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# SELECTION OF AN INDUSTRIAL ROBOT FOR ASSEMBLY JOBS USING MULTI-CRITERIA DECISION MAKING METHODS

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Abstract
The paper proposes three multi-criteria decision-making (MCDM) methods for the selection of an industrial robot for a universal, flexible assembly station, taking into consideration the technical and performance parameters of the robot. Fuzzy versions of AHP and TOPSIS methods as well as SMART were chosen from the variety of MCDM methods as they represent different attitudes to analysis. In order to minimise the impact of the method applied on the final decision, a list of results of the analyses has been developed and a final classification has been made based on decision makers' preferences concerning selected parameters of the robot.

Keywords
Robotisation, technical and performance parameters, universal assembly station, MCDM methods.

## Introduction

With Industry 4.0 in full swing, attempts are being made to replace human labour with machines through the transformation of mechanised and automated production solutions into autonomous, flexible robotic workstations. New machines and measurement systems require a new approach to the acquisition and exploration of data by production control systems [1]. Integration of robots into state-of-the-art, flexible manufacturing systems often entails selecting appropriate statistical methods and artificial intelligence (AI) tools to ensure high quality of products in the long term [2–4].

One of the most obvious applications of industrial robots is the process of product assembly. Works to design an assembly station operated by an industrial robot (robots) may be undertaken to achieve the following objectives, among others:

- Enhance the production system and meet the requirements concerning efficiency, production flow, flexibility, and quality of the end product.
- Extend the product assortment.
- Tackle the problem of staff shortages, especially for monotonous, tedious jobs, as well as reduce the costs of employment.
- Improve productivity at the workstation (organisation of the process, spatial arrangement).
- Improve the health and safety at work through complete or partial replacement of human staff with machines.

Increased interest in industrial robots has been driving the growth of and competition on the industrial robotics market, as well as improving cost-effectiveness of implementation of robotic solutions. Finding an industrial robot for a particular application is no longer a problem. The challenge now is to compare the available models and select the one which best meets specific requirements, i.e., conduct a complex multi-criteria decision-making process. In this paper, the authors compare selected multi-criteria decision-making (MCDM) methods for effectiveness, on the basis of an industrial robot selection for a universal, flexible assembly station in a mid-sized manufacturing company with little of automation or robotisation of processes. Given a large number of the MCDM methods, varying in characteristics and underlying assumptions [5–7], the authors have applied three of them to list and compare the obtained results.

## Multi-criteria decision making methods

As discussed in the literature dealing with the MCDM, the key challenges in the decision making process are faced when:

- selecting the best variant (a variant in the MCDM terminology is an object or a subject defined with a set of criteria) based on predefined criteria.
- establishing the ranking list, i.e. arranging the variants in a certain order according to the preferences of the decision-maker(s).
- classifying, i.e., assigning the variants to predefined classes.

The classification presented below guides through the variety of MCDM methods available and approaches proposed within some of them. Out of the many classifications available in the literature [5, 8–13], the groups proposed by [14] seem to classify the MCDM methods in one of the most perceptible and comprehensive ways:

- the analytic hierarchy process and derivative methods (AHP – Analytic Hierarchy Process , F-AHP – Fuzzy AHP, REMBRANDT – Ratio Estimation in Magnitudes or deciBells to Rate Alternatives which are Non-DominaTed, ANP – Analytic Network Process, F-ANP – Fuzzy ANP, MACBETH – Measuring Attractiveness by a Categorical Based Evaluation Technique).
- methods based on the reference point approach (TOPSIS – Technique for Order Preference by Similarity to an Ideal Solution Method, F-TOPSIS – Fuzzy TOPSIS, VIKOR – in Serbian: Vlse Kriterijumska Optimizacija Kompromisno Resenje - Multicriteria Optimization and Compromise Solution, DEMATEL+ANP+VIKOR – Decision making trial and evaluation laboratory, BIPOLAR).
- additive methods (SAW - Simple Additive Weighting Method, F-SAW – Fuzzy SAW, SMART – Simple Multi-Attribute Ranking Technique, SMARTER – Simple Multi-Attribute Ranking Technique Exploiting Ranks), verbal methods (ZAPROS – in Russian: ЗАмкнутые ПРоцедуры у Опорных Ситуаций – Closed Procedures at Reference Situations, ZAPROS III).
- ELECTRE (ELECTRE I-III – in French: Elimination Et Choix Traduisant La Realite - Elimination and Choice Expressing The Reality, ELECTRE Iv, ELECTRE Is, ELECTRE TRI).
- PROMETHEE (PROMETHEE I-II - Preference Ranking Organization Methods for Enrichment Evaluation I-II, EXPROM I-II - EXtension of the PROMethee method, and versions of the methods with the veto option), interactive methods (STEM-DPR - Step Method for Discrete Decision Making Problems under Risk, INSDECM - interactive procedure for stochastic multicriteria decision problems, ATO-DPR - Analysis of Trade-Offs for Discrete Decision Making Problems under Risk).

To solve the research problem, i.e., select an industrial robot for a universal, flexible assembly station, the authors have compared results obtained by three methods which seemed most reliable and derived from different groups of methods:

- Fuzzy Analytic Hierarchy Process (F-AHP).
- Fuzzy TOPSIS method based on the reference point approach.
- SMART additive method.

Fuzzy versions of the first two methods have been used, taking into account possible uncertainty of the decision maker resulting from, e.g., insufficient knowledge, incomplete information, or a complex decision-making environment, i.e., factors which can be anticipated in the case of a universal, flexible assembly station.

### F-AHP

The Fuzzy Analytic Hierarchy Process (F-AHP) is a version of the Analytic Hierarchy Process (AHP) which uses fuzzy numbers. The classical AHP method, including some basic information about sets, fuzzy numbers and operations made on them, as well as the application of the F-AHP and the algorithm used by the authors, are presented below.

Developed by American scientist Thomas L. Saaty in 1970, the Analytical Hierarchy Process (AHP), with its numerous modifications and applications, supports complex decision making processes with a predefined number of variants, taking into account human psychology [15,16]. It is a structured technique of breaking down a problem into factors independent of one another.

The AHP consists of seven major steps [17]:

- Describing the problem.
- Selecting criteria and variants, structuring the problem.
- Selecting a scale of comparison.
- Comparing the criteria and variants in pairs with the use of comparison matrices.

- Quantifying relative weights of the criteria and variants.
- Ensuring consistency of the matrices.
- Obtaining the final relative weights.

The Fuzzy Set Theory (FST), presented by Zadeh in 1965, represents an extension of the traditional set to accommodate uncertainty and unclear data. A fuzzy set is a class of objects with an assigned degree of membership. The assignment is described by the function of membership, which takes a value from 0 to 1 [18].

Triangle fuzzy number (TFN – $\widetilde{M}$ see Fig. 1) is represented by $\widetilde{M} = (l, m, u)$, where $l$ represents the minimum possible value, $m$ — the most likely value, and $u$ – the maximum possible value. This representation, referred to as the function of membership, takes the following values (Eq. 1):

$$\mu_{\widetilde{M}}(x) = \begin{cases} 0 & x < l, \\ \dfrac{x-l}{m-l} & l \le x \le m, \\ \dfrac{u-x}{u-m} & m \le x \le u, \\ 0 & x > u. \end{cases} \tag{1}$$

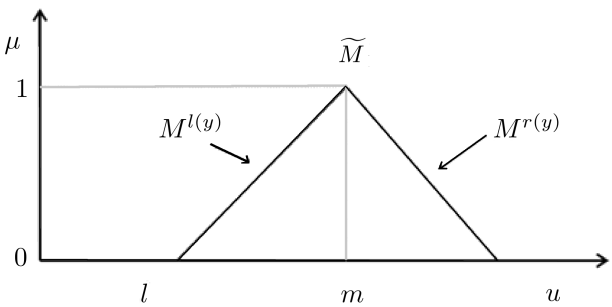


Fig. 1. Triangle fuzzy number $\widetilde{M}(l, m, u)$ [own work based on [18]].

A fuzzy number can be represented by the left-hand side $M^{l(y)}$ and the right-hand side $M^{r(y)}$ part of the function of membership [18]. Some important mathematical operations made on triangle fuzzy numbers are shown below (Eq. (2)). The following relations occur for two fuzzy numbers $\widetilde{M}_1 = (l_1, m_1, u_1)$ and $\widetilde{M}_2 = (l_2, m_2, u_2)$:

$$\widetilde{M}_1 \otimes \widetilde{M}_2 = (l_1, m_1, u_1) \otimes (l_2, m_2, u_2), \tag{2}$$

$$\begin{aligned} \widetilde{M}_1 \Theta \widetilde{M}_2 &= (l_1, m_1, u_1) \Theta (l_2, m_2, u_2) \\ &= (l_1 - l_2, m_1 - m_2, u_1 - u_2), \end{aligned} \tag{3}$$

$$\begin{aligned} \widetilde{M}_1 \odot \widetilde{M}_2 &= (l_1, m_1, u_1) \odot (l_2, m_2, u_2) \\ &= (l_1 \times l_2, m_1 \times m_2, u_1 \times u_2), \end{aligned} \tag{4}$$

$$\begin{aligned} \widetilde{M}_1 / \widetilde{M}_2 &= (l_1, m_1, u_1)/(l_2, m_2, u_2) \\ &= (l_1/u_2, m_1/m_2, u_1/l_2), \end{aligned} \tag{5}$$

$$\widetilde{M}_1^{-1} = (l_1, m_1, u_1)^{-1} = (1/u_1, 1/m_1, 1/l_1). \tag{6}$$

The algorithm used in the F-AHP, similar to the classical one used in the AHP, is enhanced with operations on fuzzy numbers. The steps of the algorithm applied in [18–20] include:

1. Describing the problem.
2. Selecting criteria, variants and decision maker(s).
3. Selecting the scale of comparison – the traditional scale used in Saaty's original approach (1, 3, 5, 7, 9, where 1 means that there is no difference between two criteria/variants, and 9 — that a given variant/criterion is definitely better) is replaced with a fuzzy scale, e.g., as shown in Table 1 [19, 21].
4. Building matrices for the comparison of criteria (variants are compared in the same way, based on given criteria)

$$\widetilde{A}_k = \begin{bmatrix} \widetilde{d}_{11}^k & \dots & \dots \\ \dots & \dots & \dots \\ \dots & \dots & \widetilde{d}_{nn}^k \end{bmatrix}, \tag{7}$$

where $\widetilde{d}_{ij}^k$ – the $k$-th assessment by the decision maker, according to the scale (Table 1), used for a comparison of criteria $i$ and $j$; if there is more than one decision maker, the assessment is averaged. Thus, aggregated assessments $\widetilde{d}_{ij}$ and matrix $\widetilde{A}$ are obtained:

$$\widetilde{d}_{ij} = (l_{ij}, m_{ij}, u_{ij}), \tag{8}$$

$$\widetilde{A} = \begin{bmatrix} \widetilde{d}_{ij}^k & \dots & \dots \\ \dots & \dots & \dots \\ \dots & \dots & \widetilde{d}_{nn} \end{bmatrix}. \tag{9}$$

5. Working out the geometric mean for each criterion:

$$\widetilde{r}_l = \left( \prod_{j=1}^{n} \widetilde{d}_{ij} \right)^{1/n} = (l_i, m_i, u_i), \quad i, j = 1, 2, ..., n, \tag{10}$$

$$l_i = (l_{i1} \otimes l_{i2} \otimes ... \otimes l_{in})^{1/n}, \quad i, j = 1, 2, ..., n, \tag{11}$$

$$m_i = (m_{i1} \otimes m_{i2} \otimes ... \otimes m_{in})^{1/n}, \quad i, j = 1, 2, ..., n, \tag{12}$$

$$u_i = (u_{i1} \otimes u_{i2} \otimes ... \otimes u_{in})^{1/n}, \quad i, j = 1, 2, ..., n, \tag{13}$$

6. Working out fuzzy weights of the criteria, in three steps:
   (a) finding the vector, being the sum $\widetilde{r}_l - \widetilde{r}_{l_{\text{total}}}$

$$\widetilde{r}_{l_{\text{total}}} = \left( \sum_{i=1}^{n} l_i, \sum_{i=1}^{n} m_i, \sum_{i=1}^{n} u_i \right), \tag{14}$$

Table 1
Fuzzy scale used in the FAHP (own work based on [19, 20]).

| Assessment of criteria/ variants | Assessment in words | Numerical rating | | | |
|---|---|---|---|---|---|
| | | FAHP (triangle fuzzy scale) | | AHP – scale | |
| Equality | Both elements (variants, criteria) equally contribute to the achievement of an objective (both elements are equally important) | (1, 1, 1) | (1, 1, 1) | 1 | 1 |
| Slight or moderate | Slight prevalence of one element over the other (one element is slightly more important than the other) | (1, 3, 5) | (1/5, 1/3.1) | 3 | 1/3 |
| Strong, fundamental | Fundamental or strong prevalence of one element over the other (one element is significantly more important than the other) | (3, 5, 7) | (1/7, 1/5, 1/3) | 5 | 1/5 |
| Definite or very strong | Definite or very strong prevalence of one element over the other (one element is definitely more important than the other) | (5, 7, 9) | (1/9, 1/7, 1/5) | 7 | 1/7 |
| Absolute | Absolute prevalence of one element over the other | (7, 9, 9) | (1/9, 1/9, 1/7) | 9 | 1/9 |
| For comparisons where results do not match any of the above values | In case there is a need of numerical interpolation of opinions due to the fact that no words can describe them, intermediate values are used | (1, 2, 4)<br>(2, 4, 6)<br>(4, 6, 8)<br>(6, 8, 9) | (1/4, 1/2, 1/1)<br>(1/6, 1/4, 1/2)<br>(1/8, 1/6, 1/4)<br>(1/9, 1/8, 1/6) | 2, 4, 6, 8 | 1/2; 1/4; 1/6; 1/8 |

(b) working out $(\widetilde{r}_{l_{\text{total}}})^{-1}$ and rearranging elements of the fuzzy number in the ascending order,

(c) working out the fuzzy weight for each criterion with the following formula:

$$\widetilde{w}_l = \widetilde{r}_l \otimes (\widetilde{r}_{l_{\text{total}}})^{-1} = \left( \frac{l_i}{\sum\limits_{i=1}^{n} u_i}, \frac{m_i}{\sum\limits_{i=1}^{n} m_i}, \frac{u_i}{\sum\limits_{i=1}^{n} l_i} \right), \quad i,j = 1,2,...,n, \tag{15}$$

$$\widetilde{w}_l = (l_{w_i}, m_{w_i}, u_{w_i}). \tag{16}$$

7. Defuzzifying – determining non-fuzzified weight for each criterion, with the following formula:

$$M_i = \frac{l_{w_i} + m_{w_i} + u_{w_i}}{3}. \tag{17}$$

8. Determining the normalised weight for each criterion, with the following formula:

$$w_i = \frac{M_i}{\sum\limits_{i=1}^{n} M_i}. \tag{18}$$

9. Repeating steps 3–7 in order to determine normalised weights for particular variants relative to the criteria.
10. Calculating the aggregate assessment for each variant through multiplication of the normalised weights of criteria and variants.
11. Selecting the variant with the highest aggregate assessment as the one which best reflects the preferences of the decision-maker(s).

## F-TOPSIS

The procedure which the authors followed using the F-TOPSIS (22,23,24) method consists of the following steps:

1. Describing the problem.
2. Selecting criteria, variants and decision maker(s).
3. Selecting scales for the assessment of criteria and variants – the F-TOPSIS method uses linguistic scales, different for the assessment of criteria and variants (Table 2).
4. Assessing all the criteria and variants relative to particular criteria, using the scales; unlike the F-AHP, rather than the criteria and variants being compared with one another, they are assessed using a predefined scale (Sec. 3); in the event of several experts, weights of criteria and assessments of variants are averaged.
5. Building a fuzzy decision matrix and fuzzy weight matrix:

$$\widetilde{D}_k = \begin{bmatrix} \widetilde{d}_{11}^k & ... & ... \\ ... & ... & ... \\ ... & ... & \widetilde{d}_{nm}^k \end{bmatrix}, \tag{19}$$

where $(i = 1,2,...,n;\ j = 1,2,...,m)$ – assessment $A_i$ of the $i$-th variant by the $k$-th decision maker relative to the $j$-th criterion to the predefined scale of comparison (Table 2) of criteria $i$ and $j$.

Table 2
Scales for the assessment of criteria and variants relative to given criteria.

| Assessment of criterion | Numerical rating | Assessment of a variant relative to the criterion | Numerical rating |
|---|---|---|---|
| of little importance | (0; 0; 0.25) | very low | (0; 0; 0.25) |
| of medium importance | (0; 0.25; 0.5) | low | (0; 2.5; 5) |
| important | (0.25; 0.5; 0.75 | good | (2.5; 5; 7.5 |
| very important | (0.5; 0.75; 1) | very good | (5; 7.5; 10) |
| absolutely important | (0.75; 1, 1) | excellent | (7.5; 10; 10) |

If there is more than one decision maker, the assessment is averaged; thus, aggregated assessment $\widetilde{d}_{ij}$ and fuzzy decision matrix $\widetilde{D}$ [25] are obtained. Fuzzy weight matrix $\widetilde{W}$ is also built

$$\widetilde{d}_{ij} = (l_{ij}, m_{ij}, u_{ij}), \tag{20}$$

$$\widetilde{D} = \begin{bmatrix} \widetilde{d}_{ij}^{k} & \dots & \dots \\ \dots & \dots & \dots \\ \dots & \dots & \widetilde{d}_{nm} \end{bmatrix}, \tag{21}$$

$$\widetilde{W} = \begin{bmatrix} \widetilde{w}_1 \\ \widetilde{w}_2 \\ \dots \\ \widetilde{w}_m \end{bmatrix}. \tag{22}$$

6. Transforming matrix $\widetilde{D}$ into normalised $\widetilde{R}$
Fuzzy decision matrix $\widetilde{D}$ is transformed into normalised $\widetilde{R}$, where:

$$\widetilde{R} = [\widetilde{r}_{ij}]_{nxm}. \tag{23}$$

The matrix is normalised for:
– benefit criterion:

$$\widetilde{r}_{ij} = \left(\frac{l_{ij}}{u_j^+}, \frac{m_{ij}}{u_j^+}, \frac{u_{ij}}{u_j^+}\right), \tag{24}$$

where $u_j^+ = \max_i u_{ij} - \max\ u_{ij}$ for a given variant
– cost criterion:

$$\widetilde{r}_{ij} = \left(\frac{l_j^-}{u_{ij}}, \frac{l_j^-}{m_{ij}}, \frac{l_j^-}{l_{ij}}\right), \tag{25}$$

where $l_j^- = \min_i l_{ij} - \min\ l_{ij}$ for a given variant.

7. Calculating the weighted normalised matrix of weights $\widetilde{V}$:

$$\widetilde{V} = [\widetilde{v}_{ij}]_{nxm}, \tag{26}$$

where

$$\widetilde{v}_{ij} = \widetilde{r}_{ij} \times \widetilde{w}_j. \tag{27}$$

8. Defining the Fuzzy Positive Ideal Solution (FPIS) $A^+$ and the Fuzzy Negative Ideal Solution (FNIS) $A^-$

$$A^+ = (\widetilde{v}_1^+, \widetilde{v}_j^+, \dots, \widetilde{v}_m^+), \tag{28}$$

$$A^- = (\widetilde{v}_1^-, \widetilde{v}_j^-, \dots, \widetilde{v}_m^-), \tag{29}$$

where

$$\widetilde{v}_j^+ = (1, 1, 1), \tag{30}$$

$$\widetilde{v}_j^- = (0, 0, 0). \tag{31}$$

9. Calculating the distance of each variant from $A^+$ and $A^-$:

$$d_i^+ = \sum_{j=1}^{m} d_v(\widetilde{v}_{ij}, \widetilde{v}_j^+), \tag{32}$$

$$d_i^- = \sum_{j=1}^{m} d_v(\widetilde{v}_{ij}, \widetilde{v}_j^-), \tag{33}$$

where $d_v$ represents the distance between two fuzzy numbers, expressed by the following formula:

$$d_v(\widetilde{x}, \widetilde{z}) = \sqrt{\frac{1}{3}[(l_x - l_z)^2 + (m_x - m_z)^2 + (u_x - u_z)^2]}. \tag{34}$$

10. Calculating the closeness coefficient (CC):

$$\mathrm{CC}_i = \frac{d_i^-}{d_i^+ + d_i^-}. \tag{35}$$

11. Arranging the variants in a descending order in terms of the CC; the best variant is the one closest to the FPIS and farthest from the FNIS.

**SMART**

The procedure followed by the authors using the SMART method [26–28] consists of the following steps:

1. Describing the problem.
2. Selecting criteria, variants and decision maker(s).
3. Assigning weights to the criteria and assessing variants relative to the criteria, according to predefined scales (Table 3); the final weight assigned to a criterion is the average weight assigned by the experts.
4. Normalising the weights with the following formula:

$$\frac{w_j}{\sum\limits_{j=1}^{m} w_j}, \qquad j = 1, 2, \dots, m. \tag{36}$$

Table 3
Scales for the assessment of criteria and variants relative to given criteria.

| Importance of criterion | | Assessment of a variant relative to the criterion | |
|---|---|---|---|
| of little importance | 0 | very low | 0 |
| of medium importance | 0.25 | low | 2.5 |
| important | 0.5 | good | 5 |
| very important | 0.75 | very good | 7.5 |
| absolutely important | 1 | excellent | 10 |

5. Calculating usefulness of variants relative to each criterion, with the following formula:

$$u_j(a_i) = \frac{c_j - c_{\min_j}}{c_{\max_j} - c_{\min_j}}, \qquad i = 1, 2, ..., n; \qquad j = 1, 2, ..., m. \tag{37}$$

6. Final assessment of each variant through multiplying the normalised weights of particular criteria by usefulness of each variant relative a given criterion.
7. Arranging the variants in an order from the best to the worst.

## Methodology of industrial robot selection

There is a wide range of industrial robots for specific industrial applications, which offer various technical parameters and performance. The key parameters which differentiate particular models are:

- Number of axles.
- Maximum lifting capacity (kN).
- Working volume ($mm^3$).
- Maximum working range (°) – maximum range of movement of the axles.
- Maximum velocity (°/s, °/rad) – maximum velocities of the axles.
- Repeatability (mm) – the range of differences between positions repeatedly obtained from one direction.
- Positioning accuracy (mm) – the difference between the predefined position and the average position obtained, from one direction.
- Ambient temperature (°C) – the recommended range of operating temperature.
- Recommended relative ambient humidity (% +°C).
- Occupied space ($m^3$).
- Additional arm load (kN).
- Total weight (kg).
- Types of drives.
- Presence of mechanical bumper stops.
- Mounting options.
- Additional information by the manufacturer – a description of accessories or an instruction manual for mounting the base (according to relevant standards).
- Power consumption.

Further analysis focuses on the parameters relevant for a flexible assembly station in a mid-sized manufacturing company. The number of axles is not considered, since the parameter has the same value for all the robots under analysis. A list of the industrial robots under analysis and their parameters is shown in Table 4. Price has been added as one of the criteria. Although it does not fall into the category of technical or operational parameters, it is always considered when making investment decisions.

Table 4
Parameters considered in the selection of an industrial robot.

| Parameters – criteria selected for the assessment of an industrial robot | Robot 1 | Robot 2 | Robot 3 | Robot 4 | Robot 5 |
|---|---|---|---|---|---|
| | W1 | W2 | W3 | W4 | W5 |
| Number of axles | 6 | 6 | 6 | 6 | 6 |
| Lifting capacity [kN] | 0.06 | 0.12 | 0.06 | 0.06 | 0.08 |
| Weight [kg] | 250 | 98 | 270 | 250 | 180 |
| Working range [mm] | 2006 | 1385 | 1373 | 1450 | 1598 |
| Repeatability +/− [mm] | 0.1 | 0.05 | 0.08 | 0.005 | 0.1 |
| Axles – range of movement [°] | | | | | |
| J1 | 340 | 340 | 340 | 360 | 340 |
| J2 | 255 | 230 | 250 | 240 | 255 |
| J3 | 375 | 290 | 315 | 310 | 475 |
| J4 | 360 | 320 | 380 | 400 | 540 |
| J5 | 280 | 240 | 280 | 230 | 255 |
| J6 | 720 | 720 | 720 | 800 | 800 |
| Axles – velocity [°/s] | | | | | |
| J1 | 165 | 230 | 150 | 180 | 170 |
| J2 | 165 | 172 | 160 | 180 | 170 |
| J3 | 175 | 200 | 170 | 180 | 175 |
| J4 | 350 | 352 | 400 | 320 | 360 |
| J5 | 340 | 375 | 400 | 400 | 350 |
| J6 | 520 | 660 | 500 | 460 | 540 |
| Price [EUR] | 37,000 | 37,000 | 48,000 | 39,000 | 34,000 |

The selection of an industrial robot using the F-AHP was conducted according to the procedure discussed in Subsec. 2.1.

The selected group of experts determined the most important criteria (parameters) and variants (specific models of industrial robots) for the defined decision problem. Next, they compared the criteria for importance, using fuzzy numbers. The results of the comparison (being a consensus of the experts' opinions) are shown in Table 5.

Next, the geometric means of assessments of particular criteria and their fuzzy weights were calculated. The fuzzy weights were then defuzzified and normalised weights were computed, what facilitated the selection of the most important parameters. The results of these stages of the procedure are shown in Table 6.

Working range and repeatability were found to be the most important criteria. Normalised weights of all the seven criteria were determined and multiplied by the weights of robots relative to the criteria to obtain the final assessment (Table 7). Robot 1, with the largest working range, was found to be the best.

Table 5
Comparison of parameters (criteria) in pairs – matrix $\widetilde{A}$.

| Criterion (parameter) | Lifting capacity | Weight | Working range | Repeatability | Range of movement | Price | Velocity |
|---|---|---|---|---|---|---|---|
| Lifting capacity | **(1, 1, 1)** | (1, 1, 1) | (1/5, 1/3, 1) | (1/7, 1/5, 1/3) | (1, 1, 1) | (1, 1, 1) | (7, 9, 9) |
| Weight | (1, 1, 1) | **(1, 1, 1)** | (1/5, 1/3, 1) | (1/7, 1/5, 1/3) | (1/5, 1/3, 1) | (1, 1, 1) | (7, 9, 9) |
| Working range | (1, 3, 5) | (1, 3, 5) | **(1, 1, 1)** | (1, 3, 5) | (1, 3, 5) | (3, 5, 7) | (3, 5, 7) |
| Repeatability | (3, 5, 7) | (3, 5, 7) | (1/5, 1/3, 1) | **(1, 1, 1)** | (1, 3, 5) | (1, 3, 5) | (3, 5, 7) |
| Range of movement | (1, 1, 1) | (1, 3, 5) | (1/5, 1/3, 1) | (1/5, 1/3, 1) | **(1, 1, 1)** | (1/5, 1/3, 1) | (1, 3, 5) |
| Price | (1, 1, 1) | (1, 1, 1) | (1/7, 1/5, 1/3) | (1/5, 1/3, 1) | (1, 3, 5) | **(1, 1, 1)** | (3, 5, 7) |
| Velocity | (1/9, 1/9, 1/7) | (1/9, 1/9, 1/7) | (1/7, 1/5, 1/3) | (1/7, 1/5, 1/3) | (1/5, 1/3, 1) | (1/7. 1/5, 1/3) | **(1, 1, 1)** |

Table 6
Aggregate results obtained in the consecutive steps of the F-AHP.

| Criterion (parameter) | Geometric mean $\widetilde{r}_i$ | Fuzzy weight $\widetilde{w}_i$ | Defuzzified weight $M_i$ | Final relative weight $w_i$ |
|---|---|---|---|---|
| Lifting capacity | (0.7946; 0.9296; 1.1699) | (0.0579; 0.1021; 0.2144) | 0.1248 | 0.0957 |
| Weight | (0.6314; 0.7946; 1.1699) | (0.0460; 0.0873; 0.2144) | 0.1159 | 0.0889 |
| Working range | (1.3687; 2.9672; 4.3739) | (0.0997; 0.3258; 0.8015) | 0.4090 | **0.3136** |
| Repeatability | (1.2724; 2.3319; 3.6466) | (0.0927; 0.2561; 0.6682) | 0.3390 | **0.2600** |
| Range of movement | (0.5017; 0.8548; 1.5838) | (0.0366; 0.0939; 0.2902) | 0.1402 | 0.1075 |
| Price | (0.7040; 1.0000; 1.4204) | (0.0513; 0.1098; 0.2603) | 0.1405 | 0.1077 |
| Velocity | (0.1842; 0.2289; 0.3581) | (0.0134; 0.0251; 0.0656) | 0.0347 | 0.0266 |
| $\widetilde{r}_{i_{\text{total}}}$ | (5.4571; 9.1070; 13.7228) | Total | 1.3041 | |
| $(\widetilde{r}_{i_{\text{total}}})^{-1}$ | (0.1832; 0.1098; 0.0729 | | | |

Table 7
Assessment of five industrial robots by the F-AHP.

| Robot/ Criterion (parameter) | Lifting capacity | Weight | Working range | Repeatability | Range of movement | Price | Velocity | Final assessment | Order of preference, by the F-AHP |
|---|---|---|---|---|---|---|---|---|---|
| Robot 1 | 0.0742 | 0.0720 | 0.5446 | 0.0559 | 0.1468 | 0.2097 | 0.1153 | **0.2403** | **1** |
| Robot 2 | 0.5352 | 0.5687 | 0.0694 | 0.1536 | 0.0970 | 0.2097 | 0.3312 | 0.2053 | 4 |
| Robot 3 | 0.0773 | 0.0451 | 0.0488 | 0.1673 | 0.1599 | 0.0514 | 0.1412 | 0.0967 | 5 |
| Robot 4 | 0.0773 | 0.0758 | 0.1172 | 0.5294 | 0.2082 | 0.1040 | 0.2323 | 0.2283 | 3 |
| Robot 5 | 0.2359 | 0.2384 | 0.2200 | 0.0939 | 0.3881 | 0.4252 | 0.1801 | 0.2295 | 2 |

The F-TOPSIS method was used following the procedure discussed in Subsec. 2.2. The same experts were employed, so the criteria and variants had already been determined. Three experts assessed the criteria and variants based on the scales presented above. Averaged results of the assessment are presented in Table 8 (matrices $\widetilde{D}$ and $\widetilde{W}$). Having transformed matrix $\widetilde{D}$ into normalised matrix $\widetilde{R}$ (Table 9), weighted normalised matrix of weights $\widetilde{V}$ was found (Table 10) through multiplication of the weights of criteria by assessments of the variants relative to particular criteria.

Table 8
Matrix $\widetilde{D}$ and transposed matrix $\widetilde{W}$ – averaged experts' assessment of criteria and variants.

| Robot/ Criterion (parameter) | Lifting capacity | Weight | Working range | Repeatability | Range of movement | Price | Velocity |
|---|---|---|---|---|---|---|---|
| Robot 1 | (2.5; 5; 7.5) | (0.83; 3.33; 5.83) | (7.5; 10; 10) | (3.33; 5.83; 8.33) | (3.33; 5.83; 8.33) | (3.33; 5.83; 8.33) | (0.83; 3.33; 5.83) |
| Robot 2 | (5.83; 8.33; 10) | (6.67; 9.17; 10) | (0; 2.5; 5) | (5; 7.5; 10) | (3.33; 5.83; 8.33) | (3.33; 5.83; 8.33) | (5.83; 8.33; 10) |
| Robot 3 | (2.5; 5; 7.5) | (0.83; 3.33; 5.83) | (0; 2.5; 5) | (3.33; 5.83; 8.33) | (4.17; 6.67; 9.17) | (0; 2.5; 5) | (2.5; 5; 7.5) |
| Robot 4 | (2.5; 5; 7.5) | (0.83; 3.33; 5.83) | (2.5; 5; 7.5) | (7.5; 10; 10) | (4.17; 6.67; 9.17) | (3.33; 5.83; 8.33) | (3.33; 5.83; 8.33) |
| Robot 5 | (4.17; 6.67; 9.17) | (2.5; 5; 7.5) | (4.17; 6.67; 9.17) | (3.33; 5.83; 8.33) | (7.5; 10; 10) | (6.67; 9.17; 10) | (2.5; 5; 7.5) |
| Criterion's weight – transposed matrix | (0; 0.25; 0.5) | (0; 0.25; 0.5) | (0.75; 1; 1) | (0.5; 0.75; 1) | (0.25; 0.5; 0.75) | (0.25; 0.5; 0.75) | (0; 0; 0.25) |

Table 9
Normalised matrix $\widetilde{R}$ and transposed matrix $\widetilde{W}$.

| Robot/ Criterion (parameter) | Lifting capacity | Weight | Working range | Repeatability | Range of movement | Price | Velocity |
|---|---|---|---|---|---|---|---|
| Robot 1 | (0.25; 0.5; 0.75) | (0.08; 0.33; 0.58) | (0.75; 1; 1) | (0.33; 0.58; 0.83) | (0.33; 0.58; 0.83) | (0.33; 0.58; 0.83) | (0.08; 0.33; 0.58) |
| Robot 2 | (0.58; 0.83; 1) | (0.67; 0.92; 1) | (0; 0.25; 0.5) | (0.5; 0.75; 1) | (0.33; 0.58; 0.83) | (0.33; 0.58; 0.83) | (0.58; 0.83; 1) |
| Robot 3 | (0.25; 0.5; 0.75) | (0.08; 0.33; 0.58) | (0; 0.25; 0.5) | (0.33; 0.58; 0.83) | (0.42; 0.67; 0.92) | (0; 0.25; 0.5) | (0.25; 0.5; 0.75) |
| Robot 4 | (0.25; 0.5; 0.75) | (0.08; 0.33; 0.58) | (0.25; 0.5; 0.75) | (0.75; 1; 1) | (0.42; 0.67; 0.92) | (0.33; 0.58; 0.83) | (0.33; 0.58; 0.83) |
| Robot 5 | (0.42; 0.67; 0.92) | (0.25; 0.5; 0.75) | (0.42; 0.67; 0.92) | (0.33; 0.58; 0.83) | (0.75; 1; 1) | (0.67; 0.92; 1) | (0.25; 0.5; 0.75) |
| Criterion's weight – transposed matrix | (0; 0.25; 0.5) | (0; 0.25; 0.5) | (0.75; 1; 1) | (0.5; 0.75; 1) | (0.25; 0.5; 0.75) | (0.25; 0.5; 0.75) | (0; 0; 0.25) |

Table 10
Weighted normalised matrix of weights $\widetilde{V}$.

| Robot/ Criterion (parameter) | Lifting capacity | Weight | Working range | Repeatability | Range of movement | Price | Velocity |
|---|---|---|---|---|---|---|---|
| Robot 1 | (0; 0.125; 0.375) | (0; 0.083; 0.292) | (0.563; 1; 1) | (0.167; 0.438; 0.833) | (0.083; 0.292; 0.625) | (0.083; 0.292; 0.625) | (0; 0; 0.146) |
| Robot 2 | (0; 0.208; 0.5) | (0; 0.229; 0.5) | (0; 0.25; 0.5) | (0.25; 0.563; 1) | (0.083; 0.292; 0.625) | (0.083; 0.292; 0.625) | (0; 0; 0.25) |
| Robot 3 | (0; 0.125; 0.375) | (0; 0.083; 0.292) | (0; 0.25; 0.5) | (0.167; 0.438; 0.833) | (0.104; 0.333; 0.688) | (0; 0.125; 0.375) | (0; 0; 0.188) |
| Robot 4 | (0; 0.125; 0.375) | (0; 0.083; 0.292) | (0.188; 0.5; 0.75) | (0.375; 0.75; 1) | (0.104; 0.333; 0.688) | (0.083; 0.292; 0.625) | (0; 0; 0.208) |
| Robot 5 | (0; 0.167; 0.458) | (0; 0.125; 0.375) | (0.313; 0.667; 0.917) | (0.167; 0.438; 0.833) | (0.188; 0;5 0.75) | (0.167; 0.458; 0.75) | (0; 0; 0.188) |

Table 11
Distances of robots to ideal solutions $A^+$.

| Robot/ Criterion (parameter) | Lifting capacity | Weight | Working range | Repeatability | Range of movement | Price | Velocity | Total di+ |
|---|---|---|---|---|---|---|---|---|
| Robot 1 | 0.848 | 0.884 | 0.253 | 0.588 | 0.703 | 0.703 | 0.954 | 4.932 |
| Robot 2 | 0.791 | 0.784 | 0.777 | 0.501 | 0.703 | 0.703 | 0.924 | 5.184 |
| Robot 3 | 0.848 | 0.884 | 0.777 | 0.588 | 0.669 | 0.848 | 0.942 | 5.556 |
| Robot 4 | 0.848 | 0.884 | 0.569 | 0.389 | 0.669 | 0.703 | 0.936 | 4.998 |
| Robot 5 | 0.814 | 0.848 | 0.444 | 0.588 | 0.569 | 0.592 | 0.942 | 4.797 |

Table 12
Distances of robots to ideal solutions $A^-$.

| Robot/ Criterion (parameter) | Lifting capacity | Weight | Working range | Repeatability | Range of movement | Price | Velocity | Total di− |
|---|---|---|---|---|---|---|---|---|
| Robot 1 | 0.228 | 0.175 | 0.879 | 0.552 | 0.401 | 0.662 | 0.084 | 2.982 |
| Robot 2 | 0.313 | 0.318 | 0.323 | 0.678 | 0.401 | 0.662 | 0.144 | 2.839 |
| Robot 3 | 0.228 | 0.175 | 0.323 | 0.552 | 0.445 | 0.621 | 0.108 | 2.452 |
| Robot 4 | 0.228 | 0.175 | 0.532 | 0.753 | 0.445 | 0.662 | 0.120 | 2.916 |
| Robot 5 | 0.282 | 0.228 | 0.679 | 0.552 | 0.532 | 0.699 | 0.108 | 3.080 |

In the next step of the methodology, ideal matrices and were defined and distances of particular robots to the ideal solutions were found (Tables 11 and 12). Having calculated the closeness coefficients (Table 13), a ranking list of robots was developed.

Table 13
Closeness coefficients and ranking list of robots.

| | Closeness coefficient | Ranking list of the assessed industrial robots |
|---|---|---|
| Robot 1 | 0.377 | 2 |
| Robot 2 | 0.354 | 4 |
| Robot 3 | 0.306 | 5 |
| Robot 4 | 0.368 | 3 |
| Robot 5 | 0.391 | 1 |

The SMART method was used following the procedure discussed in Subsec. 2.3. The same experts were employed to assess the robots, so the criteria (parameters) and variants (robots compared) had already been determined. Three experts assessed the criteria and variants based on the scales presented above. Weights assigned to the criteria as well as their normalised values are shown in Table 14.

Next, the robots were assessed relative to the criteria. Averaged assessments are shown in Table 15.

After that, usefulness of each industrial robot relative to each criterion was determined (Table 16).

Assessments of particular robots were obtained through multiplication of normalised weights by usefulness relative to particular criteria (Table 17).

Table 14
Normalised weights of criteria.

| Criterion (parameter) | Weight | Normalised weight |
|---|---|---|
| Lifting capacity | 0.25 | 0.08 |
| Weight | 0.25 | 0.08 |
| Working range | 0.75 | 0.25 |
| Repeatability | 0.75 | 0.25 |
| Range of movement | 0.5 | 0.17 |
| Price | 0.5 | 0.17 |
| Velocity | 0 | 0.00 |
| Total | 3 | |

Table 15
Averaged assessments of industrial robots relative to decision criteria.

| Robot/Criterion (parameter) | Lifting capacity | Weight | Working range | Repeatability | Range of movement | Price | Velocity |
|---|---|---|---|---|---|---|---|
| Robot 1 | 5.00 | 3.33 | 10.00 | 5.83 | 5.83 | 5.83 | 3.33 |
| Robot 2 | 8.33 | 9.17 | 2.50 | 7.50 | 5.83 | 5.83 | 8.33 |
| Robot 3 | 5.00 | 3.33 | 2.50 | 5.83 | 6.67 | 2.50 | 5.00 |
| Robot 4 | 5.00 | 3.33 | 5.00 | 10.00 | 6.67 | 5.83 | 5.83 |
| Robot 5 | 6.67 | 5.00 | 6.67 | 5.83 | 10.00 | 9.17 | 5.00 |

Table 16
Usefulness of industrial robots relative to parameters.

| Robot/Criterion (parameter) | Lifting capacity | Weight | Working range | Repeatability | Range of movement | Price | Velocity |
|---|---|---|---|---|---|---|---|
| Robot 1 | 0.00 | 0.00 | 1.00 | 0.00 | 0.00 | 0.50 | 0.00 |
| Robot 2 | 1.00 | 1.00 | 0.00 | 0.40 | 0.00 | 0.50 | 1.00 |
| Robot 3 | 0.00 | 0.00 | 0.00 | 0.00 | 0.20 | 0.00 | 0.33 |
| Robot 4 | 0.00 | 0.00 | 0.33 | 1.00 | 0.20 | 0.50 | 0.50 |
| Robot 5 | 0.50 | 0.29 | 0.56 | 0.00 | 1.00 | 1.00 | 0.33 |

Table 17
Final assessments of industrial robots by the SMART method.

| Robot/Criterion (parameter) | Lifting capacity | Weight | Working range | Repeatability | Range of movement | Price | Velocity | Final assessment | Ranking list |
|---|---|---|---|---|---|---|---|---|---|
| Robot 1 | 0.00 | 0.00 | 1.00 | 0.00 | 0.00 | 0.50 | 0.00 | 0.33 | 3 |
| Robot 2 | 1.00 | 1.00 | 0.00 | 0.40 | 0.00 | 0.50 | 1.00 | 0.35 | 4 |
| Robot 3 | 0.00 | 0.00 | 0.00 | 0.00 | 0.20 | 0.00 | 0.33 | 0.03 | 5 |
| Robot 4 | 0.00 | 0.00 | 0.33 | 1.00 | 0.20 | 0.50 | 0.50 | 0.45 | 2 |
| Robot 5 | 0.50 | 0.29 | 0.56 | 0.00 | 1.00 | 1.00 | 0.33 | **0.54** | **1** |
| Weight | 0.08 | 0.08 | 0.25 | 0.25 | 0.17 | 0.17 | 0.00 | | |

The SMART method gave the same result as F-TOPSIS – robot 5 was found to be the best.

## Summary

The paper looks at three multi-criteria decision-making (MCDM) methods applied for the selection of an industrial robot for an assembly station in a medium-sized manufacturing company. Each method has its own advantages and downsides, and involves subjective decisions made by the decision maker. In order to minimise the impact of the MCDM method on the selection, results of the analyses conducted by the three methods and the final classification resulting from the experts' preferences have been listed in Table 18.

Table 18
Assessments using F-AHP, F-TOPSIS and SMART.

| Robot/ Method | a* | b* | c* | Averaged assessment | Final classification |
|---|---|---|---|---|---|
| Robot 1 | 1 | 2 | 3 | 2 | 2 |
| Robot 2 | 4 | 4 | 4 | 4 | 4 |
| Robot 3 | 5 | 5 | 5 | 5 | 5 |
| Robot 4 | 3 | 3 | 2 | 2.67 | 3 |
| Robot 5 | 2 | 1 | 1 | 1.33 | 1 |

a* – F-AHP, b* – F-TOPSIS, c* – SMART

Taking into consideration the technical and operational parameters, robot 5 was found to be the best. All the three methods yielded similar results. The approach discussed in the paper can find a wide range of applications in machine operation and maintenance.

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