INDUSTRIAL ROBOT SELECTION BY USING CHOQUET INTEGRAL METHOD AND MACBETH APPROACH

(CHOQUET İNTEGRAL YÖNTEMİ VE MACBETH YAKLAŞIMIYLA ENDÜSTRİYEL ROBOT SEÇİMİ)

by

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The increasing use of robots at home, in manufacturing, and in almost every aspect of our daily lives, as well as the advancement of technology and the production of a wide range of robot numbers and types, constitute a major objectives. In a market with so many different types of robots, selecting the most suitable robots, particularly for industrial production facilities, is critical. Using the Choquet integral and MACBETH (Measuring Attractiveness by a Categorical Based Evaluation Technique), we designed a system for industrial robot selection based on the criteria we defined.

First of all and primarily, I'd like to express my gratitude to [redacted], who directed this master thesis, for the time he devoted to it, for the courage he gave me, and for his assistance throughout my studies. I am extremely grateful to him for all of his help and valuable ideas that guided me through this study.

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LIST OF SYMBOLS

MCDM	**:** Multi-Criteria Decision-Making
IR	: Industrial Robots
MACBETH	: Measuring Attractiveness by a Category-Based Evaluation Technique
AHP	**:** Analytical Hierarchal Process
ANP	**:** Analytical Network Process
IFR	**:** International Robotics Federation's
MADM	**:** Multi-Attribute Decision Making
$\boldsymbol{c}$	**:** Criteria
AI	: Artifical Intelligent
DM	: Desicion Maker

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ABSTRACT

In order to maintain or increase competitiveness, manufacturing productivity and flexibility must be improved in light of the increasing diversity of products and variants. The use of industrial robots (IR) is one suitable method of achieving the required productivity and flexibility in automation.

The term "robot" literally means laborious force. However, in a technical sense, industrial robots are distinguished from other automation devices and working machines. Nonetheless, there is some international ambiguity surrounding the term, as similar systems, such as manipulators or loading devices, are frequently counted as robots and included in statistics. This is because the mechanical structure of all such systems consists of a kinematic chain with a fixed part and an arm (or several arms) on which a wrist with a gripper or tool (e.g. welding torch) is mounted.

Considering that there are thousands, even millions, of industrial robots available, selecting the most appropriate and effective robot for use in an industry is critical. The primary aim of robot selection studies is to determine the best robot for a specific industry by comparing the robot's features in light of what the industry expects from the robot and comparing similar robots based on specific criteria. The different methods and criteria used in the studies were applied by experts as the most effective method and the most critical criteria.

In this study, we will build a Multi-Criteria Decision-Making (MCDM) system for industrial robot selection using the Choquet integral method and MACBETH approach. We used the Choquet integral and the MACBETH to show how the criteria interact with one another and to determine the significance of each factor in selecting the most efficient robot alternative.

RÉSUMÉ

Afin de maintenir ou d'accroître la compétitivité, la productivité et la flexibilité de la fabrication doivent être améliorées compte tenu de la diversité croissante des produits et des variantes. L'utilisation de robots industriels est une méthode appropriée pour atteindre la productivité et la flexibilité requises en matière d'automatisation.

Le terme "robot" signifie littéralement "force laborieuse". Toutefois, d'un point de vue technique, les robots industriels se distinguent des autres dispositifs d'automatisation et des machines de travail. Néanmoins, il existe une certaine ambiguïté internationale autour de ce terme, car des systèmes similaires, tels que des manipulateurs ou des dispositifs de chargement, sont fréquemment comptabilisés comme des robots et inclus dans les statistiques. En effet, la structure mécanique de tous ces systèmes consiste en une chaîne cinématique avec une partie fixe et un bras (ou plusieurs bras) sur lequel est monté un poignet avec une pince ou un outil (par exemple, une torche de soudage).

Étant donné qu'il existe des milliers, voire des millions, de robots industriels, il est essentiel de sélectionner le robot le plus approprié et le plus efficace pour une utilisation dans une industrie. L'objectif des études de sélection de robots est de déterminer le meilleur robot pour une industrie spécifique en comparant les caractéristiques du robot à la lumière des attentes de l'industrie vis-à-vis du robot et en comparant des robots similaires sur la base de critères spécifiques. Les différentes méthodes et critères utilisés dans les études ont été appliqués par les experts comme la méthode la plus efficace et les critères les plus critiques.

Dans cette étude, nous allons construire un système de prise de décision multicritères (MCDM) pour la sélection de robots industriels en utilisant la méthode intégrale de Choquet et l'approche MACBETH. Nous avons choisi la méthode intégrale de Choquet

et l'approche MACBETH pour démontrer l'interaction des critères entre eux ainsi que pour déterminer l'importance des critères dans la sélection de l'alternative de robot la plus efficace.

ÖZET

Rekabet gücünü korumak veya arttırmak için, artan ürün ve varyant çeşitliliği ışığında üretim verimliliği ve esnekliği geliştirilmelidir. Endüstriyel robotların kullanımı, otomasyonda gerekli esnekliği ve verimliliği elde etmenin uygun yöntemlerinden birisidir.

"Robot" terimi geldiği köken anlamıyla işçi gücü anlamı taşır. Ancak teknik anlamda endüstriyel robotlar diğer otomasyon cihazlarından ve çalışan makinelerden ayrılmaktadır. Bununla birlikte, manipülatörler veya yükleme cihazları gibi benzer sistemler sıklıkla robot olarak sayıldığından ve istatistiklere dahil edildiğinden, terimi çevreleyen bazı uluslararası belirsizlikler vardır. Bunun nedeni, bu tür tüm sistemlerin mekanik yapısının, sabit bir parçaya sahip bir kinematik zincir ve üzerine bir kavrayıcı veya alet (örneğin kaynak torcu) ile bir bilek monte edilmiş bir kol (veya birkaç kol) içermesidir.

Binlerce, hatta milyonlarca endüstriyel robot olduğu düşünüldüğünde, bir endüstride kullanım için en uygun ve etkili robotu seçmek çok önemlidir. Robot seçim çalışmalarının amacı, robotun özelliklerini, sektörün robottan beklentilerini ve benzer robotları belirli kriterlere göre karşılaştırarak belirli bir sektör için en iyi robotu belirlemektir. Çalışmalarda kullanılan farklı yöntem ve kriterler, uzmanlar tarafından en etkili yöntem ve en kritik kriter olarak uygulanmıştır.

Bu çalışmada Choquet integral yöntemini ve MACBETH yaklaşımını kullanarak endüstriyel robot seçimi için çok kriterli karar verme (MCDM) sistemi oluşturacağız. En uygun robot alternatifini seçerken kriterlerin birbirleri ile etkileşimini göstermek ve kriterlerin görece önemlerini belirlemek için Choquet integral yöntemini ve MACBETH yaklaşımını seçtik.

1. INTRODUCTION

The usage of robots in the logistics business, like in other areas, has dramatically grown as technology has advanced. This increase resulted in a decrease in labour use and costs while an increase in productivity. The expanded use of robotics has increased the number of businesses developing robots, and the kinds of robots created by manufacturing companies have begun to diversify.

The massive increase in robot use, as well as forecasting future of use, raises some questions and concerns. People's economic concerns naturally rise, such as what will happen to those who are replaced by robots, and will the unemployment rate skyrocket when there is almost no need for human labor. It should be emphasized that manpower will always be required, but the roles that people play in business will change. More software engineers, robot programmers, and maintenance technicians, for example, will be needed. If we keep up with technological advancements, technology will take our jobs, create new job opportunities, and make our lives easier, rather than causing us financial difficulties.

Robots are capable of performing repetitive, difficult, and dangerous tasks with high accuracy, and when used correctly, they can considerably increase efficiency and productivity. As a result, manufacturers continue to use robotics in various industrial applications where routine, complex, or dangerous activities must be done, such as material processing, assembling, finishing, machine filling, spray painting, welding, transportation, and delivery. Many businesses are implementing different robotics, automation, and information systems to boost profitability and productivity. A company's profitability and productivity can be improved by appropriately evaluating robots and choosing the most suitable one for a specific area.

According to the International Robotics Federation's (IFR) October 2021 report, there are more than 3 million robots in operation worldwide. Every country where manufacturing occurs, particularly developed countries, has begun to benefit from the use of robots rather than labor force. We must not ignore how important robots are for production, especially since Covid-19 entered our lives, and that the rate at which robot use will increase. Let us not forget that 'robots do not require masks, can be easily disinfected, and, of course, do not get sick!

In addition to increasing production speed and volume, the use of robots provides benefits such as improved production quality, reduced waste in the production line, more precisely meeting the expected production time, and safer production. The subject can be examined in greater depth by looking at the statistics generated as a result of these studies.

1.1 GETTING TO KNOW THE TERM ROBOT

Robots are reprogrammable mechanical structures that aim for maximum efficiency and minimum labor force. Czech playwright Karel Apek coined the term "robot" in his famous 1920 play R.U.R. (Rossumovi Univerzáln Roboti). In 1923, Rossum's Universal Robots was adapted for the English stage. Robotnik is a Czech term that translates as "forced laborer". They are named after the Slavic word "robota," which means "difficult work."

When we think of robots, we should not limit ourselves to physical mechanisms. Robots can also be software and artificial intelligence products. The most prominent examples of artificial intelligence, namely software robots, are brands that produce self-driving cars like Tesla, smart phones like Apple that interact with you through artificial intelligence, and block chain systems that enter our lives with cryptocurrencies. As a result, when we hear the term "robot," we should consider not only the mechanisms that have taken shape, but also all mechanisms that make our lives easier and provide high efficiency by minimizing human power. The focus of this research will be on industrial production line robots with payloads ranging from 12 to 20 kg.

1.2 HISTORY OF ROBOT

Robots are reprogrammable mechanical structures that aim for maximum efficiency and minimum labor force. Around 3000 B.C., Egyptian water clocks used human figurines to strike the hour bells. Archytus of Taremtum, the inventor of the pulley and screw, also invented a flying wooden pigeon in 400 B.C.

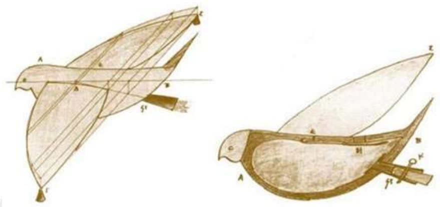

Figure 1.1 Wooden pigeon that could fly invented by Tarentum

George C. Devol, an inventor from Louisville, Kentucky, invented the first robots in the early 1950s. He invented and patented "Unimate," from "Universal Automation," a reprogrammable manipulator. He failed to sell his product in the industry for the next decade. In the late 1960s, businessman/engineer Joseph Engleberger bought Devol's robot patent and modified it into an industrial robot, forming Unimation to manufacture and market the robots. Engleberger is known in the industry as the "Father of Robotics" for his efforts and successes.

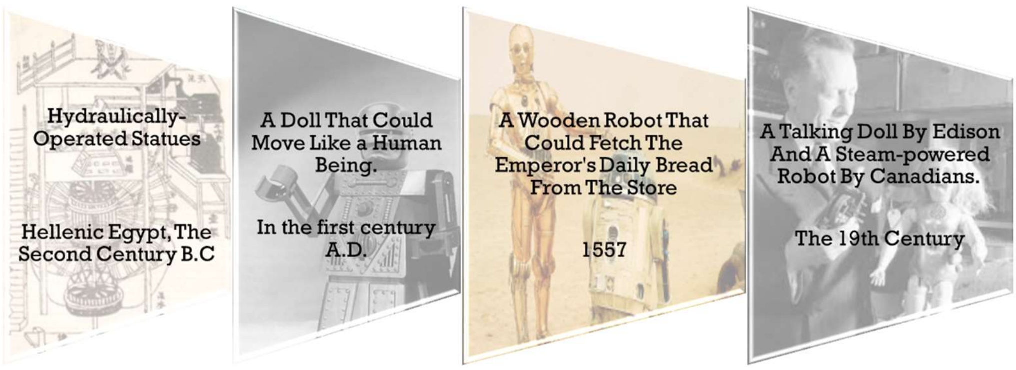

Figure 1.2 Historical development of robots

1.3 ROBOT TYPES

Generally, there are six types of robots:

1) AMRs

Autonomous Mobile Robots are any machine which can recognize and navigate its surroundings without the direct supervision of a human. This is typically accomplished through the use of advanced and powerful on-board detectors, computers, and maps.

2) Articulated Robots

They are described as rotary-jointed robots. In the robotics world, those certain joints are usually referred to as axes. They are as simple as two axes or as complex as ten or even more axes. Most industrial robots have six axes.

3) Humanoids

Humanoids are robots that are shaped like human bodies. The design could be for purposes, including such having to interact with human technologies and tools, unconventional purposes, such as studying bipedal locomotion, or other reasons.

4) Cobots

A cobot, or collaborative robot, is a robot designed for direct human-robot interaction within a shared space or in close proximity to humans and robots. Traditional industrial robot applications, wherein robots are isolated from human contact, contrast with cobot applications.

5) Hybrids

Robots of various types are frequently blended to create combination solutions capable of performing more complex tasks. An AMR, for example, could be merged with a robot to establish a robot capable of handling packages within a warehouse. As more feature is consolidated into required to fulfill, compute capabilities are consolidated as well.

6) Software bots

Software bots are simple or complicated computer software designed to do certain activities, such as automating repetitive chores or emulating human users. A computer bot, short for "robot," is nothing other than a piece (or parts) of code.

1.4 ROBOT SELECTION USING MCDM

When there are multiple options for robotic selection in terms of manufacturer and type of robot, a study should be prepared to determine the best robot selection using MCDM methods. Assume that three different companies manufacturer similar robots for a manufacturing facility. These three companies will sell the robots at varying prices based on their profit margins and costs. These robots will also differ in terms of many other criteria such as load capacity, velocity, and so on. While we understand that the most expensive is not always the best, we may be unsure whether what we require is the most expensive, even if it is the best. Even if these three companies try to produce the same type of robot in all with all their features, there will be at least one difference between them. This distinction can be based on cost, robot life cycle, ease of use, or other factors. At around this point, the best robot for a given expectation is selected using MCDM methods such as the Analytical Hierarchical Process (AHP), the Analytical Network Process (ANP), and TOPSIS. We will need some benchmarks when using these methods, such as cost, robot life cycle, ease of use, or else. These are referred to as criteria. According to the method to be used, numerical values are assigned to these criteria based on the comments received from experts, previous studies on the subject, and data obtained as a result of the experiments. The method is then used to determine a numerical order of importance, namely the robot preference order. When selecting a robot, the most appropriate one is chosen based on the results obtained in this context. In a market in which different manufacturers and different types of robots exist, companies place a high value on robot selection. The criteria used in the robot selection can vary depending on organization policies, and their relative significance in this sense can shift. This selection is more complex than it seems.

Many studies on robot selection have been conducted in this context, and each new study aims to make more effective and accurate choices than the previous ones. In this study, we will develop an effective and efficient multi-criteria industrial production robot selection mechanism by combining the Choquet integral method and the MACBETH approach within the parameters of the criteria we have established. We will be able to visualize the effect of the binary combinations of the criteria on robot selection using numerical data thanks to this selection mechanism. In the methodology section, these criteria will be mentioned and explained. We will investigate the effects of the criteria on each other in addition to determining their importance.

2. LITERATURE REVIEW

Given the wide range of robots available with varying features for a variety of applications, robot selection has become a critical task. The literature has presented MCDM techniques which allow decision-makers to examine some factors for the selection of alternatives based on their relative relevance.

Karsak created a robot selection choice model based on the deployment of a quality function and fuzzy regression (Karsak, 2007). This model may contain human demands as well as robot technical characteristics. In the study, robot attributes such as repeatability, velocity, load capacity, horizontal reach, and warranty term were employed to match customer expectations, while increased product quality, shorter cycle time, more production flexibility, cheaper cost, and vendor support were also used. Athawale, Chatterjee, and Chakraborty solve the robot selection issue to illustrate the advantages and applicability of the VIKOR approach (Narayanamoorthy et al., 2019). The VIKOR and ELELCTRE techniques are utilized with MCDM to solve a robot selection problem, and their respective performance is evaluated. Devi adapted the VIKOR approach to a triangle intuitionistic environment wherein the degree of options is evaluated. Ghorabaee presented the VIKOR approach for robot selection based on interval type-2 fuzzy numbers (Efe & Kurt 2021). The Spearman's correlation coefficient was used to evaluate the stability of the proposed approach. Liu, Ren, Wu, and Lin (Liu, H., Et al., 2014) employed the TOPSIS approach to tackle the robot selection problem.

Parameshwaran, Kumar, and Saravanakumar used the Fuzzy Delphi method to select the set of criteria for the educational purpose robot selection problem, and the fuzzy analytical hierarchy was used to calculate the weights of the criteria. Eventually, the alternatives were ranked using the fuzzy TOPSIS and fuzzy VIKOR methods.

Samantra, Datta, and Mahapatra provided a logical and systematic approach to the industrial robot selection problem by integrating the VIKOR method with interval-valued trapezoidal fuzzy numbers (Narayanamoorthy et al., 2019). Tansel, Yurdakul, and Dengiz proposed a two-phase ROBSEL technique based on a fuzzy analytic hierarchy approach, yielding a framework for robot selection challenges that reduces reliance on experts. For a specific industrial application, Koulouriotis and Ketipi devised a fuzzy digraph technique for robot evaluation and selection (Gul et al., 2016; Narayanamoorthy et al., 2019). All information concerning factual and subjective traits was conveyed in language words, with fuzzy numbers representing them. The process was completed by converting the fuzzy output to a crisp value and computing the selection index (Datta et al., 2016). Karsak formed an industrial robot selection decision model based on fuzzy linear regression (Karsak et al., 2011). When the connections are ambiguous on the data set does not meet the statistical regression assumptions, fuzzy linear regression was discovered as an alternative to statistical regression for modeling scenarios (Datta et al., 2016). Goh used the analytic hierarchy process (AHP), which takes both objective and subjective factors into account (Goh C-H, 1997).

Liang and Wang postulated a robot selection method based on fuzzy set theory and hierarchical structure analysis (Mahapatra et al., 2016). The method was used to aggregate decision-makers' fuzzy judgments of robot selection factor weightings and produce fuzzy appropriateness indices. The appropriateness ratings were then graded in order to select the best robot. The shortcomings of Liang and Wang's technique were highlighted by Chu and Lin, who suggested a fuzzy TOPSIS technique for robot selection (Kentli & Kar, 2011). Bhattacharya utilized a mixed AHP/QFD model to see if deploying robots in the workplace helps improve performance from a requirement standpoint (Bhattacharya et al., 2005). The research aided in the economic justification of the adoption of a robotic system in the manufacturing industry by incorporating a simple and unique cost factor measure in the proposed integrated AHP/QFD model. Technical needs were discovered first, followed by consumer requirements, using the above-mentioned integrated methodology. In this work, an integrated model integrating AHP and QFD was developed for the industrial robot selection method. Wang introduced a robot selection decision assistance system that uses a fuzzy set technique (Wang MJ et al., 1991; Mahapatra et al., 2016). The subjective variables were assessed using a fuzzy set membership function, whereas the objective factors were assessed using marginal value functions. Finally, the data from both assessments were combined to create a fuzzy set decision vector. The fuzzy approach offered, on the other hand, is more sophisticated and takes more computing. Xue created a linguistic MCDM model that incorporates hesitant linguistic word sets with an improved QUALIFLEX methodology for robot selection using incomplete criteria weight information (Yi-Xi Xue et al., 2016).

Gupta and Goel attempted to develop a complete approach for determining the viability of robotization for a given application (Gupta R & Goel DK, 1986). Offodile devised a scripting and classification system for recording robot features in a database, and then used economic modeling to select a robot (Offodile et al., 1986). Whereas the attempt will be advantageous in the final selection stage, it will be prohibitively expensive in the initial selection stage, where the number of possible robots is vast and many other factors must be considered (Rao, R.V., 2005). Parkash Garg and Sharma proposed a hybrid VIKOR-BWM method for selecting and evaluating sustainable outpouring partners (Garg CP & Sharma A., 2020).

Mokhtarzadeh prioritize twenty-three technology options for a high-tech company by finding their weights with the help of BWM (Mokhtarzadeh et al., 2018). Adakane and Narkhade provided a robot selection approach for powder coating activities that is based on three distinct MCDM approaches (AHP, TOPSIS, and PROMETHEE) (Adakane, R.V. & Narkhede, A.R., 2014). Bhangale stipulated a large number of robot selection criteria, rated the robots using TOPSIS and graphical approaches, and compared the rankings produced by these approaches (Bhangale et al., 2004). Graphs and matrices have been used as methods. Baker and Talluri pointed out some shortcomings in Khouja's basic radial efficiency ratings and recommended using cross-efficiency analysis for AMT selection (Karsak, 2012). Talluri and Yoon proposed a cone-ratio DEA strategy for robot selection that included prior knowledge about factor prioritization via weight restriction constraints (Baker, R.C. & Talluri, S., 1997; Talluri, S. & Yoon, K.P., 2000).

Table 2.1 : Distribution of the articles reviewed in the literature by years

Author(S)	Name of Article	Year	Method Used	Criteria Used
Gupta R. Goel DK.	Computer Aided Selection of Robots	1986	The Multiple Attribute Decision Making Approach	Load, Capacity, Repeatability, Velocity Ratio, Degree of Freedom
Offodile OF. Lambert BK. Dudek RA.	Development of a Computer Aided Robot Selection Procedure	1987	Min of Total Cost Utility Function Mathematical Algorithm	
Wang MJ. Singh HP. Huang WV	A Decision Support System for Robot Selection.	1991	Fuzzy Set MCDM	Purchase cost, Load capacity, Repeatability, Vendor’s service quality, Programming flexibility
Liang GH. Wang MJ	A Fuzzy Multi-Criteria Decision Making Approach for Robot Selection	1993	Fuzzy Logic MCDM	Man-machine interface, Programming flexibility, Vendor's service quality, Purchase cost, Load capacity, Positioning accuracy
Chon-Huat Goh	Goh C-H. Analytic Hierarchy Process for Robot Selection.	1996	Analytic Hierarchy Process	Performance, Cost, Quality
Baker, R.C. Talluri, S.	A Closer Look at the Use of Data Envelopment Analysis for Technology Selection	1997	Cross Efficiency Analysis	Cost, Load capacity, Velocity, Repeatability, Efficiency
Talluri, S. Yoon, K.P	A Cone-Ratio DEA Approach for AMT Justification.	2000	AMT- IDEF0	Cost, Repeat, Load, Velocity
Chu TC. Lin YC.	A Fuzzy TOPSIS Method for Robot Selection.	2003	Fuzzy MCDM TOPSIS	Man–machine interface, purchase cost, programming flexibility, load capacity, vendor’s service contract, positioning accuracy

Bhangale PP. Agrawal VP. Saha SK.	Attribute Based Specification, Comparison and Selection of a Robot.	2004	TOPSIS	Load capacity, repeatability, maximum speed, type of drives, memory capacity, manipulator reach, degree of freedom
Arijit Bhattacharya Bijan Sarkar Sanat Kumar Mukherjee	Integrating AHP with QFD for Robot Selection Under Requirement Perspective.	2005	AHP/QFD	Payload, Accuracy, Life-expectancy, Velocity of robot, Programming flexibility, Total cost
Ertuğrul Karsak	Robot Selection Using an Integrated Approach Based on Quality Function Deployment and Fuzzy Regression.	2008	QFD, Fuzzy Linear Regression	Load capacity, repeatability, vertical reach, horizontal reach, warranty period
Prasenjit Chatterjeea Vijay Manikrao Athawaleb Shankar Chakrabortya	Selection af Industrial Robots Using Compromise Ranking and Outranking Methods.	2010	MCDM/VIKOR-ELECTRE	Velocity, load capacity, cost, repeatability, vendor's service quality, programming flexibility
Chitrasen Samantra Saurav Datta Siba Sankar Mahapatra	Selection of Industrial Robot Using Interval-Valued Trapezoidal Fuzzy Numbers Set Combined With VIKOR Method	2011	VIKOR	Cost, velocity, repeatability, load capacity Man-machine interface, Programming flexibility,

E. Ertugrul Karsak Zeynep Sener Mehtap Dursun	Robot Selection Using a Fuzzy Regression-Based Decision-Making Approach	2012	Fuzzy Linear Regression	Cost, velocity, repeatability, load capacity
Hu-Chen Liu Ming-Lun Ren Jing Wu Qing-Lian Lin	An Interval 2-Tuple Linguistic MCDM Method for Robot Evaluation and Selection.	2013	ITL-TOPSIS	Man-machine interface, Programming flexibility, Vendor's service contract, Purchase cost, Load capacity, Positioning accuracy
Yusuf Tansel İç Mustafa Yurdakul Berna Dengiza	Development of a Decision Support System for Robot Selection.	2013	ROBSEL	Load capacity, Repeatability, Reach distances, S-Axis Motion range , U-Axis Motion range, B-Axis Motion range and T-Axis motion range
D. E. Koulouriotis M. K. Ketipi	Robot Evaluation and Selection PartA: An Integrated Review and Annotated Taxonomy	2014	RSP	

Adakane, R.V. Narkhede, A.R.	Multi Attribute Decision Making : A Tool for Robot Selection	2014	AHP-TOPSIS-PROMETHEE	Vertical reach , Horizontal reach , Pay lad capacity, Repeatability, Cost of Robot, Mass Of Robot and Speed of Robot
Mehdi Keshavarz Ghorabaee	Developing An MCDM Method for Robot Selection With Interval Type-2 Fuzzy Sets.	2016	VIKOR	Inconsistency with infrastructure, Man–machine interface, Programming flexibility, Vendor's service contract, Supporting channel partner's performance, Compliance, Stability
Yi-Xi Xue Jian-Xin You Xufeng Zhao & Hu-Chen Liu	An Integrated Linguistic MCDM Approach for Robot Evaluation and Selection with Incomplete Weight Information.	2016	Hesitant 2-Tuple Linguistic Term Sets/Extended QUALIFLEX	Man-machine interface, Programming flexibility, Vendor's service contract, Purchase cost, Load capacity, Positioning accuracy
Ajit Kumar Dharmender Kumar S.K. Jarial	A Hybrid Clustering Method Based on Improved Artificial Bee Colony and Fuzzy C-Means Algorithm.	2017	IABCFCM	The objective function, The F-measure, The error rate
Mokhtarzadeh N. Mahdiraji H. Beheshti M. Zavadskas E.	A Novel Hybrid Approach for Technology Selection in the Information Technology Industry Technologies.	2018	BWM-Henceforward TAOV	

Garg CP. Sharma A.	Sustainable Outsourcing Partner Selection and Evaluation Using an Integrated BWM-VIKOR Framework.	2020	BWM–VIKOR	Environmental factors, Social factors, Economic factors, and their sub-factors
Kavita Devi	Extension of VIKOR Method in Intuitionistic Fuzzy Environment for Robot Selection.	2021	VIKOR	Man–Machine interface, Programming flexibility, Vendor's service Contract, Purchase cost, Load capacity, Positioning accuracy

As can be seen, many studies have been conducted on the subject, and different MCDM methods have been used in the studies. The common purpose of these studies is to determine the important criteria in robot selection and to make the most effective choice with a correct methodology. The right choice will provide a great return on issues such as cost, efficiency and speed.

The information obtained from the literature review was used to select the criteria. Initial Purchase Cost, Repeatability, User Friendliness (Ease of Use), and Programming Flexibility were chosen because they are commonly used in similar studies in the literature. With the participation of expert opinions, these criteria were deemed important in robot selection. In addition to these, it was decided to use the Energy Consumption, which we had not seen in the literature but has become more important both in the long and short term, especially with recent energy increases.

3. METHODOLOGY

In this study, we develop a mechanism to select the most appropriate robot among six different branded robots with similar functions, within the five parameters of the robot selection criteria that we have established. We will also look at how the selection criteria interact with one another. Weights calculated independently of each other and weights obtained by considering their binary combinations will be applied separately and two rankings will be made. The effect of binary criteria combinations on ranking and performance score will thus be investigated.

Instead of TOPSIS, Fuzzy, and AHP methods, which are commonly used in current studies, we chose Choquet Integral and MACBETH approaches, which we believe will add originality to our work and result in successful robot selection mechanisms. These two techniques will be expressed mathematically in this section, along with the criteria to be used and a brief explanation of why these criteria are important.

3.1 THE CHOQUET INTEGRAL METHOD

The fuzzy integral is a method for determining the importance of a criterion as well as their interactions. A base significance value is required to define fuzzy integrals. These are the results of a fuzzy measurement. As a result, each attribute subset requires a significance value.

Definition 1. A monotonic set function is a fuzzy measure on X. $\mu: P(X) \mapsto [0,1]$ with $\mu(\emptyset) = 0, \mu(X) = 1$, and $A \subset B \subset X$ implies $\mu(A) \leq \mu(B)$.

Definition 2. Let μ be a fuzzy measure on X. The Choquet integral of a function $f: X \mapsto [0,1]$ in relation to μ is defined as

$$C_\mu\big(f(x_1), \dots, f(x_n)\big) := \sum_{i=1}^{n} \Big(f\big(x_{(i)}\big) - f\big(x_{(i-1)}\big)\Big)\, \mu(A(i)) \tag{3.1}$$

where (i) indicates that the indices have been permuted in such a way that $0 \leq f\left(x_{(1)}\right) \leq \cdots \leq f\left(x_{(n)}\right) \leq 1, A(i) := \{x(i), \ldots, x(n)\}$, and $f(x(0)) = 0$.

Definition 3. Let μ be a fuzzy measure on X. The Shapley value or importance index for each $i \in X$ is defined as

$$\Phi_i = \sum_{A \subset X - i} \frac{(n - |A| - 1)!\,|A|!}{n!} [\mu(A \cup \{i\}) - \mu(A)] \tag{3.2}$$

where $|A|$ represents A's cardinal and the Shapley value of and the Shapley value of μ is the vector $\Phi(\mu) = [\Phi_1, \Phi_2, \ldots, \Phi_n]$. The Shapley values have the estate as

$$\textstyle\sum_{i=1}^{n} \Phi_i = \mu(X).$$

When dealing with n criteria necessitates the use of 2^n coefficients in $[0,1]$ identify the fuzzy measure on each subset is required, culminating in a time-consuming process of obtaining vast amounts of information from an expert. To address this issue, the concept of k-order fuzzy measure has been proposed, which has been proposed to rectify this difficulty, which represents a k-order approximation of the polynomial expression of a fuzzy measure in the vicinity of the origin. The k-order fuzzy measure can be represented by at most $\sum_{i=1}^{k} \binom{n}{i}$ coefficients. The 2 order fuzzy measure, which has only quadratic complexity, requires only $n + \binom{n}{2}$ coefficients to define the fuzzy measure for a problem involving n criteria. Throughout this paper, we assume that interaction between more than two criteria does not exist, so the model is limited to the

2-order case to reduce computational burden. In this case, the Choquet integral is as follows:

$$C_{\mu}(x) = \sum_{i \in N} a(i)x_i + \sum \ \{i,j\} \subseteq N^{a}(ij)\left(x_i \wedge x_j\right),\ x \in \Re^{n} \tag{3.3}$$

A linear program can be used to solve the problem of finding a 2-order fuzzy measure. The model used in this paper for identifying weights of the selection criteria is expressed in terms of the Möbius representation as follows:

$$m\, z = \varepsilon \tag{3.4}$$

subject to

where A represents the set of alternatives, N represents the set of criteria, $\geq_A$ signifies preferences over the alternatives, z_{ki} reflects the normalized value of the k th alternative on the i th criteria, and δ is a fixed preference threshold (Karsak, 2005).

3.2 MACBETH APPROACH

MACBETH is a multi-criteria value calculation decision-aid method. The main objective of the conceptualization is to enable measurement of option attractiveness or value via a non-numerical pairwise comparison questioning mode based on seven qualitative attractiveness difference categories: is there no difference (indifference), or is the difference very weak, weak, moderate, strong, very strong, or extreme? (Keeney, R.L. & Raiffa, H., 1976).

MACBETH assists in option evaluation by providing a qualitative representation in terms of attractiveness preferences. The method facilitates the development of a quantitative scale based on qualitative data about attractiveness. As a result, explaining the same to decision-makers is simple, as is explaining preferences (Roubens et al., 2006).

Table 3.1: The level of semantic attraction

Category	Semantic Judgment	Quantitative Expression
$-$	No Attribute Distinction	0
$C1$	Very Weak Attribute Distinction	1
$C2$	Weak Attribute Distinction	2
$C3$	Moderate Attribute Distinction	3
$C4$	Strong Attribute Distinction	4
$C5$	Very Strong Attribute Distinction	5
$C6$	Extreme Attribute Distinction	6

To ordinarily measure the attractiveness of options "x" from a finite set "X," Naciff de Andrade et al. (2016) state that a real number v(x) must be assigned to each "x" that meets the stricter preference and indifference conditions (Silva et al., 2018).

$$x, y \in X: xPy \Leftrightarrow v(x) > v(y) \tag{3.5}$$

$$x, y \in X: xIy \Leftrightarrow v(x) = v(y) \tag{3.6}$$

where: P - preference and I - indifference.

$w, x, y, z \in X$ with x more appealing than y and w more appealing than z : As a result, the quotient $(v(x) - v(y))/(v(w) - v(z))$ measures the desirability difference between x and y when the unit of measure is the attractiveness difference between w and z.

In accordance with these conditions, a numerical scale of intervals is established ($v : X \to R: x \to v(x)$). At MACBETH, ordinal information is converted to cardinal information by qualitatively comparing options in pairs.

3.3 CRITERIA

When making the decision between several options, we need some criteria to make comparisons. We will discuss the criteria which we will use for robot selection, as well as why they are important, under this heading. To develop our criteria, we drew on the expertise of industry experts, previous studies, and our own research. In our numerical application, we will process these criteria using the methods described above. This is referred to as MCDM research. The objective is to identify the most useful, convenient, or best alternative. There are various approaches to the subject, as evidenced by the literature review, but the goal is always the same.

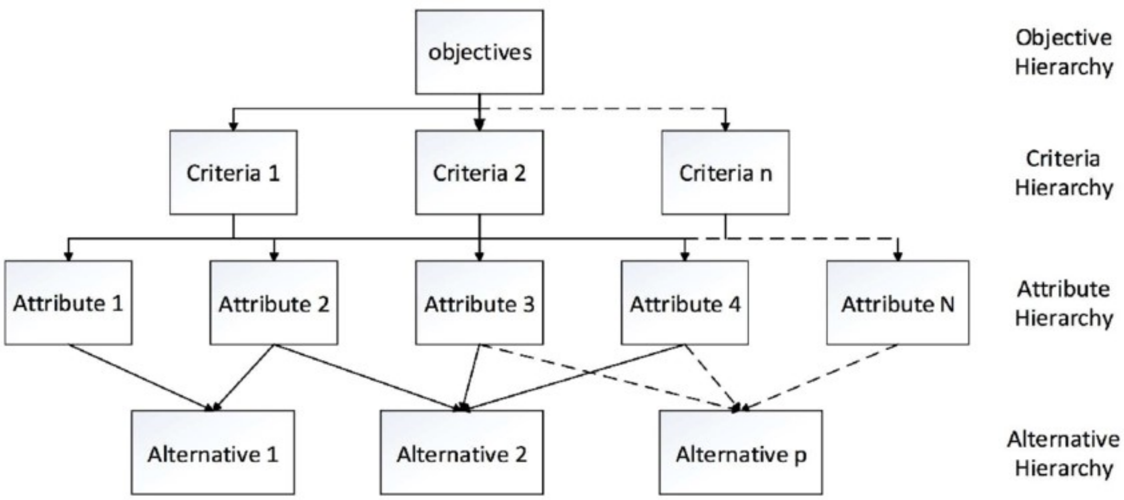

Figure 3.1: The structure of the MCDM hierarchy

There are multiple MCDM methods available here. Although these are separate in terms of operation, the result is again aimed at determining more than one alternative within the threshold of a certain ranking or priority-superiority value. Simply see below how some of these methods are grouped.

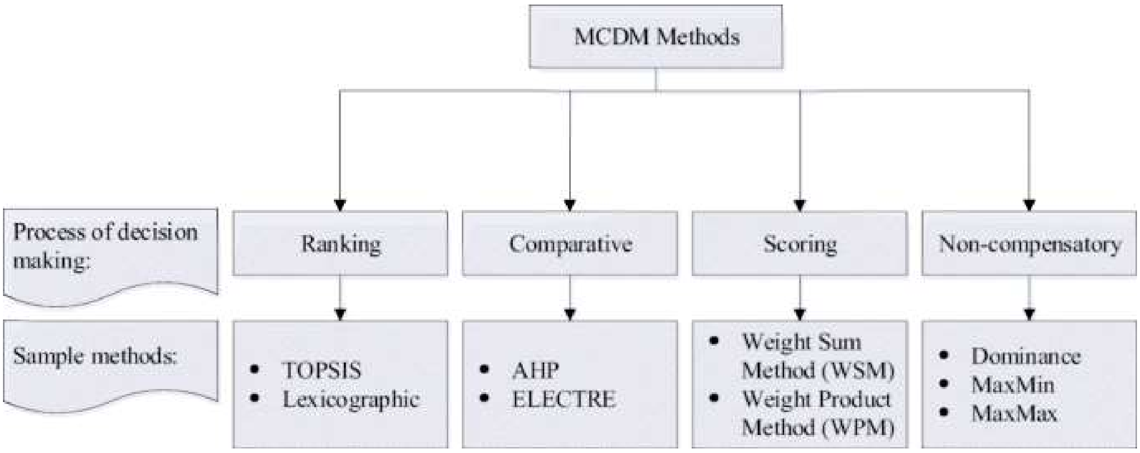

Figure 3.2: MCDM methods grouping

From now on, the abbreviation c will be used for criteria, and ci will indicate the ith criterion.

$c1$ Initial Purchase Cost

For the majority of businesses, one of the most important criteria is the purchase price. Robots, like most consumer goods, appear more appealing when purchased at a lower price. High initial purchase fees, particularly for small and medium-sized businesses, can be vexing. It should be noted that lower-cost robots may incur additional costs in the long run. It is important to remember that robots and other low-cost consumer products should be evaluated alongside other cost-affecting criteria to determine whether they are truly cost-effective.

As a direct consequence, “cheaper” may tend to come with a lower price and a higher cost. Expensive” may tend to come with a higher price and a lower cost.

$c2$ Energy Consumption

We revealed that previous multi-criteria robot selection studies almost never considered energy (electricity) consumption as a criterion. In these days of rising energy prices, which have recently created a significant economic burden, robots that use less electricity play an important role for businesses. Robots that are less expensive but consume more electricity will almost certainly cost more in the long run. Obviously, we cannot claim that higher-priced robots use less electricity than lower-priced robots. When the purchase price and the cost of energy consumption are combined, a more reasonable robot choice is made. We have included this criterion for use in our research because it is consistent with our beliefs.

On a per-unit basis, industrial and manufacturing robots consume an average of over 21,000 kWh per year. Using electricity prices in Germany as a reference, we can see that prices have increased fourfold in the last two years. During this period of price increases, robots with lower electricity consumption will undoubtedly save money. Saving money is a desirable behavior regardless of the size of the company. Over this, the cost of electricity consumption should be considered as a robot selection criterion.

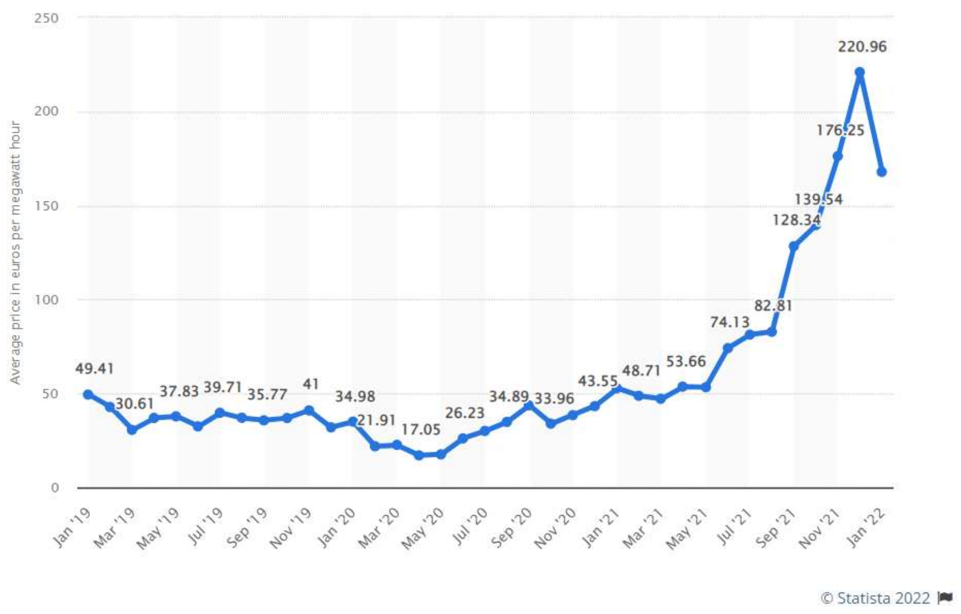

Figure3.3: Increase in energy prices in Germany over the last two years

$c3$ Repeatability (Accuracy and Precision)

Precision refers to how near a calculated value is to the true worth, whereas accuracy refers to how close the measured values are to each other. The calibration of measuring instruments determines accuracy specifically. The smaller the margin of error and the more accurate the instrument, the better calibrated they are. Precision relies heavily on repeatability. That is, how regularly a number of measures or behavior are repeated whenever similar instruments and conditions are used.

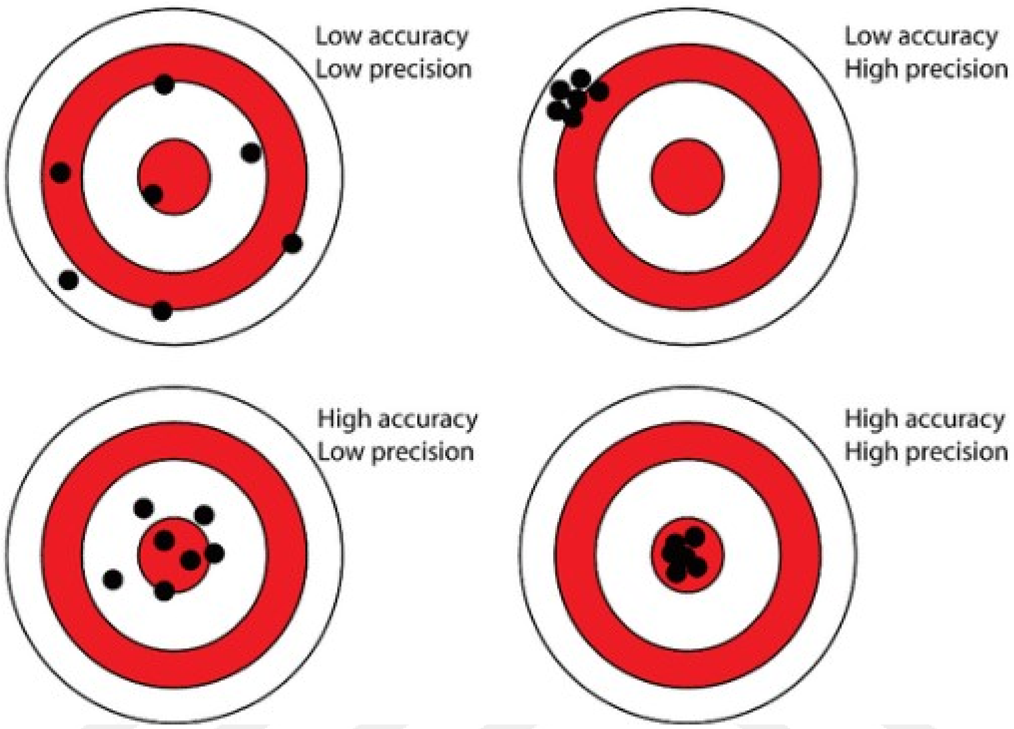

Figure 3.4: Accuracy and precision and their difference

Kinematic parameter errors and joint flex deformation are two factors that affect industrial robot positioning accuracy and precision. The positioning accuracy and precision of conventional robots are typically in the range of one to several millimeters, which is insufficient to meet the high precision requirements. Despite recent improvements in industrial robot positioning accuracy as a result of design and control approaches, achieving the required accuracy remains difficult for a variety of reasons. However, research into this subject is ongoing.

It is important to remember that the goal of using robots is to achieve accuracy, speed, and precision. Robots are expected to prevent human errors in production and to perform the same tasks repeatedly and correctly. Accuracy and precision are important criteria to consider when selecting a more efficient, accurate, and precise robot.

$c4$ User Friendliness (Ease of Use)

Robots are important not only for what they can do, but also for how quickly and easily they can do it. Keep in mind that robot users are not always expert users or robot programmers. Users who are unfamiliar with robots and their applications may rely heavily on robots. At this point, simple-to-use robots with an easy-to-understand interface will be the preferred option

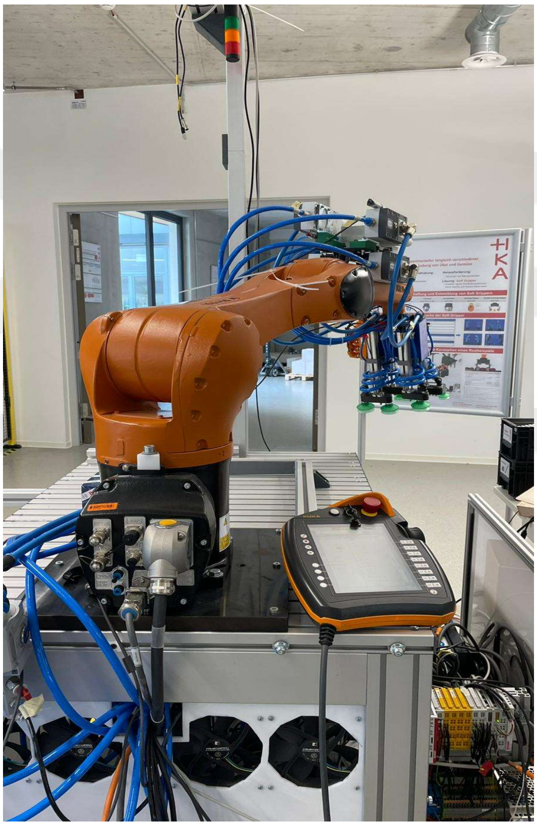

Figure 3.5: Hochschule Karlsruhe robotic laboratory

$c5$ Programming Flexibility

We examined the programming flexibility criterion in two contexts. When a different product is switched in production, the first advantage is the ease with which a different product can be produced by writing a new program for the same robot. As a result, businesses will be able to use their robots for a variety of production purposes. Avoiding the purchase of a new robot will undoubtedly save time and money.

The second point of view is the flexibility and ease of integration in terms of the programming languages used. Assume that for the time being, a robot built today is only equipped with a programming language. This will not only prevent interaction with new programming in the coming years, but it will also limit the programmer's options. Given that there are fewer specialists in that language, this could result in a higher labor cost.

3.4 EXPLANATION OF IMPLEMENTATION OF METHODOLOGY

The goal is to choose the most convenient robot from among six different robot alternatives using the five criteria specified in the previous section and to display the effect of criteria binary combination on performance score of alternative robots. Our study will consist of two applications and a comparison of their results. The weights obtained without considering the binary criteria combinations will be used as criterion weights in the first application, and the weights obtained by considering the binary criteria combinations will be used in the second application.

First and foremost, the decision makers will weigh the relative importance/superiority of the criteria. They will then assess the relative importance degrees and superiority of binary criterion combinations. At this point, six experts will meet, and the values will be determined by the experts' collective decisions. Following this grading and ranking process, the MACBETH approach steps will be taken, and the weight of each criterion and binary combination will be calculated.

The weights obtained by the MACBETH approach will be used in the Choquet integral method as second step. Before using the Choquet integral, numerical data for each criterion for each of the six robots will be collected. Furthermore, a ranking will be found using the weights obtained by considering the binary combinations of the criteria in the same selection mechanism. The findings of these two studies will be compared, and the effects of combining binary criteria will be investigated and discussed.

In this data collection process, robot manufactures, experts, and companies that work and/or have worked with those robots were used.

The experts will be informed of the selection order obtained after obtaining the methodology's overall rankings. Based on the selection process, it will be discussed whether the robot considered to be the most suitable as a result of the application is preferred relatively in real life. This is because, for a variety of reasons, some robots that appear to be the best fit in theory may not be the best choice in practice.

I'd like to provide some background on our six experts, who contributed their knowledge and experience from the beginning to the end of the study. I will only mention their current jobs because they prefer to remain anonymous.

Expert 1. Former KUKA robotics manager. He resigned from his position after the Chinese purchased the KUKA brand and is now retired.

Expert 2. Head of the Robotics and Artificial Intelligence Department at Hochschule Karlsruhe.

Expert 3. ABB robotics robotic programmer expert

Expert 4. Hochschule Karlsruhe Robotics and AI department software support team engineer.

Expert 5. Hochschule Karlsruhe Robotics and AI division software support team engineer.

Expert 6. Fanuc robotics purchasing engineer.

3.4.1 Explanation of Implementation of the MACBETH Approach

The MACBETH approach's main goal is to convert qualitative data collected from decision makers (DM) into quantitative data. The plot of MACBETH is built around a series of criteria comparisons. This method promotes collaborative problem solving and prioritizes the preferred option. Furthermore, when ordering the alternatives, it allows for individual and group evaluations of the outcomes (Costa et al. 2008).

The methodology is composed of 4 steps (Burgazoğlu 2015: 260):

Step 1. Basic Expression of Performance

The first process is to get a preferred option from the possible choices. The experts decide the preference strengths after having to follow the preference perseverance.

Let a_j and a_l represent different alternative j and alternative l respectively. Let x_i^j and x_i^l be performance values for criterion i of alternative j and alternative l, respectively. Let h denote the preference strength, with a value ranging from 0 to 6 (null, very weak, weak, moderate, strong, very strong, and extreme). Then, if the experts for criterion i prefers a_j to a_l with strength h then $a_j \succ^h a_l \Leftrightarrow x_i^j - x_i^l = h\alpha$ where α is a coefficient necessary to meet the condition $x_i^j, x_i^l \in [0,1]$. If the decision maker is indifferent (null) between the situations, then $a_j \approx a_l \Leftrightarrow x_i^j = x_i^l$.

The performance forms are measured by solving the equation culminating from all the preferential strengths h between a_j and a_l, which is written as $x_i^j - x_i^l = h\alpha$. To demonstrate the procedure briefly, a numerical example is used.

Consider the alternatives a_1, a_2, a_3 with the succeeding preference and strength: $a_{\text{good}} \succ^{\text{strong}} a_3 \succ^{\text{very strong}} a_2 \succ^{\text{moderate}} a_1 \succ^{\text{week}} a_{\text{neutral}}$. Then, in order to find $hrm\ x_i$, The following equation system must be solved:

$$
\begin{aligned}
x_i^{\text{good}} - x_i^3 = \quad & 1 - x_i^3 = 4\alpha \\
& x_i^3 - x_i^2 = 5\alpha \\
& x_i^2 - x_i^1 = 3\alpha \\
x_i^1 - x_i^{\text{neutral}} = \quad & x_i^1 - 0 = 2\alpha
\end{aligned}
\tag{3.7}
$$

Using any standard method for resolving a system of equations, we have: $x_i^1 = 0.1429, x_i^2 = 0.3571, x_i^3 = 0.714$, and $\alpha = 0.071$.

This operation defines the elementary performance scores on the interval in a proportional manner [0, 1].

Step 2. Determination of Weights

A pairwise comparison of the characteristic situations is required in MACBETH. Each comparison generates an equation, which can be written as follows:

$$x_{\mathrm{Ag}}^{i} - x_{\mathrm{Ag}}^{g} = h\alpha = w_i - w_{g.} \tag{3.8}$$

As a result, we have a set of n distinct equations. As a result, in order to identify the criteria weights, the DM must provide n relations.

Example: Consider three criteria (c_1, c_2, c_3) and c_0 a state of neutrality. The DMs rank the multiple possibilities and then convey their preferences in the following manner:

$$c_3 \succ^{\text{strong}} c_1 \succ^{\text{weak}} c_2 \succ^{\text{very weak}} c_0$$

Using the strength of preference h as an absolute value, we can write the following system (Cliville, V., 2007):

$$\begin{gathered} x_{\mathrm{Ag}}^{3} - x_{\mathrm{Ag}}^{1} = 5\alpha = w_3 - w1, \\ x_{\mathrm{Ag}}^{3} - x_{\mathrm{Ag}}^{1} = 5\alpha = w_3 - w1, \\ x_{\mathrm{Ag}}^{2} - x_{\mathrm{Ag}}^{0} = \alpha = w_2, \\ w1 + w2 + w3 = 1. \end{gathered} \tag{3.9}$$

When we solve this system of equations, we get: $w_1 = 0.25, w_2 = 0.08, w_3 = 0.67$, and $\alpha = 0.083$.

Step 3. Extensions to the 2-Additive Choquet Integral by MACBETH

The following formulation gives the aggregation formula of the performance expression for the 2-additive Choquet Integral:

$$x_{\mathrm{Ag}}^{l} = \sum_{j=1}^{n} w_j x_j^l - \frac{1}{2}\sum_{j=1}^{n} u_{jk}\left|x_j^l - x_k^l\right|. \tag{3.10}$$

Example: Let c_l and (c_l, c_k) be criterion l and interaction between criterion l and criterion $k(l \neq k)$, respectively$(l, k = 1,2,3)$. Consider the following order and strengths of preferences (Szedlak-Stinean et al., 2018):

$$(c_2, c_3) \succ^4 (c_1, c_2) \succ^1 (c_1, c_3) \succ^2 c_2 \succ^2 c_3 \succ^4 c_1 \succ^2 c_0$$

Then we must solve the following system of equations:

$$\begin{aligned}
\left[w_2 + w_3 - \frac{1}{2}(u_{12} + u_{13})\right] - \left[w_1 + w_2 - \frac{1}{2}(u_{13} + u_{23})\right] &= 4\alpha \\
\left[w_1 + w_2 - \frac{1}{2}(u_{13} + u_{23})\right] - \left[w_1 + w_3 - \frac{1}{2}(u_{12} + u_{23})\right] &= \alpha \\
\left[w_1 + w_3 - \tfrac{1}{2}(u_{12} + u_{23})\right] - \left[w_2 - \tfrac{1}{2}(u_{12} + u_{23})\right] &= 2\alpha \\
\left[w_2 - \frac{1}{2}(u_{12} + u_{23})\right] - \left[w_3 - \frac{1}{2}(u_{13} + u_{23})\right] &= 2\alpha \\
\left[w_3 - \frac{1}{2}(u_{13} + u_{23})\right] - \left[w_1 - \frac{1}{2}(u_{12} + u_{13})\right] &= 4\alpha \\
\left[w_1 - \frac{1}{2}(u_{12} + u_{13})\right] - 0 &= 2\alpha \\
w_1 + w_2 + w_3 &= 1
\end{aligned} \tag{3.11}$$

which can be shortened to:

$$\begin{gathered}
-w_1 + w_3 - \frac{1}{2}(u_{12} - u_{23}) = 4\alpha \\
w_2 - w_3 - \frac{1}{2}(-u_{12} + u_{13}) = \alpha \\
w_1 - w_2 + w_3 = 2\alpha \\
w_2 - w_3 - \tfrac{1}{2}(u_{12} - u_{13}) = 2\alpha \\
-w_1 - w_3 - \frac{1}{2}(-u_{12} + u_{23}) = 4\alpha \\
w_1 - \frac{1}{2}(u_{12} + u_{13}) = 2\alpha \\
w_1 + w_2 + w_3 = 1
\end{gathered} \tag{3.12}$$

When we solve this system of equations, we get: criterion weights $w_1 = 0.18, w_2 = 0.45$, $w_3 = 0.37$, and interactions $u_{12} = 0.05, u_{13} = 0.1, u_{23} = 0.05$ and $\alpha = 0.05$.

Step 4. Explanation of the Findings

Assume that, according to the Choquet integral in equation 3.7, the alternative a_s is the best is ranked as the best one; i.e., $C_\mu^s \geq C_\mu^j$ for all $j = 1, \ldots, m$. as the sum of marginal contributions (Rogna, 2019). C_μ^s must first be reformulated as the sum of marginal contributions in order to provide absolute and relative explanations for why a_s has such a rank. (Büyüközkan et al. (2003); Akharraz, 2002):

$$\begin{aligned} C_\mu^s &= \left(\mu_{[1]}^s - \mu_{[2]}^s\right)x_{[1]}^s + \cdots + \left(\mu_{[i]}^s - \mu_{[i+1]}^s\right)x_{[i]}^s + \cdots + \mu_{[n]}^s x_{[n]}^s \\ &= \sum_{i=1}^{n} \Delta\mu_{[i]}^s x_{[i]}^s \end{aligned} \tag{3.13}$$

where $\mu_{[i]}^s = \mu\left(\mathcal{N}_{[i]}^s\right), \mu_{[n+1]}^s = 0$, and $\Delta\mu_{[i]}^s = \mu_{[i]}^s - \mu_{[i+1]}^s$. Given that $\mathcal{N}_{[i]}^s \supseteq \mathcal{N}_{[i+1]}^s$ and the measure μ meets the requirement for monotonicity, we have $\Delta\mu_{[i]}^s \geq 0$ for $i = 1, \ldots, n$. We can deduce that through simple manipulations

$$\sum_{i=1}^{n} \Delta\mu_{[i]}^s = \sum_{i=1}^{n} \left(\mu_{[i]}^s - \mu_{[i+1]}^s\right) = \mu_{[1]}^s - \mu_{[n+1]}^s = 1 - 0 = 1 \tag{3.14}$$

We refer to the term $\Delta\mu_{[k]}^s x_{[k]}^s$ as the criterion's absolute potential $c_{[k]}$. We could indeed purely reorder the terms in equation 3.11 so that

$$\Delta\mu_{[k]}^s x_{[k]}^s \geq \Delta\mu_{[k+1]}^s x_{[k+1]}^s,\ k = 1, \ldots, n-1 \tag{3.15}$$

The absolute contributions of the scores, $\Delta\mu_{[k]}^s x_{[k]}^s, k = 1, \ldots, n$, can then be ranked with regard to the values of the $\Delta\mu_{[k]}^s x_{[k]}^s / \Delta\mu_{[1]}^s x_{[1]}^s$ ratio. The fairly close this ratio is to one, the greater the contribution of criterion $c_{[k]}$, and the more $c_{[k]}$ represents a crucial dimension in the decision-making process. In the particular instance of 2 -additive fuzzy measure, the expression $\Delta\mu_{[i]}^5$ in equation 3.9 becomes as

$$\Delta\mu_{[i]}^s = w_{[i]} + \tfrac{1}{2}\textstyle\sum_{k>i} u_{[i][k]} - \tfrac{1}{2}\textstyle\sum_{k<i} u_{[k][i]} \tag{3.16}$$

where $w_{[i]}$ is the relative importance of criterion $c_{[i]}$ and $u_{[i][k]}$ is the relationship between criteria $c_{[i]}$ and $c_{[k]}$ (Berrah et al., 2008).

The following equation is used to calculate how much each criterion has influenced to prefer a_s over a_j:

$$\Delta C_{\mu}^{sj} = \Delta C_{\mu}(\mathbf{x}^s, \mathbf{x}^j) = C_{\mu}^{s} - C_{\mu}^{j} = \sum_{i=1}^{n} R_i^{sj},\ a_s, a_j \in A, s \neq j \tag{3.17}$$

where $R_i^{sj} = \Delta\mu_{[i]}^{s} x_{[i]}^{s} - \Delta\mu_{[i]}^{j} x_{[i]}^{j}$. Similar to C_{μ}^{s}, ΔC_{μ}^{sj} is defined as the sum of individual relative potentials R_i^{sj}, which can be expressed as the sum of absolute potentials in equation 3.11.

3.4.2 Explanation of Implementation of the Choquet Integral

The methodology is composed of eight steps (Tsai & Lu, 2006; Kahraman et al., 2013):

Step 1. In responding to criterion i.respondents' linguistic preferences for the degree of importance, perceived performance levels of alternative robots, and tolerance zone are surveyed.

Step 2. Because of their compatibility with perceived performance levels and the tolerance zone, trapezoidal fuzzy numbers are used to quantify all linguistic terms in this study. The linguistic terms for the degree of importance are parameterized by given a respondent t and a set of criteria I.

$\tilde{Z}_i^t = (z_{i1}^t, z_{i2}^t, z_{i3}^t, z_{i4}^t)$, perceived performance levels by $\tilde{r}_i^t = (r_{i1}^t, r_{i2}^t, r_{i3}^t, r_{i4}^t)$, and the tolerance zone by $\tilde{e}_i^t = (e_{i1L}^t, e_{i2L}^t, e_{i3U}^t, e_{i4U}^t)$. In this case study $t = 1, \ldots, 5, i = 1, 2, \ldots\ldots, n_j, j = 1, \ldots, 6$; $n_1 = 3,\ n_2 = 3,\ n_3 = 4$; $n_4 = 3$; $n_5 = 3$; $n_6 = 4$; where n_j is the number of criteria in dimension is represented j (Demirel et al., 2017).

Step 3. Average $\tilde{A}_i^t, \tilde{p}_i^t$ and $\tilde{e}_i^t$ into $\tilde{A}_i$, and $\bar{e}_i$, using the following equation:

$$\tilde{A}_i = \frac{\sum_{t=1}^{k} \tilde{A}_i^t}{k} = \left(\frac{\sum_{t=1}^{k} a_{i1}^t}{k}, \frac{\sum_{t=1}^{k} a_{i2}^t}{k}, \frac{\sum_{t=1}^{k} a_{i3}^t}{k}, \frac{\sum_{t=1}^{k} a_{i4}^t}{k}\right) \tag{3.18}$$

Step 4. Using the formula below, normalize the importance factor of each criterion:

$$\tilde{f}_i == \|_{\alpha\in[0,1]} \bar{f}_i^{\alpha} = \|_{\alpha\in[0,1]} \left[f_{i,\alpha}^{-}, f_{i,\alpha}^{+}\right] \tag{3.19}$$

where $f_i \in F(S)$ is a fuzzy-valued function. $\tilde{F}(S)$ is the set of all fuzzy-valued functions $f, f_i^{\alpha} = \left[f_{i,\alpha}^{-}, f_{i,\alpha}^{+}\right] = \frac{\bar{p}_i^{x} - \bar{e}_i^{\alpha} + [1,1]}{2}, \bar{p}_i^{\alpha}$ and $\bar{e}_i^{\alpha}$ are α-level cuts of $\tilde{p}_i$ and $\tilde{e}_i$ for all $\alpha = [0,1]$.

Step 5. Using the equation below, calculate the robot importance factor of dimension j:

$$(\mathrm{C})\int \tilde{f} d\tilde{g} = \|_{\alpha=[0,1]} \left[(C)\int f_{\alpha}^{-} dg_{\alpha}^{-}, (C)\int f_{\alpha}^{+} dg_{\alpha}^{+}\right] \tag{3.20}$$

where $\bar{g}_i: P(S) \to I(R^{+}), \bar{g}_i = [g_i^{-}, g_i^{+}], \bar{g}_i^{\alpha} = \left[g_{i,\alpha}^{-}, g_{i,\alpha}^{+}\right], \bar{f}_i: S \to I(R^{+})$, and $f_i = [f_i^{-}, f_i^{+}]$for $i = 1,2,3, \dots, n_j$.

A λ value and the fuzzy measures $g\left(A_{(i)}\right), i = 1,2, \dots, n$, are needed. These are obtained from the following equations (Sugeno, 1974; Ishii & Sugeno, 1985):

$$g\left(A_{(n)}\right) = g\left(\{s_{(n)}\}\right) = g_{n}, \tag{3.21}$$

$$g\left(A_{(i)}\right) = g_i + g\left(A_{(i+1)}\right) + \lambda g_i g\left(A_{(i+1)}\right), \tag{3.22}$$

where $1 \leqslant i < n$,

where

$$1 = g(S) = \begin{cases} 1/\lambda\{\prod_{i=1}^{n} [1 + \lambda g(A_i)] - 1\} & \text{if } \lambda \neq 0 \\ \sum_{i=1}^{n} g(A_i) & \text{if } \lambda = 0 \end{cases} \tag{3.23}$$

where, $A_i \cap A_j = \phi$ for all $i, j = 1,2,3, \dots, n$ and $i \neq j$, and $\lambda \in (-1, \infty]$.

Let μ be a fuzzy measure on $(I, P(I))$ and an application $f: I \to \mathfrak{R}^{+}$. The Choquet integral of f with respect to μ is defined by:

$$(C) \int \_1 f d\mu = \sum\_(i = 1)\^n (f(\sigma(i)) - f(\sigma(i-1)))\mu(A\_((i))) \tag{3.24}$$

where σ is a permutation of the indices that results in $f(\sigma(1)) \leqslant \cdots \leqslant f(\sigma(n)), A_{(i)} = \{\sigma(i), \ldots, \sigma(n)\}$ and $\times f(\sigma(0)) = 0$, by convention.

Until the indices are reordered, the Choquet integral is obviously a Lebesgue integral. The Choquet integral is lowered to a Lebesgue integral if the fuzzy measure μ is additive. Modave and Grabisch (1998) demonstrate that, under rather general assumptions about the set of alternatives X and the weak orders orders $\succeq_i$, there exists a unique fuzzy measure over I such as:

$$\forall x, y \in X,\ x \succeq y \Leftrightarrow u(x) \geqslant u(y), \tag{3.25}$$

where

$$\mathrm{u}(x) = \sum_{i=1}^{n} \left[u_{(i)}\left(x_{(i)}\right) - u_{(i-1)}\left(x_{(i-1)}\right)\right]\mu\left(A_{(i)}\right), \tag{3.26}$$

which is purely the accumulation of the mono-dimensional utility functions with respect to μ using the Choquet integral.

Step 6. Using a hierarchical process based on the two-stage aggregation process of the generalized Choquet integral, aggregate all dimensional performance of the robot alternatives into cumulative performance. This is illustrated in equation 3.16. The overall performance is represented by the fuzzy number $\tilde{V}$ (Ozkır et al., 2015).

$maincriterion_{\ (1)} = (C)\int f dg$

$$\rangle V = (C) \int \text{maincriterion}\ dg \tag{3.27}$$

$maincriterion_{\ (m)} = (C)\int f dg$

Step 7. Presume that the participation of $\tilde{V}$ is $\mu_{\tilde{V}}(x)$; using equation 3.17, the fuzzy set $\tilde{V}$ into a sharp value v and correlate the maximum performance of alternative robots.

$$F(\tilde{A}) = \frac{a_1 + a_2 + a_3 + a_4}{4}. \tag{3.28}$$

Step 8. Using equations, compare the robot alternatives' weak and advantageous criteria. (7)

4. NUMERICAL APLICATION

4.1 APPLICATION AND FINDINGS

The criteria and their binary combinations are ranked in order of importance from most important to least important, at the threshold of the six experts' joint decisions. This is shown in the following order:

$$(c_2, c_3) \succ^3 (c_3, c_4) \succ^4 (c_2, c_4) \succ^1 (c_3, c_5) \succ^1 (c_2, c_5) \succ^2 (c_4, c_5) \succ^6 (c_1, c_3) \succ^2 (c_1, c_2) \succ^3$$
$$(c_1, c_4) \succ^0 (c_1, c_5) \succ^6 c_3 \succ^3 c_2 \succ^3 c_4 \succ^2 c_5 \succ^6 c_1 \succ^6 c_0$$

(c_i, c_j) indicates that the criteria i and j should be considered concurrently. For example, (c_2, c_3) denotes the binary combination of energy consumption and repeatability criteria, i.e., taking both into account.

We calculated a value using the formulation that we created and solved in MATLAB by determining the weights of each criterion and the weights of the binary combinations of the criteria. There is one critical issue that we must address here. Technical information obtained from data sheets for the Initial Purchase Cost and Energy Consumption criteria, as well as prices obtained from manufacturers, are inversely proportional. In other words, a robot that consumes more energy will have a lower performance score based on this criterion. Similarly, the inverse rate will be used to calculate the initial purchase cost of a more expensive robot. While the values for these two criteria were discovered in this study, as were the values for the other three criteria, the data obtained from these two criteria was included in the performance score as a minus. The logic here is that making a robot more expensive or consuming more energy does not make it a better option, but rather the opposite.

Table 4.1: MATLAB calculated values

Criteria / Binary Combination/Alpha	Symbol	Weight/Value
c_1	w_1	0.1194
c_2	w_2	0.2290
c_3	w_3	0.2419
c_4	w_4	0.2129
c_5	w_5	0.1968
c_1, c_2	$u_{1,2}$	0.0387
c_1, c_3	$u_{1,3}$	0.0323
c_1, c_4	$u_{1,4}$	0.0387
c_1, c_5	$u_{1,5}$	0.0516
c_2, c_3	$u_{2,3}$	0.0710
c_2, c_4	$u_{2,4}$	0.0645
c_2, c_5	$u_{2,5}$	0.0645
c_3, c_4	$u_{3,4}$	0.0710
c_3, c_5	$u_{3,5}$	0.0516
c_4, c_5	$u_{4,5}$	0.0710
$alpha$	a	0.0065

Table 4.2: Numerical data for five criteria in application 1

		Criteria Weights				
		0.1194	0.229	0.2419	0.2129	0.1968
Robot Brand	Model	Initial Purchase Cost (Euro)	Energy Consumption (kWh)	Accuracy and Precision (mm)	User Friendliness (1 – 10)	Programming Flexibility (1 – 10)
ABB	IRB 2600-12/1.85	50,000.00	0.92	± 0.04	5.00	4.00
KUKA	KR 12 R1810-2	49,390.00	1.27	± 0.04	4.67	5.50
FANUC	M-10iD/12	24,820.00	1.00	± 0.02	6.33	6.67
KAWASAKI	RS013N-A	22,000.00	1.60	± 0.03	5.67	3.33
YASKAWA MOTOMAN	GP12	32,000.00	1.20	± 0.03	4.33	3.80
UNIVERSAL ROBOTS	UR10e	35,500.00	0.35	± 0.05	6.33	5.67

The Choquet integral method is applied using the criterion weights obtained in MATLAB and to equation 3.14. The numerical data of each criteria of the six different robots to be chosen are listed in the table below. The weights shown in the table above are the weights before the 2-additive values are applied.

While the data for $c_1, c_2, and\ c_3$ came from the robot data sheets of robots, the values for c_4, c_5 came from the average of six experts' evaluation. When we glance at the values in the table, we can see that Kuka is the most expensive brand and Kawasaki is the cheapest. If the decision were made without using an MCDM method, Kawasaki would be the most likely choice due to the price difference. In such cases, we employ MCDM applications. When we look at the other values in the table, we see that Universal Robots uses the least amount of energy, while Kawasaki uses the most. Fanuc is the best for repeatability, while Universal Robots is relatively the worst. Universal Robots and Fanuc are together the most user friendly, while Yaskawa Motoman is the least user friendly. We can see that Fanuc has the highest rate of programming flexibility, while Kawasaki and Yaskawa Motoman has the lowest.

Because the units differ for each criterion value used in the application, we must first create a normalization matrix in order to use all data of the same type. For example, the as initial purchase price in Euro and the repeatability value in mm are in different units, they cannot be compared in this manner. As a result, we should abandon units and convert values to a comparable one, i.e. the same type.

The normalized values and one criterion weight are then used to create a weighted normalization matrix. After completing these steps, we are now ready to generate performance scores for robot alternatives based on our data. The values of each criterion are added to obtain the performance values for each brand. In other words, the Fanuc brand robot's performance score is determined by adding the values of the Fanuc brand robot's five criteria. Following this process, if the robot with the highest value is evaluated within the threshold of these 5 criteria, the ranking is made so that the robot with the highest performance score is the relatively best alternative, and the robot with the lowest performance score is the relatively worst alternative.

The normalized matrix values table, weighted normalized matrix table, and performance scores table are shown below, respectively.

Table 4.3: Normalized matrix values in application 1

		Criteria Weights				
		0.1194	0.229	0.2419	0.2129	0.1968
Robot Brand	Model	Normalized Matrix Values				
		c_1	c_2	c_3	c_4	c_5
ABB	IRB 2600-12/1.85	-0.55	-0.33	0.45	0.11	0.34
KUKA	KR 12 R1810-2	-0.54	-0.46	0.45	0.10	0.42
FANUC	M-10iD/12	-0.27	-0.36	0.23	0.85	0.56
KAWASAKI	RS013N-A	-0.24	-0.58	0.34	0.09	0.28
YASKAWA MOTOMAN	GP12	-0.35	-0.44	0.34	0.09	0.28
UNIVERSAL ROBOTS	UR10e	-0.39	-0.13	0.56	0.14	0.48

Table 4.4: Weighted normalized matrix values in application 1

Robot Brand	Model	Criteria Weights				
		0.1194	0.229	0.2419	0.2129	0.1968
		Weighted(w) Normalized Matrix Values				
		c_1	c_2	c_3	c_4	c_5
ABB	IRB 2600-12/1.85	-0.0654	-0.0765	0.1089	0.0227	0.0666
KUKA	KR 12 R1810-2	-0.0646	-0.1056	0.1089	0.0212	0.0832
FANUC	M-10iD/12	-0.0325	-0.0832	0.0544	0.1810	0.1110
KAWASAKI	RS013N-A	-0.0290	-0.1331	0.0816	0.0258	0.0555
YASKAWA MOTOMAN	GP12	-0.0419	-0.0998	0.0816	0.0197	0.0555
UNIVERSAL ROBOTS	UR10e	-0.0464	-0.0291	0.1361	0.0288	0.0943

Table 4.5: Performance scores in application 1

	Performance Score	Ranking
FANUC	0.231	1
UNIVERSAL ROBOTS	0.184	2
ABB	0.056	3
KUKA	0.043	4
YASKAWA MOTOMAN	0.015	5
KAWASAKI	0.001	6

The results of our application are shown in the table above without taking into account the effect of the binary interactions of the criteria. As having the most user friendly rate, according to the result of application Fanuc is the best robot alternative.

Every one of the criteria and binary combinations of each criterion will be used in the second part of the application. In the table below, iterated weights are shown. In order to obtain these weights equation 3.16 is used. Normalized matrix table, weighted normalized matrix table and new performance score table are also shown following.

Table 4.6: Numerical data for five criteria in application 2

		Criteria Weights				
		0.0388	0.2774	0.3540	0.2000	0.1291
Robot Brand	Model	Initial Purchase Cost (Euro)	Energy Consumption (kWh)	Accuracy and Precision (mm)	User Friendliness (1 – 10)	Programming Flexibility (1 – 10)
ABB	IRB 2600-12/1.85	50,000.00	0.92	± 0.04	5.00	4.00
KUKA	KR 12 R1810-2	49,390.00	1.27	± 0.04	4.67	5.50
FANUC	M-10iD/12	24,820.00	1.00	± 0.02	6.33	6.67
KAWASAKI	RS013N-A	22,000.00	1.60	± 0.03	5.67	3.33
YASKAWA MOTOMAN	GP12	32,000.00	1.20	± 0.03	4.33	3.80
UNIVERSAL ROBOTS	UR10e	35,500.00	0.35	± 0.05	6.33	5.67

Table 4.7: Normalized matrix values in application 2

		Criteria Weights				
		0.0388	0.2774	0.3540	0.2000	0.1291
Robot Brand	Model	Normalized Matrix Values				
		c_1	c_2	c_3	c_4	c_5
ABB	IRB 2600-12/1.85	-0.55	-0.33	0.45	0.11	0.31
KUKA	KR 12 R1810-2	-0.54	-0.46	0.45	0.10	0.38
FANUC	M-10iD/12	-0.27	-0.36	0.23	0.97	0.66
KAWASAKI	RS013N-A	-0.24	-0.58	0.34	0.09	0.26
YASKAWA MOTOMAN	GP12	-0.35	-0.44	0.34	0.09	0.26
UNIVERSAL ROBOTS	UR10e	-0.39	-0.13	0.56	0.14	0.43

Table 4.8: Weighted normalized matrix values in application 2

		Criteria Weights				
		0.1194	0.229	0.2419	0.2129	0.1968
Robot Brand	Model	Weighted(w) Normalized Matrix Values				
		c_1	c_2	c_3	c_4	c_5
ABB	IRB 2600-12/1.85	-0.0212	-0.0927	0.1597	0.0214	0.0395
KUKA	KR 12 R1810-2	-0.0210	-0.1279	0.1597	0.0200	0.0494
FANUC	M-10iD/12	-0.0105	-0.1007	0.0798	0.1942	0.0857
KAWASAKI	RS013N-A	-0.0094	-0.1612	0.1198	0.0186	0.0329
YASKAWA MOTOMAN	GP12	-0.0136	-0.1209	0.1198	0.0186	0.0329
UNIVERSAL ROBOTS	UR10e	-0.0151	-0.0353	0.1996	0.0271	0.0560

Table 4.9: Performance scores in application 2

	Performance Score	Ranking
FANUC	0.248	1
UNIVERSAL ROBOTS	0.232	2
ABB	0.107	3
KUKA	0.080	4
YASKAWA MOTOMAN	0.037	5
KAWASAKI	0.001	6

4.2 DISCUSSION OVER RESULTS

In both cases, a Fanuc-branded robot is the best option. The first scenario has a performance score of 0.231 without the effect of binary criteria combinations; the performance ranking remains first as the performance score rises to 0.248 with the effect of binary criteria combinations. Similarly, the Kawasaki brand robot appears to be the least desirable option in both scenarios. While it has a performance score of 0.001, it remains at 0.001 in the scenario implemented with the effect of binary criteria combinations, and it ranks last in the ranking of performance scores.

The point to notice here is that criterion interactions influence the selection process. Although our ranking list did not change in this study, we did notice that the performance scores did. When we integrate this mechanism into an application with different criterion weights or criterion weights obtained as a result of criterion interactions, we must remember that the selection order, that is, the performance score ranking, may also change. Indeed, one of the goals of our research is to demonstrate the impact of criterion pairwise interactions on the outcome.

The experts were given the results of the two applications as well as the performance score ranking. Experts debated the study's accuracy, or more specifically, the study's parallelism with real life. After communicating the robot selection ranking results to each expert, we asked if the Fanuc brand robot, which appeared to be the most suitable robot alternative, was a priority choice over other brands. In practice, the majority of experts stated that Fanuc is actually most of the the time preferred by medium and large scale enterprises. It was discussed that each of the six options has a market share and that there is a parameter that prioritizes the selection of each of these robots. And when we look at the market share of the Fanuc brand, it is easy to see that it is one of the, some years as the most popular, most sold robot brands. It was essential to share the findings of our study with the experts and have them confirm the study's suitability and accuracy. Because, for various reasons, the alternative that appears to be the best in theory may not be preferred in practice.

At the end of this title, I'd like to mention a topic that was discussed with experts but was not used as a criterion in this study. Brand worth. Sometimes, even if it is not the most cost-effective option, a robot brand known solely for its brand value is preferred by manufacturers. The buyer believes that trusting the brand will result in greater contribution and profit in the long run. The German Kuka brand is a prime example of this. The brand, which was sold to the Chinese six years ago, has recently suffered a significant drop in sales and customers. Although they continue to argue that they are an innovative robot company with the dedication and discipline of the first day, research and statistics show that its old value is being lost as a result of customers shifting from German to Chinese brand.

5. CONCLUSION

Using MCDM techniques, this thesis investigated an appropriate robot selection process among industrial robot alternatives. The diversity of robots is increasing with technology, and how robots are increasingly entering our lives is discussed. There were allusions to the question marks that came with the robots. The increasing use and production of robots, as well as what they bring, are explained using numerical data gathered as a result of the researches. A review of the literature covering previous studies and methods on this subject was carried out. We discovered in this study that energy consumption was never used as a criterion in the robot selection process. We created a robot selection mechanism using this criterion and the other four criteria we determined. We used the MACBETH approach and Choquet integral methods in this mechanism. The reason for using these methods is to observe not only the effect of the criteria on the selection process, but also the effect of the criteria's binary interaction on the process.

The methods we will use are theoretically explained in Chapter 3. The criteria to be used were explained, as well as why they were chosen. To select a good robot, the criteria to be used in MCDM methods must be determined. It is critical to gather accurate data on the criteria to be used. The real data from the robot laboratory where I did my thesis on this subject, the robot manufacturers I was able to easily contact thanks to this laboratory, and the experiences of experts in the field made data collection simple. MACBETH aids in option evaluation by providing a qualitative representation of attractiveness preferences. It is very simple to convert qualitative data to numerical data using this method. The MACBETH procedure is based on decision makers' comparisons of various situations. Because decision makers are involved in determining criterion weights and interactions, this method outperforms simple scaling methods. There are six different robot brands and five different criteria presented. We notice that interactions between certain criteria are important. When a criterion is considered alone, it may become less important as a result of binary combination. The methodology and steps to be taken are explained in detail at the end of the chapter.

The data collected for the numerical application is shared in the chapter 4. Some of the collected data was obtained through the use of data sheets, while others were obtained through expert opinions. Our work has been mathematically represented in two ways. The application was created by combining the criteria weights obtained by considering the binary combinations of the criteria and those obtained without considering the binary combinations of the criteria. Because the data units for the five criteria are different, we had to convert all of these data into a single unit or, more accurately, unit-less. This is referred to as normalization. The performance scores that will be used for the robot selection order were calculated using the normalized values and criterion weights for both cases. Our application allowed us to see how the effect of the binary combinations of the criteria adds a change to the selection robot selection order and creates an effect in two ways. It should be noted that the theoretical results obtained in such studies may not correspond to real life for a variety of reasons. As a result, the study's findings were shared with experts in the field, and their approvals were obtained for the accuracy of interpretation and application.

The outcomes of two different numerical applications are compared in this thesis. The comparison clearly shows that the robot selection order has not changed, but the performance scores of the robots have changed. If the robot brands' criteria data or the order of importance of the criteria change, the order may not always remain the same. One of the most important points to emphasize here is that binary combinations result in a significant change in criterion weights. Perhaps the performance ranking has not changed in this study, but in another application with different data, the rankings in both scenarios will be easily visible.

Technological advancements will undoubtedly have a significant impact on robot production. Every day, new robots with various features and brands are being introduced. Along with these advancements, it will alter the robot selection applications created with MCDM, as described in this thesis. Many subjects will change, including the criteria used, the data for the criteria, and the number of brands to be compared. As a result, each study can be thought of as a newer and more effective version of the previous one. More recent studies to be conducted in the future will serve the same purpose, namely, to select the most appropriate robot from among various alternatives, taking into account the conditions of the time and the data of that period.

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