1018	0.1193	0.1253	0.1184	0.1546	0.2713
	0.2222	0.1364	0.1086	0.1177	0.1297	0.1159	0.1455	0.2462
	0.3333	0.1638	0.1156	0.1161	0.1343	0.1134	0.1363	0.2206
	0.4444	0.1916	0.1226	0.1144	0.1389	0.1109	0.1269	0.1947
	0.5556	0.2198	0.1298	0.1128	0.1436	0.1083	0.1174	0.1684
	0.6667	0.2484	0.1370	0.1111	0.1484	0.1057	0.1078	0.1417
	0.7778	0.2774	0.1444	0.1094	0.1532	0.1030	0.0980	0.1147
	0.8889	0.3068	0.1518	0.1077	0.1581	0.1003	0.0881	0.0872
	0.99999	0.3367	0.1594	0.1059	0.1631	0.0976	0.0780	0.0594
MUL-PAL	**Input Value**	**T1**	**T2**	**T3**	**T4**	**T5**	**T6**	**T7**
	0.00001	0.0865	0.0972	0.1287	0.1287	0.1287	0.1571	0.2732
	0.1111	0.1043	0.1015	0.1279	0.1370	0.1260	0.1503	0.2530
	0.2222	0.1224	0.1059	0.1272	0.1455	0.1232	0.1434	0.2325
	0.3333	0.1408	0.1104	0.1264	0.1542	0.1204	0.1363	0.2115
	0.4444	0.1596	0.1150	0.1257	0.1630	0.1175	0.1290	0.1902
	0.5556	0.1787	0.1197	0.1249	0.1720	0.1146	0.1217	0.1684
	0.6667	0.1982	0.1245	0.1241	0.1812	0.1116	0.1142	0.1462
	0.7778	0.2181	0.1293	0.1233	0.1905	0.1086	0.1066	0.1236
	0.8889	0.2384	0.1343	0.1224	0.2000	0.1055	0.0988	0.1006
	0.99999	0.2591	0.1394	0.1216	0.2097	0.1024	0.0908	0.0771
FLO-PAL	**Input Value**	**T1**	**T2**	**T3**	**T4**	**T5**	**T6**	**T7**
	0.00001	0.0871	0.0987	0.1207	0.1207	0.1207	0.1634	0.2888
	0.1111	0.1067	0.1036	0.1203	0.1283	0.1189	0.1559	0.2663
	0.2222	0.1264	0.1086	0.1200	0.1359	0.1172	0.1482	0.2436
	0.3333	0.1464	0.1136	0.1197	0.1437	0.1154	0.1405	0.2207
	0.4444	0.1665	0.1187	0.1193	0.1515	0.1136	0.1327	0.1976
	0.5556	0.1869	0.1239	0.1190	0.1594	0.1118	0.1248	0.1742
	0.6667	0.2074	0.1291	0.1187	0.1674	0.1100	0.1169	0.1506
	0.7778	0.2282	0.1343	0.1183	0.1755	0.1081	0.1088	0.1267
	0.8889	0.2492	0.1396	0.1180	0.1836	0.1062	0.1007	0.1026
	0.99999	0.2703	0.1450	0.1176	0.1919	0.1044	0.0925	0.0783

C2 – Quality criteria

	Input Value	T1	T2	T3	T4	T5	T6	T7
MUL-CAS	0.00001	0.2200	0.1273	0.1153	0.1471	0.1107	0.1141	0.1655
	0.1111	0.2052	0.1242	0.1156	0.1438	0.1114	0.1199	0.1800
	0.2222	0.1905	0.1211	0.1158	0.1404	0.1122	0.1256	0.1944
	0.3333	0.1757	0.1180	0.1160	0.1371	0.1129	0.1314	0.2088
	0.4444	0.1610	0.1149	0.1162	0.1338	0.1137	0.1372	0.2232
	0.5556	0.1463	0.1117	0.1164	0.1305	0.1144	0.1430	0.2377
	0.6667	0.1316	0.1086	0.1167	0.1272	0.1151	0.1488	0.2521
	0.7778	0.1168	0.1055	0.1169	0.1239	0.1159	0.1545	0.2665
	0.8889	0.1021	0.1024	0.1171	0.1206	0.1166	0.1603	0.2809
	0.99999	0.0874	0.0993	0.1173	0.1173	0.1173	0.1661	0.2953
MUL-PAL	**Input Value**	**T1**	**T2**	**T3**	**T4**	**T5**	**T6**	**T7**
	0.00001	0.1654	0.1109	0.1254	0.1705	0.1156	0.1234	0.1887
	0.1111	0.1592	0.1116	0.1257	0.1657	0.1170	0.1272	0.1937
	0.2222	0.1530	0.1122	0.1259	0.1609	0.1183	0.1309	0.1987
	0.3333	0.1468	0.1129	0.1262	0.1561	0.1197	0.1346	0.2037
	0.4444	0.1406	0.1136	0.1264	0.1514	0.1210	0.1383	0.2087
	0.5556	0.1344	0.1143	0.1267	0.1466	0.1223	0.1420	0.2137
	0.6667	0.1283	0.1149	0.1269	0.1419	0.1237	0.1456	0.2187
	0.7778	0.1221	0.1156	0.1272	0.1371	0.1250	0.1493	0.2236
	0.8889	0.1160	0.1163	0.1274	0.1324	0.1263	0.1530	0.2286
	0.99999	0.1099	0.1169	0.1277	0.1277	0.1277	0.1567	0.2335
FLO-PAL	**Input Value**	**T1**	**T2**	**T3**	**T4**	**T5**	**T6**	**T7**
	0.00001	0.2053	0.1265	0.1181	0.1675	0.1093	0.1169	0.1564
	0.1111	0.1931	0.1243	0.1186	0.1623	0.1108	0.1220	0.1689
	0.2222	0.1810	0.1222	0.1190	0.1572	0.1122	0.1270	0.1813
	0.3333	0.1689	0.1201	0.1195	0.1521	0.1137	0.1321	0.1936
	0.4444	0.1569	0.1180	0.1200	0.1471	0.1151	0.1371	0.2059
	0.5556	0.1450	0.1159	0.1204	0.1420	0.1165	0.1420	0.2181
	0.6667	0.1331	0.1138	0.1209	0.1370	0.1180	0.1470	0.2302
	0.7778	0.1214	0.1117	0.1213	0.1321	0.1194	0.1519	0.2423
	0.8889	0.1096	0.1096	0.1217	0.1271	0.1208	0.1568	0.2543
	0.99999	0.0980	0.1076	0.1222	0.1222	0.1222	0.1616	0.2662

C3 – Wellbeing criteria

	Input Value	T1	T2	T3	T4	T5	T6	T7
MUL-CAS	0.00001	0.1894	0.1239	0.1126	0.1360	0.1092	0.1300	0.1987
	0.1111	0.1758	0.1196	0.1144	0.1350	0.1114	0.1335	0.2105
	0.2222	0.1624	0.1153	0.1160	0.1339	0.1134	0.1368	0.2220
	0.3333	0.1492	0.1111	0.1177	0.1329	0.1155	0.1402	0.2334
	0.4444	0.1363	0.1070	0.1193	0.1319	0.1175	0.1434	0.2446
	0.5556	0.1235	0.1029	0.1209	0.1309	0.1195	0.1467	0.2556
	0.6667	0.1110	0.0989	0.1225	0.1299	0.1214	0.1498	0.2664
	0.7778	0.0986	0.0950	0.1241	0.1290	0.1234	0.1529	0.2771
	0.8889	0.0865	0.0911	0.1256	0.1280	0.1252	0.1560	0.2876
	0.99999	0.0745	0.0873	0.1271	0.1271	0.1271	0.1590	0.2979
MUL-PAL	**Input Value**	**T1**	**T2**	**T3**	**T4**	**T5**	**T6**	**T7**
	0.00001	0.1939	0.1296	0.1242	0.1739	0.1134	0.1196	0.1454
	0.1111	0.1788	0.1238	0.1249	0.1686	0.1153	0.1241	0.1645
	0.2222	0.1640	0.1181	0.1255	0.1634	0.1172	0.1285	0.1832
	0.3333	0.1495	0.1125	0.1261	0.1583	0.1191	0.1329	0.2017
	0.4444	0.1352	0.1071	0.1267	0.1533	0.1209	0.1372	0.2197
	0.5556	0.1212	0.1017	0.1272	0.1483	0.1227	0.1414	0.2375
	0.6667	0.1074	0.0964	0.1278	0.1435	0.1244	0.1456	0.2549
	0.7778	0.0939	0.0912	0.1284	0.1387	0.1261	0.1496	0.2721
	0.8889	0.0806	0.0861	0.1289	0.1341	0.1278	0.1536	0.2889
	0.99999	0.0675	0.0811	0.1295	0.1295	0.1295	0.1575	0.3054
FLO-PAL	**Input Value**	**T1**	**T2**	**T3**	**T4**	**T5**	**T6**	**T7**
	0.00001	0.2128	0.1325	0.1191	0.1686	0.1103	0.1156	0.1410
	0.1111	0.1972	0.1276	0.1191	0.1629	0.1113	0.1213	0.1605
	0.2222	0.1817	0.1228	0.1191	0.1573	0.1123	0.1269	0.1799
	0.3333	0.1663	0.1179	0.1191	0.1517	0.1133	0.1325	0.1991
	0.4444	0.1510	0.1131	0.1191	0.1462	0.1143	0.1381	0.2181
	0.5556	0.1358	0.1084	0.1191	0.1407	0.1153	0.1436	0.2370
	0.6667	0.1208	0.1037	0.1191	0.1353	0.1163	0.1491	0.2558
	0.7778	0.1059	0.0990	0.1191	0.1298	0.1172	0.1545	0.2744
	0.8889	0.0910	0.0944	0.1191	0.1245	0.1182	0.1599	0.2929
	0.99999	0.0763	0.0898	0.1191	0.1191	0.1191	0.1652	0.3113

C11 – Cost subcriterion

	Input Value	T1	T2	T3	T4	T5	T6	T7
MUL-CAS	0.00001	0.1197	0.1045	0.1218	0.1581	0.1165	0.1459	0.2334
	0.1111	0.1285	0.1067	0.1206	0.1529	0.1159	0.1440	0.2312
	0.2222	0.1374	0.1089	0.1194	0.1477	0.1153	0.1422	0.2290
	0.3333	0.1462	0.1112	0.1182	0.1425	0.1147	0.1403	0.2268
	0.4444	0.1551	0.1134	0.1170	0.1373	0.1141	0.1384	0.2247
	0.5556	0.1641	0.1156	0.1158	0.1321	0.1134	0.1366	0.2225
	0.6667	0.1730	0.1179	0.1146	0.1268	0.1128	0.1347	0.2203
	0.7778	0.1820	0.1201	0.1134	0.1215	0.1122	0.1328	0.2181
	0.8889	0.1910	0.1223	0.1122	0.1162	0.1116	0.1309	0.2158
	0.99999	0.2000	0.1246	0.1109	0.1109	0.1109	0.1290	0.2136
MUL-PAL	**Input Value**	**T1**	**T2**	**T3**	**T4**	**T5**	**T6**	**T7**
	0.00001	0.1171	0.1043	0.1313	0.1778	0.1212	0.1391	0.2091
	0.1111	0.1287	0.1073	0.1294	0.1709	0.1204	0.1369	0.2064
	0.2222	0.1404	0.1103	0.1276	0.1639	0.1196	0.1346	0.2036
	0.3333	0.1522	0.1132	0.1257	0.1568	0.1189	0.1324	0.2008
	0.4444	0.1640	0.1162	0.1238	0.1498	0.1181	0.1301	0.1980
	0.5556	0.1758	0.1192	0.1219	0.1427	0.1173	0.1278	0.1953
	0.6667	0.1877	0.1222	0.1200	0.1356	0.1165	0.1255	0.1924
	0.7778	0.1996	0.1253	0.1180	0.1285	0.1158	0.1232	0.1896
	0.8889	0.2115	0.1283	0.1161	0.1214	0.1150	0.1209	0.1868
	0.99999	0.2235	0.1313	0.1142	0.1142	0.1142	0.1186	0.1840
FLO-PAL	**Input Value**	**T1**	**T2**	**T3**	**T4**	**T5**	**T6**	**T7**
	0.00001	0.1350	0.1114	0.1257	0.1796	0.1161	0.1373	0.1950
	0.1111	0.1501	0.1150	0.1234	0.1715	0.1148	0.1341	0.1911
	0.2222	0.1652	0.1186	0.1211	0.1633	0.1136	0.1309	0.1872
	0.3333	0.1805	0.1222	0.1188	0.1551	0.1124	0.1277	0.1833
	0.4444	0.1958	0.1259	0.1165	0.1468	0.1111	0.1244	0.1794
	0.5556	0.2112	0.1296	0.1142	0.1385	0.1099	0.1211	0.1754
	0.6667	0.2268	0.1333	0.1119	0.1302	0.1086	0.1178	0.1714
	0.7778	0.2424	0.1370	0.1095	0.1218	0.1074	0.1145	0.1674
	0.8889	0.2581	0.1408	0.1072	0.1133	0.1061	0.1111	0.1634
	0.99999	0.2739	0.1446	0.1048	0.1048	0.1048	0.1078	0.1594

C31 – Physical workload subcriterion

	Input Value	T1	T2	T3	T4	T5	T6	T7
MUL-CAS	0.00001	0.1667	0.1193	0.1145	0.1323	0.1119	0.1380	0.2174
	0.1111	0.1638	0.1170	0.1154	0.1331	0.1128	0.1376	0.2203
	0.2222	0.1610	0.1148	0.1162	0.1338	0.1137	0.1372	0.2232
	0.3333	0.1583	0.1127	0.1171	0.1346	0.1145	0.1368	0.2261
	0.4444	0.1555	0.1105	0.1179	0.1353	0.1154	0.1364	0.2289
	0.5556	0.1528	0.1084	0.1188	0.1361	0.1162	0.1361	0.2316
	0.6667	0.1501	0.1063	0.1196	0.1368	0.1171	0.1357	0.2344
	0.7778	0.1475	0.1042	0.1204	0.1375	0.1179	0.1353	0.2371
	0.8889	0.1448	0.1022	0.1212	0.1383	0.1187	0.1350	0.2398
	0.99999	0.1422	0.1002	0.1220	0.1390	0.1196	0.1346	0.2424
	Input Value	**T1**	**T2**	**T3**	**T4**	**T5**	**T6**	**T7**
MUL-PAL	0.00001	0.1603	0.1211	0.1229	0.1559	0.1157	0.1343	0.1898
	0.1111	0.1564	0.1180	0.1241	0.1568	0.1169	0.1338	0.1941
	0.2222	0.1525	0.1149	0.1252	0.1577	0.1181	0.1332	0.1983
	0.3333	0.1487	0.1119	0.1263	0.1586	0.1193	0.1327	0.2025
	0.4444	0.1450	0.1089	0.1275	0.1594	0.1205	0.1322	0.2065
	0.5556	0.1413	0.1059	0.1286	0.1603	0.1216	0.1318	0.2106
	0.6667	0.1377	0.1030	0.1296	0.1611	0.1228	0.1313	0.2145
	0.7778	0.1341	0.1002	0.1307	0.1619	0.1239	0.1308	0.2184
	0.8889	0.1306	0.0974	0.1317	0.1627	0.1250	0.1303	0.2223
	0.99999	0.1271	0.0946	0.1328	0.1635	0.1261	0.1299	0.2260
	Input Value	**T1**	**T2**	**T3**	**T4**	**T5**	**T6**	**T7**
FLO-PAL	0.00001	0.1809	0.1236	0.1183	0.1555	0.1116	0.1285	0.1817
	0.1111	0.1781	0.1214	0.1193	0.1563	0.1127	0.1280	0.1842
	0.2222	0.1753	0.1193	0.1203	0.1571	0.1138	0.1276	0.1867
	0.3333	0.1725	0.1172	0.1213	0.1578	0.1148	0.1271	0.1892
	0.4444	0.1698	0.1152	0.1223	0.1586	0.1158	0.1267	0.1916
	0.5556	0.1672	0.1131	0.1233	0.1594	0.1168	0.1262	0.1940
	0.6667	0.1645	0.1111	0.1242	0.1601	0.1178	0.1258	0.1964
	0.7778	0.1619	0.1091	0.1252	0.1608	0.1188	0.1254	0.1987
	0.8889	0.1593	0.1072	0.1261	0.1616	0.1198	0.1250	0.2010
	0.99999	0.1568	0.1052	0.1271	0.1623	0.1208	0.1245	0.2033

C32 – Mental workload subcriterion

	Input Value	T1	T2	T3	T4	T5	T6	T7
MUL-CAS	0.00001	0.1626	0.1162	0.1178	0.1353	0.1153	0.1360	0.2169
	0.1111	0.1615	0.1152	0.1167	0.1343	0.1141	0.1369	0.2215
	0.2222	0.1603	0.1143	0.1155	0.1332	0.1129	0.1377	0.2261
	0.3333	0.1592	0.1133	0.1143	0.1321	0.1118	0.1386	0.2307
	0.4444	0.1581	0.1123	0.1132	0.1310	0.1106	0.1395	0.2355
	0.5556	0.1569	0.1113	0.1120	0.1298	0.1094	0.1404	0.2402
	0.6667	0.1558	0.1103	0.1108	0.1287	0.1082	0.1413	0.2450
	0.7778	0.1546	0.1093	0.1096	0.1276	0.1070	0.1422	0.2498
	0.8889	0.1534	0.1082	0.1084	0.1264	0.1057	0.1432	0.2546
	0.99999	0.1523	0.1072	0.1072	0.1253	0.1045	0.1441	0.2595
MUL-PAL	**Input Value**	**T1**	**T2**	**T3**	**T4**	**T5**	**T6**	**T7**
	0.00001	0.1505	0.1134	0.1272	0.1594	0.1202	0.1320	0.1973
	0.1111	0.1494	0.1124	0.1257	0.1580	0.1187	0.1331	0.2027
	0.2222	0.1482	0.1114	0.1241	0.1566	0.1171	0.1343	0.2082
	0.3333	0.1471	0.1104	0.1226	0.1553	0.1155	0.1355	0.2138
	0.4444	0.1459	0.1093	0.1210	0.1538	0.1138	0.1367	0.2194
	0.5556	0.1447	0.1083	0.1194	0.1524	0.1122	0.1379	0.2251
	0.6667	0.1435	0.1073	0.1177	0.1510	0.1105	0.1391	0.2309
	0.7778	0.1423	0.1062	0.1161	0.1495	0.1088	0.1403	0.2367
	0.8889	0.1410	0.1052	0.1144	0.1480	0.1071	0.1416	0.2426
	0.99999	0.1398	0.1041	0.1128	0.1466	0.1054	0.1428	0.2486
FLO-PAL	**Input Value**	**T1**	**T2**	**T3**	**T4**	**T5**	**T6**	**T7**
	0.00001	0.1806	0.1236	0.1207	0.1575	0.1141	0.1269	0.1766
	0.1111	0.1793	0.1224	0.1197	0.1567	0.1131	0.1276	0.1811
	0.2222	0.1779	0.1213	0.1188	0.1558	0.1121	0.1284	0.1857
	0.3333	0.1766	0.1201	0.1178	0.1550	0.1111	0.1291	0.1903
	0.4444	0.1752	0.1189	0.1168	0.1541	0.1102	0.1299	0.1949
	0.5556	0.1739	0.1178	0.1158	0.1532	0.1092	0.1306	0.1995
	0.6667	0.1725	0.1166	0.1148	0.1523	0.1082	0.1314	0.2042
	0.7778	0.1711	0.1154	0.1139	0.1514	0.1071	0.1322	0.2089
	0.8889	0.1697	0.1142	0.1129	0.1506	0.1061	0.1330	0.2136
	0.99999	0.1683	0.1130	0.1119	0.1497	0.1051	0.1337	0.2183

C35 – Injury (risk of) subcriterion

	Input Value	T1	T2	T3	T4	T5	T6	T7
MUL-CAS	0.00001	0.1482	0.1043	0.1132	0.1309	0.1106	0.1402	0.2525
	0.1111	0.1515	0.1070	0.1140	0.1316	0.1114	0.1394	0.2450
	0.2222	0.1548	0.1097	0.1148	0.1324	0.1122	0.1387	0.2375
	0.3333	0.1581	0.1125	0.1155	0.1332	0.1130	0.1379	0.2299
	0.4444	0.1614	0.1152	0.1163	0.1339	0.1137	0.1371	0.2224
	0.5556	0.1647	0.1178	0.1171	0.1347	0.1145	0.1363	0.2149
	0.6667	0.1680	0.1205	0.1178	0.1354	0.1153	0.1355	0.2074
	0.7778	0.1713	0.1232	0.1186	0.1362	0.1160	0.1348	0.1998
	0.8889	0.1746	0.1259	0.1194	0.1370	0.1168	0.1340	0.1923
	0.99999	0.1779	0.1286	0.1202	0.1377	0.1176	0.1332	0.1848
MUL-PAL	Input Value	T1	T2	T3	T4	T5	T6	T7
	0.00001	0.1332	0.0992	0.1232	0.1554	0.1162	0.1361	0.2369
	0.1111	0.1379	0.1030	0.1240	0.1562	0.1170	0.1352	0.2266
	0.2222	0.1427	0.1069	0.1248	0.1571	0.1178	0.1342	0.2164
	0.3333	0.1475	0.1108	0.1257	0.1579	0.1186	0.1333	0.2062
	0.4444	0.1522	0.1147	0.1265	0.1588	0.1195	0.1324	0.1959
	0.5556	0.1570	0.1186	0.1274	0.1597	0.1203	0.1314	0.1857
	0.6667	0.1618	0.1225	0.1282	0.1605	0.1211	0.1305	0.1754
	0.7778	0.1666	0.1264	0.1290	0.1614	0.1220	0.1295	0.1651
	0.8889	0.1714	0.1303	0.1299	0.1622	0.1228	0.1286	0.1548
	0.99999	0.1762	0.1342	0.1307	0.1631	0.1237	0.1277	0.1445
FLO-PAL	Input Value	T1	T2	T3	T4	T5	T6	T7
	0.00001	0.1663	0.1116	0.1145	0.1518	0.1078	0.1321	0.2157
	0.1111	0.1695	0.1143	0.1157	0.1530	0.1091	0.1311	0.2073
	0.2222	0.1727	0.1170	0.1169	0.1541	0.1103	0.1300	0.1990
	0.3333	0.1759	0.1196	0.1182	0.1553	0.1115	0.1289	0.1906
	0.4444	0.1790	0.1222	0.1194	0.1564	0.1127	0.1279	0.1824
	0.5556	0.1822	0.1248	0.1206	0.1575	0.1140	0.1268	0.1741
	0.6667	0.1853	0.1274	0.1218	0.1586	0.1152	0.1258	0.1659
	0.7778	0.1884	0.1300	0.1229	0.1597	0.1164	0.1248	0.1577
	0.8889	0.1915	0.1326	0.1241	0.1608	0.1176	0.1237	0.1496
	0.99999	0.1946	0.1352	0.1253	0.1619	0.1188	0.1227	0.1415

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