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A MULTI-CRITERIA DECISION-MAKING APPROACH FOR ROBOT SELECTION IN A MANUFACTURING ENVIRONMENT

THE GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES
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RASİM ATAKAN ARSLAN

A MASTER OF SCIENCE THESIS
IN
THE DEPARTMENT OF MECHATRONICS ENGINEERING

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Prof. Dr. Ender KESKİNKILIÇ
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I certify that this thesis satisfies all the requirements as a thesis for the degree of **Master of Science in Mechatronics Engineering, Atılım University.**

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This is to certify that we have read the thesis A MULTI-CRITERIA DECISION-MAKING APPROACH FOR ROBOT SELECTION IN A MANUFACTURING ENVIRONMENT submitted by RASİM ATAKAN ARSLAN and that in our opinion it is fully adequate, in scope and quality, as a thesis for the degree of Master of Science.

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ABSTRACT

A MULTI-CRITERIA DECISION MAKING APPROACH FOR ROBOT SELECTION IN A MANUFACTURING ENVIRONMENT

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In this thesis, we apply SWARA-WASPAS method as a multi-criteria decision-making (MCDM) method for selecting the most suitable mechatronic systems to be used for the conversion of human-based production lines to production lines with robot-based automation systems. Robots are becoming not only quicker and more precise than people, but they are also frequently more cost-effective in the long term. Getting high efficiency from the robots used for different missions and choosing the most suitable robot are among the most difficult problems. To select the most suitable systems among different alternatives, SWARA-WASPAS hybrid decision making method, which suggest making the most appropriate choice among different alternatives by considering different criteria and the opinions of different experts, is applied according to the characteristic criteria of these systems, and a sensitivity analysis was carried out. As a result of the thesis, the most suitable robots from each robot selection problem are determined and it is seen that the most suitable robot is not change with the sensitivity analysis made for each robot class, but the other alternatives could change depending on the combined optimality coefficient value used.

Keywords: Robot selection, Production automation, Multi-Criteria Decision Making, SWARA, WASPAS.

ÖZ

BİR ÜRETİM HATTINDA ROBOT SEÇİMİ İÇİN ÇOK KRİTERLİ KARAR VERME YAKLAŞIMI

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Bu tezde, insan tabanlı üretim hatlarının robot tabanlı otomasyon sistemleri kullanılan üretim hatlarına dönüştürülmesinde kullanılacak en uygun mekatronik sistemlerin seçilmesi için çok kriterli karar verme (MCDM) yöntemi olarak SWARA-WASPAS yöntemini uyguluyoruz. Robotlar insanlardan daha hızlı ve daha hassas hale gelmekle kalmıyor, aynı zamanda uzun vadede genellikle daha uygun maliyetli oluyorlar. Farklı görevler için kullanılan bu robotlardan yüksek verim almak ve en uygun robotu seçmek en zor problemlerden biridir. En uygun olan sistemin seçilmesi için farklı kriterler ve farklı uzmanların görüşleri dikkate alınarak, SWARA-WASPAS hibrit karar verme yöntemi, bu sistemlerin karakteristik kriterlerine göre uygulanmış ve uygulama sonunda her seçim problemi için duyarlılık analizi yapılmıştır. Tez sonucunda her bir robot seçim probleminden en uygun robotlar belirlenmiş ve her robot sınıfı için yapılan duyarlılık analizi ile en uygun robotun değişmediği, ancak diğer alternatiflerin kullanılan optimallik katsayısı değerine bağlı olarak değişebileceği görülmüştür.

Anahtar Kelimeler: Robot seçimi, Üretim otomasyonu, Çok Kriterli Karar Verme, SWARA, WASPAS.

To My Family …

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TABLE OF CONTENTS

LIST OF TABLES

TABLES

LIST OF FIGURES

FIGURES

LIST OF ABBREVIATIONS

AGV	Automated Guided Vehicle
BF	Box Folding
CoBot	Collaborative Robot
CR	Cartesian Robot
DM	Decision Maker
IP	Image Processor
IR	Industrial Robot
MCDM	Multi-Criteria Decision Making
SWARA	Step-Wise Weight Assessment Ratio Analysis
WASPAS	Weighted Aggregated Sum Product Assesment

CHAPTER 1

INTRODUCTION

1.1. Automation in Production Systems – A Historical Perspective

At the beginning of the 21st century, the whole world is witnessing a digital transformation in many business areas from production to logistics with the fourth industrial revolution, also known as Industry 4.0 [1]. Similar ideas are advocated by some constructionists as smart manufacturing/factory, cyber-physical systems, Internet of Things (IoT) or industrial Internet [2]. The term Industry 4.0 was first used in a report presented at the Hannover Fair in Germany in 2011 by a working group of political, academic, and business representatives aiming to strengthen the German manufacturing industry and to bring the information technologies and industry together [3]. The purpose of industrial revolution 4.0 is to increase computerization and automatization in production with the production equipment which use high technology [4]. While Industry 4.0 provides improvements in production processes such as flexibility, speed, and quality, it helps companies to overcome difficulties such as custom-made products, short production times and manufacturing high quality products [5].

Industry 4.0 serves many different purposes in various industries such as product development, logistics, and warehouse management. The role of mechatronics, which is a basic concept in the design of production systems, has changed with Industry 4.0 in accordance with cyber-physical systems [6]. Automated manufacturing methods supported by robots that can perform operations autonomously, is an important feature of Industry 4.0, with a focus on safety, adaptability, flexibility, and collaboration [7]. Industry 4.0 has become a leading topic for manufacturing facilities that use robotics and communication technologies to achieve fast and good production goals with high efficiency. Robots are becoming not only quicker and more precise than people, but they are also frequently more cost-effective in the long term. Robots can perform different tasks similar to humans, and they do not get tired easily or emotionally affected while working. On the grounds of these, different type’s robots can be integrated into production lines for reconfigurable, flexible, and highly efficient automation. One of the most important trends in today's world is to combine and link various production systems so that they can be highly flexible and efficient. Due to the important role played by robots in the modern manufacturing industry, the number of multi-purpose robots has nearly doubled in Europe since 2004 [8]. In industry, companies need to increase the use of industrial robots not only to ensure safety and reduce occupational accidents, but also to meet the need for faster and more accurate production with economic gain [9].

1.2. Problem Definition, Motivation, Objectives and Research Question

Since automation is at the focus of many industrial areas, the field of robotics continues to develop rapidly. Within the scope of automation and smart systems, the importance of which has increased in recent years, the selection of robots to be used for specific industrial operations is one of the most challenging issues for investors. Robots, which are in different price ranges in the market today, have many different abilities, technical features and potentials depending on the usage area and cost [10].

In hybrid production lines, industrial robots can be used in operations such as spray painting, pick-n-place operations where heavy load lifting capability is required, and placing products in boxes, while collaborative robots that take up little space and can work in close contact with humans have been used in sensitive operations such as siliconization, testing and barcode printing. In addition, Automated Guided Vehicles (AGVs) plays an important role in the transportation of materials to be used in assembly to production lines, while the Cartesian robots used in the assembly of these materials are involved in highly sensitive and repeatable operations such as screwing, box folding and pick-n-place operations. Image processing stations, on the other hand, have an important role in meeting the need for precise and high-resolution visual control due to their ability to measure more consistently than humans. The increase in the number of hybrid production concepts in which both humans and robots work together and various robot types such as an industrial robot, an AGV, a cartesian robot in many different operations from material handling to assembly, has been an important source of motivation for this study.

In this study, a built-in oven production line, in which human operators work predominantly, was examined. The aim of the company managers of the company is to decrease production time per unit for increasing production numbers. For this purpose, they want to replace some of the human operators with robots, thereby automating corresponding processes in the production line.

In the current production line, an industrial robot and a cartesian robot work with a total of nineteen human operators, to perform twenty main production operations. In order to reduce the number of human operators in the current production line, to increase the use of automation technologies and to increase the number of productions, we suggested to use industrial robots, collaborative robots, AGVs, image processing systems and cartesian robots. While the number of human operators is reduced to four in the targeted production line, the rate of automated operations is increased by adding three industrial robots, three collaborative robots, four AGVs, four Cartesian robots and an image processing system in addition to the existing robotic stations. With this automation transition, it is aimed to increase the production speed, reduce human-induced errors and adaptation problems, and reduce long-term costs. Each of the mentioned robot types are different brands and models. So, the technical features of these robot types differ. Therefore, the main problem addressed in this thesis is how to select the most suitable robot in each category among several alternatives for the operations in the current production line.

Getting high efficiency from these robots used in the production line for different purposes and choosing the most suitable robot are challenging problems. Although decision makers working in the industry, have wide knowledge regarding the applications and technical details of such robots, systematic decision making is required for robot selection in this problem. Multi-criteria decision-making methods suggest the most appropriate choice among several alternatives by considering different criteria and the opinions of experts. Thus, the research question of this study are as follows, is it possible to systematically select the robots to be used in the new production line based on different criteria sets, and if possible, which method will be applied while making the selections?

1.3. Scope and Methodology of the Thesis

In line with the digitalization trends in the industry, there is a need for a production environment concept that includes industrial robot, collaborative robot, AGV, cartesian robot and image processing systems. In order to meet the need for this hybrid production line, no study has been found in which different robot types (AGV, cartesian collaborative etc.) are selected. When the literature is examined, it is seen that SWARA and WASPAS methods are applied in many studies separately or integrated. However, no study has been found on the selection of robotic systems to be used in the conversion of manned production lines to robot-based automation production lines by using these methods. Therefore, the originality of the study and its contribution to the literature are based on this. Considering other MCDM methods, it has been evaluated that the SWARA and WASPAS integrated method is the most appropriate, efficient, and easy evaluation method, using the data types we have. In this study, a MCDM approach is applied for the selection of robotic systems to be used for the conversion of human-based production lines to production lines with robot-based automation systems.

The new production line design, in which the number of robots is increased, is used as an input for this study. The main purpose here is to select the most suitable robot among various alternatives for different robot categories to be used in this production line. To select the most suitable systems among different alternatives, SWARA and WASPAS hybrid decision making method will be applied according to the characteristic criteria of these systems. In the selection process, first, robot types and alternatives are determined. After that, experts who could give their opinions on the robot selection issue for the new production line were found and the criteria to be used in robot selection were decided together with the experts. After the criteria and robot alternatives are determined, the SWARA-WASPAS method is applied, and a sensitivity analysis is carried out. As a result of the study, the most suitable robots from each robot class are determined and it is seen that the most suitable robot did not change with the sensitivity analysis made for each robot class, but the other alternatives could change depending on the combined optimality coefficient value used.

The remaining part of this thesis is organized as the: Chapter 2 provides a review of the literature related to use of MCDM methods in robotics and as well as applications of SWARA-WASPAS method in different problems. Chapter 3 explains the SWARA-WASPAS MCDM method. Chapter 4 introduces MCDM for robot selection using SWARA-WASPAS method. Finally, in Chapter 5, discussion and conclusions regarding this work are provided, together with future research directions.

CHAPTER 2

LITERATURE REVIEW

Robots that are starting to enter the production environment with Industry 4.0 are more intelligent and secure. In industry, a selection of robot that perform its function well is an important issue. In the literature, there are many different studies about robot selection problems and also various multi-criteria decision-making (MCDM) problems in literature. When we examine the literature, it is seen that many studies have been performed on robot selection problems as shown in Table 2.1. This chapter explains previous work on both robot selection and use of MCDM in manufacturing.

In one of these studies, Chatterjee, Athawale and Chakraborty [10] evaluate the relative performance of two MCDM approaches for a certain industrial application in order to tackle the robot selection problem. ELECTRE, an outranking method, is one of the methods which are used, while VIKOR, a compromise ranking method, is the other MCDM methodology. These MCDM approaches, which are evaluated by several real-world examples, such as industrial robot selection for pick-n-place operations, are demonstrated and validate the applicability and potentiality of either of these MCDM approaches. Athawale and Chakraborty [12] conducted another study and compare ten popular MCDM methods, such as TOPSIS, AHP, GTMA, VIKOR, ELECTRE II, PROMETHEE II for industrial robot selection. Even though the performance of some methods was better, it has been emphasized that it is more important to carefully select alternatives and criteria rather than the MCDM method for evaluating the selection process of an industrial robot that performs a specific operation such as pick-n-place.

In a study conducted by Chakraborty [13], the MOORA method has been applied to six different systems, such as industrial robots, flexible manufacturing environments, control systems, rapid prototyping and automated control systems, where manufacturing companies face difficulties in choosing them to improve their production methods, designs and production technologies. In order to show the applicability and convenience of the MOORA method is compared to different MCDM methods such as TOPSIS, ELECTRE, PROMETHEE, and VIKOR.

Table 2.1 Multi-criteria decision-making applications about robotics

Author(s)/year	**Method**	**Research Area**
Chakraborty (2011) [12]	MOORA	Industrial robot selection FMS selection Machine tool selection Automated inspection system selection
Ic, Yurdakul and Dengiz (2013) [62]	ROBSEL AHP and TOPSIS VIKOR	Robot selection
Bairagi, Dey, Sarkar and Sanyal (2014) [14]	FTOPSIS FVIKOR COPRAS-G	Robot selection
Sen, Datta, Patel and Mahapatra (2015) [20]	PROMETHEE II	Industrial robot selection problem
Mondal, Kuila, Singh and Chatterjee (2017) [26]	COPRAS	Industrial robot selection problem
Mathew and Sahu (2018) [27]	CODAS EDAS WASPAS MOORA	Conveyor selection AGV selection
Zhou, Wang and Goh (2018) [28]	Fuzzy extended VIKOR	Mobile robot selection for hospital pharmacy

Table 1 (cont.)

Author(s)/year	Method	Research Area
Liu, Quan, Shi and Guo (2019) [29]	QFD and QUALIFLEX	Robot selection
Nirmal and Bhatt (2019) [63]	SVNS	Ranking of AGVs with industrial material handling purpose
Yalçin and Nuşin (2019) [30]	EDAS	Industrial robot selection problem
Ahmad, Bingöl and Wakeel (2020) [31]	CRITIC and MABAC	Robot selection for Flexible Manufacturing System
Nasrollahi, Ramezani and Sadraei (2020) [32]	FBWM-PROMETHEE	Industrial robot selection problem
Agarwal, Chakraborty, Prasad and Chakraborty (2021) [34]	MABAC	Arc welding robot selection
Goswami and Behera (2021) [37]	COPRAS and ARAS	Selection of conveyor Selection of AGV Selection of industrial robot
Rashid, Ali, Guirao and Valverde (2021) [38]	GITrF-TOPSIS GITrF-VIKOR	Robot selection
Zhao, Sui, Xu and Lai (2021) [40]	MCGDM-IP	Industrial robot selection problem
Chodha, Dubey, Kumar, Singh and Kaur (2022) [41]	TOPSIS and Entropy	Industrial arc welding robot selection
Kumar, Kalita, Chatterjee, Zavadskas and Chakraborty (2022) [42]	SWARA-CoCoSo	Spray painting robot selection

For a wide range of applications in production systems, robots with radically diverse capabilities and specifications are offered. Therefore, choosing a robot among many alternatives to fit a certain application and manufacturing environment is a challenging task. To date, many robot selection approaches have already been developed and applied. In one of the studies on industrial robot selection, a quantitative and qualitative integrated MCDM method is proposed [14]. In this method, both the objective order of importance and the subjective importance preferences of the decision makers are considered in order to decide on the order of importance of the attributes. In doing so, fuzzy logic is used to transform qualitative features into quantitative ones. In order to demonstrate the usability of the proposed method in the study, three examples of the industrial robot selection problem are presented.

In order to assess and choose robots for automated foundry activities, three Fuzzy Multi-Criteria Decision Making (FMCDM) approaches, namely FTOPSIS, FVIKOR, and COPRAS-G are combined with a Fuzzy Analytical Hierarchy Process (FAHP) [15]. A real-life example of the robot selection problem among five alternatives is given in that study, which deals with the selection of the most suitable robot to be supplied by a company for use in a foundry for a certain pick-n-place type operation where robots carry some load or avoid some obstacles.

Chakraborty and Zavadskas [16], discuss the applicability of the WASPAS method as an effective MCDM tool for solving eight decision-making problems in manufacturing, such as industrial robot selection, arc welding process, milling condition, machinability of materials and electroplating system. This study shows the fact that the ranking performance of the WASPAS method is better at higher combined optimality coefficient values. As a result of the decision making problems in that study, WASPAS method has the ability to correctly sort the alternatives in the specified selection problems, which can be about both single and multi-response optimization problems in various machining operations.

Decision-makers, according to Liu, Ren, Wu, and Lin [17], are in tendency to identify their assessments on subjective criteria using multipartite language term sets, and there is frequently ambiguous and partial evaluation data. An interval 2-tuple linguistic TOPSIS (ITL-TOPSIS) approach is studied in that paper to solve the robot selection problem for an industrial organization which needs an industrial robot to execute material handling operations in such an unpredictable and partial information environment. The method offers an integrated process for hybridizing expert knowledge and experience to be used in identifying the appropriate robot for a specified industrial application. The method used in that study perceives both subjective judgments and objective information in practical uses, allowing the suggested model being more realistic, feasible, and responsive. With all that, models the unpredictability and variety of decision-makers' judgements using interval 2-tuple linguistic variables to state their decisions. The efficiency and achievability of the suggested solution are presented with a case study, and the findings reveal that the ITL-TOPSIS is an effective decision-making tool for robot identification and comparison with ambiguous and partial information.

Chakraborty, Zavadskas, and Antucheviciene [18], aim to prove the stability and logical results of the WASPAS method. The study helps to increase the usage areas of WASPAS method by evaluating the selection process of five different production systems, which include a flexible production system, a machine in a flexible manufacturing cell, an automatic guided vehicle, an automatic quality control system and an industrial robot.

An effective strategy is proposed [19] for the best robot choice using both objective and subjective criteria. For robot selection, the methodology employs the Fuzzy Delphi Method (FDM), Fuzzy Analytical Hierarchical Process (FAHP), Fuzzy modified TOPSIS or Fuzzy VIKOR, and Brown–Gibson model. While the FDM approach is used to determine the substantial criteria based on the decision makers' standpoint, the FAHP technique calculates the weight of both objective and subjective criteria. After that, the fuzzy modified TOPSIS or fuzzy VIKOR approach is used to evaluate the candidates based on objective and subjective parameters. After the rankings are utilized to compute the robot selection approach that relies on Brown–Gibson model [20], it is discovered that the best performing option according to Fuzzy VIKOR is roughly equivalent to the optimal solution. Sen, Datta, Patel and Mahapatra [21], highlights the application potential of the PROMETHEE II method, regarding the robot selection problem subjected to a set of objective evaluation data gathered from existing literature studies. The method is considered as an efficient decision-making tool that attemperly provides the exact ranking of all available alternatives, thus avoiding errors in decision making. At the end of the study, the advantages and disadvantages of the PROMETHEE II method are reported by comparing them with other available MCDM techniques.

Ghorabaee [22] studied a multi-criteria group decision-making approach which is based on VIKOR method with interval type-2 fuzzy sets to make a robot selection for an auto company. To demonstrate the plausibility of the extended method which is evaluated with eight different robots and seven widely used criteria, the findings are compared with some available solutions. The method's stability is further assessed using seven sets of criteria weights and the Spearman correlation coefficient [23]. The suggested method's rankings are shown to be somewhat comparable with other approaches and to have decent stability across various criteria weights.

WSM, WPM, WASPAS, MOORA and MULTIMOORA methods, were implemented on the selection of industrial robots in production lines to perform pick-n-place operations while avoiding obstacles [24]. It has been shown that MULTIMOORA is the most robust and least affected method by weight changes of important criteria. A hybrid decision-making model for milling machine selection, rapid prototyping selection, industrial robot selection and flexible manufacturing system selection problems is developed by using an experimental design approach to designate weights of criteria and mix various MCDM evaluation methods such as SAW, TOPSIS, and GRA methods [25]. Without the expert opinions, specialized qualifications, or considerable experience that many MCDM methods require, this model can assist a decision maker in reaching a smart conclusion. In this study, four different numerical examples employing the suggested technique are used to prove that the acknowledged outcomes obtained with multiple MCDM methods are more accurate and useful than among created with a single MCDM method in a real-life application situation of an IC logistics company. In every scenario, the suggested method's results have been found to be quite consistent with the results obtained from existing research in the literature, confirming the method's reliability and capability in handling complex MCDM problems.

Xue, You, Zhao and Liu [26], aimed to propose an integrated model based on hesitant 2-tuple linguistic term sets and an extended QUALIFLEX approach to address robot selection problems with missing weight information. In their study, robot selection is considered as a MCDM problem whose objective is evaluating robots, determining criterion weights and prioritizing alternatives. Based on the extended QUALIFLEX algorithm, this model can clearly determine the priority order of the robots and provides a more conceivable and trustworthy solution in a specific manufacturing application. The proposed method is not only handling the decision makers' ambiguous and inexact assessment data with the aid of hesitant 2-tuple linguistic term sets, but it might also impartially obtain the crucial weights of the robots in cases where the weight information is not fully defined.

To demonstrate the COPRAS method's appropriateness in addressing such sophisticated production problems, Mondal, Kuila, Singh, and Chatterjee [27] apply COPRAS as a very promising multi-criteria approach, to overcome an industrial robot selection problem with seven alternatives and five determinant criteria in a specific production line.

In the study conducted by Mathew and Sahu [28], CODAS, EDAS, WASPAS and MOORA methods, which are recently developed MCDM methods, are applied for the selection of material handling systems such as AGV and conveyors. The study presents conveyor selection procedure with six determining criteria, and AGV selection problem with six criteria determined specifically for the problem. The rankings obtained as a result of the study were compared with the results of TOPSIS and MOORA methods. As a result of this comparison, it was seen that the CODAS, EDAS and WASPAS methods gave consistent results with each other.

Multi-criteria decision-making is also studied for a mobile robot selection problem in healthcare operations [29]. The fuzzy extended analytic hierarchy process technique is integrated into VIKOR-based implementation processes. The study uses fuzzy ranking technique based on the degree of possibility to select the optimal mobile robot option. The minimum fuzzy comprehensive value is determined for preventing loss of data to ensure the authenticity of the VIKOR-based computations. The performance and reliability of the fuzzy extended VIKOR approach for the mobile robot selection problem are demonstrated by the result obtained using a given scenario and the related sensitivity analysis.

A combination of the QFD theory with QUALIFLEX in an interval-valued Pythagorean uncertain linguistic context result in an unique robot selection approach [30]. In that study, a comparison demonstration of an auto manufacturing firm is undertaken using several known MCDM methods, including the IVF-VIKOR, ITL-TOPSIS, and IVIF-COPRAS, to prove the reliability and feasibility of the suggested integrated MCDM framework for robot selection.

The feasibility and effectiveness of an efficient and relatively new MCDM method, called EDAS, for the robot selection problem is demonstrated by considering a few numerical examples from the literature. A comparative analysis between the EDAS method and other methods for industrial robot selection problem is provided by studying four robot selection cases. While Spearman's rank correlation analysis shows that this method can correctly sort selected robots [31].

Ahmad, Bingöl, and Wakeelu [32] used the correlation coefficient and standard deviation method to establish the weight of each criterion. They developed a hybrid CRITIC and MABAC strategy to rank the seven robot options and five vital requirements. Also, VIKOR and ELECTRE II approaches were used to compare ranking results of the proposed method.

Selecting a robot that gives the most sensitive application output with the lowest cost was studied by using FBWM and PROMETHEE methods, which are two of the most suitable MCDM processes that should be supported by decision makers' opinions [10].

Suszyński and Rogalewicz [33] examined three MCDM strategies for the selection of an industrial robot in the production line of a medium-sized factory. To reduce the effect of the approach used on the final decision, a list of results obtained was created, and an overall result was created relating to decision makers' choices about specified robot parameters.

The difficulty of selecting a robot for a given task, such as arc welding is handled by combining rough numbers with the MABAC technique [34]. To prevent bias in the decision-making phase, decision makers' opinions are pooled based on rough numbers, and the MABAC approach is used to prioritize the candidate options and choosing the appropriate robot for the specified application. The usefulness of the Rough-MABAC technique in complicated decision-making problems is demonstrated by comparing sequencing performance with other MCDM methods. Even though the Rough-MABAC approach is demonstrated to be a valuable decision-making technique by successfully predicting the precise ranking of the arc welding robots in that research, it has several drawbacks, such as the difficulty of obtaining appropriate results when the criteria weights are unclear.

In this study, Büyüközkan, Ilıcak and Feyzioğlu is applied a MCDM method named COPRAS, which uses the combination of QFD and MPR to determine customer requirements and selection criteria for the selection of a robot to be used in a production line [35]. The results of the MCDM process were compared with the results of the TOPSIS method, and it was seen that the results could be different from each other. The reason for this is that the real-world experiences of decision makers may differ depending on subjectivity.

A real-world robot decision problem with 12 alternative robots and five selection criteria is presented in [36] to exemplify the functionality and performance of two new hybrid models. These models, namely TOPSIS-ARAS and COPRAS-ARAS are generated by combining ARAS with TOPSIS and COPRAS. The standings of robot options from these two hybrid models are compared with eight other non-hybrid MCDM tools. In addition, sensitivity analysis is used to analyze the implications of weight modification and confirm the resilience of the MCDM methodologies proposed.

The capabilities and usability of two MCDM approaches, ARAS and COPRAS is further studied [37], showing that they are both resilient and effective in tackling material handling equipment selection problems such conveyor selection, automated guided vehicles (AGV) selection, and industrial robot selection. In that study, the ARAS and COPRAS methods' outcome rankings were also verified by comparing the findings of other six MCDM methods collected from earlier research. Rashid, Ali, and Chu [38], demonstrated an example of industrial robot selection, to show that the best-worst method is a useful, highly reliable method to obtain the weights of the criteria. The method, which requires less computation, is more applicable than other methods and suitable for integration with the EDAS method.

The generalized interval-valued trapezoidal fuzzy best-worst method (GITrF-BWM) has been combined with the extended TOPSIS and extended VIKOR methods for the selection of the optimal industrial robot using fuzzy information by Rashid, Ali, Guirao, and Valverde [39]. The study demonstrates that GITrF-BWM provides more reliable and consistent criteria weights for multiple criteria group decision making problems. The opinions of decision makers are turned into fuzzy information for that study, which evaluates both subjective and objective criteria. The methods' reliability and efficiency were assessed using sensitivity analysis, which revealed that the ranking results of both methodologies are dissimilar, and that the integration of GITrF-BWM with the extended TOPSIS method produces more consistent and predictable results than the integration of GITrF-BWM with the extended VIKOR method.

Zhao, Sui, Xu, and Lai [40] proposed a multi criteria group decision making with individual preferences (MCGDM-IP) approach to resolve the robot selection problem by eliciting individual decision makers using four objective criteria elicitation strategies: Shannon entropy approach, CRITIC approach, distance-based approach, and ideal-point approach. The profitability and applicability of MCGDM-IP are demonstrated through an illustrated case employing data from earlier publications, demonstrating that MCGDM-IP might produce a more suitable scheme for evaluating and selecting industrial robots.

Selecting an arc welding robot from among eight alternatives using a simple MCDM methodology based on the TOPSIS method is studied in [41]. The criteria weights were obtained with objective preferences using the entropy weight method, and the ranking results obtained with the TOPSIS-Entropy technique are presented.

Based on seven determining criteria as payload, mechanical weight, speed, repeatability, reach, cost and power consumption, Kumar, Kalita, Chatterjee, Zavadskas, and Chakraborty [42] recommend combining SWARA and CoCoSo methods to identify the most appropriate spray painting robots with many viable alternatives on the market for the automotive manufacturing applications. The ranking results obtained at the end of the application were evaluated by comparing with other popular MCDM techniques such as TOPSIS, VIKOR, PROMETHEE, and MOORA, as well as the subjective criterion weighting methods AHP, PIPRECIA, BWM, and FUCOM. As a result, a high degree of similarity was observed in the ranking results of the alternatives, demonstrating the applicability of combined SWARA and CoCoSo approach in tackling different industrial robot problems.

Insights alone cannot function effectively, but the SWARA method is a method where experts and decision makers can think freely and convey their views. Decision makers can efficiently promote criteria evaluation process with their subjective comments depending on their experience and knowledge. SWARA method allows us to determine the weight and importance order of the criteria by systematically benefiting from the views of more than one decision maker. With the determination of the weights of the criteria, the need to evaluate the alternatives with a stable and powerful method arises, and this need is met with the WASPAS method, whose efficiency and effectiveness are emphasized in this study by combining it with SWARA method. Table 2.2 shows the use of SWARA-WASPAS methodology used for various problems from different industries in literature. The following paragraphs are investigating these studies mentioned in Table 2.2 to show the application areas of SWARA-WASPAS method as a MCDM approach.

Decision makers require robust tools for shopping mall location selection processes. The SWARA-WASPAS method is used on a real-world example of a very risky and complex shopping mall location selection problem in [43]. The opinions of eight specialists from various age groups and experience levels were included in that study. For this purpose, researchers conducted studies to prove the applicability of the SWARA-WASPAS method, which is a hybrid method used in MCDM problems. The results showed that the SWARA-WASPAS hybrid approach is an efficient, useful, effective, and rational method for evaluating various alternatives and criteria.

Heidarzade, Varzandeh, Rahbari, Zavadskas and Vafaeipour [44], aim to help the government officials in their energy strategy planning, to prioritize the potential cities where wind farms will be established. The criteria determined together with the expert opinions on wind farm selections were included and the SWARA-WASPAS hybrid method and MCDM solution were applied.

In that specific MCDM problem, in which both objective and subjective criteria are evaluated based on the experience of 12 experts for 25 different cities in order to overcome the complex problems of determining the installation location of future solar power plants due to the existence of various criteria, and to assist decision makers in the energy sector. Vafaeipour , Zolfani, Varzandeh, Derakhti, and Eshkalag [45] used the integrated SWARA-WASPAS approach to evaluate criteria robustly and consistently without bias about alternatives.

Ghorshi Nezhad, Zolfani, Moztarzadeh, Zavadskas, and Bahrami [46], aims to apply an innovative approach by evaluating the experiences of other countries and other research in the literature. In order to guide authorities in planning the development and future of the nanotechnology industry, which has a strategic significance for governments, evaluated the criteria using the SWARA method, which has a strong and coherent standpoint for decision making and strategy making, and evaluated and ranked the alternatives with WASPAS, a rigorous and trustworthy approach for computations. Forty specialists with professional knowledge of nanotechnology and nanotechnology-related subjects, who were chosen based on the Nanotechnology Association's recommendations, collaborated to that study, which used the proposed hybrid MADM model.

Karabašević, Stanujkić, Urošević and Maksimović [47], underlined the importance of the recruitment and personnel selection phase in the field of human resources, suggested using SWARA and WASPAS methodologies and proposed a solution to the personnel selection problem. They evaluated four alternative sales manager candidates using seven criteria thought to be critical for human resources to show that the proposed method is an effective, simple, and practical approach to the personnel selection problem.

Yurdoglu and Kundakci [48] demonstrates the assessment of a number of various servers from the same class, based on seven decisive criteria as processor speed, number of cores, internal storage, memory capacity, disk space, brand image, and cost. The alternatives are compared by five authorized decision makers in order to select the most suitable server to be used in a textile manufacturer in Turkey. The most essential server selection criteria were determined using the SWARA approach, which was used to define the weights of the criteria, and then WASPAS was used to rank the alternatives.

SWARA and WASPAS methods were applied in order to carry out the supplier selection process for the grinding of a machine part belonging to the pickling line of a heavy metal company in Turkey [49]. While making the choice, they worked with the participation of experts and senior managers from the 3 suppliers. The team determined the evaluation criteria to be used with SWARA. Then, after evaluating the alternatives using the WASPAS method, the most suitable supplier to meet the company's needs was selected.

Cavallaro [50] offered a hesitant fuzzy linguistic stepwise weight assessment ratio analysis with the weight aggregated sum product assessment (HFL-SWARA-WASPAS) model to evaluate a MCDM problem, which is described as the location selection of electric vehicle charging stations. The HFL- WASPAS approach is used to analyze the linguistic assessment data provided by professionals and to determine the standings of options. HFL-SWARA is utilized to establish the weights of criteria to bring a new perspective to MCDM methods.

Table 2.2 Various applications of SWARA and WASPAS MCDM methods

Author(s)/year	**Method**	**Research Area**
Ghorshi Nezhad, Zolfani, Moztarzadeh, Zavadskas and Bahrami (2015) [46]	SWARA-WASPAS	Priority of nanotechnology applications
Karabašević, Stanujkić, Urošević and Maksimović (2016) [47]	SWARA-WASPAS	Personnel selection
Mardani, Nilashi, Zakuan, Loganathan, Soheilirad, Saman and Ibrahim (2017) [65]	SWARA-WASPAS	Review Paper
Yurdoğlu and Kundakçı (2017) [48]	SWARA-WASPAS	Selection of the most suitable server for a department of a textile company
Toklu, Çağıl, Pazar and Faydalı (2018) [49]	SWARA-WASPAS	Selection of the most suitable supplier for a production line of a heavy metal company
Prajapati, Kant and Shankar (2019) [51]	SWARA-WASPAS	Prioritize the solutions for mitigating the impact of barriers to reverse logistics implementation
Cavallaro (2019) [50]	SWARA-WASPAS	Electric vehicle charging station site selection
Singh and Modgil (2020) [53]	SWARA-WASPAS	Supplier selection in Indian cement industry

Table 2 (cont.)

Author(s)/year	Method	Research Area
Yörükoğlu and Aydın (2020) [54]	SWARA-WASPAS	Making a digital library more useful
Baç (2020) [52]	SWARA-WASPAS	Smart card system evaluation
Erdogan and Tosun (2021) [57]	SWARA-WASPAS	Supplier selection for the electronics sector
Yücenur and Ipekçi (2021) [58]	SWARA-WASPAS	A location selection problem for Turkish first marine current energy production plant
Alvand, Mirhosseini, Ehsanifar, Zeighami and Mohammadi (2021) [55]	SWARA-WASPAS	The construction projects of the Iranian Road and Urban Development Organization
Bac, Alaloosi and Turhan (2021) [56]	SWARA-WASPAS	Selection of the most suitable HVAC system for a furniture factory
Saraç, Dedebaş, Hastaoğlu and Arslan (2022) [59]	SWARA-WASPAS	Determination of the most preferred cake sample

Prajapati, Kant, and Shankar [51] conducted an experimental study on the power generation industry to provide a systematic strategy to assist organizations in reducing and solving many barriers in reverse logistics applications utilizing the hybrid modified SWARA-WASPAS method. The effect of impediments was analyzed with modified SWARA, while WASPAS was used to determine the priority of resolution of barriers logically and decisively in a real-world scenario, which was created to prove the applicability of the suggested method.

Baç [52] proposed an integrated multi-criteria decision-making methodology that combines two new and well-liked methodologies to evaluate the various smart card systems within the structure of MCDM, to identify the best one, and verify their advantages in comparison to the conventional payment systems. The proposed method can be utilized as a reference for choosing the suitable smart card system and defining the areas in need of enhancement throughout the project execution. The SWARA approach is used to estimate the criterion weights in the decision model and the WASPAS method is used to evaluate the alternatives, and it demonstrates advancements in smart card system efficiency, durability, and customer satisfaction.

A combined SWARA-WASPAS method is proposed in [53] for evaluating 5 alternatives and 12 criteria obtained through literature review in order to assist the managers of a cement producer company. The study is unique in terms of the industry and the methods they examined. The company purchases raw materials of different grades from different suppliers and the proposed method is used to choose the most suitable supplier.

Yörükolu and Aydın [54] employ the SWARA-WASPAS approach to examine the user requirements that make a digital library more serviceable from many aspects. The method is adaptable and includes simple computation procedures. The assessment of three alternative digital libraries was made under the consultancy of information technology professionals and took into account five interrelated major criteria.

Alvand, Mirhosseini, Ehsanifar, Zeighami and Mohammadi [55] proposes a fuzzy approach that incorporates Failure Mode and Effects Analysis (FMEA), SWARA, and WASPAS methodologies to emphasize the influence of FMEA, one of the most significant techniques in the field of risk evaluation, and to address some of its deficiencies. A construction case study was examined to prove the efficiency and applicability of this fuzzy method of FMEA, SWARA and WASPAS. A comparison of the FAHP and FTOPSIS methodologies was performed to determine the merits of that hybrid strategy. As a result of the investigation, FSWARA was chosen for criterion evaluations, while the FWASPAS approach was employed to analyze and prioritize key risks in decision making for a construction case.

Hybrid SWARA-WASPAS method is used to select the most suitable and high-performing system for a furniture production facility in Turkey among eleven Heating, Ventilating and Air Conditioning (HVAC) system alternatives [56]. The study uses the objective criteria obtained from a robust building energy simulation tool and the subjective criteria determined by the opinions of three experts using their professional experiences. The vision of that study, in which HVAC systems are evaluated from many aspects such as ergonomics, cost, flexibility and technique, is to guide designers in the light of all these criteria in designing the most efficient HVAC systems for industrial facilities.

In a study on supplier selection, a two-stage MCDM approach has been proposed for a company operating in the electronics sector [57]. The study includes the evaluation of both quantitative and qualitative criteria determined for many factors such as sensitivity, sustainability, legal pressures. Due to the fact that the company works in the international arena and its reputation is high, the need to verify the preferences of the decision makers using a rational and efficient method has arisen. 4 alternatives using a total of 16 criteria created in 3 different fields are evaluated in order to fill the literature gap in the supplier selection field and to confirm the systematic and sustainable approach of the SWARA-WASPAS method.

As one of the original studies in the literature due to specifically examining the problem of site selection for the first marine current power plant to be established in Turkey, Yücenur and Ipekçi [58] evaluated 12 criteria and 3 alternatives by using SWARA and WASPAS methods together.

An interesting application of the SWARA-WASPAS method is conducted by Saraç, Dedebaş, Hastaoğlu and Arslan [59], in order to produce a cake rich in protein as possible by using different types of flour that can be used in vegan products in different proportions. 30 experts evaluated the textural properties of the cakes such as taste, aroma, and appearance, and the most preferred cake was found by evaluating the criteria and alternatives followed by the SWARA-WASPAS method.

As a result of the literature survey, it is seen that many different MCDM methods, such as CODAS, EDAS, MOORA and FBWM-PROMETHEE, are used for robot selection problems. In addition, it is seen that the SWARA-WASPAS method used in this thesis is applied integratedly or separately as SWARA and WASPAS to examine many different selection problems such as HVAC system selection, supplier selection, server selection. The main gap here is no study has been found on the selection of robotic systems for different robot categories to be used in the conversion of manned production lines to robot-based hybrid automation production lines by using SWARA-WASPAS methods.

CHAPTER 3

METHODOLOGY OF SWARA AND WASPAS METHOD

In this thesis, two multi criteria decision-making (MCDM) methods, namely SWARA and WASPAS are applied to select the most suitable mechatronic systems for a given industrial automation system selection problem. This section explains the SWARA-WASPAS methodological framework which is depicted in Figure 3.1 as a flow diagram.

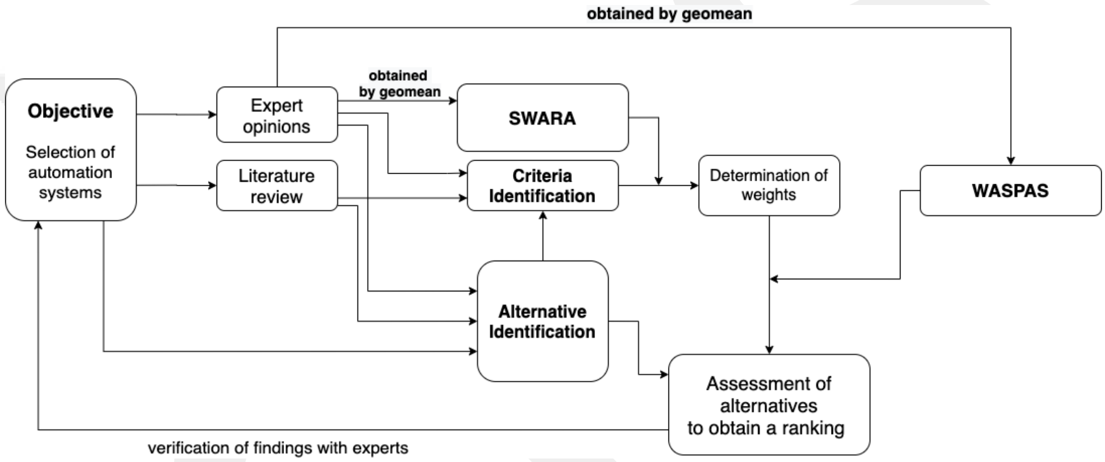

Figure 3.1 Framework of proposed SWARA-WASPAS MCDM approach

3.1 Step-Wise Weight Assessment Ratio Analysis (SWARA)

The Step-Wise Weight Assessment Ratio Analysis (SWARA) method, is one of the criterion weighting methods and it has been used recently. The SWARA method was first proposed by Keršuliene, Zavadskas and Turskis [60].

In this method, first of all, criteria are determined together with decision makers to be used in the evaluation of the alternatives specific to the selection problem examined. As a result of the consensus of decision makers, minor criteria are eliminated, and the remaining criteria are ranked according to their importance. When calculating the significance weights of the remaining criteria, the order created by each decision maker is taken into account. Decision makers are chosen to evaluate alternatives and criteria according to their knowledge and practical experience. To be used in Weighted Aggregated Sum Product Assessment (WASPAS) method, geometrical means of the decision maker opinions are calculated as applied by Bac [52] for creating one alternative table.

The steps of the SWARA method are given below:

Step 1: Each decision maker determines the criterion that is the most important for him/her. Here, the most important criterion gets 1.00 point. Decision makers assign points to other criteria by considering the most important criterion. Points are assigned to be multiples of five from 0 to 1. Points assigned to the criteria:

p_j^k; j=1,2,…,k and k=1,2,…,l ; $0 \leq p_j^k \leq l$ where j=criterion and k=decision maker

Step 2: The relative importance score ($\overline{p_j}$) is calculated for each criterion. The geomean of the relative importance points, which are assigned by the decision makers to the criteria, is calculated for each criterion with the help of Equation (1).

$$\overline{p_J} = \left(\prod_{k=1}^{l} p_j^k\right)^{\frac{1}{l}}; j = 1,2,\ldots,n \quad (1)$$

where l =number of decision maker n=number of criteria

Step 3: All criteria are compared according to their relative importance scores, sorted from largest to smallest. As a result of this comparison, comparative significance values (s_j) of the geomean value are calculated. The coefficient value (c_j) show how important the “j + 1” criterion is compared to the “j” criterion and it is obtained by binary comparison.

Step 4: The coefficient value c_j for each criterion is calculated using Equation (2). The coefficient for the criterion with the largest s_j value is $c_j = 1$.

$$c_j = s_j + 1 \,; j = 1,2,\ldots,n \quad (2)$$

Step 5: Corrected weights (s_j') for all criteria are calculated with the help of Equation (3). The corrected weight of the criterion in the first row is s_j'= 1.

$$s_j' = \frac{s_{j-1}'}{c_j} \quad (3)$$

Step 6: Final weights (w_j) are calculated with the help of Equation (4) for all criteria.

$$w_j = \frac{s'_j}{\sum_{j=1}^{n} s'_j} ; j = 1,2, \dots, n \tag{4}$$

4.1 Weighted Aggregated Sum Product Assessment (WASPAS)

The Weighted Aggregated Sum Product Assessment (WASPAS) method was developed by Chakraborty and Zavadskas [16], as a combination of results of two different models: "Weighted Sum Model" and "Weighted Product Model". The alternatives are ranked based on the value of the combined optimality criterion calculated according to the results of these two models. The WASPAS method can control the consistency in alternative rankings by conducting sensitivity analysis in its own functioning.

The steps of the WASPAS method are given below:

Step 1: Alternatives and criteria are determined.

Alternatives are represented as $A_i (i = 1, \dots, m)$, and criteria as $C_j (j = 1, \dots, n)$

where m =number of alternatives n=number of criteria

Step 2: The first individual decision matrix, consisting of n criteria and m alternatives, should be constructed using the views of l decision makers.

Step 3: After the criteria weights are determined, an initial decision matrix is created and normalized. Some of the criteria taken into account in the decision process may be benefit type depending on the nature of the problem and some may be cost-effective. Benefit type criteria are the criteria that the decision maker wants to maximize values, whereas cost type criteria are those whose values are desired to be minimized. To normalize the initial decision matrix, Equality (5) and (6) are used for benefit and cost type criteria, respectively.

For Benefit Type Criteria, $\overline{x_{ij}} = \frac{x_{ij}}{max_i x_{ij}}$ (5)

For Cost Type Criteria, $\overline{x_{ij}} = \frac{min_i x_{ij}}{x_{ij}}$ (6)

where $\overline{x_{ij}}$=normalized decision matrix value

Step 4: The total relative significance value for each alternative is first calculated based on the "Weighted Total Model". This value is calculated by using Equation (7), and it is called the first total relative importance value ($Q_i^{(1)}$).

Note: w_j value is the importance weight of the criteria obtained by the SWARA method.

$$Q_i^{(1)} = \sum_{j=1}^{n} \overline{x_{ij}}\, w_j \tag{7}$$

Step 5: Then, the total relative significance value for each alternative is calculated according to the "Weighted Product Model". This value is called the second total relative importance value ($Q_i^{(2)}$) and it is calculated using Equation (8).

$$Q_i^{(2)} = \prod_{j=1}^{n} \left(\overline{x_{ij}}\right)^{w_j} \tag{8}$$

Step 6: The combined optimality value is calculated for each alternative. Using Equation (9), by considering the results of the Weighted Total Model and Weighted Product Model.

$$Q_i = \lambda Q_i^{(1)} + (1 - \lambda) Q_i^{(2)} \tag{9}$$

Where; λ = Combined optimality coefficient and λ Є [0,1] as mentioned by Bac [56].

Step 7: Each alternative is ordered by considering the combined optimality value (Q_i). The alternative with the largest Q_i value is the best alternative and ranks first.

CHAPTER 4

MCDM FOR ROBOT SELECTION USING SWARA-WASPAS METHOD

In this chapter, SWARA and WASPAS methods are used as a useful combined multi criteria decision-making (MCDM) method, to the robot selection problem in an existing production line of an oven manufacturing company. Figure 4.1 shows the production process flow of built-in ovens in the current production line. The current production line has one industrial robot for cover painting and one cartesian robot which is for box folding operation. The aim of the managers of the company is to decrease production time per unit for increasing production numbers. For this purpose, they want to replace some of the human operators with robots, thereby automating corresponding processes in the production line. Figure 4.2 depicts the process flow diagram of the intended production line with automated systems including different types of robots such as AGV, collaborative robots, an image processor station, cartesian robots and industrial robots. The comparison of two production lines is shown in Table 4.1 with number of operators and automation systems.

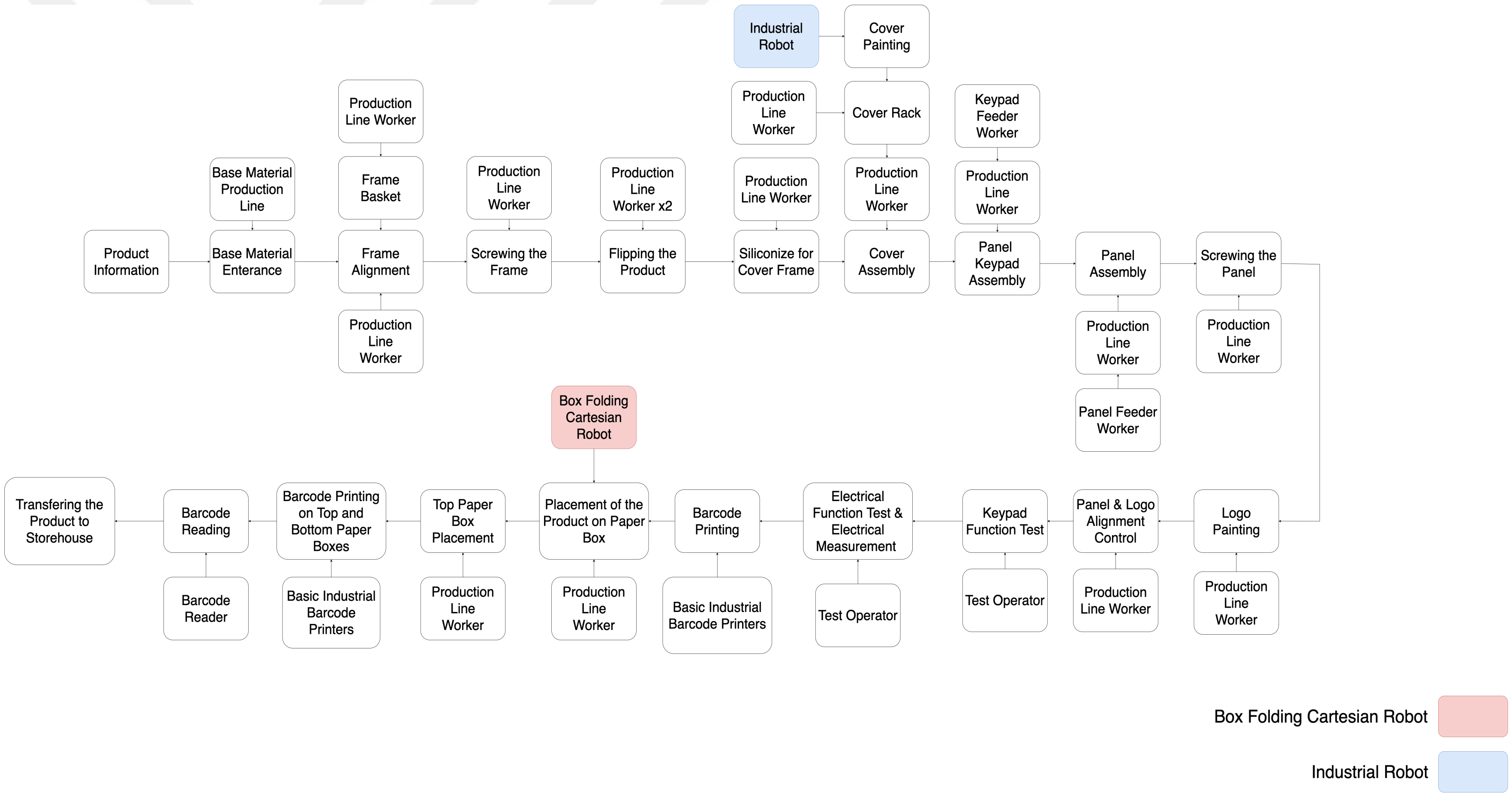

Figure 4.1 Process flow diagram of current production line

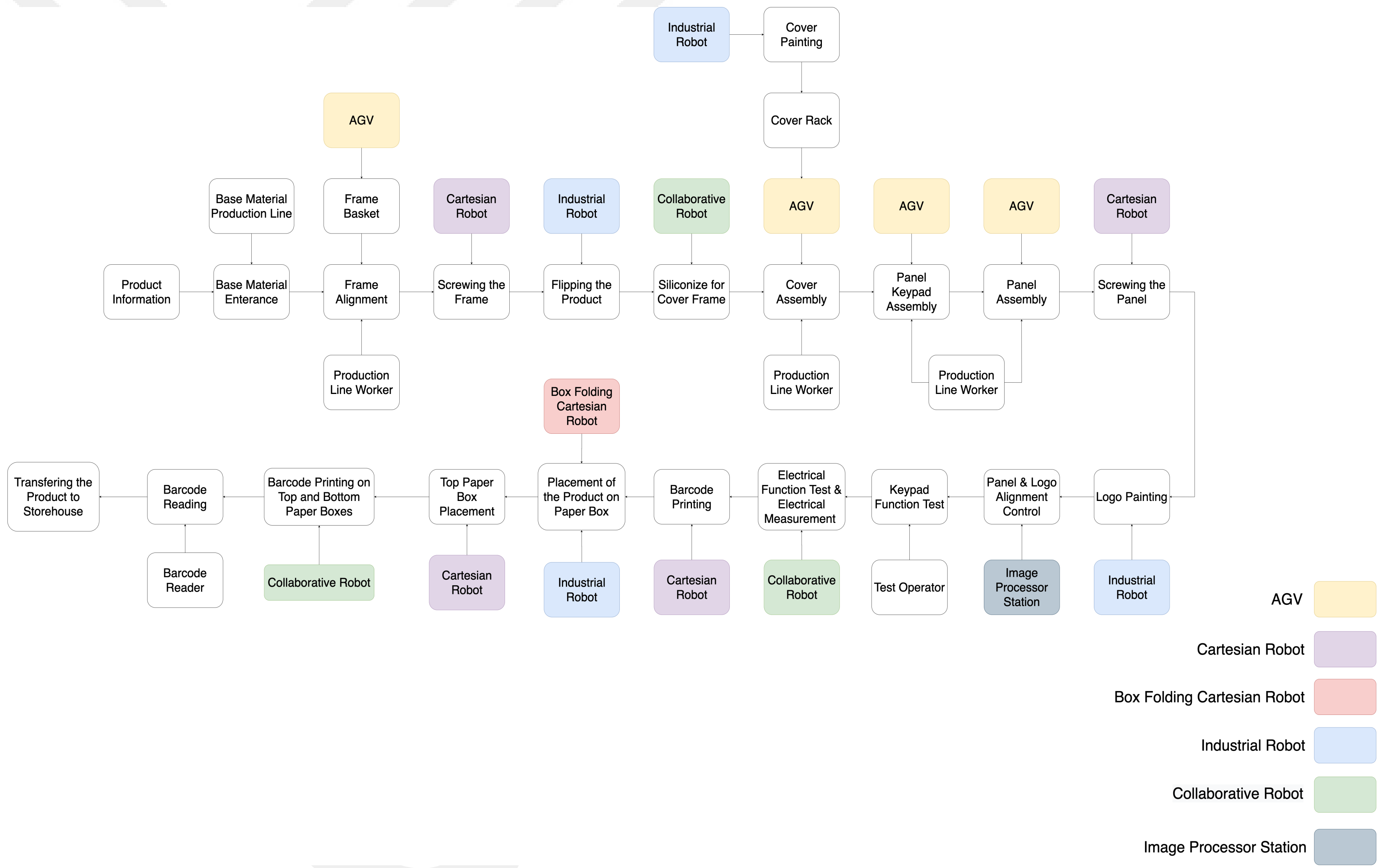

Figure 4.2 Process flow diagram of intended production line

Table 4.1 Comparison of the current and intended production lines

	Current Production Line	**Intended Production Line**
Number of Operators	19	4
Number of AGVs	0	4
Number of Collaborative Robots	0	3
Number of Industrial Robots	1	4
Number of Cartesian Robots	1	5
Number of Image Processor Stations	0	1

There are some advantages and disadvantages for both systems in terms of production performance related headlines such as work parameters, flexibility, cost, and failure rates as shown in Table 4.2 [61]. Taking everything into account, the intended production line, was decided as a long-term investment, as a company strategy.

Table 4.2 Comparison of current and projected production lines [61]

	Current Production Line	**Projected Production Line**
Work Parameters	Unstable, slow work	Stable, fast work
Adaptation for New Task	Fast adaptation	Slow programming
Flexibility & Working area	Large flexibility, large operating range	Lower flexibility, limited range
Errors and Failures	High human errors rate	Low failures rate
Replacement and Repair	Can be replaced	Require repairing
Labour Cost	High	Low
Investment Cost for Human/Robot Workstation	Low	High

In current production line, generally human operators used for production steps. There are only two automated production stations, which are painting of the oven cover and paper box folding operations. Cover painting operation is conducted by an industrial robot and paper box folding operation is done using a box folding cartesian robot. All the other production steps, such as frame screwing, cover frame siliconizing and product flipping, are conducted by human operators.

For intended production line there are four industrial robots for product flipping operation, cover painting operation, logo painting process and placing the product on paper box. Industrial robots preferred for these operations because product flipping, and product placement operations are considered as basic pick-n-place operations which requires high load capacity. Those kinds of pick-n-place operations can be done by industrial robots easily. Besides, industrial robots are preferred for painting operations which requires high repeatability rate.

Collaborative robots are used for production steps which is needed to be sensitive, fast and precise. The main purpose of using collaborative robots is to ensure work safety in stations where humans and robots must work side by side. In the intended production line, collaborative robots are used for cover frame siliconizing, electrical function test and measurement process, and barcode printing on product boxes.

AGVs offer labor cost reductions, quality assurance, effective and fast material management, and customizable routing in mass production lines. Since most organizations are now designing and implementing modular and automated manufacturing systems, AGVs play an essential role in the manufacturing industry for material handling [37]. AGVs are preferred for material transfers for assembly operations. There are four AGVs used for material handling operations such as transfer of painted covers from cover painting department, frame, panel keypad and panel transportations from storehouse to production line.

Cartesian robots can be designed with various combinations and the number of axes can be increased or decreased as needed. This capability allows companies to design cost-effective and efficient systems. In the intended production line, five cartesian robotics solutions, including a box folding robot, are used for screwing operations, basic material placement operations such as paper box placement on product and repetitive operations like barcode label printing. Box folding cartesian robot solution is also a cartesian robot, but it is evaluated as a different robot class because there is no need to add any special tooling for this robot class.

For panel and logo alignment process, an image processor station is used in the intended production line. This system checks whether the distance between the panel and the oven door complies with the standards, and whether the logo on the door is printed in the correct place with the required quality. It has been evaluated that this system gives much more accurate and faster results than the measurement and quality control processes performed by human operators.

There are four human operators working in the intended line for five different production steps, such as frame alignment, cover assembly, panel keypad assembly, panel assembly and keypad function test. The use of robots is not preferred for frame alignment, cover assembly, panel keypad assembly and panel assembly operations. Since these operations are assembly operations that work on the vertical axis, there would be a need to use two robots, one robot for holding and aligning the material to be assembled, and another robot where a special tool should be used to perform the assembly process. Since this is a disadvantageous situation in terms of cost and programming, no robot is used here. Instead, a single human operator was used for two sequential assembly operations, panel keypad assembly and panel assembly, as a cost-saving solution. On the other hand, when we want to use a robot for the keypad function test, there is a need to use a system that can both turn and press the buttons and come to a conclusion by observing the reactions of the product. Since this need can only be met with a costly robot solution that must have both gripping, pressing and image processing capabilities, it was decided that the existing human operator should continue to work in this operation.

While determining the robots to be used in this study, it is assumed that the robots to be selected from each robot class to be used in the intended production line, are identical robots. For example, it is assumed that the robot alternative selected as a result of the MCDM application for industrial robot selection can be used in all industrial robotic production steps.

The following six decision making problems are discussed for the selection of the above mentioned robots in the intended production line. To determine the criteria for these selection processes, a detailed literature review was studied. To finalize the criteria selection, considering the concept, environment, and structure of the white appliances industry, 3 decision makers were interviewed, and their comments and opinions were used to ensure that all criteria were chosen properly. Decision Maker 1 (DM1), he is a well-experienced engineer in automated production lines for white appliances manufacturers, is currently working as the Digital Transformation Manager of an Association of Metal Industries. Decision Maker 2 (DM2), he has been employed in many different industries such as white appliances, defense industry and automotive industry for years: is an Automation Systems Integration Consultant in a global automation technologies company. Lastly, Decision Maker 3 (DM3) is working with the title of "robotic automation specialist" for a global industrial robot manufacturer and he is quite experienced in many different industrial robots such as welding robots, painting robots, screwing robots, pick-n-place robots, from the design stage to production, integration, and programming. As a result of this study with DMs, all robot classes and criteria set for each class were listed in Table 4.3.

Table 4.3 Criteria sets for robot classes in the intended production line

Criterion Name	Robot Types						Definition	Reference
	IR	CoBot	CR	BF	AGV	IP		
Robot Weight	X	X	X	X			total weight of a robot including mounting parts	[10], [60]
Load Capacity	X	X	X	X	X		the maximum load that a robot can carry without affecting its performance	[10], [60]
Repeatability	X	X	X	X		X	repeatability is the measure of the ability of a system to process the same operation or to return to the same position and orientation over and over again	[10], [13], [18], [60]
Maximum tip speed	X	X	X	X			the maximum speed that a manipulator arm can achieve	[10], [60]
Memory Capacity	X	X	X	X			memory capacity of a robot is measured in terms of number of points or steps that it can store in its memory while traversing along its predefined path	[10], [60]
Manipulator Reach	X	X	X	X			the maximum distance that can be covered by the robotic manipulator so as to grasp the object for the given pick-n-place	[10], [60]
Man-Machine Interface	X	X	X	X	X		an interface which permits interaction between a human being and a machine	[10], [18], [26], [60], [62]

Table 5 (cont.)

Criterion Name	Robot Types						Definition	Reference
	IR	CoBot	CR	BF	AGV	IP		
Programming Flexibility	X	X	X	X	X		programming flexibility refers to a robot's ability to accept different programming codes	[10], [18], [26], [60], [62]
Cost	X	X	X	X	X		involves purchase, installation, operation and training costs	[10], [18], [26], [60], [62]
Maintenance Cost	X	X	X	X			involves maintenance costs for a robot	[10], [60]
Special Tooling Cost			X				this includes the cost of the end effector, parts positioners, and other fixtures and tools required to operate the work cell.	[61]
Initial cost						X	involves purchase, installation and training costs	[13], [18]
Operation cost						x	involves operation and maintenance costs	[13], [18]
Vendor's service Contract	X	X	X	X			vendor's service quality refers to the satisfactory level and variety of services offered by a robot vendor	[10], [60]
Controllability					X		the ability of a control system to reach a definite state from a fixed (initial) state in a finite time	[18], [26], [62]

Table 5 (cont.)

Criterion Name	Robot Types						Definition	Reference
	IR	CoBot	CR	BF	AGV	IP		
Accuracy					X	X	the measure of closeness between the robot end effectors and the target point, and can usually be defined as the distance between the target point and the center of all points to which the robot goes on repeated trials	[13], [18], [26], [62]
Range					X		the distance an electric or hybrid vehicle can travel before the battery needs to be recharged	[13], [18], [26], [62]
Reliability					X	X	the probability that a product, system, or service will perform its intended function adequately for a specified period of time, or will operate in a defined environment without failure	[18], [26], [62]
Battery Capacity					X		refers to battery capacity value in terms of VDC or working hours	Expert suggestion
Guidance Type					X		the method of steering an AGV uses for its movement such as Aluminium Tape, Magnetic Tape, Laser Navigation, Natural Navigation	Expert suggestion
Speed					X		the maximum speed that an AGV can achieve	[18], [26], [62]

Table 5 (cont.)

Criterion Name	Robot Types						Definition	Reference
	IR	CoBot	CR	BF	AGV	IP		
Resolution						X	a measure used to describe the sharpness and clarity of an image or picture. It is often used as a metric for judging the quality of monitors, printers, digital images and various other hardware and software technologies.	[13], [18]
Response Time						X	refers to duration taken for a system to react to a given stimulus or event	[13], [18]
Operating System						X	the program that, after being initially setup into a system, manages all of the other programs in a system	[13], [18]
Hardware Interface						X	specifies the types of plugs and sockets that provide communication and network between the system and controller or CPU	[13], [18]
Frame Rate						X	the frequency rate at which image frames are captured	[13], [18]
Maintainability						X	the measure of the ability of an item to be retained in or restored to a specified condition when maintenance is performed by personnel having specified skill levels using prescribed procedures and resources at each prescribed level of maintenance and repair	[13], [18]

Table 5 (cont.)

Criterion Name	Robot Types						Definition	Reference
	IR	CoBot	CR	BF	AGV	IP		
Flexibility in software interface						X	refers to an image processor station's ability to accept different programming codes, flexibility for interface which permits interaction between a human being and a machine	[13], [18]

4.1 Industrial Robot (IR) Selection

In this study, evaluation and selection of the industrial robot is based on 11 criteria determined as a result of the consensus of three decision makers, who are a Digital Transformation Manager (DM1), an Automation Systems Integration Consultant (DM2) and a robotic automation specialist (DM3). The criteria were determined as 'Robot Weight', 'Load Capacity', 'Repeatability', 'Maximum tip speed', 'Memory Capacity', 'Manipulator Reach', 'Man-Machine Interface', 'Programming Flexibility', 'Cost', 'Vendor's service Contract' and 'Maintenance Cost'. 10 industrial robot (IR) alternatives (IR1-IR10) are decided for comparison as a result of a market survey. These alternatives are robots produced by worldwide robot manufacturing companies and they currently in the market.

Criteria weights are calculated using the SWARA method with the following steps.

First, a questionnaire was administered to three decision makers, and they was asked to rank the criteria from 0 to 1.00 in the order of importance each decision makers. The decision makers assigned the most important criterion a score of 1.00 and evaluated the other criteria by considering the most important criterion with changing values of 0.05 and its multiples. Table 4.4, consisting of p_j^k values, was obtained as a result of the decision makers assigning points to the criteria.

Table 4.4 Scoring the Criteria for IR Selection According to the Degree of Importance on the Basis of the Decision Maker (p_j^k values)

Criteria \ Decision Maker		DM1	DM2	DM3
C1	Robot Weight (kg)	0,20	0,10	0,40
C2	Load Capacity (kg)	1,00	0,60	1,00
C3	Repeatability (mm)	0,80	0,70	0,75
C4	Maximum tip speed (°/s)	0,70	0,50	0,55
C5	Memory Capacity (MC)	0,35	0,30	0,25
C6	Manipulator Reach (mm)	0,90	0,20	0,90
C7	Man-Machine Interface (MMI)	0,65	0,35	0,15
C8	Programming Flexibility (PF)	0,60	0,40	0,50
C9	Cost (C)	0,85	1,00	0,85
C10	Vendor's service Contract (VSC)	0,45	0,75	0,65
C11	Maintenance Cost (MeC)	0,50	0,85	0,70

As a second step, relative geomean importance score ($\overline{p_j}$) for all criteria was calculated using Equation (1) on page 25 and the results are shown in Table 4.5.

Table 4.5 Relative Importance Scores ($\overline{p_j}$) for IR Selection Criteria

Criteria	Relative Importance Scores ($\overline{p_j}$)
C1	0,2000
C2	0,8434
C3	0,7489
C4	0,5774
C5	0,2972
C6	0,5451
C7	0,3244
C8	0,4932
C9	0,8973
C10	0,6031
C11	0,6676

In the 3rd step, all criteria were ordered from largest to smallest according to their relative importance scores, and the comparative importance (s_j) values of the mean value for the criteria were calculated as given in Table 4.6.

Table 4.6 Comparison of Relative Significance Scores for IR Selection Criteria

Criteria	Relative Importance Scores ($\overline{p_j}$)	Comparative Importance of Geomean Value (s_j)
C9	0,8973	-
C2	0,8434	0,0539
C3	0,7489	0,0945
C11	0,6676	0,0813
C10	0,6031	0,0645
C4	0,5774	0,0257
C6	0,5451	0,0323
C8	0,4932	0,0519
C7	0,3244	0,1688
C5	0,2972	0,0272
C1	0,2000	0,0972

After that, the coefficient value c_j for all criteria was calculated using Equation (2) on page 25 as depicted in Table 4.7.

Table 4.7 Coefficient Values (c_j) of the IR Selection Criteria

Criteria	Coefficient Values (c_j)
C9	1,0000
C2	1,0539
C3	1,0945
C11	1,0813
C10	1,0645
C4	1,0257
C6	1,0323
C8	1,0519
C7	1,1688
C5	1,0272
C1	1,0972

In the penultimate step, the corrected weights (s'_j) for all criteria were calculated with the help of Equation (3) and the values in Table 4.8 were obtained. Here, the corrected weight of the first-ranked criterion is s'_j=1.

Table 4.8 Corrected Weight Values (s'_j) of the IR Selection Criteria

Criteria	Corrected Weight Values (s'_j)
C9	1,0000
C2	0,9489
C3	0,8669
C11	0,8017
C10	0,7532
C4	0,7343
C6	0,7113
C8	0,6762
C7	0,5786
C5	0,5632
C1	0,5133

As a final step, the final weights for all criteria were calculated using Equation (4) and these weights are shown in Table 4.9.

Table 4.9 Final Weight Values (w_j) of the IR Selection Criteria

Criteria	Final Weight Values (w_j)
C9	0,1227
C2	0,1166
C3	0,1064
C11	0,0984
C10	0,0924
C4	0,0901
C6	0,0873
C8	0,0830
C7	0,0710
C5	0,0691
C1	0,0630

After calculating the criteria weights with the SWARA method, the WASPAS method was used to rank the alternatives. The steps of the WASPAS method are applied as follows.

As first step, robot alternatives that may be suitable for the production line were compared according to the criteria. In this thesis, the criteria for industrial robot are classified as cost type or benefit type as shown in Table 4.10 according to SWARA-WASPAS method steps. The values of the alternatives for memory capacity, man-machine interface, programming flexibility, vendor's service contract and maintenance cost were obtained by the decision makers giving the alternatives values between 1 and 10 by consensus. (1=worst, 10=best).

Table 4.10 IR Selection Criteria classifications as cost type or benefit type

Type	**Criteria**		**Units**	
Cost Type	C1	Robot Weight	kg	
Benefit Type	C2	Load Capacity	kg	
Cost Type	C3	Repeatability	mm	
Benefit Type	C4	Maximum tip speed	deg/s	
Benefit Type	C5	Memory Capacity	Worst = 1	Best = 10
Benefit Type	C6	Manipulator Reach	mm	
Benefit Type	C7	Man-Machine Interface	Worst = 1	Best = 10
Benefit Type	C8	Programming Flexibility	Worst = 1	Best = 10
Cost Type	C9	Cost	$	
Benefit Type	C10	Vendor's service Contract	Worst = 1	Best = 10
Benefit Type	C11	Maintenance Cost	Worst = 1	Best = 10

After the criterion weights were determined by the SWARA method, the initial decision matrix was created. As an example, which is shown in Table 4.11, an alternative table was created by calculating the geometric means of the evaluations of the decision makers who gave their opinions for man-machine interface criterion and IR1 alternative. Detailed tables for all robot classes and all alternatives are given in Appendix A.

Table 4.11 Geometric mean calculation example for a criterion

Criteria / **Decision Maker opinion for IR1**	**Man-Machine Interface (MMI) subjective (rate between 1-10)** **1: worst** **10: best**
Decision Maker 1 (DM1)	8
Decision Maker 2 (DM2)	8
Decision Maker 3 (DM3)	6
Geometric means of the DM opinions = 7,2685	

The initial decision matrix for IR selection was created as seen in Table 4.12. These data regarding the robot alternatives in this decision matrix were obtained from robot manufacturers.

After the initial decision matrix was prepared, the normalized initial decision matrix values are calculated using Equation (5) for the benefit type criteria and Equation (6) for the cost type criteria and the results are shown in Normalized İnitial Decision Matrix given as Table 4.13.

Table 4.12 Initial Decision Matrix for IR Selection

IR Alternatives \ Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
IR 1	1069	120	0,0500	260	7,8622	2701	7,2685	6,8683	50000	8,6535	4,3089
IR 2	536	70	0,0500	320	7,8622	2101	7,2685	6,8683	25000	8,6535	5,0000
IR 3	425	60	0,0600	360	7,3186	2050	8,0000	8,0000	30000	9,0000	6,8399
IR 4	2250	125	0,9000	235	7,3186	3500	7,6117	7,3186	25000	9,0000	6,8399
IR 5	620	80	0,0300	350	7,6517	2230	5,5934	5,5934	35000	5,8480	6,0000
IR 6	790	120	0,0300	250	7,6517	2230	5,5934	5,5934	40000	5,8480	6,6494
IR 7	1000	80	0,1000	400	4,6416	2594	6,0000	6,2573	40000	5,2415	7,0000
IR 8	980	130	0,0600	400	4,6416	2194	6,0000	6,2573	40000	5,2415	7,0000
IR 9	630	88	0,0300	350	5,6462	2236	7,6517	7,6517	25000	6,8399	5,2415
IR 10	790	110	0,0400	255	5,6462	2236	7,6517	7,6517	30000	6,8399	4,6416

Table 4.13 Normalized Initial Decision Matrix for IR Selection

IR Alternatives \ Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
IR 1	0,3976	0,9231	0,6000	0,6500	1,0000	0,7717	0,9086	0,8585	0,5000	0,9615	0,6156
IR 2	0,7929	0,5385	0,6000	0,8000	1,0000	0,6003	0,9086	0,8585	1,0000	0,9615	0,7143
IR 3	1,0000	0,4615	0,5000	0,9000	0,9309	0,5857	1,0000	1,0000	0,8333	1,0000	0,9771
IR 4	0,1889	0,9615	0,0333	0,5875	0,9309	1,0000	0,9515	0,9148	1,0000	1,0000	0,9771
IR 5	0,6855	0,6154	1,0000	0,8750	0,9732	0,6371	0,6992	0,6992	0,7143	0,6498	0,8571
IR 6	0,5380	0,9231	1,0000	0,6250	0,9732	0,6371	0,6992	0,6992	0,6250	0,6498	0,9499
IR 7	0,4250	0,6154	0,3000	1,0000	0,5904	0,7411	0,7500	0,7822	0,6250	0,5824	1,0000
IR 8	0,4337	1,0000	0,5000	1,0000	0,5904	0,6269	0,7500	0,7822	0,6250	0,5824	1,0000
IR 9	0,6746	0,6769	1,0000	0,8750	0,7181	0,6389	0,9565	0,9565	1,0000	0,7600	0,7488
IR 10	0,5380	0,8462	0,7500	0,6375	0,7181	0,6389	0,9565	0,9565	0,8333	0,7600	0,6631

The first total relative significance value for each alternative was first calculated using Equation (7) according to the Weighted Sum Model and the values given in Table 4.14 are obtained.

Table 4.14 First Total Relative Significance Values ($Q_i^{(1)}$) for IR Selection

Industrial Robot	**Q1**
IR 1	0,7381
IR 2	0,7878
IR 3	0,8114
IR 4	0,7869
IR 5	0,7627
IR 6	0,7650
IR 7	0,6731
IR 8	0,7298
IR 9	0,8260
IR 10	0,7602

Then, the second total relative significance value for each alternative was calculated using Equation (8) according to the Weighted Product Model. The results are provided in Table 4.15.

Table 4.15 Second Total Relative Significance Values ($Q_i^{(2)}$) for IR Selection

Industrial Robot	**Q2**
IR 1	0,7143
IR 2	0,7773
IR 3	0,7637
IR 4	0,5672
IR 5	0,7075
IR 6	0,7078
IR 7	0,6345
IR 8	0,6995
IR 9	0,8200
IR 10	0,7512

The combined optimality value (Q_i) for each alternative was calculated using Equation (9). Here, calculations are made for λ= [0,1] with an increment of 0.1 to show that using different λ values can create different alternative rankings. The sensitivity analysis based on different λ value is given in Figure 4.

Each alternative is ranked by considering the combined optimality value. The ranking results of the alternatives revealed that the most suitable alternative maintain its ranks across all λ values, whereas the rankings of the other alternatives fluctuate depending on the λ values.

As it can be seen from Figure 4.3, since the alternative with the highest Q_i value for every λ value is IR 9, which should be selected for the new production line.

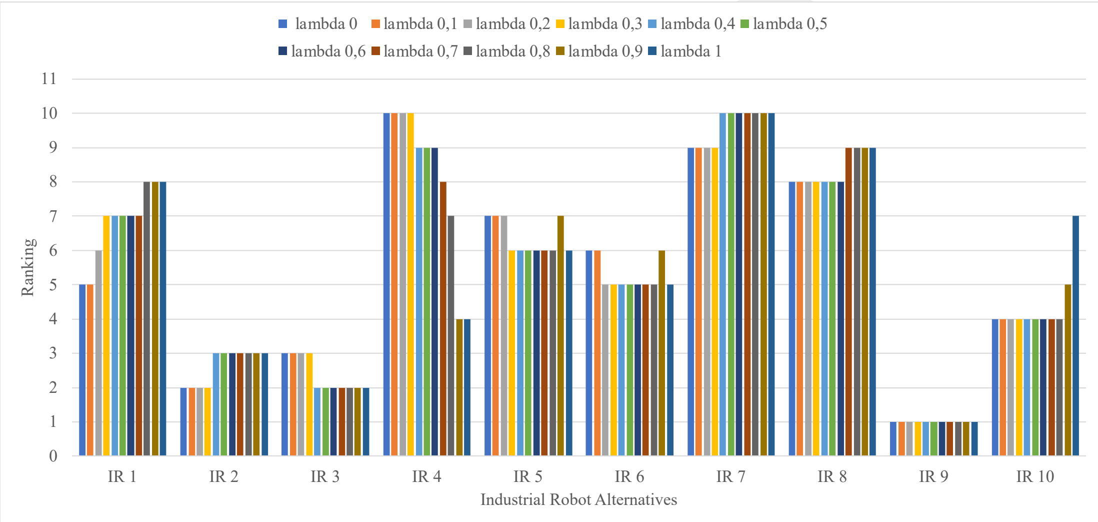

Figure 4.3 Sensitivity analysis for industrial robot alternatives

4.2 Collaborative Robot (CoBot) Selection

Considering the collaborative robot (CoBot) selection problem for a built-in oven production line, there were eight alternatives and eleven criteria, and it was solved by using SWARA and WASPAS method. The criteria and alternatives were determined by the same decision makers, who are evaluated the industrial robot selection problem for previous application. The calculations are explained in the following paragraphs.

First, three decision makers were given a questionnaire and asked to rank the criteria from 0 to 1.0 in order of significance to them by giving the most important criterion a score of 1.00. After that, decision makers rated the other criteria by taking the most important criterion into account with changing values of 0.05 and its multiples. The ranking chart in Table 4.16, consisting of p_j^k values, was obtained based on the points that decision makers assigned to each item in the questionnaires.

Table 4.16 Scoring the CoBot Selection Criteria According to the Degree of Importance on the Basis of the Decision Maker (p_j^k values)

Criteria	Decision Maker	DM1	DM2	DM3
C1	Robot Weight (kg)	0,20	0,10	0,40
C2	Load Capacity (kg)	1,00	0,60	1,00
C3	Repeatability (mm)	0,80	0,70	0,75
C4	Maximum tip speed (°/s)	0,70	0,50	0,55
C5	Memory Capacity (MC)	0,35	0,30	0,25
C6	Manipulator Reach (mm)	0,90	0,20	0,90
C7	Man-Machine Interface (MMI)	0,65	0,35	0,15
C8	Programming Flexibility (PF)	0,60	0,40	0,50
C9	Cost (C)	0,85	1,00	0,85
C10	Vendor's service Contract (VSC)	0,45	0,75	0,65
C11	Maintenance Cost (MeC)	0,50	0,85	0,70

As a second step, relative importance score ($\overline{p_j}$) for all criteria was calculated using Equation (1). The results obtained are shown in Table 4.17.

Table 4.17 Relative Importance Scores ($\overline{p_j}$) for the CoBot Selection Criteria

Criteria	Relative Importance Scores ($\overline{p_j}$)
C1	0,2000
C2	0,8434
C3	0,7489
C4	0,5774
C5	0,2972
C6	0,5451
C7	0,3244
C8	0,4932
C9	0,8973
C10	0,6031
C11	0,6676

In the 3rd step, all criteria were ordered from largest to smallest according to their relative importance scores, and the comparative importance values (s_j) of the mean value for the criteria were calculated as given in Table 4.18.

Table 4.18 Comparison of Relative Significance Scores for the CoBot Selection Criteria

Criteria	Relative Importance Scores ($\overline{p_j}$)	Comparative Importance of Geomean Value (s_j)
C9	0,8973	-
C2	0,8434	0,0539
C3	0,7489	0,0945
C11	0,6676	0,0813
C10	0,6031	0,0645
C4	0,5774	0,0257
C6	0,5451	0,0323
C8	0,4932	0,0519
C7	0,3244	0,1688
C5	0,2972	0,0272
C1	0,2000	0,0972

After that the coefficient value c_j for each criteria was calculated using Equation (2) and these values are provided in Table 4.19.

Table 4.19 Coefficient Values (c_j) of the CoBot Selection Criteria

Criteria	Coefficient Values (c_j)
C9	1,0000
C2	1,0539
C3	1,0945
C11	1,0813
C10	1,0645
C4	1,0257
C6	1,0323
C8	1,0519
C7	1,1688
C5	1,0272
C1	1,0972

In the next step, the corrected weights (s_j') for all criteria were calculated with the help of Equation (3) and the values in Table 4.20 were obtained. Here, the corrected weight of the first-ranked criterion is s_j'=1.

Table 4.20 Corrected Weight Values (s_j') of the CoBot Selection Criteria

Criteria	Corrected Weight Values (s_j')
C9	1,0000
C2	0,9489
C3	0,8669
C11	0,8017
C10	0,7532
C4	0,7343
C6	0,7113
C8	0,6762
C7	0,5786
C5	0,5632
C1	0,5133

As a final step, the final weights for all criteria were calculated using Equation (4) and these weights are shown in Table 4.21.

After calculating the criteria weights with the SWARA method, the WASPAS method was used to rank the alternatives as it is explained below.

Table 4.21 Final Weight Values (w_j) of the CoBot Selection Criteria

Criteria	Final Weight Values (w_j)
C9	0,1227
C2	0,1166
C3	0,1064
C11	0,0984
C10	0,0924
C4	0,0901
C6	0,0873
C8	0,0830
C7	0,0710
C5	0,0691
C1	0,0630

As a first step in the WASPAS method, robot alternatives that may be suitable for the current production line were compared according to the criteria. The criteria are classified as cost type or benefit type as shown in Table 4.22 The values of the alternatives for memory capacity, man-machine interface, programming flexibility, vendor's service contract and maintenance cost were obtained by the decision makers giving the alternatives values between 1 and 10 by consensus. (1=worst, 10=best)

Table 4.22 CoBot Selection Criteria classifications as cost type or benefit type

Type	**Criteria**		**Units**
Cost Type	C1	Robot Weight	kg
Benefit Type	C2	Load Capacity	kg
Cost Type	C3	Repeatability	mm
Benefit Type	C4	Maximum tip speed	deg/s
Benefit Type	C5	Memory Capacity	Worst = 1 Best = 10
Benefit Type	C6	Manipulator Reach	mm
Benefit Type	C7	Man-Machine Interface	Worst = 1 Best = 10
Benefit Type	C8	Programming Flexibility	Worst = 1 Best = 10
Cost Type	C9	Cost	$
Benefit Type	C10	Vendor's service Contract	Worst = 1 Best = 10
Benefit Type	C11	Maintenance Cost	Worst = 1 Best = 10

After the criterion weights were determined by the SWARA method, the initial decision matrix given in Table 4.23 was generated. Data regarding the collaborative robot alternatives in this decision matrix were obtained from worldwide robot manufacturers.

After the initial decision matrix was created, the normalized initial decision matrix was generated using Equation (5) for the benefit type criteria and using Equation (6) for the cost type criteria as shown in Table 4.24.

Table 4.23 Initial Decision Matrix for CoBot Selection

Criteria / CoBot Alternatives	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**	**C11**
CoBot 1	1069	120	0,0500	260	5,9439	2701	8,6535	6,9521	35000	8,3203	6,9521
CoBot 2	536	70	0,0500	320	6,9521	2101	3,6840	3,4200	85000	6,0732	3,5569
CoBot 3	425	60	0,0600	360	7,5595	2050	5,1925	4,3795	65000	5,1925	5,3133
CoBot 4	2250	125	0,9000	235	7,9581	3500	7,3186	7,8622	90000	8,2768	3,6342
CoBot 5	620	80	0,0300	350	4,6416	2230	3,9149	4,3089	40000	5,3133	5,6462
CoBot 6	790	120	0,0300	250	3,6342	2230	2,6207	2,2894	65000	4,9324	6,9521
CoBot 7	1000	80	0,1000	400	7,6117	2594	8,3203	7,6517	60000	8,3203	8,2768
CoBot 8	980	130	0,0600	400	6,6039	2194	7,6517	7,6517	50000	6,9521	7,3186

Table 4.24 Normalized Initial Decision Matrix for CoBot Selection

CoBot Alternatives \ Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
CoBot 1	0,3976	0,9231	0,6000	0,6500	0,7469	0,7717	1,0000	0,8842	1,0000	1,0000	0,8399
CoBot 2	0,7929	0,5385	0,6000	0,8000	0,8736	0,6003	0,4257	0,4350	0,4118	0,7299	0,4297
CoBot 3	1,0000	0,4615	0,5000	0,9000	0,9499	0,5857	0,6000	0,5570	0,5385	0,6241	0,6420
CoBot 4	0,1889	0,9615	0,0333	0,5875	1,0000	1,0000	0,8457	1,0000	0,3889	0,9948	0,4391
CoBot 5	0,6855	0,6154	1,0000	0,8750	0,5833	0,6371	0,4524	0,5480	0,8750	0,6386	0,6822
CoBot 6	0,5380	0,9231	1,0000	0,6250	0,4567	0,6371	0,3029	0,2912	0,5385	0,5928	0,8399
CoBot 7	0,4250	0,6154	0,3000	1,0000	0,9565	0,7411	0,9615	0,9732	0,5833	1,0000	1,0000
CoBot 8	0,4337	1,0000	0,5000	1,0000	0,8298	0,6269	0,8842	0,9732	0,7000	0,8355	0,8842

The first total relative significance value for each alternative was first calculated using Equation (7) according to the Weighted Sum Model and the values are given in Table 4.25 are obtained.

Table 4.25 First Total Relative Significance Values ($Q_i^{(1)}$) for CoBot Selection

Collaborative Robot	Q1
CoBot 1	0,8162
CoBot 2	0,5880
CoBot 3	0,6436
CoBot 4	0,6628
CoBot 5	0,7072
CoBot 6	0,6406
CoBot 7	0,7628
CoBot 8	0,7929

Then, the second total relative significance value for each alternative was calculated using Equation (8) according to the Weighted Product Model. The results are provided in Table 4.26.

Table 4.26 Second Total Relative Significance Values ($Q_i^{(2)}$) for CoBot Selection

Collaborative Robot	Q2
CoBot 1	0,7939
CoBot 2	0,5678
CoBot 3	0,6240
CoBot 4	0,4825
CoBot 5	0,6902
CoBot 6	0,5987
CoBot 7	0,7125
CoBot 8	0,7683

Equation (9) was used to compute the combined optimality value for each alternative. Calculations are performed for λ = [0,1] with a 0.1 increment to demonstrate how various values can result in different ranks. Detailed table about the sensitivity analysis based on different λ values is given in Figure 4.4.

Each alternative is ranked by considering the combined optimality value. The ranking result of the alternatives was obtained, as the four highest ranked alternatives (CoBot 1, CoBot 5, CoBot 7 and CoBot 8) hold their rankings but the other four alternatives' rankings may differ according to λ value. CoBot 1 is ranked as the best alternative for all λ values.

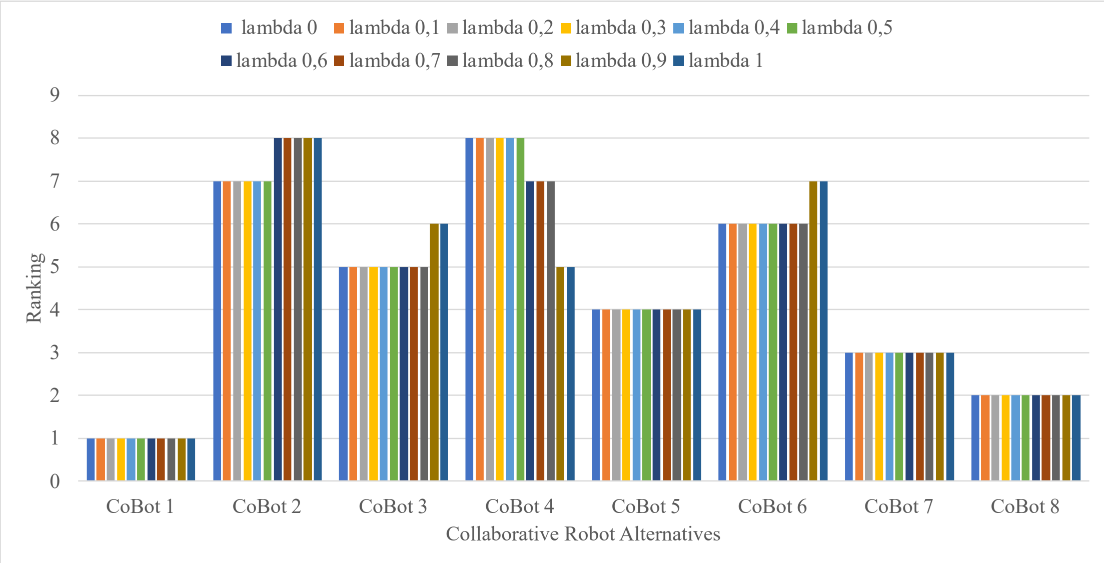

Figure 4.4 Sensitivity analysis for collaborative robot alternatives

4.3 Cartesian Robot (CR) Selection

In the current production line, it is planned to use cartesian robots (CR) for specific jobs such as barcode printing and screwing. There were nine alternatives and twelve criteria in the cartesian robot selection problem for a built-in oven production line, which was addressed using the SWARA and WASPAS methods. There is an additional criterion which is defined as 'Special Tooling Cost'. This indicates the cost of the end effector, parts positioners, and other fixtures and tools required for specific operations. The criteria and alternatives were chosen by the same decision makers who had assessed the previous selection problems. In the following steps, the calculations are completed as follows.

First, three expert decision makers were given a questionnaire and asked to rank the criteria by giving the most important criterion a score of 1.00. After that, decision makers rated the other criteria by taking the most important criterion into account with changing values of 0.05 and its multiples. The ranking chart in Table 4.27, which consists of p_j^k values, was developed based on the value that decision makers assigned to each item in their questionnaires.

Table 4.27 Scoring the CR Selection Criteria According to the Degree of Importance on the Basis of the Decision Maker (p_j^k values)

Criteria \ Decision Maker		DM1	DM2	DM3
C1	Robot Weight (kg)	0,15	0,10	0,25
C2	Load Capacity (kg)	1,00	0,60	1,00
C3	Repeatability (mm)	0,70	0,70	0,75
C4	Maximum tip speed (°/s)	0,60	0,50	0,40
C5	Memory Capacity (MC)	0,10	0,30	0,20
C6	Manipulator Reach (mm)	0,90	0,20	0,95
C7	Man-Machine Interface (MMI)	0,50	0,35	0,10
C8	Programming Flexibility (PF)	0,40	0,40	0,30
C9	Cost (C)	0,80	1,00	0,85
C10	Vendor's service Contract (VSC)	0,25	0,75	0,60
C11	Maintenance Cost (MeC)	0,35	0,85	0,70
C12	Special Tooling Costs (STC)	0,75	0,90	0,50

As a second step, relative importance score ($\overline{p}_j$) for all criteria was calculated with the help of Equation (1). The results obtained are shown in Table 4.28.

Table 4.28 Relative Importance Scores ($\overline{p}_j$) for CR Selection Criteria

Criteria	Relative Importance Points ($\overline{p}_j$)
C1	0,1554
C2	0,8434
C3	0,7163
C4	0,4932
C5	0,1817
C6	0,5550
C7	0,2596
C8	0,3634
C9	0,8794
C10	0,4827
C11	0,5927
C12	0,6962

All criteria were arranged from largest to smallest based on their relative importance scores in the third phase, and the comparative importance values (s_j) of the mean value for the criteria were obtained, as given in Table 4.29.

Table 4.29 Comparison of Relative Significance Scores for CR Selection Criteria

Criteria	Relative Importance Scores ($\overline{p}_j$)	Comparative Importance of Geomean Value (s_j)
C9	0,8794	-
C2	0,8434	0,0360
C3	0,7163	0,1271
C12	0,6962	0,0201
C11	0,5927	0,1035
C6	0,5550	0,0377
C4	0,4932	0,0618
C10	0,4827	0,0105
C8	0,3634	0,1193
C7	0,2596	0,1038
C5	0,1817	0,0779
C1	0,1554	0,0263

After that, the coefficient value c_j for all criteria was calculated using Equation (2) on page 25 as depicted in Table 4.30.

Table 4.30 Coefficient Values (c_j) of the CR Selection Criteria

Criteria	Coefficient Values (c_j)
C9	1,0000
C2	1,0360
C3	1,1271
C12	1,0201
C11	1,1035
C6	1,0377
C4	1,0618
C10	1,0105
C8	1,1193
C7	1,1038
C5	1,0779
C1	1,0263

In the following step, the corrected weights (s_j') for all criteria were calculated with the help of Equation (3) and the values in Table 4.31 were obtained. Here, the corrected weight of the first-ranked criterion is s_j'=1.

Table 4.31 Corrected Weight Values (s_j') of the CR Selection Criteria

Criteria	Corrected Weight Values (s_j')
C9	1,0000
C2	0,9653
C3	0,8564
C12	0,8395
C11	0,7608
C6	0,7331
C4	0,6905
C10	0,6833
C8	0,6105
C7	0,5531
C5	0,5131
C1	0,4999

As the last step, the final weights for all criteria were calculated using Equation (4) and these weights are shown in Table 4.32.

After calculating the criteria weights with the SWARA method, the WASPAS method was used to rank the alternatives. The steps of the WASPAS method are applied as follows.

Table 4.32 Final Weight Values (w_j) of the CR Selection Criteria

Criteria	Final Weight Values (w_j)
C9	0,1149
C2	0,1109
C3	0,0985
C12	0,0964
C11	0,0874
C6	0,0842
C4	0,0793
C10	0,0785
C8	0,0701
C7	0,0635
C5	0,0589
C1	0,0574

As first step of WASPAS method, cartesian robot alternatives that may be suitable for the production line were compared according to the criteria. In this thesis, the criteria for cartesian robots are classified as cost type or benefit type as shown in Table 4.33. The decision makers obtained the values of the alternatives for memory capacity, man-machine interface, programming flexibility, vendor's service contract, and maintenance cost by consensus, assigning the alternatives values between 1 and 10. (1=worst, 10=best)

Table 4.33 CR Selection Criteria classifications as cost type or benefit type

Type	Criteria		Units	
Cost Type	C1	Robot Weight	kg	
Benefit Type	C2	Load Capacity	kg	
Cost Type	C3	Repeatability	mm	
Benefit Type	C4	Maximum tip speed	deg/s	
Benefit Type	C5	Memory Capacity	Worst = 1	Best = 10
Benefit Type	C6	Manipulator Reach	mm	
Benefit Type	C7	Man-Machine Interface	Worst = 1	Best = 10
Benefit Type	C8	Programming Flexibility	Worst = 1	Best = 10
Cost Type	C9	Cost	$	
Benefit Type	C10	Vendor's service Contract	Worst = 1	Best = 10
Benefit Type	C11	Maintenance Cost	Worst = 1	Best = 10
Cost Type	C12	Special Tooling Cost	$	

After the criterion weights were determined by the SWARA method, the initial decision matrix was created as shown in Table 4.34. The information in this decision matrix about cartesian robot choices are obtained from well-known robot manufacturers.

After the initial decision matrix was created, the normalized initial decision matrix was obtained using Equation (5) for the benefit type criteria and using Equation (6) for the cost type criteria as shown in Table 4.35.

Table 4.34 Initial Decision Matrix for CR Selection

Criteria / CR Alternatives	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**	**C11**	**C12**
CR 1	25	5	0,02	0,8	8,0000	950	7,6517	8,6535	8.000	6,6494	9,0000	4.000
CR 2	35	25	0,08	3,0	8,0000	950	7,6517	8,6535	10.000	6,6494	4,0000	4.000
CR 3	15	10	0,08	3,0	8,0000	450	7,6517	8,6535	5.000	6,6494	6,6494	2.500
CR 4	25	150	0,02	3,0	8,0000	400	7,6517	8,6535	3.500	6,6494	9,0000	2.000
CR 5	25	150	0,02	3,0	8,0000	400	7,6517	8,6535	3.500	6,6494	9,0000	2.000
CR 6	45	25	0,08	3,0	8,0000	1100	7,6517	8,6535	12.000	6,6494	4,3089	2.500
CR 7	32	20	0,01	1,2	6,0000	1250	8,6535	6,3164	14.000	8,0000	7,6517	4.000
CR 8	27	4,5	0,02	0,7	6,0000	700	8,6535	6,3164	12.000	8,0000	9,0000	2.500
CR 9	35	20	0,01	1,2	6,0000	1250	8,6535	6,3164	18.000	8,0000	5,6462	2.500

Table 4.35 Normalized Initial Decision Matrix for CR Selection

Criteria / CR Alternatives	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
CR 1	0,6000	0,0333	0,5000	0,2667	1,0000	0,7600	0,8842	1,0000	0,4375	0,8312	1,0000	0,5000
CR 2	0,4286	0,1667	0,1250	1,0000	1,0000	0,7600	0,8842	1,0000	0,3500	0,8312	0,4444	0,5000
CR 3	1,0000	0,0667	0,1250	1,0000	1,0000	0,3600	0,8842	1,0000	0,7000	0,8312	0,7388	0,8000
CR 4	0,6000	1,0000	0,5000	1,0000	1,0000	0,3200	0,8842	1,0000	1,0000	0,8312	1,0000	1,0000
CR 5	0,6000	1,0000	0,5000	1,0000	1,0000	0,3200	0,8842	1,0000	1,0000	0,8312	1,0000	1,0000
CR 6	0,3333	0,1667	0,1250	1,0000	1,0000	0,8800	0,8842	1,0000	0,2917	0,8312	0,4788	0,8000
CR 7	0,4688	0,1333	1,0000	0,4000	0,7500	1,0000	1,0000	0,7299	0,2500	1,0000	0,8502	0,5000
CR 8	0,5556	0,0300	0,5000	0,2333	0,7500	0,5600	1,0000	0,7299	0,2917	1,0000	1,0000	0,8000
CR 9	0,4286	0,1333	1,0000	0,4000	0,7500	1,0000	1,0000	0,7299	0,1944	1,0000	0,6274	0,8000

The first total relative significance value for each alternative was first calculated using Equation (7) according to the Weighted Sum Model and the values shown in Table 4.36 are obtained.

Table 4.36 First Total Relative Significance Values ($Q_i^{(1)}$) for CR Selection

Cartesian Robot	Q1
CR 1	0,6088
CR 2	0,5763
CR 3	0,6592
CR 4	0,8499
CR 5	0,8499
CR 6	0,6062
CR 7	0,6447
CR 8	0,5855
CR 9	0,6454

Then, the second total relative significance value for each alternative was calculated using Equation (8) according to the Weighted Product Model. The results are provided in Table 4.37.

Table 4.37 Second Total Relative Significance Values ($Q_i^{(2)}$) for CR Selection

Cartesian Robot	Q2
CR 1	0,4553
CR 2	0,4697
CR 3	0,4955
CR 4	0,8059
CR 5	0,8059
CR 6	0,4834
CR 7	0,5385
CR 8	0,4244
CR 9	0,5304

Equation (9) was used to compute the combined optimality value for each alternative. Calculations are performed for λ = [0,1] with a 0.1 increment to demonstrate how various values can result in different ranks. The sensitivity analysis based on different λ values is given in Figure 4.5.

Each alternative is ranked by considering the combined optimality value. The ranking result of the alternatives shows that the most suitable two alternatives (CR 4 and CR 5) hold their rankings for all λ values, but the other options' rankings show differences according to λ value. Therefore, it is decided to select CR 4 as the best alternative for all λ values.

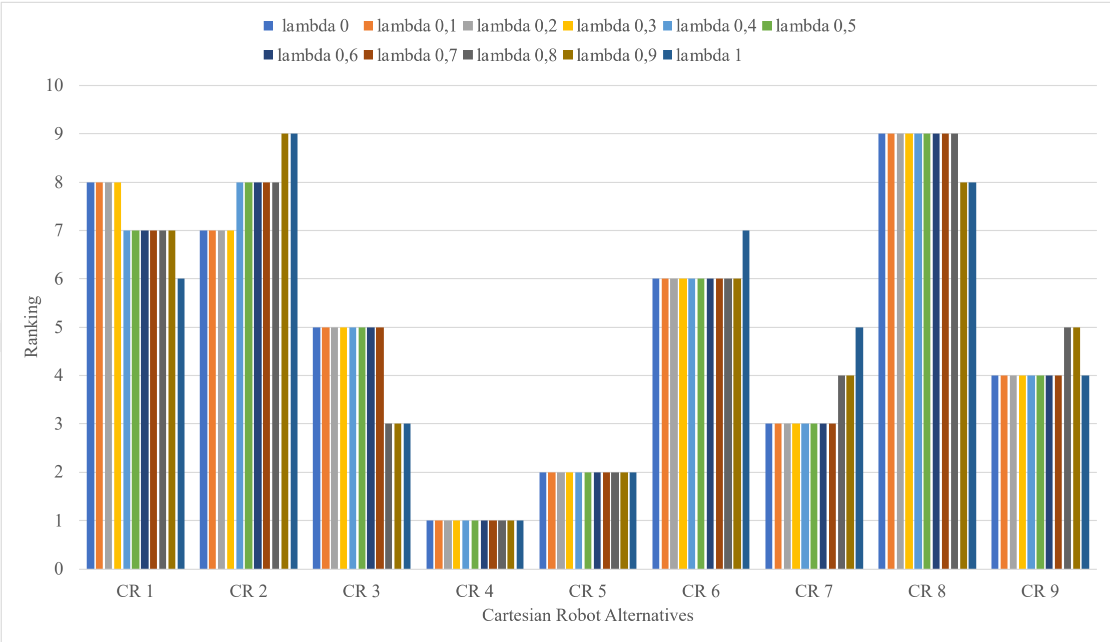

Figure 4.5 Sensitivity analysis for cartesian robot alternatives

4.4 Box Folding Cartesian Robot (BF) Selection

The box folding operation is also planned to be performed with cartesian robots (CRs), but since the cartesian robot to zbe used for this operation will have a different configuration from the other CRs is considered as a separate category. In order to select a box folding robot (BF) for a built-in oven production line, SWARA and WASPAS methods are jointly used with four alternatives and eleven criteria. The criteria and alternatives were determined by the same decision makers as before and the following steps are applied for BF selection.

First, three decision makers were given a questionnaire and asked to rank the criteria from 0 to 1.00 in order of significance to them. The decision makers then gave the most important criterion a score of 1.00 and rated the other criteria by taking the most important criterion into account with changing values of 0.05 and its multiples. The ranking chart in Table 4.38, which is consists of p_j^k values, was obtained as a result of the decision makers assigning points to the related criteria.

Table 4.38 Scoring the BF Selection Criteria According to the Degree of Importance on the Basis of the Decision Maker (p_j^k values)

Criteria	Decision Maker	DM1	DM2	DM3
C1	Robot Weight (kg)	0,15	0,10	0,25
C2	Load Capacity (kg)	1,00	0,60	1,00
C3	Repeatability (mm)	0,70	0,70	0,75
C4	Maximum tip speed (°/s)	0,60	0,50	0,50
C5	Memory Capacity (MC)	0,10	0,30	0,20
C6	Manipulator Reach (mm)	0,90	0,20	0,95
C7	Man-Machine Interface (MMI)	0,50	0,35	0,10
C8	Programming Flexibility (PF)	0,40	0,40	0,40
C9	Cost (C)	0,80	1,00	0,85
C10	Vendor's service Contract (VSC)	0,25	0,80	0,60
C11	Maintenance Cost (MeC)	0,35	0,90	0,70

As a second step, relative importance score ($\overline{p}_j$) for all criteria was calculated with the help of Equation (1). The results obtained are shown in Table 4.39.

Table 4.39 Relative Importance Scores ($\overline{p}_j$) for BF Selection Criteria

Criteria	Relative Importance Scores ($\overline{p}_j$)
C1	0,1554
C2	0,8434
C3	0,7163
C4	0,5313
C5	0,1817
C6	0,5550
C7	0,2596
C8	0,4000
C9	0,8794
C10	0,4932
C11	0,6041

In the 3rd step, all criteria were ordered from largest to smallest according to their relative importance scores, and the comparative importance (s_j) values of the mean value for the criteria were calculated as given in Table 4.40.

Table 4.40 Comparison of Relative Significance Scores for BF Selection Criteria

Criteria	Relative Importance Scores ($\overline{p}_j$)	Comparative Importance of Geomean Value (s_j)
C9	0,8794	
C2	0,8434	0,0360
C3	0,7163	0,1271
C11	0,6041	0,1122
C6	0,5550	0,0491
C4	0,5313	0,0237
C10	0,4932	0,0381
C8	0,4000	0,0932
C7	0,2596	0,1404
C5	0,1817	0,0779
C1	0,1554	0,0263

Then, the coefficient value c_j for all criteria was calculated using Equation (2) on page 25. The obtained values are given in Table 4.41.

Table 4.41 Coefficient Values (c_j) of the BF Selection Criteria

Criteria	Coefficient Values (c_j)
C9	1,0000
C2	1,0360
C3	1,1271
C11	1,1122
C6	1,0491
C4	1,0237
C10	1,0381
C8	1,0932
C7	1,1404
C5	1,0779
C1	1,0263

In the next step, the corrected weights (s_j') for all criteria were calculated with the help of Equation (3) and the values in Table 4.42 were obtained. Here, the corrected weight of the first-ranked criterion is s_j'=1.

Table 4.42 Corrected Weight Values (s_j') of the BF Selection Criteria

Criteria	Corrected Weight Values (s_j')
C9	1,0000
C2	0,9653
C3	0,8564
C11	0,7700
C6	0,7340
C4	0,7170
C10	0,6907
C8	0,6318
C7	0,5540
C5	0,5140
C1	0,5008

Then, the final weights for all criteria were calculated using Equation (4) and these weights are shown in Table 4.43.

Table 4.43 Final Weight Values (w_j) of the BF Selection Criteria

Criteria	Final Weight Values (w_j)
C9	0,1261
C2	0,1217
C3	0,1079
C11	0,0971
C6	0,0925
C4	0,0904
C10	0,0871
C8	0,0796
C7	0,0698
C5	0,0648
C1	0,0631

After calculating the criteria weights with the SWARA method, the WASPAS method was used to rank the alternatives. The steps of the WASPAS method are applied as follows.

As the first step, robot alternatives that may be suitable for the production line were compared according to the criteria. In this thesis, the criteria for box folding cartesian robot are classified as cost type or benefit type as shown in Table 4.44. The values of the alternatives for memory capacity, man-machine interface, programming flexibility, vendor's service contract and maintenance cost were obtained by the decision makers giving the alternatives values between 1 and 10 by consensus. (1=worst, 10=best)

Table 4.44 BF Selection criteria classifications as cost type or benefit type

Type	**Criteria**		**Units**	
Cost Type	C1	Robot Weight	kg	
Benefit Type	C2	Load Capacity	kg	
Cost Type	C3	Repeatability	mm	
Benefit Type	C4	Maximum tip speed	deg/s	
Benefit Type	C5	Memory Capacity	Worst = 1	Best = 10
Benefit Type	C6	Manipulator Reach	mm	
Benefit Type	C7	Man-Machine Interface	Worst = 1	Best = 10
Benefit Type	C8	Programming Flexibility	Worst = 1	Best = 10
Cost Type	C9	Cost	$	
Benefit Type	C10	Vendor's service Contract	Worst = 1	Best = 10
Benefit Type	C11	Maintenance Cost	Worst = 1	Best = 10

After the criterion weights were determined by the SWARA method, the initial decision matrix was prepared as shown in Table 4.45, in which data regarding the box folding system alternatives in this decision matrix were obtained from robot manufacturers.

After the initial decision matrix was created, the normalized initial decision matrix was created using Equation (5) for the benefit type criteria and using Equation (6) for the cost type criteria as shown in Table 4.46.

The first total relative significance value for each alternative was first calculated using Equation (7) according to the Weighted Sum Model and the values given in Table 4.47 are obtained.

Table 4.45 Initial Decision Matrix for BF Selection

Criteria / BF Alternatives	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
BF 1	5	30	0,08	3	8,0000	800	8,0000	9,0000	2.500	6,6494	5,6462
BF 2	5	50	0,05	5	8,0000	800	8,0000	9,0000	3.500	6,6494	5,6462
BF 3	9	25	0,1	2	6,0000	1200	9,0000	6,0000	5.000	8,0000	7,0000
BF 4	8	10	0,05	1,2	6,0000	950	9,0000	6,0000	3.000	8,0000	8,3203

Table 4.46 Normalized Initial Decision Matrix for BF Selection

Criteria / BF Alternatives	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
BF 1	1,00	0,60	0,63	0,60	1,00	0,67	0,89	1,00	1,00	0,83	0,68
BF 2	1,00	1,00	1,00	1,00	1,00	0,67	0,89	1,00	0,71	0,83	0,68
BF 3	0,56	0,50	0,50	0,40	0,75	1,00	1,00	0,67	0,50	1,00	0,84
BF 4	0,63	0,20	1,00	0,24	0,75	0,79	1,00	0,67	0,83	1,00	1,00

Table 4.47 First Total Relative Significance Values ($Q_i^{(1)}$) for BF Selection

Box Folding Robot	Q1
BF 1	0,7903
BF 2	0,8796
BF 3	0,6818
BF 4	0,7274

Then, the second total relative significance value for each alternative was calculated using Equation (8). The results are provided in Table 4.48.

Table 4.48. Second Total Relative Significance Values ($Q_i^{(2)}$) for BF Selection

Box Folding Robot	Q2
BF 1	0,7722
BF 2	0,8677
BF 3	0,6478
BF 4	0,6377

The combined optimality value (Q_i) for each alternative was calculated using Equation (9). Here, calculations are made for λ= [0,1] with an increment of 0.1 to show that using different λ values can create different alternative rankings. The sensitivity analysis based on different λ values is given in Figure 4.6. The combined optimality value is used to rate each choice. The ranking results of the alternatives revealed that the most suited two alternatives (BF 1 and BF 2) maintain their ranks across all λ values, whereas the rankings of the other two alternatives fluctuate depending on the λ value.

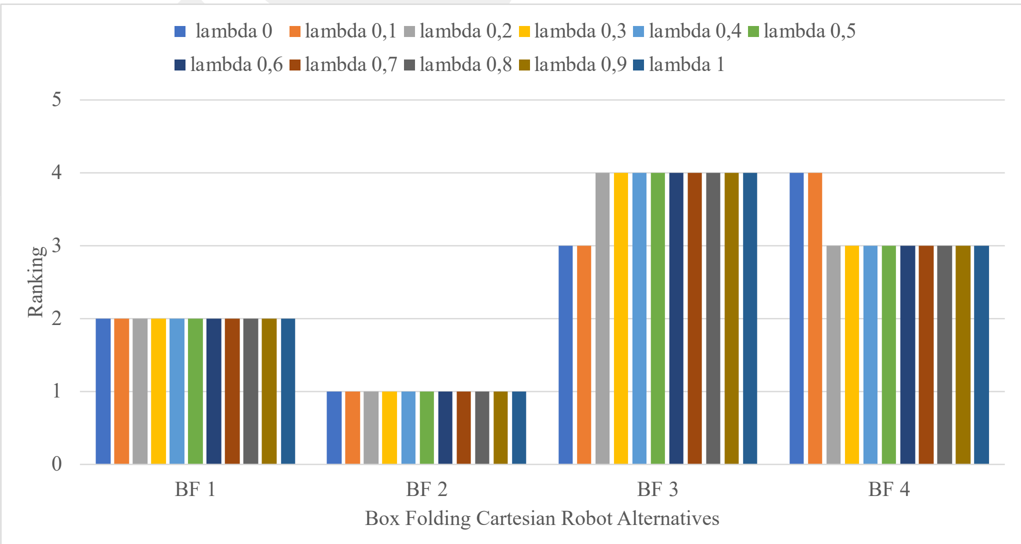

Figure 4.6 Sensitivity analysis for box folding system alternatives

4.5 AGV Selection

In this real-world case study, the aim is to find the best alternative and rank automated guided vehicles (AGV) to be used for industrial material handling in the current built-in oven production line. There were four options and eleven criteria to consider when choosing an AGV for a built-in oven production line, and it was evaluated using the SWARA and WASPAS methods. The criteria and alternatives were determined by the same decision makers who reviewed earlier application selection challenges. In the following steps, the calculations are completed as follows. The criteria were determined as 'Controllability', 'Accuracy', 'Cost', 'Range', 'Reliability', 'Programming Flexibility', 'Speed', 'Man-machine Interface', 'Battery Capacity', 'Guidance Type' and 'Load Capacity'. Afterwards, 8 alternative AGVs (AGV 1 to AGV 2) were determined based on a market research and the offers were received. The weights of the determined criteria were calculated using the SWARA method by following the steps given below.

First, three professional decision makers were given a questionnaire and asked to score the criteria in order of importance by giving the most important criterion a score of 1.00 and rated the other criteria by taking the most important criterion into account with changing values of 0.05 and its multiples. The value they allocated to each item in their questionnaires was used to create the ranking chart in Table 4.49.

Table 4.49 Scoring the AGV Selection Criteria According to the Degree of Importance on the Basis of the Decision Maker (p_j^k values)

Criteria	Decision Maker	DM1	DM2	DM3
C1	Controllability	0,10	0,50	0,60
C2	Accuracy	0,50	0,20	0,65
C3	Cost	0,85	1,00	1,00
C4	Range	0,70	0,45	0,75
C5	Reliability	0,25	0,35	0,50
C6	Programming Flexibility	0,30	0,60	0,35
C7	Speed	0,75	0,40	0,40
C8	Man-machine Interface	0,45	0,30	0,25
C9	Battery Capacity	0,60	0,85	0,80
C10	Guidance Type	0,90	0,75	0,15
C11	Load Capacity	1,00	0,90	0,85

Equation (1) was used to obtain the relative importance score ($\overline{p_j}$) for all criteria in the second stage and Table 4.50 displays the results.

Table 4.50 Relative Importance Scores ($\overline{p_j}$) for AGV Selection Criteria

Criteria	Relative Importance Scores ($\overline{p_j}$)
C1	0,3107
C2	0,4021
C3	0,9473
C4	0,6182
C5	0,3524
C6	0,3979
C7	0,4932
C8	0,3232
C9	0,7417
C10	0,4661
C11	0,9146

All criteria were arranged from largest to smallest based on their relative important scores in the third phase, and the comparative importance values (s_j) of the mean value for the criteria were obtained, as shown in Table 4.51.

Table 4.51 Comparison of Relative Significance Scores for AGV Selection Criteria

Criteria	Relative Importance Scores ($\overline{p_j}$)	Comparative Importance of Geomean Value (s_j)
C3	0,9473	-
C11	0,9146	0,0327
C9	0,7417	0,1729
C4	0,6182	0,1235
C7	0,4932	0,1250
C10	0,4661	0,0272
C2	0,4021	0,0640
C6	0,3979	0,0042
C5	0,3524	0,0455
C8	0,3232	0,0292
C1	0,3107	0,0124

After that the coefficient value c_j for all criteria was calculated using Equation (2) on page 25 as given in Table 4.52.

Table 4.52 Coefficient Values (c_j) of the AGV Selection Criteria

Criteria	Coefficient Values (c_j)
C3	1,0000
C11	1,0327
C9	1,1729
C4	1,1235
C7	1,1250
C10	1,0272
C2	1,0640
C6	1,0042
C5	1,0455
C8	1,0292
C1	1,0124

In the penultimate step, the corrected weights (s_j') for all criteria were calculated with the help of Equation (3) and the values in Table 4.53 were obtained. Here, the corrected weight of the first-ranked criterion is s_j'=1.

Table 4.53 Corrected Weight Values (s_j') of the AGV Selection Criteria

Criteria	Corrected Weight Values (s_j')
C3	1,0000
C11	0,9683
C9	0,8256
C4	0,7349
C7	0,6532
C10	0,6360
C2	0,5977
C6	0,5952
C5	0,5693
C8	0,5531
C1	0,5463

In the last step, the final weights for all criteria were calculated using Equation (4) and these weights are shown in Table 4.54.

Table 4.54 Final Weight Values (w_j) of the AGV Selection Criteria

Criteria	Final Weight Values (w_j)
C3	0,1302
C11	0,1261
C9	0,1075
C4	0,0957
C7	0,0851
C10	0,0828
C2	0,0778
C6	0,0775
C5	0,0741
C8	0,0721
C1	0,0711

After calculating the criteria weights with the SWARA method, the WASPAS method was used to rank the alternatives. The WASPAS method's steps are applied as follows.

In the first step of WASPAS method, AGV alternatives that may be suitable for the current production line were compared according to the criteria. In this thesis, the criteria for AGV are classified as cost type or benefit type as shown in Table 4.55. The values of the alternatives for controllability, accuracy, range, reliability, man-machine interface, programming flexibility and guidance type were obtained by the decision makers giving the alternatives values between 1 and 10 by consensus. (1=worst, 10=best).

Table 4.55 AGV Selection criteria classifications as cost type or benefit type

Type	**Criteria**		**Units**	
Benefit Type	C1	Controllability	Worst = 1	Best = 10
Benefit Type	C2	Accuracy	Worst = 1	Best = 10
Cost Type	C3	Cost	$	
Benefit Type	C4	Range	Worst = 1	Best = 10
Benefit Type	C5	Reliability	Worst = 1	Best = 10
Benefit Type	C6	Programming Flexibility	Worst = 1	Best = 10
Benefit Type	C7	Speed	m/min	
Benefit Type	C8	Man-machine Interface	Worst = 1	Best = 10
Benefit Type	C9	Battery Capacity	VDC	
Benefit Type	C10	Guidance Type	Worst = 1	Best = 10
Benefit Type	C11	Load Capacity	kg	

After the criterion weights were determined by the SWARA method, the initial decision matrix was prepared as seen in Table 4.56, in which data regarding the robot alternatives were obtained from domestic and world-wide AGV manufacturers.

After the initial decision matrix was prepared, the normalized initial decision matrix values were calculated using Equation (5) for the benefit type criteria and using Equation (6) for the cost type criteria and the results are shown in the normalized initial decision matrix given as Table 4.57.

Table 4.56 Initial Decision Matrix for AGV Selection

Criteria / AGV Alternatives	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**	**C11**
AGV 1	7,0000	7,0000	37500	6,3164	8,0000	7,0000	90	7,0000	24	7,0000	1000
AGV 2	5,3133	6,0000	32000	6,0000	6,0000	7,0000	90	7,0000	24	8,0000	800
AGV 3	8,3203	8,3203	28000	9,0000	6,0000	7,6517	62	6,3164	48	8,0000	1000
AGV 4	7,0000	7,0000	36000	7,6517	7,3186	7,6517	62	6,3164	48	8,0000	1000
AGV 5	8,6535	8,6535	90000	6,2573	8,6535	5,3133	60	7,2685	96	8,6535	1500
AGV 6	4,5789	5,5934	50000	6,3164	5,3133	7,6517	50	7,6517	24	5,3133	750
AGV 7	5,3133	6,3164	50000	7,0000	6,0000	6,3164	107	7,0000	24	7,0000	4535
AGV 8	6,3164	7,3186	60000	7,6517	7,3186	6,3164	45	7,0000	24	6,3164	1000

Table 4.57 Normalized Initial Decision Matrix for AGV Selection

Criteria / AGV Alternatives	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
AGV 1	0,8089	0,8089	0,7467	0,7018	0,9245	0,9148	0,8411	0,9148	0,2500	0,8089	0,7500
AGV 2	0,6140	0,6934	0,8750	0,6667	0,6934	0,9148	0,8411	0,9148	0,2500	0,9245	0,9375
AGV 3	0,9615	0,9615	1,0000	1,0000	0,6934	1,0000	0,5794	0,8255	0,5000	0,9245	0,7500
AGV 4	0,8089	0,8089	0,7778	0,8502	0,8457	1,0000	0,5794	0,8255	0,5000	0,9245	0,7500
AGV 5	1,0000	1,0000	0,3111	0,6953	1,0000	0,6944	0,5607	0,9499	1,0000	1,0000	0,5000
AGV 6	0,5291	0,6464	0,5600	0,7018	0,6140	1,0000	0,4673	1,0000	0,2500	0,6140	1,0000
AGV 7	0,6140	0,7299	0,5600	0,7778	0,6934	0,8255	1,0000	0,9148	0,2500	0,8089	0,1654
AGV 8	0,7299	0,8457	0,4667	0,8502	0,8457	0,8255	0,4206	0,9148	0,2500	0,7299	0,7500

The first total relative significance value for each alternative was first calculated using Equation (7) according to the Weighted Sum Model and the values are given in Table 4.58.

Table 4.58 First Total Relative Significance Values ($Q_i^{(1)}$) for AGV Selection

AGV	**Q1**
AGV 1	0,7502
AGV 2	0,7568
AGV 3	0,8316
AGV 4	0,7769
AGV 5	0,7534
AGV 6	0,6667
AGV 7	0,6289
AGV 8	0,6701

Then, the second total relative significance value for each alternative was calculated using Equation (8). The obtained values are given in Table 4.59.

Table 4.59 Second Total Relative Significance Values ($Q_i^{(2)}$) for AGV Selection

AGV	**Q2**
AGV 1	0,7116
AGV 2	0,7130
AGV 3	0,8102
AGV 4	0,7635
AGV 5	0,7009
AGV 6	0,6195
AGV 7	0,5484
AGV 8	0,6257

Equation (9) was used to compute the combined optimality value (Q_i) for each alternative. Calculations are performed for λ = [0,1] with a 0.1 increment to demonstrate how various values can result in different ranks. Figure 4.7 presents this sensitivity analysis based on different λ values. Each alternative is ranked by considering the combined optimality value. According to the ranking results of the alternatives the three highest ranked alternatives (AGV 6, AGV 7 and AGV 8) and three lowest ranked alternatives (AGV 2, AGV 3 and AGV 4) are hold their rankings but the rankings of two alternatives in the middle may differ according to λ value.

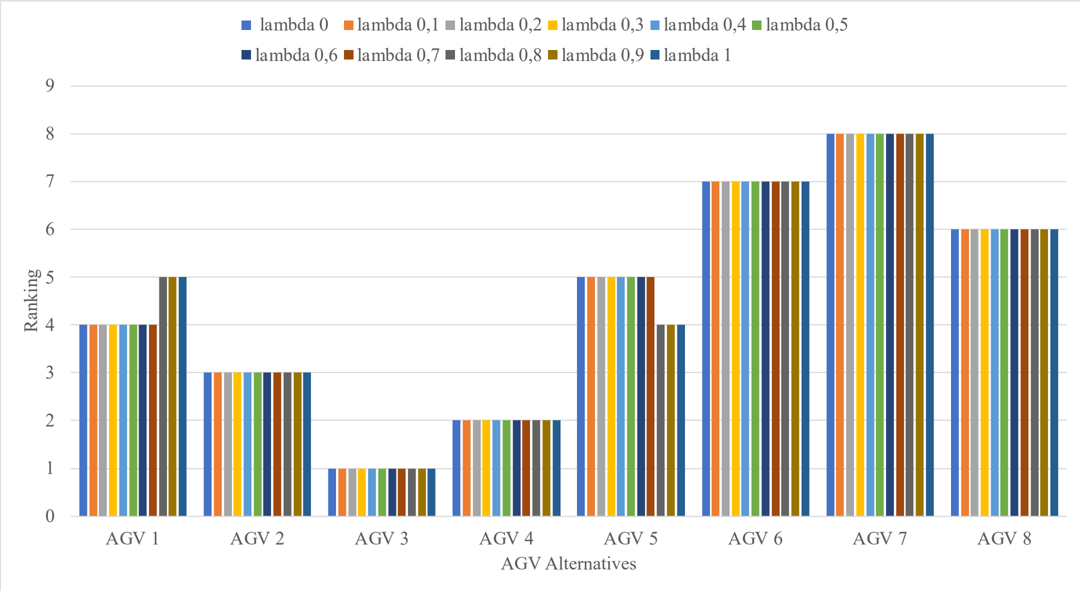

Figure 4.7. Sensitivity analysis for AGV alternatives

4.6 Image Processor (IP) System Selection

Automation is a frequently used method in industries where mass production is concerned, to cope with different challenges such as quality, efficiency, time, and cost. Digital cameras, whose efficiency and quality have increased while their costs have decreased with Industry 4.0, have started to be preferred for many different digital technology operations such as autonomous robots, autonomous vehicles, quality control operations when evaluated in terms of criteria such as speed, efficiency, and cost with the increase in communication interfaces. In this study, image processing systems that examine the final products and detect the defects are used in order to control the quality, increase the product quality, and eliminate the human error factor. The operation in which the image processing system (IP) is used are controlling the distance between the panels of the product produced, controlling the logo placement and controlling the logo printing quality. There were seven options and twelve criteria to consider when choosing an image processor system for a built-in oven production line, and it was evaluated using the SWARA and WASPAS methods. The criteria and alternatives were determined by the same decision makers who reviewed earlier application selection challenges. The criteria were determined as 'Accuracy', 'Repeatability', 'Resolution', 'Response Time', 'Operating System', 'Hardware Interface', 'Frame Rate', 'Maintainability', 'Reliability', 'Initial cost', 'Operation cost', and 'Flexibility in software interface'. Afterwards, 7 alternatives were determined in line with the market research and the offers received (IP1-IP7). The weights of the determined criteria were calculated using the SWARA method by following the steps given below.

First, three decision makers were given a questionnaire and asked to score the twelve criteria in the order of importance from 0 to 1.00. To rank the criteria, the decision makers then gave the most important criterion a score of 1.00 and rated the other criteria by taking the most important criterion into account with changing values of 0.05 and its multiples. As a result, the value they allocated to each item in their questionnaires was used to create the ranking in Table 4.60, consisting of p_j^k values.

Table 4.60 Scoring the IP System Selection Criteria According to the Degree of Importance on the Basis of the Decision Maker (p_j^k values)

Criteria	Decision Maker	DM1	DM2	DM3
C1	Accuracy (A)	0,85	0,15	0,70
C2	Repeatability	0,90	0,85	0,60
C3	Resolution (S)	1,00	0,70	0,50
C4	Response Time	0,50	0,55	0,75
C5	Operating System	0,60	0,80	0,20
C6	Hardware Interface	0,40	0,25	0,90
C7	Frame Rate	0,55	0,40	0,30
C8	Maintainability (M)	0,25	0,30	0,25
C9	Reliability (L)	0,15	0,45	0,40
C10	Initial cost (I)	0,75	1,00	1,00
C11	Operation cost (O)	0,05	0,90	0,80
C12	Flexibility in software interface	0,35	0,60	0,10

Equation (1) was used to obtain the relative importance score ($\overline{p}_j$) for all criteria in the second stage. Table 4.61 shows the results calculated.

Table 4.61 Relative Importance Scores ($\overline{p_j}$) for the IP System Selection Criteria

Criteria	Relative Importance Scores ($\overline{p_j}$)
C1	0,4469
C2	0,7714
C3	0,7047
C4	0,5908
C5	0,4579
C6	0,4481
C7	0,4041
C8	0,2657
C9	0,3000
C10	0,9086
C11	0,3302
C12	0,2759

All criteria were arranged from largest to smallest based on their relative important scores in the third phase, and the comparative importance values (s_j) of the mean value for the criteria were obtained, as shown in Table 4.62.

Table 4.62 Comparison of Relative Significance Scores for the IP System Selection Criteria

Criteria	Relative Importance Scores ($\overline{p_j}$)	Comparative Importance of Geomean Value (s_j)
C10	0,9086	
C2	0,7714	0,1372
C3	0,7047	0,0667
C4	0,5908	0,1139
C5	0,4579	0,1329
C6	0,4481	0,0098
C1	0,4469	0,0012
C7	0,4041	0,0428
C11	0,3302	0,0739
C9	0,3000	0,0302
C12	0,2759	0,0241
C8	0,2657	0,0102

Then, the coefficient value c_j for all criteria was calculated using Equation (2) on page 25 as depicted in Table 4.63.

Table 4.63 Coefficient Values (c_j) of the IP System Selection Criteria

Criteria	Coefficient Values (c_j)
C10	1,0000
C2	1,1372
C3	1,0667
C4	1,1139
C5	1,1329
C6	1,0098
C1	1,0012
C7	1,0428
C11	1,0739
C9	1,0302
C12	1,0241
C8	1,0102

In the penultimate step, the corrected weights (s_j') for all criteria were calculated with the help of Equation (3) and the values in Table 4.64 were obtained. Here, the corrected weight of the first-ranked criterion is s_j'=1.

Table 4.64 Corrected Weight Values (s_j') of the IP System Selection Criteria

Criteria	Corrected Weight Values (s_j')
C10	1,0000
C2	0,8794
C3	0,8244
C4	0,7401
C5	0,6533
C6	0,6469
C1	0,6461
C7	0,6196
C11	0,5770
C9	0,5601
C12	0,5469
C8	0,5414

As a final step, the final weights for all criteria were calculated using Equation (4) and these weights are shown in Table 4.65.

After calculating the criteria weights with the SWARA method, the WASPAS method was used to rank the alternatives. The steps of the WASPAS method are as follows.

Table 4.65 Final Weight Values (w_j) of the IP System Selection Criteria

Criteria	Final Weight Values (w_j)
C10	0,1214
C2	0,1068
C3	0,1001
C4	0,0899
C5	0,0793
C6	0,0786
C1	0,0785
C7	0,0753
C11	0,0701
C9	0,0680
C12	0,0664
C8	0,0657

As first step, Image Processor System alternatives that may be suitable for the production line were compared according to the criteria. The criteria are classified as cost type or benefit type as shown in Table 4.66.

Table 4.66 Criteria classifications for IP System Selection as cost type or benefit type

Type	**Criteria**		**Values**	
Benefit Type	C1	Accuracy	µm	
Benefit Type	C2	Repeatability	µm	
Benefit Type	C3	Resolution	Pixel	
Benefit Type	C4	Response Time	ms	
Benefit Type	C5	Operating System	Worst = 1	Best = 10
Benefit Type	C6	Hardware Interface	Worst = 1	Best = 10
Benefit Type	C7	Frame Rate	Hz	
Benefit Type	C8	Maintainability	Worst = 1	Best = 10
Benefit Type	C9	Reliability	Worst = 1	Best = 10
Cost Type	C10	Initial cost	$	
Benefit Type	C11	Operation cost	Worst = 1	Best = 10
Benefit Type	C12	Flexibility in software interface	Worst = 1	Best = 10

The values of the alternatives for operating system, hardware interface, maintainability, reliability, operation cost and flexibility in software interface were obtained by the decision makers giving the alternatives values between 1 and 10 by consensus. (1=worst, 10=best)

After the criterion weights were determined by the SWARA method, the initial decision matrix was prepared as shown in Table 4.67, in which data regarding the image processor system options were obtained from well-known sensor and visual system manufacturers.

After the initial decision matrix was created, the normalized initial decision matrix values were calculated using Equation (5) for the benefit type criteria and using Equation (6) for the cost type criteria and the results are shown in Table 4.68.

Table 4.67 Initial Decision Matrix for IP System Selection

Criteria / IP Alternatives	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
IP 1	3,45	8	5,01	47	8,6535	9,0000	16	8,3203	9,0000	27500	8,6535	9,0000
IP 2	3,45	8	2,3	35	8,6535	5,0000	51	6,3164	7,3186	15750	7,0000	8,3203
IP 3	3,45	3	1,92	5	7,0000	6,3164	50	8,0000	6,3164	14900	6,0000	7,3186
IP 4	3,45	3	12,3	5	7,0000	3,6342	10	8,0000	6,3164	19300	5,5934	7,3186
IP 5	6	4	0,35	66	7,0000	7,3186	15	7,0000	7,3186	6900	8,3203	6,3164
IP 6	6	5	0,35	66	7,0000	7,3186	15	6,3164	6,3164	13500	4,3089	6,6039
IP 7	3,45	6	5,01	66	4,3089	8,3203	22	8,0000	8,0000	15750	7,3186	7,3186

Table 4.68 Normalized Initial Decision Matrix for IP System Selection

Criteria / IP Alternatives	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
IP 1	0,5750	1,0000	0,4073	0,7121	1,0000	1,0000	0,3137	1,0000	1,0000	0,2509	1,0000	1,0000
IP 2	0,5750	1,0000	0,1870	0,5303	1,0000	0,5556	1,0000	0,7591	0,8631	0,4381	0,8089	0,9245
IP 3	0,5750	0,3750	0,1561	0,0758	0,8089	0,7018	0,9804	0,9615	1,0000	0,4631	0,6934	0,8132
IP 4	0,5750	0,3750	1,0000	0,0758	0,8089	0,4038	0,1961	0,9615	1,0000	0,3575	0,6464	0,8132
IP 5	1,0000	0,5000	0,0285	1,0000	0,8089	0,8132	0,2941	0,8413	0,8631	1,0000	0,9615	0,7018
IP 6	1,0000	0,6250	0,0285	1,0000	0,8089	0,8132	0,2941	0,7591	1,0000	0,5111	0,4979	0,7338
IP 7	0,5750	0,7500	0,4073	1,0000	0,4979	0,9245	0,4314	0,9615	0,7895	0,4381	0,8457	0,8132

The first total relative significance value for each alternative was first calculated using Equation (7) according to the Weighted Sum Model. The obtained values are shown in Table 4.69.

Table 4.69 First Total Relative Significance Values ($Q_i^{(1)}$) for IP System Selection

Image Processor Station	**Q1**
IP 1	0,7389
IP 2	0,6963
IP 3	0,5906
IP 4	0,5766
IP 5	0,7242
IP 6	0,6517
IP 7	0,6838

Then, the second total relative significance value for each alternative was calculated using Equation (8). The obtained values are given in Table 4.70.

Table 4.70 Second Total Relative Significance Values ($Q_i^{(2)}$) for IP System Selection

Image Processor Station	**Q2**
IP 1	0,6577
IP 2	0,6295
IP 3	0,4735
IP 4	0,4665
IP 5	0,5471
IP 6	0,4962
IP 7	0,6485

The combined optimality value for each alternative is calculated using Equation (9). Calculations are performed for λ = [0,1] with a 0.1 increment to demonstrate how various values can result in different ranks. Details of the sensitivity analysis based on different λ values are given in Figure 4.8.

Each alternative is ranked by considering the combined optimality value. The ranking result of the alternatives shows that the most suitable option (IP 1) and three lowest ranked alternatives (IP 3, IP 4, and IP 6) hold their rankings, but the rankings of other alternatives (IP 2, IP 5, and IP 7) may differ according to λ value.

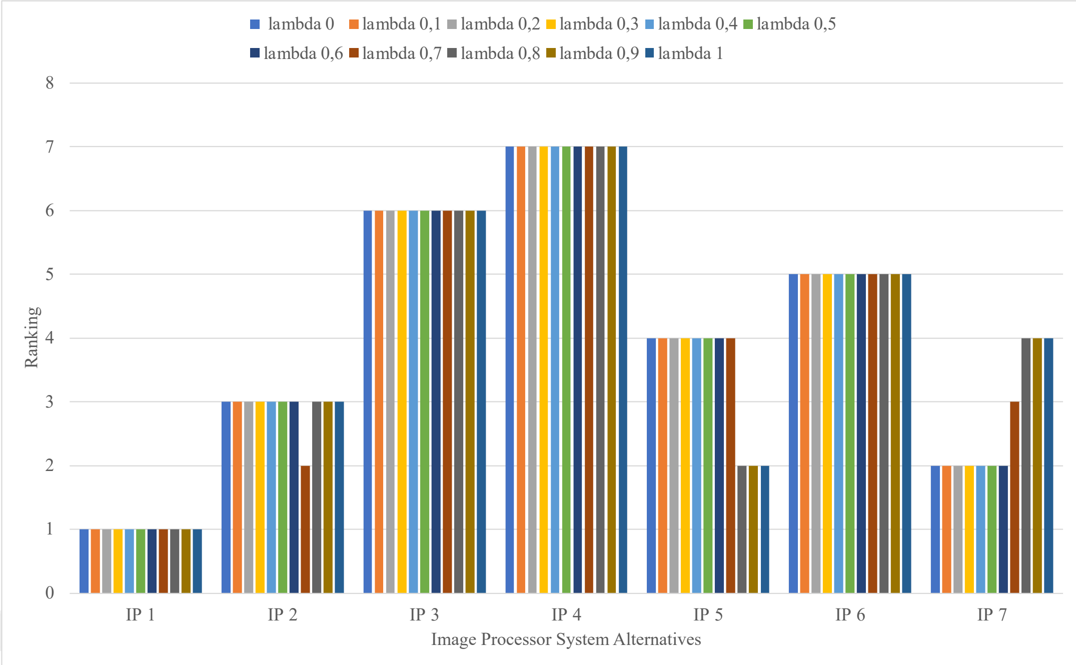

Figure 4.8 Sensitivity analysis for image processor system alternatives

When the sensitivity analysis graphs for all selection problems are examined, it is seen that the most suitable alternative does not change for different λ values, but the other alternatives' rankings may change depending on the combined optimality coefficient value used.

For industrial robot selection problem, since the alternative with the highest Q_i value for every λ value is IR 9, it should be selected for the intended production line. On the other side, for collaborative robot selection problem, when the value of λ=0.6 was evaluated, it was seen that the most appropriate results were obtained with this value compared to other combined optimality coefficient values, and CoBot 1 is ranked as the best alternative for all λ values.

As a result of the evaluations in the cartesian robot selection problem, it was agreed by decision makers that the most suitable ranking, that can be used for the cartesian robot class, is the ranking obtained as a result of the value of λ=0.8. So, it is decided that CR 4 is the most suitable alternative for all λ values.

The box folding cartesian robot selection problem shows less sensitivity according to first three selection problems despite the changing λ values. Most of the studies suggest λ=0.6 value as a suitable combined optimality coefficient value for different evaluations. When the results were examined by decision makers, rankings of the alternatives for box folding cartesian robot selection don't show any change between the λ=0.2 and λ=1 values, and the results seemed logical according to decision makers. So, λ=0.6 was decided to be used for evaluation of this selection problem. The ranking results of the alternatives showed that the most suited alternative is BF 2 and it maintains its ranks for all λ values.

For AGV selection problem, it was seen that although there are more alternatives than the box folding cartesian robot selection problem, and this selection problem was less sensitive than the other problems for different λ values between 0 and 1. When the decision makers evaluated the results here in detail, it was found that the sensitivity analysis results using the combined optimality coefficient values from λ=0 to λ=0.7 are more applicable for real life in this selection problem. According to the ranking results of the alternatives, AGV 3, AGV 4 and AGV 2 are the most suitable alternatives, respectively.

At the end of image processing system selection problem part, each alternative is ranked by considering the combined optimality values. As a result, the IP 1 system that was determined to be the most suitable alternative, and lowest ranked alternatives IP 3, IP 4, and IP 6 hold their rankings for different λ values. As a result of the evaluations made by the decision makers considering the alternatives, λ =0.7 was determined as the most appropriate combined optimality coefficient value to be applied in real life.

CHAPTER 5

DISCUSSION AND CONCLUSION

Robots have a wide range of abilities, technical characteristics, and potentials, depending on their intended use and cost. Getting high efficiency from robots employed for various purposes in different manufacturing lines, as well as selecting the most appropriate robot, are two of the most challenging problems. Multi-criteria decision-making strategies that advocate making the most appropriate choice among different options are usually created to make this right decision, even while experts with excellent knowledge and working in the area are contacted.

In order to keep up with the industry's technological trends, this study required a hybrid production environment that includes industrial robots, collaborative robots, AGVs, cartesian robots, and image processing systems. While this study was conducted in which different types of robots were selected to satisfy the needs of this hybrid production line, numerous studies in the literature used the SWARA and WASPAS approaches together, but no study employing these methods to choose a robot for a hybrid production line was found.

Taking the problem in this study into account and the data types we have, in this research, SWARA and WASPAS approach was used to identify the most efficient systems among alternatives for different robot types. This MCDM approach which is considered to be an effective, robust, and easy guide, accompanied by a detailed sensitivity analysis.

In the criterion weighting calculations made using the SWARA approach, which is guided by the opinions of the decision makers, it has been seen that the cost is the most effective criterion in all systems to be selected. In industrial robot, collaborative robot and cartesian robot systems, the weight of the robot was the least important criterion, while the load capacity of the systems, including AGVs, was the most important criterion after cost. In addition, when image processing systems are examined, repeatability, resolution and response time are the other criteria that have the highest importance after the cost criterion.

While applying the WASPAS method to select the most suitable systems among several alternatives, which are determined to be used in the hybrid production line, some criteria that are suitable to be evaluated with subjective evaluation such as operating system, software interface flexibility, routing type, controllability are obtained by the decision makers giving the alternatives values between 1 and 10 by agreeing.

When the sensitivity analysis graphs for all selection problems are examined in the studies, it is seen that the best alternative does not change for different λ values, but the other alternatives' ranking could change depending on the combined optimality coefficient value used.

For industrial robot selection problem, the results for λ=0.3, compared to the other λ values with the opinions of decision makers, give the most compatible, consistent, and logical ranking results.

On the other hand, for collaborative robot selection problem, when the value of λ=0.6, at which rank changes starts, was evaluated and it was decided that the most appropriate results for real life were obtained with this value compared to other combined optimality coefficient values.

Unlike other selection problems, in the cartesian robot selection problem, it was observed that the ranking differences started at λ=0.8 depending on the combined optimality coefficient value. As a result of the evaluations here, it was agreed by decision makers that the most appropriate ranking that can be used for the robot class in question is the ranking obtained as a result of the value of λ=0.8.

As a result of the sensitivity analysis, the problem that shows less sensitivity despite the changing λ values was the selection of the box folding cartesian robot. When the results were examined by decision makers, it was concluded that the combined optimality coefficient values from λ=0.2 to λ=1 gave logical ranking results, and λ=0.6 value is used for the evaluation of this problem.

As a result of the sensitivity analysis made at the end of the AGV selection problem, it was seen that although there are more alternatives than the box folding cartesian robot selection problem, this problem showed the least sensitivity to changing λ values. When the decision makers evaluated the results here in detail, it was found that the sensitivity analysis results using the combined optimality coefficient values from λ=0 to λ=0.7 are more suitable for real life in this selection problem.

In the image processing system selection problem, the IP 1 system that was determined to be the most suitable alternative, and the three systems (IP 4, IP 4, and IP 6) with the lowest ranking, except for IP 2, IP 5, and IP 7, remained in the ranking in the sensitivity analysis results. As a result of the evaluations made by the decision makers considering the IP 2, IP 5, and IP 7 alternatives, λ =0.7 was determined as the most appropriate combined optimality coefficient value to be applied in real life.

The originality and contribution of this study is that there is no study in literature on digitalization in production with the use of these types of automation systems, that we use in this study as industrial robots, collaborative robots, AGV, cartesian robots and image processor systems. This study provides an easy, efficient, and consistent approach to manufacturers and researchers who may face with this problem in the future, while choosing the criteria and multi-criteria decision-making method that they can use while making the most appropriate selection among different alternatives.

Suggestions for future research are provided below:

- Re-implementation of the proposed approach according to an increasing number of criteria and alternatives,
- By applying Fuzzy SWARA and Fuzzy WASPAS methods, the robot selection processes in this study can be managed in cases where the decision makers do not have clear information,
- A new study can be focused on the use of other MCDM techniques such as ARAS, ANP and PROMETHEE, and the results obtained can be compared with the results of this study,

- At the end of this thesis, using the system selections determined as the most suitable systems among the alternatives for all automation system classes, a digital twin of the production line can be created by consulting the experts, and simulations can be made on this digital twin, and analyzes such as efficiency analysis, time-production number analysis can be evaluated.

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APPENDIX A

DETAILED CRITERIA TABLES FOR ALL ROBOT CLASSES

For Industrial Robot Alternatives

Decision Maker 1 (DM1)											
Label	**Robot Weight (kg)**	**Load Capacity (kg)**	**Repeatability (mm)**	**Maximum tip speed (deg/s)**	**Memory Capacity (MC) 1: worst 10: best**	**Manipulator Reach (mm)**	**Man-Machine Interface (MMI) 1: worst 10: best**	**Programming Flexibility (PF) 1: worst 10: best**	**Cost (C) ($)**	**Vendor's service Contract (VSC) 1: worst 10: best**	**Maintenance Cost (MeC) 1: worst 10: best**
IR1	1069	120	0,05	260	9	2701	8	9	50.000	9	4
IR2	536	70	0,05	320	9	2101	8	9	25.000	9	5
IR3	425	60	0,06	360	7	2050	8	8	30.000	9	8
IR4	2250	125	0,90	235	7	3500	7	7	25.000	9	8
IR5	620	80	0,03	350	8	2230	5	5	35.000	5	6
IR6	790	120	0,03	250	8	2230	5	5	40.000	5	7
IR7	1000	80	0,10	400	5	2594	6	7	40.000	6	7
IR8	980	130	0,06	400	5	2194	6	7	40.000	6	7
IR9	630	88	0,03	350	6	2236	8	8	25.000	8	6
IR10	790	110	0,04	255	6	2236	8	8	30.000	8	5

Decision Maker 2 (DM2)											
Label	**Robot Weight (kg)**	**Load Capacity (kg)**	**Repeatability (mm)**	**Maximum tip speed (deg/s)**	**Memory Capacity (MC) 1: worst 10: best**	**Manipulator Reach (mm)**	**Man-Machine Interface (MMI) 1: worst 10: best**	**Programming Flexibility (PF) 1: worst 10: best**	**Cost (C) ($)**	**Vendor's service Contract (VSC) 1: worst 10: best**	**Maintenance Cost (MeC) 1: worst 10: best**
IR1	1069	120	0,05	260	9	2701	8	9	50.000	9	4
IR2	536	70	0,05	320	9	2101	8	9	25.000	9	5
IR3	425	60	0,06	360	7	2050	8	8	30.000	9	8
IR4	2250	125	0,90	235	7	3500	7	7	25.000	9	8
IR5	620	80	0,03	350	8	2230	5	5	35.000	5	6
IR6	790	120	0,03	250	8	2230	5	5	40.000	5	7
IR7	1000	80	0,10	400	5	2594	6	7	40.000	6	7
IR8	980	130	0,06	400	5	2194	6	7	40.000	6	7
IR9	630	88	0,03	350	6	2236	8	8	25.000	8	6
IR10	790	110	0,04	255	6	2236	8	8	30.000	8	5

Decision Maker 3 (DM3)											
Label	**Robot Weight (kg)**	**Load Capacity (kg)**	**Repeatability (mm)**	**Maximum tip speed (deg/s)**	**Memory Capacity (MC) 1: worst 10: best**	**Manipulator Reach (mm)**	**Man-Machine Interface (MMI) 1: worst 10: best**	**Programming Flexibility (PF) 1: worst 10: best**	**Cost (C) ($)**	**Vendor's service Contract (VSC) 1: worst 10: best**	**Maintenance Cost (MeC) 1: worst 10: best**
IR1	1069	120	0,05	260	6	2701	6	4	50.000	8	5
IR2	536	70	0,05	320	6	2101	6	4	25.000	8	5
IR3	425	60	0,06	360	8	2050	8	8	30.000	9	5
IR4	2250	125	0,90	235	8	3500	9	8	25.000	9	5
IR5	620	80	0,03	350	7	2230	7	7	35.000	8	6
IR6	790	120	0,03	250	7	2230	7	7	40.000	8	6
IR7	1000	80	0,10	400	4	2594	6	5	40.000	4	7
IR8	980	130	0,06	400	4	2194	6	5	40.000	4	7
IR9	630	88	0,03	350	5	2236	7	7	25.000	5	4
IR10	790	110	0,04	255	5	2236	7	7	30.000	5	4

Geometric Mean of Decision Maker Opinions											
Label	**Robot Weight (kg)**	**Load Capacity (kg)**	**Repeatability (mm)**	**Maximum tip speed (deg/s)**	**Memory Capacity (MC) 1: worst 10: best**	**Manipulator Reach (mm)**	**Man-Machine Interface (MMI) 1: worst 10: best**	**Programming Flexibility (PF) 1: worst 10: best**	**Cost (C) ($)**	**Vendor's service Contract (VSC) 1: worst 10: best**	**Maintenance Cost (MeC) 1: worst 10: best**
IR1	1069	120	0,05	260	7,8622	2701	7,2685	6,8683	50.000	8,6535	4,3089
IR2	536	70	0,05	320	7,8622	2101	7,2685	6,8683	25.000	8,6535	5,0000
IR3	425	60	0,06	360	7,3186	2050	8,0000	8,0000	30.000	9,0000	6,8399
IR4	2250	125	0,90	235	7,3186	3500	7,6117	7,3186	25.000	9,0000	6,8399
IR5	620	80	0,03	350	7,6517	2230	5,5934	5,5934	35.000	5,8480	6,0000
IR6	790	120	0,03	250	7,6517	2230	5,5934	5,5934	40.000	5,8480	6,6494
IR7	1000	80	0,10	400	4,6416	2594	6,0000	6,2573	40.000	5,2415	7,0000
IR8	980	130	0,06	400	4,6416	2194	6,0000	6,2573	40.000	5,2415	7,0000
IR9	630	88	0,03	350	5,6462	2236	7,6517	7,6517	25.000	6,8399	5,2415
IR10	790	110	0,04	255	5,6462	2236	7,6517	7,6517	30.000	6,8399	4,6416

For Collaborative Robot Alternatives

Decision Maker 1 (DM1)											
Label	**Robot Weight (kg)**	**Load Capacity (kg)**	**Repeatability (mm)**	**Maximum tip speed (deg/s)**	**Memory Capacity (MC) 1: worst 10: best**	**Manipulator Reach (mm)**	**Man-Machine Interface (MMI) 1: worst 10: best**	**Programming Flexibility (PF) 1: worst 10: best**	**Cost (C) ($)**	**Vendor's service Contract (VSC) 1: worst 10: best**	**Maintenance Cost (MeC) 1: worst 10: best**
CoBot1	28	5	0,05	200	5	950	8	8	35.000	9	8
CoBot2	230	7	0,03	1000	7	911	5	5	85.000	8	3
CoBot3	40	10	0,04	180	8	1249	4	3	65.000	5	5
CoBot4	52,5	14	0,15	135	9	820	8	9	90.000	9	4
CoBot5	47	12	0,1	180	4	1300	5	4	40.000	5	6
CoBot6	114	12	0,035	300	4	1200	3	3	65.000	6	8
CoBot7	45	12	0,05	180	9	1300	9	8	60.000	8	9
CoBot8	58	10	0,05	250	6	1200	8	8	50.000	8	7

Decision Maker 2 (DM2)											
Label	**Robot Weight (kg)**	**Load Capacity (kg)**	**Repeatability (mm)**	**Maximum tip speed (deg/s)**	**Memory Capacity (MC) 1: worst 10: best**	**Manipulator Reach (mm)**	**Man-Machine Interface (MMI) 1: worst 10: best**	**Programming Flexibility (PF) 1: worst 10: best**	**Cost (C) ($)**	**Vendor's service Contract (VSC) 1: worst 10: best**	**Maintenance Cost (MeC) 1: worst 10: best**
CoBot1	28	5	0,05	200	6	950	9	7	35.000	8	7
CoBot2	230	7	0,03	1000	8	911	5	4	85.000	7	5
CoBot3	40	10	0,04	180	9	1249	5	4	65.000	4	5
CoBot4	52,5	14	0,15	135	8	820	7	9	90.000	9	3
CoBot5	47	12	0,1	180	5	1300	4	5	40.000	6	6
CoBot6	114	12	0,035	300	3	1200	3	4	65.000	5	7
CoBot7	45	12	0,05	180	7	1300	8	8	60.000	9	9
CoBot8	58	10	0,05	250	6	1200	8	8	50.000	7	8

Decision Maker 3 (DM3)											
Label	**Robot Weight (kg)**	**Load Capacity (kg)**	**Repeatability (mm)**	**Maximum tip speed (deg/s)**	**Memory Capacity (MC) 1: worst 10: best**	**Manipulator Reach (mm)**	**Man-Machine Interface (MMI) 1: worst 10: best**	**Programming Flexibility (PF) 1: worst 10: best**	**Cost (C) ($)**	**Vendor's service Contract (VSC) 1: worst 10: best**	**Maintenance Cost (MeC) 1: worst 10: best**
CoBot1	28	5	0,05	200	7	950	9	6	35.000	8	6
CoBot2	230	7	0,03	1000	6	911	2	2	85.000	4	3
CoBot3	40	10	0,04	180	6	1249	7	7	65.000	7	6
CoBot4	52,5	14	0,15	135	7	820	7	6	90.000	7	4
CoBot5	47	12	0,1	180	5	1300	3	4	40.000	5	5
CoBot6	114	12	0,035	300	4	1200	2	1	65.000	4	6
CoBot7	45	12	0,05	180	7	1300	8	7	60.000	8	7
CoBot8	58	10	0,05	250	8	1200	7	7	50.000	6	7

Geometric Mean of Decision Maker Opinions											
Label	**Robot Weight (kg)**	**Load Capacity (kg)**	**Repeatability (mm)**	**Maximum tip speed (deg/s)**	**Memory Capacity (MC) 1: worst 10: best**	**Manipulator Reach (mm)**	**Man-Machine Interface (MMI) 1: worst 10: best**	**Programming Flexibility (PF) 1: worst 10: best**	**Cost (C) ($)**	**Vendor's service Contract (VSC) 1: worst 10: best**	**Maintenance Cost (MeC) 1: worst 10: best**
CoBot1	28	5	0,05	200	5,9439	950	8,6535	6,9521	35.000	8,3203	6,9521
CoBot2	230	7	0,03	1000	6,9521	911	3,6840	3,4200	85.000	6,0732	3,5569
CoBot3	40	10	0,04	180	7,5595	1249	5,1925	4,3795	65.000	5,1925	5,3133
CoBot4	52,5	14	0,15	135	7,9581	820	7,3186	7,8622	90.000	8,2768	3,6342
CoBot5	47	12	0,1	180	4,6416	1300	3,9149	4,3089	40.000	5,3133	5,6462
CoBot6	114	12	0,035	300	3,6342	1200	2,6207	2,2894	65.000	4,9324	6,9521
CoBot7	45	12	0,05	180	7,6117	1300	8,3203	7,6517	60.000	8,3203	8,2768
CoBot8	58	10	0,05	250	6,6039	1200	7,6517	7,6517	50.000	6,9521	7,3186

For Cartesian Robot Alternatives

Decision Maker 1 (DM1)												
Label	**Robot Weight (kg)**	**Load Capacity (kg)**	**Repeatability (mm)**	**Maximum tip speed (deg/s)**	**Memory Capacity (MC) 1: worst 10: best**	**Manipulator Reach (mm)**	**Man-Machine Interface (MMI) 1: worst 10: best**	**Programming Flexibility (PF) 1: worst 10: best**	**Cost (C) ($)**	**Vendor's service Contract (VSC) 1: worst 10: best**	**Maintenance Cost (MeC) 1: worst 10: best**	**Special Tooling Costs (STC) ($)**
CR1	25	5	0,02	0,8	8,0000	950	7	8	8.000	6	9	4.000
CR2	35	25	0,08	3	8,0000	950	7	8	10.000	6	4	4.000
CR3	15	10	0,08	3	8,0000	450	7	8	5.000	6	6	2.500
CR4	25	150	0,02	3	8,0000	400	7	8	3.500	6	9	2.000
CR5	25	150	0,02	3	8,0000	400	7	8	3.500	6	9	2.000
CR6	45	25	0,08	3	8,0000	1100	7	8	12.000	6	5	2.500
CR7	32	20	0,01	1,2	6,0000	1250	8	7	14.000	8	7	4.000
CR8	27	4,5	0,02	0,7	6,0000	700	8	7	12.000	8	9	2.500
CR9	35	20	0,01	1,2	6,0000	1250	8	7	18.000	8	5	2.500

Decision Maker 2 (DM2)												
Label	**Robot Weight (kg)**	**Load Capacity (kg)**	**Repeatability (mm)**	**Maximum tip speed (deg/s)**	**Memory Capacity (MC) 1: worst 10: best**	**Manipulator Reach (mm)**	**Man-Machine Interface (MMI) 1: worst 10: best**	**Programming Flexibility (PF) 1: worst 10: best**	**Cost (C) ($)**	**Vendor's service Contract (VSC) 1: worst 10: best**	**Maintenance Cost (MeC) 1: worst 10: best**	**Special Tooling Costs (STC) ($)**
CR1	25	5	0,02	0,8	8,0000	950	8	9	8.000	7	9	4.000
CR2	35	25	0,08	3	8,0000	950	8	9	10.000	7	4	4.000
CR3	15	10	0,08	3	8,0000	450	8	9	5.000	7	7	2.500
CR4	25	150	0,02	3	8,0000	400	8	9	3.500	7	9	2.000
CR5	25	150	0,02	3	8,0000	400	8	9	3.500	7	9	2.000
CR6	45	25	0,08	3	8,0000	1100	8	9	12.000	7	4	2.500
CR7	32	20	0,01	1,2	6,0000	1250	9	6	14.000	8	8	4.000
CR8	27	4,5	0,02	0,7	6,0000	700	9	6	12.000	8	9	2.500
CR9	35	20	0,01	1,2	6,0000	1250	9	6	18.000	8	6	2.500

Decision Maker 3 (DM3)												
Label	**Robot Weight (kg)**	**Load Capacity (kg)**	**Repeatability (mm)**	**Maximum tip speed (deg/s)**	**Memory Capacity (MC) 1: worst 10: best**	**Manipulator Reach (mm)**	**Man-Machine Interface (MMI) 1: worst 10: best**	**Programming Flexibility (PF) 1: worst 10: best**	**Cost (C) ($)**	**Vendor's service Contract (VSC) 1: worst 10: best**	**Maintenance Cost (MeC) 1: worst 10: best**	**Special Tooling Costs (STC) ($)**
CR1	25	5	0,02	0,8	8,0000	950	8	9	8.000	7	9	4.000
CR2	35	25	0,08	3	8,0000	950	8	9	10.000	7	4	4.000
CR3	15	10	0,08	3	8,0000	450	8	9	5.000	7	7	2.500
CR4	25	150	0,02	3	8,0000	400	8	9	3.500	7	9	2.000
CR5	25	150	0,02	3	8,0000	400	8	9	3.500	7	9	2.000
CR6	45	25	0,08	3	8,0000	1100	8	9	12.000	7	4	2.500
CR7	32	20	0,01	1,2	6,0000	1250	9	6	14.000	8	8	4.000
CR8	27	4,5	0,02	0,7	6,0000	700	9	6	12.000	8	9	2.500
CR9	35	20	0,01	1,2	6,0000	1250	9	6	18.000	8	6	2.500

Geometric Mean of Decision Maker Opinions												
Label	**Robot Weight (kg)**	**Load Capacity (kg)**	**Repeatability (mm)**	**Maximum tip speed (deg/s)**	**Memory Capacity (MC) 1: worst 10: best**	**Manipulator Reach (mm)**	**Man-Machine Interface (MMI) 1: worst 10: best**	**Programming Flexibility (PF) 1: worst 10: best**	**Cost (C) ($)**	**Vendor's service Contract (VSC) 1: worst 10: best**	**Maintenance Cost (MeC) 1: worst 10: best**	**Special Tooling Costs (STC) ($)**
CR1	25	5	0,02	0,8	8,0000	950	7,6517	8,6535	8.000	6,6494	9,0000	4.000
CR2	35	25	0,08	3	8,0000	950	7,6517	8,6535	10.000	6,6494	4,0000	4.000
CR3	15	10	0,08	3	8,0000	450	7,6517	8,6535	5.000	6,6494	6,6494	2.500
CR4	25	150	0,02	3	8,0000	400	7,6517	8,6535	3.500	6,6494	9,0000	2.000
CR5	25	150	0,02	3	8,0000	400	7,6517	8,6535	3.500	6,6494	9,0000	2.000
CR6	45	25	0,08	3	8,0000	1100	7,6517	8,6535	12.000	6,6494	4,3089	2.500
CR7	32	20	0,01	1,2	6,0000	1250	8,6535	6,3164	14.000	8,0000	7,6517	4.000
CR8	27	4,5	0,02	0,7	6,0000	700	8,6535	6,3164	12.000	8,0000	9,0000	2.500
CR9	35	20	0,01	1,2	6,0000	1250	8,6535	6,3164	18.000	8,0000	5,6462	2.500

For Box Folding Cartesian Robot Alternatives

Decision Maker 1 (DM1)											
Label	**Robot Weight (kg)**	**Load Capacity (kg)**	**Repeatability (mm)**	**Maximum tip speed (deg/s)**	**Memory Capacity (MC) 1: worst 10: best**	**Manipulator Reach (mm)**	**Man-Machine Interface (MMI) 1: worst 10: best**	**Programming Flexibility (PF) 1: worst 10: best**	**Cost (C) ($)**	**Vendor's service Contract (VSC) 1: worst 10: best**	**Maintenance Cost (MeC) 1: worst 10: best**
BF1	5	30	0,08	3	8	800	7	8	2.500	6	5
BF2	5	50	0,05	5	8	800	7	8	3.500	6	5
BF3	9	25	0,1	2	6	1200	8	7	5.000	8	7
BF4	8	10	0,05	1,2	6	950	8	7	3.000	8	9

Decision Maker 2 (DM2)											
Label	**Robot Weight (kg)**	**Load Capacity (kg)**	**Repeatability (mm)**	**Maximum tip speed (deg/s)**	**Memory Capacity (MC) 1: worst 10: best**	**Manipulator Reach (mm)**	**Man-Machine Interface (MMI) 1: worst 10: best**	**Programming Flexibility (PF) 1: worst 10: best**	**Cost (C) ($)**	**Vendor's service Contract (VSC) 1: worst 10: best**	**Maintenance Cost (MeC) 1: worst 10: best**
BF1	5	30	0,08	3	8	800	8	9	2.500	7	6
BF2	5	50	0,05	5	8	800	8	9	3.500	7	6
BF3	9	25	0,1	2	6	1200	9	6	5.000	8	7
BF4	8	10	0,05	1,2	6	950	9	6	3.000	8	8

Decision Maker 3 (DM3)											
Label	**Robot Weight (kg)**	**Load Capacity (kg)**	**Repeatability (mm)**	**Maximum tip speed (deg/s)**	**Memory Capacity (MC) 1: worst 10: best**	**Manipulator Reach (mm)**	**Man-Machine Interface (MMI) 1: worst 10: best**	**Programming Flexibility (PF) 1: worst 10: best**	**Cost (C) ($)**	**Vendor's service Contract (VSC) 1: worst 10: best**	**Maintenance Cost (MeC) 1: worst 10: best**
BF1	5	30	0,08	3	8	800	8	9	2.500	7	6
BF2	5	50	0,05	5	8	800	8	9	3.500	7	6
BF3	9	25	0,1	2	6	1200	9	6	5.000	8	7
BF4	8	10	0,05	1,2	6	950	9	6	3.000	8	8

Geometric Mean of Decision Maker Opinions											
Label	**Robot Weight (kg)**	**Load Capacity (kg)**	**Repeatability (mm)**	**Maximum tip speed (deg/s)**	**Memory Capacity (MC) 1: worst 10: best**	**Manipulator Reach (mm)**	**Man-Machine Interface (MMI) 1: worst 10: best**	**Programming Flexibility (PF) 1: worst 10: best**	**Cost (C) ($)**	**Vendor's service Contract (VSC) 1: worst 10: best**	**Maintenance Cost (MeC) 1: worst 10: best**
BF1	5	30	0,08	3	8,0000	800	7,6517	8,6535	2.500	6,6494	5,6462
BF2	5	50	0,05	5	8,0000	800	7,6517	8,6535	3.500	6,6494	5,6462
BF3	9	25	0,1	2	6,0000	1200	8,6535	6,3164	5.000	8,0000	7,0000
BF4	8	10	0,05	1,2	6,0000	950	8,6535	6,3164	3.000	8,0000	8,3203

For AGV Alternatives

Decision Maker 1 (DM1)											
Label	**Controllability 1: worst 10: best**	**Accuracy 1: worst 10: best**	**Cost ($)**	**Range 1: worst 10: best**	**Reliability 1: worst 10: best**	**Programming Flexibility 1: worst 10: best**	**Speed (m/min)**	**Man-machine Interface 1: worst 10: best**	**Battery Capacity (VDC)**	**Guidance Type 1: worst 10: best**	**Load Capacity (kg)**
AGV1	7	7	37.500	7	8	7	90	7	24	7	1000
AGV2	6	6	32.000	6	6	7	90	7	24	8	800
AGV3	9	9	28.000	9	6	7	62	7	48	8	1000
AGV4	7	7	36.000	7	8	7	62	7	48	8	1000
AGV5	8	8	90.000	5	8	6	60	6	96	8	1500
AGV6	6	7	50.000	7	6	7	50	7	24	6	750
AGV7	6	7	50.000	7	6	7	107	7	24	7	4535
AGV8	7	8	60.000	7	8	7	45	7	24	7	1000

Decision Maker 2 (DM2)											
Label	**Controllability 1: worst 10: best**	**Accuracy 1: worst 10: best**	**Cost ($)**	**Range 1: worst 10: best**	**Reliability 1: worst 10: best**	**Programming Flexibility 1: worst 10: best**	**Speed (m/min)**	**Man-machine Interface 1: worst 10: best**	**Battery Capacity (VDC)**	**Guidance Type 1: worst 10: best**	**Load Capacity (kg)**
AGV1	7	7	37.500	6	8	7	90	7	24	7	1000
AGV2	5	6	32.000	6	6	7	90	7	24	8	800
AGV3	8	8	28.000	9	6	8	62	6	48	8	1000
AGV4	7	7	36.000	8	7	8	62	6	48	8	1000
AGV5	9	9	90.000	7	9	5	60	8	96	9	1500
AGV6	4	5	50.000	6	5	8	50	8	24	5	750
AGV7	5	6	50.000	7	6	6	107	7	24	7	4535
AGV8	6	7	60.000	8	7	6	45	7	24	6	1000

Decision Maker 3 (DM3)											
Label	**Controllability 1: worst 10: best**	**Accuracy 1: worst 10: best**	**Cost ($)**	**Range 1: worst 10: best**	**Reliability 1: worst 10: best**	**Programming Flexibility 1: worst 10: best**	**Speed (m/min)**	**Man-machine Interface 1: worst 10: best**	**Battery Capacity (VDC)**	**Guidance Type 1: worst 10: best**	**Load Capacity (kg)**
AGV1	7	7	37.500	6	8	7	90	7	24	7	1000
AGV2	5	6	32.000	6	6	7	90	7	24	8	800
AGV3	8	8	28.000	9	6	8	62	6	48	8	1000
AGV4	7	7	36.000	8	7	8	62	6	48	8	1000
AGV5	9	9	90.000	7	9	5	60	8	96	9	1500
AGV6	4	5	50.000	6	5	8	50	8	24	5	750
AGV7	5	6	50.000	7	6	6	107	7	24	7	4535
AGV8	6	7	60.000	8	7	6	45	7	24	6	1000

Geometric Mean of Decision Maker Opinions											
Label	**Controllability 1: worst 10: best**	**Accuracy 1: worst 10: best**	**Cost ($)**	**Range 1: worst 10: best**	**Reliability 1: worst 10: best**	**Programming Flexibility 1: worst 10: best**	**Speed (m/min)**	**Man-machine Interface 1: worst 10: best**	**Battery Capacity (VDC)**	**Guidance Type 1: worst 10: best**	**Load Capacity (kg)**
AGV1	7,0000	7,0000	37.500	6,3164	8,0000	7,0000	90	7,0000	24	7,0000	1000
AGV2	5,3133	6,0000	32.000	6,0000	6,0000	7,0000	90	7,0000	24	8,0000	800
AGV3	8,3203	8,3203	28.000	9,0000	6,0000	7,6517	62	6,3164	48	8,0000	1000
AGV4	7,0000	7,0000	36.000	7,6517	7,3186	7,6517	62	6,3164	48	8,0000	1000
AGV5	8,6535	8,6535	90.000	6,2573	8,6535	5,3133	60	7,2685	96	8,6535	1500
AGV6	4,5789	5,5934	50.000	6,3164	5,3133	7,6517	50	7,6517	24	5,3133	750
AGV7	5,3133	6,3164	50.000	7,0000	6,0000	6,3164	107	7,0000	24	7,0000	4535
AGV8	6,3164	7,3186	60.000	7,6517	7,3186	6,3164	45	7,0000	24	6,3164	1000

For Image Processor Station Alternatives

Decision Maker 1 (DM1)													
Label	**Accuracy (µm)**	**Repeatability 1: worst 10: best**	**Resolution (pixel)**	**Response Time (ms)**	**Operating System 1: worst 10: best**	**Hardware Interface 1: worst 10: best**	**Frame Rate (Hz)**	**Maintainability 1: worst 10: best**	**Reliability 1: worst 10: best**	**Initial cost ($)**	**Operation cost 1: worst 10: best**	**Flexibility in software interface 1: worst 10: best**
IP1	3,45	8	5,01	47	8	9	16	9	9	27.500	8	9
IP2	3,45	8	2,3	35	8	5	51	7	8	15.750	7	9
IP3	3,45	4	1,92	5	7	7	50	8	7	14.900	6	8
IP4	3,45	4	12,3	5	7	3	10	8	7	19.300	7	8
IP5	6	5	0,35	66	7	8	15	7	8	6.900	9	7
IP6	6	6	0,35	66	7	8	15	7	7	13.500	5	8
IP7	3,45	7	5,01	66	5	9	22	8	8	15.750	8	8

Decision Maker 2 (DM2)												
Label	**Accuracy (µm)**	**Repeatability 1: worst 10: best**	**Resolution (pixel)**	**Response Time (ms)**	**Operating System 1: worst 10: best**	**Hardware Interface 1: worst 10: best**	**Frame Rate (Hz)**	**Maintainability 1: worst 10: best**	**Reliability 1: worst 10: best**	**Initial cost ($)**	**Operation cost 1: worst 10: best**	**Flexibility in software interface 1: worst 10: best**
IP1	3,45	7	5,01	47	9	9	16	8	9	27.500	9	9
IP2	3,45	7	2,3	35	9	5	51	6	7	15.750	7	8
IP3	3,45	3	1,92	5	7	6	50	8	6	14.900	6	7
IP4	3,45	3	12,3	5	7	4	10	8	6	19.300	5	7
IP5	6	5	0,35	66	7	7	15	7	7	6.900	8	6
IP6	6	5	0,35	66	7	7	15	6	6	13.500	4	6
IP7	3,45	6	5,01	66	4	8	22	8	8	15.750	7	7

Decision Maker 3 (DM3)												
Label	**Accuracy (µm)**	**Repeatability 1: worst 10: best**	**Resolution (pixel)**	**Response Time (ms)**	**Operating System 1: worst 10: best**	**Hardware Interface 1: worst 10: best**	**Frame Rate (Hz)**	**Maintainability 1: worst 10: best**	**Reliability 1: worst 10: best**	**Initial cost ($)**	**Operation cost 1: worst 10: best**	**Flexibility in software interface 1: worst 10: best**
IP1	3,45	8	5,01	47	9	9	16	8	9	27.500	9	9
IP2	3,45	8	2,3	35	9	5	51	6	7	15.750	7	8
IP3	3,45	5	1,92	5	7	6	50	8	6	14.900	6	7
IP4	3,45	5	12,3	5	7	4	10	8	6	19.300	5	7
IP5	6	4	0,35	66	7	7	15	7	7	6.900	8	6
IP6	6	7	0,35	66	7	7	15	6	6	13.500	4	6
IP7	3,45	6	5,01	66	4	8	22	8	8	15.750	7	7

Geometric Mean of Decision Maker Opinions												
Label	**Accuracy (µm)**	**Repeatability 1: worst 10: best**	**Resolution (pixel)**	**Response Time (ms)**	**Operating System 1: worst 10: best**	**Hardware Interface 1: worst 10: best**	**Frame Rate (Hz)**	**Maintainability 1: worst 10: best**	**Reliability 1: worst 10: best**	**Initial cost ($)**	**Operation cost 1: worst 10: best**	**Flexibility in software interface 1: worst 10: best**
IP1	3,45	7,6517	5,01	47	8,6535	9,0000	16	8,3203	9,0000	27.500	8,6535	9,0000
IP2	3,45	7,6517	2,3	35	8,6535	5,0000	51	6,3164	7,3186	15.750	7,0000	8,3203
IP3	3,45	3,9149	1,92	5	7,0000	6,3164	50	8,0000	6,3164	14.900	6,0000	7,3186
IP4	3,45	3,9149	12,3	5	7,0000	3,6342	10	8,0000	6,3164	19.300	5,5934	7,3186
IP5	6	4,6416	0,35	66	7,0000	7,3186	15	7,0000	7,3186	6.900	8,3203	6,3164
IP6	6	5,9439	0,35	66	7,0000	7,3186	15	6,3164	6,3164	13.500	4,3089	6,6039
IP7	3,45	6,3164	5,01	66	4,3089	8,3203	22	8,0000	8,0000	15.750	7,3186	7,3186