Multi-Criteria Model for the Selection of New Process Equipment in Casting Manufacturing: A Case Study

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Abstract: The decision to introduce new process equipment is always a complex and risky process. An important competitive advantage in the automotive industry is the integration of new process equipment into the production system using different decision-making models composed of measurable key indicators, scientific methods and empirical values, study defines a multi-criteria model based on various scientific sources combined with extensive manufacturing experience, which is an important tool for making quality decisions when introducing new equipment or technology. The study considers five main areas of indicators and characteristics: internal, external, financial, knowledge level, and other important indicators. By applying the Delphi method, the importance of the indicators is defined by multidisciplinary experts and the order of each characteristic is determined, which is then prioritized using MCDM methods to select the final solution. The paper presents the model definition and a practical application of the model to the castings manufacturing in the automotive industry.

Keywords: AHP; MCDM; new process equipment; strategic decision; TOPSIS

1 INTRODUCTION

Due to the current intense changes in the automotive market, whether due to a global pandemic or environmental requirements, the key competitive advantage lies in the introduction of new technologies or more productive and flexible equipment into the manufacturing process. Many different requirements are forcing many companies to accelerate their transformation processes through organizational changes and rapid changes in the manufacturing process. In these processes, managers and experts are confronted with many attributes such as possible solutions, deviations, potential suppliers, KPIs (Key Process Indicators), alternatives ... in order to choose the best solution for a company. The selection of the attributes to be evaluated is very important for the final decision outcome. Identifying the relevant attributes can be done in many ways. One of the common methods is to interview focus groups in combination with a protocol procedure. A very effective method for selecting attributes is to involve managers and experts based on their knowledge and experience. They are familiar with the critical requirements of a process they are working with. The managers of the case study company of Chau et al. [1] recommended the following attributes: Lead Time, Operator Qualification and Training, Flexibility, Setup Time, Equipment Availability, Equipment Maintenance and Service Support, Capability, Product Quality, Reliability, and Technology Leadership.

According to several studies, it is recommended to limit the number of KPIs to a number between four and twelve KPIs for the entire company [2]. Marek et al. [3] conducted a systematic literature review of 180 papers to identify frequently considered KPIs. The final synthesis shows eleven company relevant autonomous and redundancy-free KPIs: delivery dates, lead time, return on capital employed, unit cost, overall equipment effectiveness, product portfolio extensibility, production schedule flexibility, product volume variability, customer satisfaction, product quality, and scrap rate. These are just a few examples of reference attributes in the manufacturing industry that are closely related to the production area, market, business strategies, etc. The multi-criteria decision making (MCDM) method [4] is a discipline for evaluating conflicting criteria in the process of decision making. The key to a successful decision lies in the quality of the input data of MCDM methods. For this study, the Analytic Hierarchy Process (AHP) method [5] was used to determine the weights of each criterion, and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method [6] was used to evaluate the criteria. The objectivity of the MCDC methods was ensured by using the Delphi method [7].

The aim of this study is to define key indicators and a model to determine the best solution for the introduction of new equipment in a given company.

1.1 Problem Statement and Literature Review

The decision to introduce new process equipment is usually the responsibility of top management after analysing all relevant factors for the company's ability to implement a new technology [8]. The next step is to identify and select the best possible solution that is suitable for a particular company or process. Usually, experts from the technical department play the main role in analysing all possible solutions and submitting proposals for a final solution to the top management. Often, top management makes the final decision based on the data provided by the technical department and the purchasing department. This approach can lead to indifference between experts and operators in the phase of new equipment introduction and also in serial production. To avoid such scenarios and achieve the synergistic effect of all parties involved in the introduction of new equipment processes, it is necessary to involve representative experts from the different business areas in the decision-making process. The present study was conducted to define a model for the best solution in the introduction of

new equipment suppliers by including all relevant factors in the decision-making process using MCDM methods.

Many authors have studied different methods of decision making based on a multi-criteria approach to finding the best solution. Alvarez et al. [9] made a systematic review of MCDM sorting methods, covering 30 years of research in this field. The analysis shows that the development of MCDM methods is still in a growth phase and highlights the trends of applied methods. Bertolini et al. [10] compared seven different MCDM methods in their study to evaluate the selection of new manufacturing technologies. They found that TOPSIS is one of the optimal methods for new technology selection. In a systematic literature review of decision models for supplier selection in the era of Industry 4.0, Resende et al. [11] found that 64% of the studies combined two or more techniques in the decision models. Depczynski [12] used AHP for supplier evaluation in a case study of a steel industry company. Acar et al. [13] used a combination of AHP and TOPSIS methods to evaluate production performance. Battistoni et al. [14] found the AHP method very useful for the new product development process. Khaira et al. [15] used a two-step decision making approach to identify critical equipment using the modified AHP method along with PROMETHEE methods to validate the AHP results. The validation of this innovative methodology and the corresponding equations for normalization in the AHP was performed using the PROMETHEE method and the results obtained were the same as those of the modified AHP. Rouyendegh et al. [16] used the hybrid method AHP-TOPSIS to select sectors for ERP (Enterprise Resource Planning) implementation. Nouri et al. [17] studied the prioritization of factors affecting technology selection in petrochemical companies using a hybrid approach of TOPSIS and Shanon entropy. They concluded that the technology productivity factor has the highest priority. Using TOPSIS and entropy MCDM techniques, Choda et al. [18] defined a model for industrial arc welding robot selection. An integrated three-stage Delphi MCDM Bayesian Network was identified by Dohale et al. [19] in a study of manufacturing system selection. The applicability of MCDM methods in supplier selection was shown by Agarwal et al. [20] in their study on multi-criteria decision making methods for supplier evaluation using sixty-eight research articles on the application of AHP in supplier selection [21]. Dweiri et al. [22] proposed a decision support model for supplier selection based on AHP using a case from the automotive industry. In a selection of construction equipment tasks, Temiz et al. [23] compared the MCDM methods via a case study. They concluded that the methods are consistent with each other as well as the decision makers' initial assessments of the alternatives.

The literature review shows that MCDM techniques are also successfully used in the manufacturing industry for many selection purposes. The companies' requirements in terms of strategy, functionality, and operational capability are critical for evaluating suppliers and determining the criteria using the most appropriate methods. Some methods may be advantageous for certain companies, so it is important to evaluate suppliers according to the companies'

requirements. [20]. During the literature review, it was found that there are no available decision models and predefined indicators for our case study, which considers a specific area of the automotive industry and the specific task of selecting new equipment based on combined indicators. In view of a current case study and future similar decision processes, it was decided to define a hybrid model of MCDM methods and to select our list of most suitable indicators.
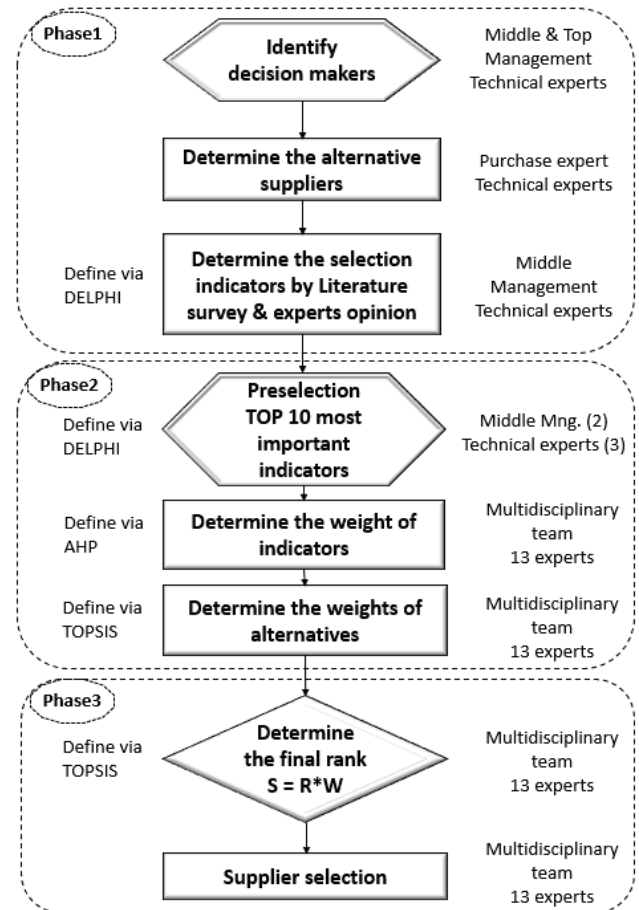

Figure 1 Decision model concept

1.2 Research Approach

The study is conducted to define a model for decision making in three phases: Phase 1 – a preparation phase with the identification of decision makers and data collection on indicators and alternative suppliers, Phase 2 - the pre-selection of indicators with the determination of the weighting of indicators and alternatives, and Phase 3 - a ranking of alternatives and the final selection of the supplier. Based on the conclusions of the literature review on the main selection indicators, the study used a hybrid application of MCDM methods combined with the experience of experts in the manufacturing company. The accepted concept of the decision process is shown in Fig. 1. Before the data were delivered to the team, the technical experts from the engineering department performed an initial analysis and excluded all indicators and suppliers that did not provide consistent results or for which relevant data were not

available. The data consisted of the final 15 indicators and 7 potential new equipment suppliers. Next, experts from middle management and technical experts from the engineering department used the Delphi method to pre-select indicators for the introduction of new process equipment.

This team consisted of two members of middle management and three technical experts. Next, the multifunctional team analysed the data provided by the technical experts and middle management on the machining area of medium-sized castings. The 13 members of the multifunctional team were from different departments of the company: Middle and Upper Management, Engineering, Quality, Maintenance, Purchasing, Planning & Controlling, and Production with more than 15 years of experience in a specific field. The AHP method was used to determine the weighting factors for each indicator and finally, the TOPSIS method was used to rank each indicator with possible alternatives and make the final solution selection.

2 DATA ANALYSIS
2.1 Phase 1 – Preparation Activities

In order to obtain reliable results of the study, one of the most important activities is the quality preparation phase with several important activities: defining the structure of the team members, predefining the key indicators, collecting objective input data for each alternative, and clearly defining and instructing all study members how to conduct the study.

Defining the team members is a very important task because it is not aimed to make a team with the loudest experts ones but with the most competent experts, that will participate in the study. Occasionally, there are many competent experts in the field with poor presentation skills who make a questionable contribution to the teamwork tasks. The Delphi method approach is a good tool to leverage expert knowledge, regardless of poor presentation skills or a public action problem. Since this is the first time the company has used MCDM methods for strategic decision making, several training workshops were set up. Based on the current corporate strategy, customer expectations, and the results of the literature review, the fifteen most important indicators for data collection were determined. The decision to reject the indicators was due to the lack of reliable data or the absence of data, as well as the priorities of the company based on the strategy in the analysed period.

2.2 Phase 2 – Preselection TOP10 Indicators with Delphi Method

The fifteen indicators were reviewed by middle management and technical experts using the Delphi method to exclude less important indicators and to simplify and accelerate the study and final decision on the introduction of new process equipment. In this study, a Likert scale from 1 (least important) to 5 (most important) was used to rate the indicators. The mean value of each indicator 4,0 is used as the criterion for acceptability. If the mean of the indicator is 4,0 and above, the indicator is accepted for further study, otherwise, it is rejected. 5 indicators were rejected and the top 10 indicators were accepted (Tab. 1). In general, due to the

different opinions of the experts based on their experience and background, it is good to recalculate these values using the Shannon entropy method, but in this analysis, it was not reasonable due to the quality of the input data or the lack of data.

Table 1 Delphi method preselection results

	Indicators	Mean	MM1	MM2	Te1	Te2	Te3	Status
1	Cost/pcs	5	5	5	5	5	5	Accept
2	Flexibility	4,4	5	5	4	4	4	Accept
3	Total investment	4,4	5	5	4	4	4	Accept
4	Clamping polyvalence	4,2	3	4	4	5	5	Accept
5	Reference	4,2	4	4	4	4	5	Accept
6	Set-up	4,2	4	3	5	4	5	Accept
7	Maintenance	4,2	4	4	5	4	4	Accept
8	Nb. of clamping devices	4	4	3	4	5	4	Accept
9	Operator number	4	4	3	5	4	4	Accept
10	Automatization	4	4	4	4	3	5	Accept
11	Load	3,8	4	4	4	3	4	Reject
12	Delivery time	3,8	4	5	3	4	3	Reject
13	Payment condition	3,6	4	4	4	3	3	Reject
14	OEE	3	3	4	3	2	3	Reject
15	Layout space	3	3	3	3	3	3	Reject

MM1-MM2: Middle management experts
Te1-Te3: Technical expert from the engineering department

The study continued with 10 accepted key indicators: Cost/unit - production cost per single product, Flexibility - flexibility of process equipment to produce similar products in the future after the EOP (end of production) of the current product, Total investment - total investment depending on the number of production, measuring and logistic equipment to be installed, Clamping polyvalence - the capability of cutting tools and clamping devices, that can be used on alternative machines, Reference - supplier references in similar manufacturing processes, Setup - complexity level and number, depending on the number of fixtures, process capability and operator skill level, Maintenance - complexity of maintenance activity and machine capability Cpm (Taguchi capability index), Nb. of fixtures - number of fixtures depends on process capability, process adjustments and maintenance costs, Number of operators - impact on production quality, productivity and costs, Automation - possibility of automation (loading/unloading) of certain machines with the environment.

The weights and ratings are usually difficult to define precisely because they are subject to uncertainties that can be dealt with using linguistic terms instead of numerical values [24].

2.3 Phase 2 – Weight of Indicator Determination with AHP Method

The AHP proposed by Saaty is one of the most popular methods in the decision-making process for solving complex decision problems because it captures both subjective and objective evaluation measures. Based on pairwise comparisons, weights are calculated by finding the dominant right eigenvector (EV) of the positive reciprocal decision matrix. This qualitative pairwise comparison follows the importance scale proposed by Saaty, as shown in Tab. 2. The

pairwise comparison is also used to determine the relative importance of the alternatives for each of the criteria. The sum of the priorities for all alternatives must equal 1. The pairwise comparison is performed in matrix form to check the consistency of the judgment [22].

Table 2 Saaty AHP scale [5]

Importance intensity	Definition	Description
1	Very bad	Equal importance
3	Bad	Moderate importance of one over another
5	Medium best	Strong importance of one over another
7	Good	Very strong importance of one over another
9	Very good	The extreme importance of one over another

Table 3 Pairwise comparison matrix

Indicators	1	2	3	4	5	6	7	8	9	10
1	1	7	1	7	3	5	1	3	3	3
2	1/7	1	1/3	1	1	1/3	1/3	1	1/3	1/3
3	1	3	1	3	1	1/3	1/	1	1	1
4	1/7	1	1/3	1	1/3	1/5	1/7	1/3	1/3	1
5	1/3	1	1	3	1	1	1	3	1	1
6	1/5	3	3	5	1	1	1/5	1	3	1/3
7	1	3	5	7	1	5	1	5	5	5
8	1/3	1	1	3	1/3	1	1/5	1	1	1/3
9	1/3	3	1	3	1	1/3	1/5	1	1	1/3
10	1/3	3	1	1	1	3	1/5	3	3	1

The weighting of the indicators in the study was determined using the AHP method in the Excel template [25] with additional adaptation for our study. The decision to work with an Excel template was made for several reasons: It was the first time the company come into contact with MCDM decision-making methods, so the investment in AHP software can be avoided, the template is easy to use, user-friendly, each questionnaire should fit on one page for printing, and the filling is done manually. Thirteen experts received an AHP template with 10 indicators to set the weights, completely independent with clear instructions and a moderator from the team available for detailed explanations. They scored the indicators according to the AHP rules and parameters to make recommendations corresponding to $CR < 10\%$ (consistency ratio). The templates can handle 8 different rating scales. Saaty's basic linear scale was chosen for the study because the simulation performed with different scales showed no significant difference in the results when the other conditions of the method were met. The result of the pairwise evaluation is shown in Tab. 3. An important step in the AHP method is to check the consistency of the decision results. A higher value of CR means that the decision maker is less consistent and vice versa, a lower value of CR means high consistency. The decision team used a standard scale with nine levels, which is shown in Tab. 2. Two consistency indices were calculated: the consistency ratio (CR) and the geometric consistency index (GCI). CR is the ratio between the consistency index (CI) and the random consistency index (RI) and can be expressed by Eq. (1).

$$CR = \frac{CI}{RI}, \text{ and } CI = \frac{\lambda_{\max} - n}{(n-1)} \tag{1}$$

$\lambda_{\max}$ - Principal Eigenvalue is a result of the summation of products between each element for Eigenvector and the sum of columns of the reciprocal matrix.

The Excel AHP template, like many other AHP programs, has a "consistency" navigator - the highlighted extreme scoring results for re-scoring to reach the CR limit. The results of the row geometric mean method (RGMM) used to calculate the priorities could be found in Tab. 4.

Table 4 Consolidated weighted geometric mean off participants

Indicators	1	2	3	4	5	6	7	8	9	10
1	1	2,26	1,14	1,29	2,14	1,36	0,72	1,43	1,65	2,32
2	0,44	1	0,41	0,5	0,58	0,49	0,26	0,6	0,48	0,5
3	0,88	2,46	1	1,18	1,17	1,18	0,5	1,12	1,18	1,25
4	0,78	2,01	0,85	1	1,07	1,62	0,32	0,81	1,01	1,5
5	0,47	1,72	0,86	0,93	1	1,32	0,55	0,94	1,07	1,13
6	0,74	2,03	0,85	0,62	0,76	1	0,43	0,65	1,0	0,91
7	1,39	3,87	2,01	3,1	1,83	2,32	1	3,06	2,13	3,23
8	0,7	1,67	0,9	1,23	1,07	1,55	0,33	1	1,12	1,49
9	0,61	2,1	0,85	0,99	0,93	1,0	0,47	0,9	1	1,07
10	0,43	2,02	0,8	0,67	0,88	1,09	0,31	0,67	0,94	1

The criteria of weight distribution among the different experts were analysed using Shannon entropy and its division into independent components (α- and β-entropy) to derive an AHP consensus indicator. The result of the Shannon entropy α is 7,604622, for the Shannon entropy β is 1,23003. The calculation of the final priority values (Tab. 5) is based on the eigenvector method (EVM) with a fixed number of 12 iterations.

Table 5 Consensus Indicator based on RGGM results

DM	1	2	3	4	5	6	7	8	9	10	$\sum$
1	0,21	0,03	0,16	0,07	0,05	0,09	0,23	0,09	0,02	0,05	1,0
2	0,14	0,07	0,06	0,05	0,19	0,02	0,28	0,05	0,03	0,10	1,0
3	0,26	0,02	0,03	0,14	0,08	0,03	0,20	0,14	0,03	0,08	1,0
4	0,05	0,03	0,16	0,11	0,05	0,01	0,31	0,03	0,22	0,02	1,0
5	0,25	0,13	0,06	0,05	0,23	0,02	0,14	0,03	0,03	0,07	1,0
6	0,21	0,09	0,03	0,03	0,21	0,21	0,04	0,03	0,07	0,09	1,0
7	0,03	0,03	0,17	0,06	0,02	0,14	0,07	0,25	0,18	0,06	1,0
8	0,05	0,02	0,15	0,12	0,04	0,05	0,21	0,07	0,24	0,05	1,0
9	0,06	0,02	0,08	0,17	0,03	0,06	0,29	0,19	0,05	0,04	1,0
10	0,09	0,02	0,08	0,21	0,02	0,19	0,10	0,18	0,08	0,03	1,0
11	0,03	0,04	0,05	0,15	0,03	0,17	0,17	0,19	0,10	0,06	1,0
12	0,23	0,04	0,13	0,02	0,25	0,04	0,13	0,02	0,06	0,08	1,0
13	0,22	0,04	0,08	0,03	0,09	0,09	0,25	0,06	0,06	0,10	1,0

The final result of the AHP method is attribute weights shown in Tab. 7. The overall consistency ratio CR reached in the study is 9,9 %, the simulation performed with different rating scales showed even better results CR (from 1,3% to 6,1%). Differences between individual RGGM and the CR results from each team member are shown in Tab. 6. All decision makers reach CR limit value. The CR result shows that the AHP method was properly done and the result is confident.

Table 6 Individual Indicator based on RGGM results

DM	1	2	3	4	5	6	7	8	9	10	CR
1	0,2235	0,0282	0,1522	0,0673	0,0539	0,0888	0,2223	0,0928	0,0187	0,0522	9%
2	0,1373	0,0693	0,0626	0,0497	0,1830	0,0273	0,2851	0,0517	0,0347	0,0994	10%
3	0,2699	0,0190	0,0309	0,1296	0,0794	0,0291	0,2064	0,1296	0,0298	0,0762	9%
4	0,0433	0,0291	0,1563	0,1133	0,0494	0,0145	0,3255	0,0312	0,2162	0,0211	9%
5	0,2536	0,1229	0,0681	0,0445	0,2190	0,0196	0,1379	0,0285	0,0343	0,0717	9%
6	0,2134	0,0905	0,0257	0,0242	0,1929	0,2191	0,0460	0,0287	0,0667	0,0929	8%
7	0,0262	0,0270	0,1668	0,0640	0,0225	0,1396	0,0767	0,2457	0,1730	0,0584	9%
8	0,0542	0,0233	0,1591	0,1248	0,0389	0,0469	0,2030	0,0754	0,2287	0,0455	8%
9	0,0643	0,0193	0,0833	0,1675	0,0338	0,0572	0,2984	0,1905	0,0453	0,0404	7%
10	0,0955	0,0275	0,0774	0,2078	0,0236	0,2032	0,0914	0,1696	0,0767	0,0274	8%
11	0,0345	0,0347	0,0573	0,1538	0,0313	0,1741	0,1780	0,1715	0,1029	0,0620	9%
12	0,2269	0,0406	0,1286	0,0247	0,2366	0,0388	0,1418	0,0228	0,0636	0,0755	8%
13	0,2108	0,0380	0,0778	0,0296	0,0897	0,0923	0,2476	0,0525	0,0598	0,1018	9%

2.4 Phase 2 – Weight of Alternatives Determination with TOPSIS Method

TOPSIS is one of the numerous MCDM methods for solving multiple criteria.

Table 7 Attribute weights final results

	Indicator	Weights
C1	Cost/pcs	0,211
C2	Flexibility	0,038
C3	Total investment	0,091
C4	Clamping polyvalence	0,078
C5	Reference	0,247
C6	Set-up	0,053
C7	Maintenance	0,059
C8	Nb. of clamping devices	0,031
C9	Operator number	0,092
C10	Automation	0,101

The concept of this method is to select the best alternatives that have the shortest distance to positive solutions and the farthest distance to negative solutions. These hypothetical solutions correspond to the maximum and minimum attribute values in the database that contain satisfactory solutions. The closest hypothetical best solution and the farthest hypothetical worst solution are used to obtain the best solutions [26]. The target and the important evaluation attributes are determined. For this study, cost/unit count is considered as a non-beneficial attribute (a lower value is better) and others are considered as beneficial attributes (a higher value is better). The input value for the cost/unit count attribute is numerical, and for all other attributes, it is the mean of the team experts' ratings to increase the objectivity of the study due to a mixed influence of two or more factors on the advantageous status. A Likert scale of 1 to 5 was also used in this case. In conducting the TOPSIS analysis, the team followed standard analysis steps.

Step 1: The expert team first evaluated each alternative based on the individual criteria. The information is presented in the form of the TOPSIS decision matrix in Tab. 8.

Step 2: Calculated normalized decision matrix using Eq. (2).

$$\bar{X}_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}} \tag{2}$$

Table 8 Decision matrix results

		A1	A2	A3	A4	A5	A6	A7
Cost/pcs	C1	2,63	2,34	3,52	1,70	1,90	5,04	1,89
Flexibility	C2	3,2	3,1	4,1	2,3	2,4	4,8	2,8
Total investment	C3	4,8	4,9	4,9	4,8	1,2	5,0	1,3
Clamping polyvalence	C4	3,3	4,9	1,2	4,2	4,9	2,8	2,3
Reference	C5	4,4	4,3	1,4	4,8	1,3	4,8	2,8
Set-up	C6	4,5	4,8	1,2	4,7	4,8	2,3	3,2
Maintenance	C7	4,1	4,5	5,0	1,3	5,0	5,0	1,3
Nb. of clamping devices	C8	2,8	5,0	2,9	1,3	4,7	3,5	2,5
Operator number	C9	2,8	3,1	4,4	1,3	4,2	4,8	1,3
Automation	C10	3,8	4,8	3,2	1,8	4,8	3,5	2,1

To allow comparison between attributes, the calculation of the normalized decision values is required, since all attributes are now in a non-dimensional form. The results of the normalized decision matrix can be found in Tab. 9.

Table 9 Normalized decision matrix results

	A1	A2	A3	A4	A5	A6	A7
C1	0,3388	0,3014	0,4535	0,2190	0,2448	0,6493	0,2435
C2	0,3441	0,3441	0,4588	0,2294	0,2294	0,5735	0,3441
C3	0,4437	0,4437	0,4437	0,4437	0,0887	0,4437	0,0887
C4	0,3180	0,5300	0,1060	0,4240	0,5300	0,3180	0,2120
C5	0,4148	0,4148	0,1037	0,5185	0,1037	0,5185	0,3111
C6	0,3904	0,4880	0,0976	0,4880	0,4880	0,1952	0,2928
C7	0,3831	0,3831	0,4789	0,0958	0,4789	0,4789	0,0958
C8	0,3216	0,5361	0,3216	0,1072	0,5361	0,3216	0,3216
C9	0,3419	0,3419	0,4558	0,1140	0,4558	0,5698	0,1140
C10	0,3254	0,5423	0,3254	0,2169	0,5423	0,3254	0,2169

Step 3: Calculate weighted normalized decision matrix.

$$V_{ij} = \bar{X}_{ij} \times W_j \tag{3}$$

The weighted normalized values (V_{ij}) of each indicator can be calculated by multiplying the normalized results of each indicator by its determined weight using Eq. (3) where $\bar{X}_{ij}$ is a normalized matrix and W_j is the weighting criterion determined by the AHP method. Tab. 10 shows the weighted normalized value.

Step 4: Identify the ideal best and ideal worst value.

Since C1 is a non-benefit attribute, the chosen value is a minimum value, and all others are beneficial attributes, so the chosen values are maximum values. The solutions were defined as in Tab. 11.

Table 10 Weighted normalized decision matrix results

	A1	A2	A3	A4	A5	A6	A7
C1	0,0715	0,0636	0,0957	0,0462	0,0517	0,1370	0,0514
C2	0,0132	0,0132	0,0176	0,0088	0,0088	0,0220	0,0132
C3	0,0345	0,0345	0,0345	0,0345	0,0069	0,0345	0,0069
C4	0,0098	0,0163	0,0033	0,0130	0,0163	0,0098	0,0065
C5	0,0376	0,0376	0,0094	0,0470	0,0094	0,0470	0,0282
C6	0,0359	0,0448	0,0090	0,0448	0,0448	0,0179	0,0269
C7	0,0945	0,0945	0,1181	0,0236	0,1181	0,1181	0,0236
C8	0,0169	0,0282	0,0169	0,0056	0,0282	0,0169	0,0169
C9	0,0203	0,0203	0,0270	0,0068	0,0270	0,0338	0,0068
C10	0,0329	0,0549	0,0329	0,0220	0,0549	0,0329	0,0220

Table 11 Ideal best and ideal worst results

	V+	V−
C1	0,04622	0,13702
C2	0,02202	0,00881
C3	0,03447	0,00689
C4	0,01627	0,00325
C5	0,04698	0,00940
C6	0,04482	0,00896
C7	0,11809	0,02362
C8	0,02820	0,00564
C9	0,03379	0,00676
C10	0,05491	0,02196

The separation measures of each alternative were calculated with Eq. (4) from the positive ideal and with Eq. (5) for the negative ideal. Tab. 12 shows the values of the separation measures for the 7 alternatives.

Table 12 Separation measures values

	S_i^+	S_i^-
A1	0,040	0,107
A2	0,025	0,123
A3	0,071	0,102
A4	0,097	0,105
A5	0,044	0,132
A6	0,095	0,101
A7	0,101	0,089

Step 5: Calculate the Euclidean distance from the ideal best.

$$S_i^+ = \left[\sum_{j=1}^{m} (V_{ij} - V_j^+)^2 \right]^{0.5} \tag{4}$$

Step 6: Calculate the Euclidean distance from the ideal worst.

$$S_i^- = \left[\sum_{j=1}^{m} (V_{ij} - V_j^-)^2 \right]^{0.5} \tag{5}$$

2.5 Phase 3 – Determine the Final Rank and Alternative Selection

Step 7: Calculate Performance Score and rank the results.

$$P_i = \frac{S_i^-}{S_i^+ + S_i^-} \tag{6}$$

Relative proximity is calculated using Eq. (6). The higher the P_i value is, the better the performance of the alternatives. The final results of the ranking, shown in Tab. 13, indicate that the best option for the introduction of new process equipment is Alternative2.

Table 13 Performance score and final rank results

	P_i	Rank
A1	0,727	3
A2	0,829	1
A3	0,589	4
A4	0,521	5
A5	0,751	2
A6	0,515	6
A7	0,469	7

Nevertheless, alternative A5 has the best result on the most important criterion (highest weighting value) and almost the best result on the second most important criterion, although the value of the other criterion was decisive for it to be "only" second. This fact is strong proof of the performance of the MCDM methods, if the input data are properly defined and the requirements for the procedure are strictly followed. In Fig. 2 are the result of weighted normalized decision matrix results for Top3 alternatives. This view clearly shows the power of TOPSIS analyse even for decision making with a similar input value of indicators.
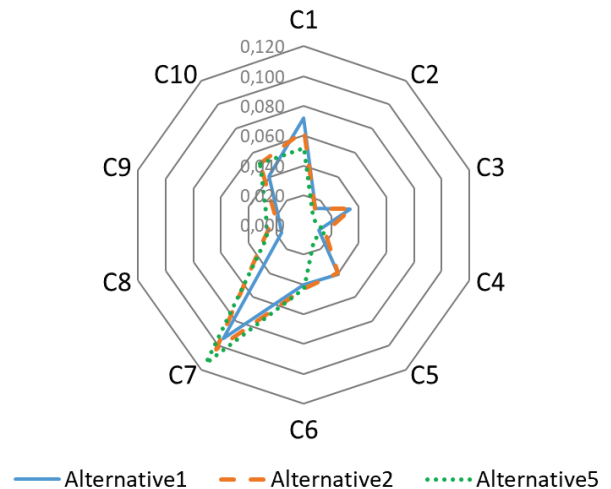
Weighted normalized values for Top3 alternatives

Figure 2 Top 3 Alternatives result

3 CONCLUSION

In the automotive industry, managers are faced with the decision making process more than ever in many areas due to often market changes because of the electrification era, pandemic issues or lack of raw material or components. One of the most important and risky decision area is introducing new equipment or technology into the manufacturing process to increase competitiveness in the market. For the decision makers is important to have standardized procedures or methods for fast and reliable decision making.

The aim of this paper was to define a simple and user-friendly tool for decision makers in the automotive industry. The novel approach is the decentralization of the decision-making process from managers to multidisciplinary teams

composed of experienced experts from various fields related to the decision making scope. The key point is to include all relevant factors from the manufacturing process in the decision making process about the introduction of a new manufacturing process to become familiar with new equipment at a very early stage of process implementation. This approach will greatly improve the relationship between all process factors and accelerate the implementation and optimization phases of the process. Seven final alternatives were used for decision making, considering ten attributes/criteria instead of the original fifteen attributes, which were reduced using the Delphi method. This step is very important due to the simplification and acceleration next steps in the decision model. The objective weights of importance of the attributes/criteria are assigned using the AHP method. According to the obtained results, among the 10 indicators, the Reference has the highest degree of importance due to the reason for introducing new equipment into running high runner SOP production process. This means there is no space for the generation of any delivery delays, so risk minimization is a mandatory task in all decision steps. We need to choose a reliable equipment supplier with excellent references and overall maintenance support. The TOPSIS analyse is used to select the best alternative, alternative 2 is the best and the first choice identified using the TOPSIS analyse. Due to the prior Delphi attributes reduction process in an early stage of the research process, the performing of TOPSIS analyse was fast and effective. The final result of this study is a standardization of the presented Decision model based on Delphi, AHP and TOPSIS MCDM methods, in standard company procedure.

The advantage of this study is the applicability of this hybrid decision model to different manufacturing areas with intelligent adjustment of input indicators. The decision making process is relatively fast because of the evaluation and reduction number of important indicators in the early stage of the research process. This is not a copy-paste tool for decision makers, but the result of the study approach and the application of MCDM methods combined with respectable knowledge and experience in the field of automotive manufacturing considering the company specifications. This decision model concept can be used for future research implementation into other manufacturing processes.

The model presented in this study can also be used in other industries where the input parameters need to be redefined due to the different characteristics of the industry.

Notice

The paper will be presented at MOTSP 2022 – 13th International Conference Management of Technology – Step to Sustainable Production, which will take place in Primošten/Dalmatia (Croatia) on June 8–10, 2022. The paper will not be published anywhere else.

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