An Integrated QFD Approach for Industrial Robot Selection

Gülçin Büyüközkan, Öykü Ilıcak, Orhan Feyzioğlu

An Integrated QFD Approach for Industrial Robot Selection

Gülçin Büyüközkan[1[0000-0002-2112-3574]], Öykü Ilıcak[2[0000-0001-6337-9773]] and Orhan Feyzioğlu[3[0000-0002-8919-191X]]

[1] Galatasaray University, Istanbul, 34349, Turkey
gbuyukozkan@gsu.edu.tr
[2] Galatasaray University, Istanbul, 34349, Turkey
oykuilicak12@gmail.com
[3] Galatasaray University, Istanbul, 34349, Turkey
ofeyzioglu@gsu.edu.tr

Abstract. Nowadays, where Industry 4.0 is discussed extensively, the selection of industrial robots has become an important issue. These robots enable production companies to produce higher quality products with high efficiency and in a cost-effective manner. However, an incorrect selection of these robots can cause significant losses for companies. Various factors need to be considered for the effective selection of industrial robots. In this study, a decision model is presented for industrial robot selection. Quality function deployment (QFD), a well-known and powerful tool that converts customer requirements into final design characteristics, is used in this study, with Group Decision Making (GDM) perspective. In GDM, decision-makers who have different backgrounds or ideas can state their preferences in various formats. The Multiple Preference Relations (MPR) technique is used to combine different assessments. Therefore, this study combines QFD with MPR to handle the different forms of information while calculating the customer requirements importance. Furthermore, the Complex Proportional Assessment (COPRAS) method is used to choose the most suitable industrial robot for the proposed study. The presented method was analyzed in a case study on the robot selection problem for the assembly line of a company operating in the manufacturing industry. The alternatives evaluated with the COPRAS method were also applied with the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method. The results of both methods were compared and found to be consistent.

Keywords: Robot Selection, QFD, Multiple Preference Relations, COPRAS.

1 Introduction

The ability of businesses to maintain their positions in an internationally competitive environment depends on their transition to automation-based systems by changing their production structures [1]. Robots can perform repetitive and dangerous tasks and complete all processes much better, more accurately, and more efficiently [2]. Robotics-based automation changes and improves manufacturing applications. Customer choice (CRs) and technical requirements (DRs) should be analyzed correctly to select industrial robots. The Quality Function Deployment (QFD) approach, known as a customer-oriented systematic method that focuses on this analysis, was used in this study. QFD is also a Group Decision Making (GDM) approach with many expert opinions. Considering the GDM approach, Decision Makers' (DMs) perspectives may differ from each other and may wish to evaluate in different formats. Multiple preference relations (MPR) are often applied to deal with varying forms of evaluations [3].

In this study, selecting an industrial robot to be used in the assembly line of ABC company is discussed. QFD approach was applied and integrated with the MPR technique to deal with evaluation structures in different formats in prioritizing the CRs. Then DRs were determined, and their weights were identified by the House of Quality (HoQ) relationship matrix. Finally, alternative robots were selected in line with DRs with the Complex Proportional Assessment (COPRAS) method. The alternatives were also evaluated with the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method, and the results of both methods were compared.

This study continues with the following sections: In Section 2, a literature review is provided. Section 3 provides the methodology, Section 4 introduces the case study, and Section 5 gives results and discussion, while Section 6 concludes the study and offers future research directions.

2 Literature Review

Robots that are starting to enter the production environment with Industry 4.0 are more intelligent and secure. The selection of the correct robot is an important issue. When we examine the literature, it is seen that many studies have been performed on robot selection problems. Vahdani et al. [4] proposed a robot selection problem based on interval-valued fuzzy COPRAS. Pasawang et al. [5] presented a QFD technique to design an autonomous underwater robot. Sen et al. [6] used an extended PROMETHEE method to select the best robot by considering subjective and objective criteria. Yalçın and Uncu [7] applied the EDAS method for the robot selection problem. Fu et al. [8] proposed a GDM approach to handle multiple criteria robot selection problems. Nasrollahi et al. [9] solved a robot selection problem using fuzzy the best-worst method (BWM) with PROMETHEE. More recently, Ali and Rashid [10] used group BWM and group AHP method for robot selection. Another recent study, Rashid et al. [11], proposed a hybrid BWM-EDAS method, which is the first study that integrates BWM with the EDAS method for the proper selection of robots.

The literature review shows that several studies have been done about the robot selection problem. However, there are no such studies on evaluating industrial robots for an assembly line using an integrated QFD methodology with MPR and COPRAS.

3 Methodology

3.1 Quality Function Deployment (QFD)

QFD is a systematic method that helps to identify the customer's design needs to reflect the needs and expectations of the product/service [12]. The fundamental structure of the QFD is the HOQ. With HOQ, “What's” and “How's” can be defined in a short time. The HOQ matrix is shown in Fig.1.

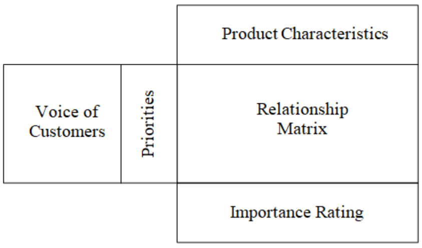

Fig. 1. HOQ matrix for the study

In this study, in the HOQ matrix, the voice of the customer will be the needs for the selection of industrial robots, priorities will be the importance of end-user needs, product characteristics will be technical requirements. The relationship matrix shows the relationship between needs and technical requirements.

3.2 Multiple Preference Relations (MPR)

In the GDM process, DMs can present evaluations in different ways. These can be linguistically, numerically, or by subsets according to their level of information. MPR allows DMs, having different backgrounds/perspectives, to submit their preferences in various ways. The advantages of this technique are: (1) It gives flexibility to DMs during the evaluation process. (2) It gives better solutions as it is based on GDM. (3) It allows collecting different types of assessments under a single group [13].

3.3 Complex Proportional Assessment (COPRAS)

This method is an MCDM method that can evaluate qualitative and quantitative criteria [14]. The advantages of the COPRAS method compared to other MCDM methods can be given as follows: (1) It compares the evaluated alternatives with each other, expresses how good or how bad it is from other alternatives as a percentage. (2) Since long binary comparisons are not made in this method, as in PROMETHEE and ELECTRE, the high number of alternatives does not complicate the process. (3) It gives easier and faster results than other MCDM methods such as ARAS, VIKOR or TOPSIS. It is possible to apply easily with Excel. One disadvantage of the method is that it cannot calculate criteria weights alone. This can be determined using different methods or depending on DMs [15].

3.4 Proposed Methodology

This study implements an improved QFD methodology by presenting a GDM approach that aggregates different preferences into a single group decision, consisting of the weighting of CRs using the MPR method followed by identification and prioritization of DRs, and ranking the alternatives using the COPRAS method. The framework of the proposed methodology is given in Fig.2 and detailed below.

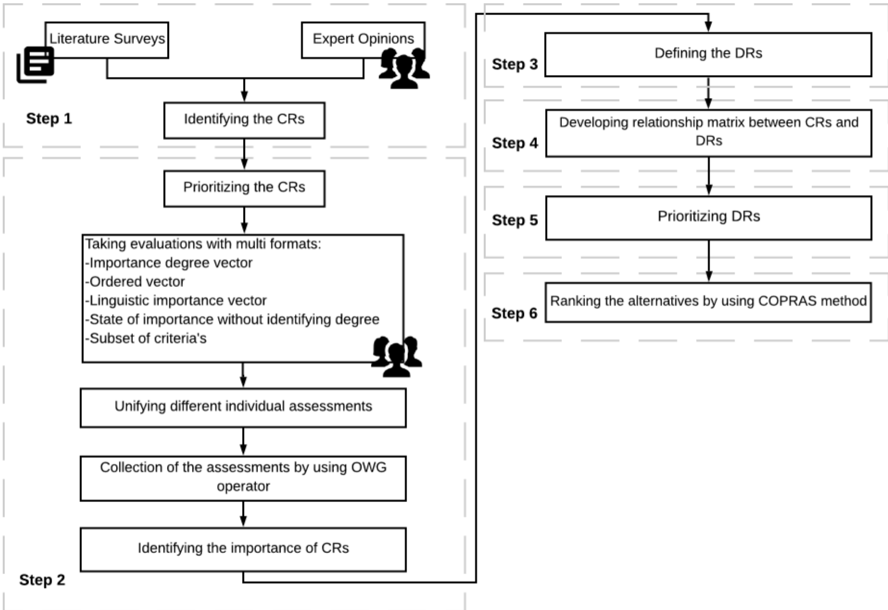

Fig. 2. The framework of the proposed methodology.

(i) Step 1- Identifying the CRs: CRs are identified by benefiting from the detailed literature researches and expert opinions.

(ii) Step 2- Prioritizing the CRs: Here, the importance of CRs is determined by expert opinions. In this step, the MPR technique is utilized [13].

(a) Step 2.1- Unifying DMs evaluations: Opinions in different formats from DMs will be combined at this stage. DMs can give preferences in different formats as follows:

- An importance degree vector $(u_1, \ldots, u_N)$ where $u_i \in [0,1]$ $i = 1,.., N$. Closer to 1 means more important for u_i. With the formula below we can turn it to relevance of relative importance:

$$z_{ij} = u_i/u_j \text{ for all } 1 \leq i \neq j \leq N \tag{1}$$

- An ordered vector (o(1),…,o(N)). Here, o(i) represents the importance ranking of CR i, where the most important is 1 and the least important is N. With the formula below we can turn it to relevance of relative importance:

$$z_{ij} = 9^{u_i - u_j} \quad \text{for all } 1 \leq i \neq j \leq N \text{ where } u_i = (N - o(i)) / (N - 1) \tag{2}$$

- DMs may present a linguistic importance vector. Given a fuzzy triangular number can be noted as (a_i, b_i, c_i) where b_i is the most common value. The membership functions of linguistic terms for fuzzy triangular quantification are: NI = (0.00, 0.00, 0.25), SI = (0.00, 0.25, 0.50), MI =(0.25, 0.50, 0.75), I = (0.50, 0.75, 1.00) and VI = (0.75, 1.00, 1.00). With the formula below the linguistics importance vector can be transformed to relative importance relation.

$$z_{ij} = 9^{b_i - b_j} \quad \text{for all } 1 \leq i \neq j \leq N \tag{3}$$

- DMs may give the importance of criteria without degree explicitly. So, $z_{ij} = 9$ and $z_{ij} = 1/9$, if criteria i is more important than j and $z_{ij} = 1$ if nothing mentioned. (4)
- DMs may choose just a subset of criteria (R'). So, the preference relation can be given as, $z_{ij} = 9$ if $i \in R'$, $j \in R/R'$ and $z_{ij} = 1/9$ if $i \in R/R'$, $j \in R'$, otherwise its equal to 1. (5)

(b) Step 2.2- Aggregating the evaluations: Each evaluation is aggregated using the order weighted geometric (OWG) operator to define a common group decision in this step by the following formula:

$$\phi^G \{(\overline{w}k1, p_{ij}^{k1}), \ldots. (\overline{w}kLk\, , p_{ij}^{kL_k})\} = \prod_{l=1}^{L_k} \left(p_{ij}^{k[l]}\right) \tag{6}$$

Here, $\{1, \ldots, L_k\} \rightarrow \{1, \ldots, L_k\}$ is a permutation such that $\overline{w}_{kl} \geq \overline{w}_k[\, l+1]$, $l = \{1, \ldots, L_{k-1}\}$, so $\overline{w}k1$ is the lth largest value in the set $(\overline{w}_{k1}, \ldots, \overline{w}_{kLk})$. Proportional quantifiers, such as "most," "as many as possible," etc., can be represented by fuzzy subsets of the unit interval [0,1]. When the ratio t is suitable with the purpose of the quantifier it demonstrates then for any $t \in [0,1]$, Q(t) indicates the degree. For a non-decreasing relative quantifier, Q, the weights can be acquired with the formula below:

$$W_k = Q(k/K) - (Q(k-1)/K) \quad k = 1, \ldots, K \tag{7}$$

where Q(t) is described as;

$$Q(t) = \begin{cases} 0, & \text{if } t < s \\ \frac{t-s}{v-s}, & \text{if } s \leq t \leq v \\ 1, & \text{if } t \geq v \end{cases} \tag{8}$$

Note that s, t, v $\in$ [0,1] and Q(t) indicates the degree to which the proportion t is compatible with the meaning of the quantifier it represents. Examples of the relative quantifiers in the literature are as follows; "most" (0.3, 0.8), "at least half" (0,0.5), and "as many as possible" (0.5,1). When the fuzzy quantifier Q is used to calculate the

OWG operator's weights Φ_W^G, it is represented by. Therefore, the collective multiplicative relative importance relation is obtained as follows:

Therefore, the collective multiplicative relative importance relation is obtained as follows:

$$p_{ij}^k = \Phi_Q^G\left(p_{ij}^{k1}, p_{ij}^{k2}, \ldots, p_{ij}^{kL_k}\right), 1 \le i \ne j \le N \tag{9}$$

(c) Step 2.3- Identifying the importance of CRs: To define the importance weights of CRs, the evaluations of DM groups aggregated in the matrix P^k must be utilized. The element ij represent the relative importance of criterion i compared to criterion j. Then, calculate the quantifier guided importance degree (QGID) of each criterion, which quantifies the importance of one criterion compared to others in a fuzzy majority sense. With using the OWG operator, Φ_0^G, defined as follows:

$$QGID_i^k = 1/2\left(1 + \log_9 \phi_Q^G\,(p_{ij}^k: j = 1, \ldots, N)\right), \text{ for all } i = 1, \ldots, N \tag{10}$$

As a final step, the $QGID_i$ values should be normalized as below equation to obtain the importance degrees in percentage for the group *k*.

$$QGID_i^k = QGID_i^k / \textstyle\sum_i QGID_i^k \tag{11}$$

(iii) Step 3- Identifying the DRs: DRs for robots have been introduced by benefiting from literature researches and expert opinions.

(iv) Step 4- Developing a relationship matrix between CRs and DRs: The relationship matrix is created to which the need influences each technical characteristic.

(v) Step 5- Prioritizing DRs: DRs are ranked according to their importance.

(vi) Step 6- Ranking the alternatives: After completing the QFD and determining the weights of the DRs, robot selection is made at this stage by using the COPRAS method.

(a) Step 6.1- Creating the decision matrix: The decision matrix includes alternatives in the rows and the criteria in the columns are created.

(b) Step 6.2- Normalizing the decision matrix: The normalized decision matrix is formed by applying the following formula to the entries of the decision matrix.

$$x_{ij}^* = \frac{x_{ij}}{\sum_{i=1}^m x_{ij}}, j=1, 2, \ldots, n \tag{12}$$

(c) Step 6.3- Determining the weighted normalized decision matrix: A weighted decision matrix is formed by multiplying the entries in every column of the normalized decision matrix among the corresponding criteria weights.

(d) Step 6.4- Calculating weighted normalized indices: At this step, the sum of the weighted normalized decision matrix values is calculated for the decision problem's criteria.

- For the maximization (benefit) criteria:

$$S_{+i} = \sum_{j=1}^k d_{+ij}, j= 1, 2, \ldots, k \tag{13}$$

- For the minimization (cost) criteria:

$$S_{-i} = \sum_{j=k+1}^n d_{-ij}, j= k+1, k+2, \ldots, n \tag{14}$$

(e) Step 6.5- Calculating the relative importance levels of alternatives: Q_i, which means relative importance for each decision alternative, is calculated as follows.

$$Q_i = \; S_{+i} + \frac{S_{-min} \sum_{i=1}^{m} S_{-i}}{S_{-i} * \sum_{i=1}^{m} \frac{S_{-min}}{S_{-i}}} \tag{15}$$

(f) Step 6.6- Calculating the performance index of decision alternatives: The index values are calculated with the formula below.

$$P_i = \frac{Q_i}{Q_{max}} * 100 \tag{16}$$

4 Case Study

In this section, a case study is carried out in line with the proposed methodology for ABC company operating in the production sector. The company wishes to expand its production capacity by increasing the production speed and producing much more efficient and quality products. Thus, a robot is required for the company. It is aimed to perform assembly line operations by this robot, thus reducing the assembly times and increasing the production speed and improving the quality. A five-expert evaluation team of company executives (DM1, DM2, DM3, DM4, DM5) will evaluate six robot alternatives. These robots are Articulated robots (A1), Cartesian robots (A2), SCARA (A3), Delta robots (A4), Cylindrical Robots (A5), and Polar Robots (A6).

In this study, to evaluate the alternatives, three main criteria and ten sub-criteria are determined as CRs by benefiting from literature review and expert opinions [5], [15]. These criteria are: Configuration criteria (CR1) includes Payload capacity (CR11), Workspace (CR12), Accuracy (CR13), and Repeatability (CR14). The second main criteria are Functional criteria (CR2) includes Life expectancy (CR21), Programmable flexibility (CR22), and Safety and security (CR23). The last main criterion is Cost criteria (CR3) includes Purchase cost (CR31), Maintenance cost (CR32) and Operation cost (CR33). Five DMs assess the CRs and provide their evaluations in the forms of an "importance degree vector", "ordered vector", "linguistic importance vector", "importance of criteria without degree" and "subset of criteria", respectively. As an example, the evaluations for the main criteria are, (0.9, 0.7, 0.8) for DM1, (3, 1, 2) for DM2, (VI, I, I) for DM3. DM4 says {C1}>{C2} and {C2}>{C3} according to their importance and DM5 says that the C1 is more important. Then by operating Eq. (6) - (9), evaluations in different formats are combined under a single group view, and the group importance relation matrices are specified. Subsequently, with the help of Eq.(10) - (11), final evaluations are given in Table 1 for all primary and sub-criteria.

After identifying and prioritizing CRs, DRs were identified which are Weight of the robot (DR1), Speed of the robot (DR2), Geometrical dexterity (DR3), Path measuring system (DR4), Material of the robot (DR5), Size of the robot (DR6), Easy Programming (DR7), Drive system (DR8) [5, 16]. HoQ relation matrix for CRs and DRs and the final importance degrees of DR are given in Table 2.

Table 1. Final evaluations of CRs.

Main criteria	Priority	Sub-criteria	Local priority	Global priority
CR1	0.452	CR11	0.333	0.150
		CR12	0.186	0.084
		CR13	0.258	0.117
		CR14	0.223	0.101
CR2	0.348	CR21	0.391	0.136
		CR22	0.320	0.112
		CR23	0.289	0.100
CR3	0.201	CR31	0.377	0.076
		CR32	0.328	0.066
		CR33	0.296	0.059

Table 2. Final HoQ matrix.

		DRs for the problem							
CRs	Weights of CRs	DR1	DR2	DR3	DR4	DR5	DR6	DR7	DR8
CR11	0.150	S	M				M		S
CR12	0.084			S		L	L		
CR13	0.117			L	S			L	S
CR14	0.101	L	S	L					L
CR21	0.136					S			M
CR22	0.112	L	M	S	S			M	
CR23	0.100					M			
CR31	0.076		S			S	S		M
CR32	0.066					L			S
CR33	0.059					L	S		
Weights of DRs		1.497	2.050	1.935	1.875	2.258	1.687	0.396	3.870
Normalized Value		9.18%	12.57%	11.86%	11.50%	13.84%	10.35%	2.43%	23.73%
(Strong Relation (S) = 9; Medium Relation (M) = 3; Low Relation (L) = 1; Blank =0)									

At the last stage, alternatives are listed using the COPRAS and TOPSIS methods and results are given in Table 3. According to Table 3, it is seen that in the COPRAS method, A2 has the first priority when A1 the third. When we look at the TOPSIS method, it is the opposite, and it is seen that A1 has the first priority when A2 has the third.

Table 3. Rankings of alternatives by COPRAS and TOPSIS.

COPRAS Method				TOPSIS Method		
Alternatives	Q_i	P_i	Ranking	Alternatives	Weights	Ranking
A1	0.126	96.02	3	A1	0.729	1
A2	0.131	100.00	1	A2	0.588	3
A3	0.123	93.68	4	A3	0.495	4
A4	0.129	98.42	2	A4	0.699	2
A5	0.108	82.58	5	A5	0.267	5
A6	0.098	75.05	6	A6	0.253	6

5 Results and Discussion

Determining the relative importance of CRs is a significant challenge in QFD applications. In order to achieve success in QFD applications, there must be effective communication between DMs and a decision process that reflects the preferences of each. Therefore, the primary purpose of this study is to select an industrial robot for the assembly line by considering the QFD with the GDM approach. Because DMs have different education levels/different perspectives, they may want to express their preferences in various formats. Therefore, using the MPR technique in the GDM application allows us to get valuable results. Although the method may seem confusing and complicated, it can easily be implemented using Microsoft Excel, and results can be obtained quickly. Using such a detailed methodology for industrial robot selection will ensure that decision-making processes will be more transparent with higher quality. As a result of the study, the most essential CR is determined as “Payload capacity,” and the most important DR is defined as “Drive system”. In the final, alternatives are ranked with the COPRAS, and Cartesian robots (A2) seemed to have the highest importance among the other alternatives. Afterward, the alternatives were also evaluated with the TOPSIS method, and the results were compared with the COPRAS. The highest priority alternative identified as Articulated robots (A1) in TOPSIS. This shows that problems applying different evaluation approaches can lead to different decisions. The reason why the methods cause different results can be shown as the inability to extract the subjectivity that plays a role in the perception of objective world environments depending on the expertise of DMs.

6 Conclusion

Industry 4.0 is an essential issue from a robotics perspective. It enables a better understanding of how automation can improve process efficiency, quality, and safety. Choosing the right robot for the company is a strategic decision. Industrial robot selection is a GDM process that requires customer expectations and technical requirements to be well analyzed by multiple DMs. In this study, a QFD approach is presented to select industrial robots for use in the assembly line. QFD is integrated with MPR to deal with evaluations in different formats when evaluating the criteria, and COPRAS is used to assess the alternatives. In future studies, a more comprehensive study will be introduced by expanding the criteria and alternatives specified. Furthermore, incomplete preference relations will be used to reduce the uncertain nature of GDM.

Acknowledgments

The authors would like to express their sincere gratitude to the experts. This work has been supported by the Scientific Research Projects Commission of Galatasaray University.

References

1. Karsak EE, Sener Z, Dursun M (2012) Robot selection using a fuzzy regression-based decision-making approach. International Journal of Production Research 50:6826–6834.
2. Bhattacharya A, Sarkar B, Mukherjee SK (2005) Integrating AHP with QFD for robot selection under requirement perspective. International Journal of Production Research 43:3671–3685.
3. Büyüközkan G, Feyzioğlu O (2005) Group decision making to better respond customer needs in software development. Computers and Industrial Engineering 48:427–441.
4. Vahdani B, Mousavi SM, Tavakkoli-Moghaddam R, et al (2014) Robot selection by a multiple criteria complex proportional assessment method under an interval-valued fuzzy environment. Int J Adv Manuf Technol 73:687–697.
5. Pasawang T, Chatchanayuenyong T, Sa-Ngiamvibool W (2015) QFD-based conceptual design of an autonomous underwater robot. 10
6. Sen DK, Datta S, Mahapatra SS (2016) Extension of PROMETHEE for robot selection decision making: Simultaneous exploration of objective data and subjective (fuzzy) data. Benchmarking 23:983–1014.
7. Yalçın N, Uncu N (2019) Applying EDAS as an applicable MCDM method for industrial robot selection. Sigma J Eng & Nat Sci 3:779–796
8. Fu Y, Li M, Luo H, Huang GQ (2019) Industrial robot selection using stochastic multicriteria acceptability analysis for group decision making. Robotics and Autonomous Systems 122:103304.
9. Nasrollahi M, Ramezani J, Sadraei M (2020) A FBWM-PROMETHEE approach for industrial robot selection. Heliyon 6:e03859.
10. Ali A, Rashid T (2021) Best-worst method for robot selection. Soft Comput 25:563–583.
11. Rashid T, Ali A, Chu Y-M (2021) Hybrid BW-EDAS MCDM methodology for optimal industrial robot selection. PLoS One 16:e0246738.
12. Chan L-K, Wu M-L (2002) Quality Function Deployment: A Literature Review. European Journal of Operational Research 143:463–497.
13. Büyüközkan G, Çifçi G (2015) An Extended Quality Function Deployment Incorporating Fuzzy Logic and GDM Under Different Preference Structures. International Journal of Computational Intelligence Systems 8:438–454.
14. Zavadskas EK, Kaklauskas A, Turskis Z, Tamošaitienė J (2008) Selection of the Effective Dwelling House Walls by Applying Attributes Values Determined at Intervals. Journal of Civil Engineering and Management 14:85–93.
15. Rishi Kanth N, Srinath A, Suresh Kumar J (2018) Selection of Industrial Robots for Automation Applications in Multiple Attribute Decision Making Environment using the Analytical Network Process. IJET 7:392.
16. Mateo Ferrús R, Domínguez Somonte M (2016) Design in robotics based in the voice of the customer of household robots. Robotics and Autonomous Systems 79:99–107.