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Low-Pressure Die Casting Machine Selection Using a Combined AHP and TOPSIS Method

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Abstract

Decision making is the process of making choices by identifying a decision, gathering information, and assessing alternative solutions. This research is standing with the decision to change the foundry department with low-pressure die casting technologies. It is highly related to machine selection, which should meet the requirements of the manufacturer. However, this decision-making process is rather complicated because various parameters must be considered such as melting rate, production cycle time, the capacity of the furnace, energy consumption, etc. Hence, a decision support system has been developed in this article using a combined Analytic Hierarchy Process (AHP) and Technique of Order Preference Similarity to the Ideal Solution (TOPSIS) method to select the best Low Pressure Die Casting (LPDC) machine among a list of machine alternatives. A case study of brass valve manufacturing in Thailand is used to illustrate the presented method. The results from the study showed that decision-makers can effectively select new LPDC machinability as expected.

Keywords: Low-pressure die casting, Decision support system, Analytic hierarchy process, TOPSIS method, Multi-criteria decision making

1. INTRODUCTION

Low-Pressure Die Casting (LPDC) is an economical solution to producing high-quality brass parts, e.g. sanitary fittings, valve housings, water meter housings, and building hardware due to its advantages of smooth filling and good feeding capabilities. Likewise, it is widely used because LPDC technology can reduce scrap waste and operation time while increasing production throughput. Consequently, many companies have considered using this technology to increase their manufacturing capability. The advantages of LPDC include high yield capacity, the reduction of machining costs, excellent control of process parameters, a high degree of automation, good metallurgical quality, and good mechanical as well as metallurgical properties, etc.

The quality of LPDC parts is mostly influenced by machine technology and process conditions such as filling pressure, filling speed, holding pressure, pressure holding time, casting temperature, die temperature, etc. Hence, the selection of the proper LPDC machine is an overly critical aspect of the casting processes for products. If the decision-maker can choose the correct casting machine, the production quality, speed, flexibility, scrap, energy consumption, and investment costs enable good results by the casting processes' performance. On the other hand, dramatic problems could occur in casting production performance when decided with incorrect casting machines, such as poor quality, high scrap percentage, high energy consumption etc.

In this work, the following research questions are raised: What is the most suitable methodology to select the LPDC machine? What is the result of decision-making? In light of these questions, several research papers related to this topic have been investigated. Tabucanon et al. (1997) developed a decision support system to solve the multi-criteria machine selection problem of machine selection in flexible manufacturing systems. Arslan (2004) designed a decision support system that was developed for the selection of machine tools. Fu et al. (2008) indicated the influence of different parameters on the mechanical properties of LPDC magnesium alloy AM50. Merlin et al. (2009) investigated the impact behavior of A356 alloy for automotive wheels. The results showed that the impact strength of T6 heat-treated wheels was higher than as-cast ones. Meanwhile, higher impact strength always showed correspondence with finer microstructure. Ahmadzadeh et al. (2016) suggested that differences among machines in terms of cost, speed, quality, after-sale services, type, and the number of machines were important parameters to be considered. Hafezalkotoba et al. (2018) proposed a decision support system for agricultural machines and equipment selection to develop and improve the economic conditions in the agriculture field to maintain food demand with a case study on olive harvester machines. Li et al. (2020) developed a novel hybrid Multi-Criteria Decision Making (MCDM) model for machine tool selection using fuzzy DEMATEL. The indication is that the presented hybrid model has advantages in granting flexibility to the preferences of decision-makers for machine tools selection problems. Breaz et al. (2017) presented a decision-making process for selecting between CNC milling, robot milling and a process of additive manufacturing using the AHP method. This method has a certain degree of generality, specifically targeting metal accurate parts form the machine-building industry. It can be applied for every part considered for manufacturing.

As mentioned above, numerous researches are related in this area, but only a few researchers have published papers related to the topic of selecting appropriate machine technology and parameters, especially the manufacturing of the LPDC machine. Since it is a complex problem with many criteria and parameters for consideration that affects product quality and costs to firms, it needs to deal with both qualitative and quantitative criteria. This is particularly true in the early decision-making phases of machine selection, which have the potential to reduce production impact and manufacturing costs.

To address the above issues, this study presents a decision support system method that has been developed using integrated the AHP and TOPSIS methods and presents a numerical example for solving this problem. The AHP is one of the most famous and extensively used soft computing MCDM methodologies. It is based on priority theory and deals with complex problems that involve the consideration of multiple criteria and alternatives simultaneously. Its ability to incorporate data and the judgment of experts in a logical way provides a scale for measuring intangible qualities.

Applying AHP in combination with TOPSIS methods allows for more decision- making flexibility and performance. The AHP is used to define the weight of each criterion and sub-criterion through qualitative and quantitative comparisons. AHP is suitable for determining the quantitative and qualitative data which limitation for large numbers of numerical data that has a high chance of bias in making decisions. TOPSIS is another famous MCDM approach used in solving decision- making problems. The TOPSIS concept provides the best rankings for each criterion as it is described in the form of a simple mathematical formula. TOPSIS allows the results from decision-making to correlate with a solution target concept that is not paying attention to only pairwise comparisons as AHP. Accordingly, combining the two techniques is a great way to counter their weaknesses. This type of integration will lead to better results in decision-making efficiency, as shown in the researches of Prakash and Barua (2015) and Hasnain et al. (2020).

The structure of this paper is organized as follows: Section 2 presents the basic approaches used in LPDC. Section 3 presents the deciding multi-criteria decision-making model, while Section 4 presents the verification and validation techniques with a case study. Section 5 presents the research results and discussions, and Section 6 presents the research conclusions and recommendations.

2. Low-Pressure Die Casting (LPDC) method

Die casting is a metal casting process that is characterized by forcing molten metal under high pressure into a mold cavity. The mold cavity is created using two hardened tool steel dies which have been machined into shape and work similarly to an injection mold during the process. Most die castings are made from non-ferrous metals, specifically zinc, copper, aluminum, magnesium, lead, pewter, and tin- based alloys. Depending on the type of metal being cast, a hot or cold chamber machine is used. Low- pressure die casting primarily uses alloys with low melting points, allowing for the production of components up to approximately 150 kg. The advantages are high strength and the ability to form complex geometries while maximizing material usage. The LPDC process by Powell and Luo is illustrated in Figure 1. (Powell et al., 2012)

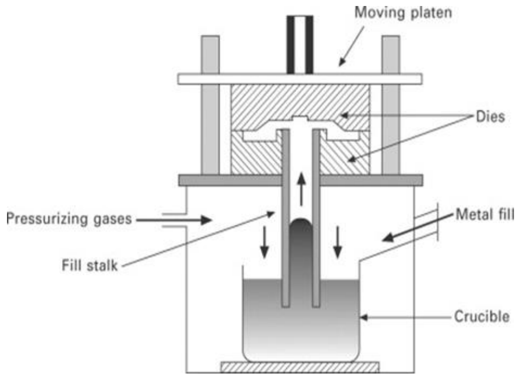

Figure 1 Low-Pressure Die Casting Process

The mold is located above the sprue. Metal flows up the sprue and into the runner system and the casting cavity. The metal flow for the arrangement is accomplished by pressurizing the furnace, which is located below the mold. The rate of metal flow is controlled by the rate of pressurization of the furnace. Metal flow can also be directed by electromagnetic pumping, but the principle of low-pressure casting is the same. Zhang and Wang (2012) stated that LPDC is one of the most widely used casting processes for manufacturing light- weight components in industrial sectors, including automotive, energy, electronics, etc. This process allows an excellent compromise between quality, costs, productivity, and geometrical feasibility.

Another advantage of this process is the precise control of die cavity filling. Molten metal flows quickly and smoothly through the feeding conduits, reducing oxide formation and preventing porosity. This process was created to produce axially symmetrical parts such as car wheels or water valves. Bonollo et al. (2005) concluded that the advantages of low pressure die casting process were numerous: the high yield achievable (typically over 90%), the reduction of machining costs, the absence of feeders, the excellent control of process parameters which can be obtained with a high degree of automation, the good metallurgical quality, a homogeneous filling, and controlled solidification dynamics, resulting in good mechanical and technological properties of the castings.

Selecting the appropriate LPDC machine is quite complicated as many parameters are concerned, such as correlating processes with material preference, melting rate, cycle time, maximize production rate, energy consumption, the number of workers, etc. Therefore, the aim of this paper is to propose a Multi-Criteria Decision Making (MCDM) model that can support LPDC machine selection. The MCDM literature review and the decision-making tools are presented in the next section.

3. MULTIPLE-CRITERIA DECISION MAKING (MCDM)

The MCDM evaluation procedure for supporting LPDC machine selection by using the AHP and TOPSIS is presented in this paper. It consists of four main steps as summarized in Figure 2.

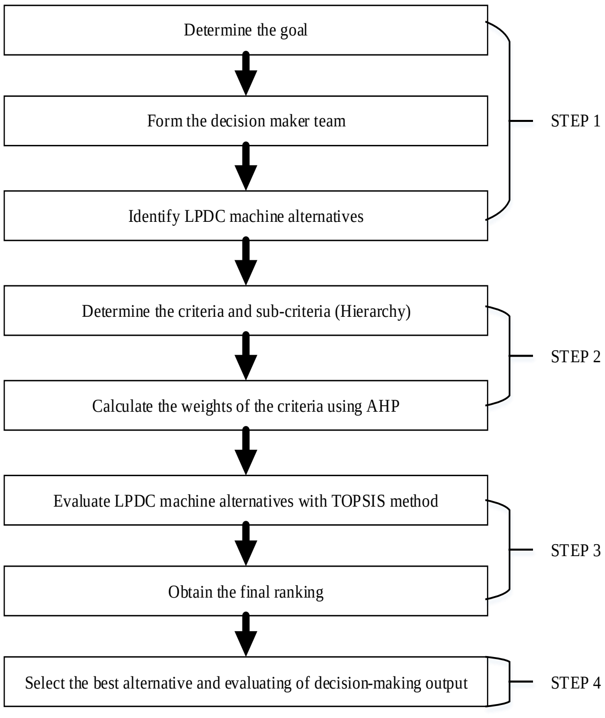

Figure 2 The MCDM evaluation procedure by using the AHP and TOPSIS (Developed by the author)

Step 1: Determine the goal and construct a decision-making team, then determine the machine decision alternative. Decision making is a central responsibility of managers and leaders. It requires problem defining and related factors identification. Doing so helps create a clear understanding of what needs to be decided and can influence the choice among alternatives. An important aspect of any decision is its purpose or objective. This is different from identifying a specific decision outcome; rather, it has to do with the motivation to decide in the first place.

Step 2: Determine the criteria and sub-criteria (Hierarchy). Identifying the evaluation criteria is considered the most important performance measure for the machine selection problem. The decision-making hierarchy structure is constructed for the evaluation of criteria and calculating the weights of these criteria using the AHP method. The AHP was introduced by Saaty in 1980. This method benefits from its similarity to the decision-making mechanisms of human beings, namely decomposition, judgment, and synthesis. It is particularly distinguished by its ability to manage different classes of criteria: qualitative and quantitative criteria Saaty, 1980). Nowadays, it is widely used in various fields including economics, ecology, and industry. This method is used to solve complex decision-making problems that have several attributes by modeling unstructured problems under study into hierarchical forms of elements (Boonkanit & Kengpol, 2010). The AHP is widely used by decision-makers and researchers. Kengpol and Boonkanit (Kengpol & Boonkanit, 2011) developed the decision support framework for developing an ecodesign at the conceptual phase based upon ISO/TR14062. Khamhong et al. (2019) implemented the fuzzy AHP based criteria analysis for 3D printer selection in additive manufacturing that is related to selecting the best alternative of 3D printers by analyzing two types of decision-makers. Chaiyaphan and Ransikarbum (2020) presented criteria analysis of food safety using the AHP by applying a case study in Thailand's fresh markets which subject from the viewpoints of stakeholders. Busaba (2012) presented the selection of a cellular layout for an Electronics Manufacturing Service (EMS) by AHP. Then, a computer simulation was done for the evaluation of the layout design. From the results of the simulation, the cellular layout design can increase the throughput rate by 32%, decrease the average time in the system by 28%, and increase the average utilization of a workstation by 13%. Busaba and Piyanan (2013) proposed an inventory classification method based on AHP and lot sizing policy for purchasing materials in group A for a case study factory. Satirasetthavee et al. (2018) offered the determination criteria of an appropriate location for the construction of a truck terminal in Thailand by using AHP; the study aims to explore more factors and the appropriate weight of each factor to determine an appropriate location to more effectively decrease transportation costs in Thailand.

To obtain the degree of relative importance for the elements at each level, a pairwise comparison matrix is developed using Saaty 1-9 preference scale, as shown in Table 1.

Table 1 Pairwise comparison scale

Scale	Definition
1	Equally important
3	Minimally important
5	Highly important
7	Very highly important
9	Extremely important
2,4,6,8	The intermediate value between adjacent scales

Then, the eigenvector and the maximum eigenvalue (λ_{max}) are derived from the pairwise comparison matrices. The significance of the eigenvalue is to assess the strength of the consistency ratio CR of the comparative matrix in order to validate whether the pairwise comparison matrix provides a completely consistent evaluation. The final step is to derive the consistency index and the consistency ratio (Saaty & Vargas, 2001).

The procedure of AHP is presented as follows:

Process 1: Build the structural hierarchy of the problem.

Process 2: Calculate the pairwise comparison matrix. The scoring average of the clustered expert will be used for determination by Geometric mean (Gm.) as Equation 1.

$$Gm = \sqrt[n]{N_1 \times N_2 \times N_3 \times N_n} \tag{1}$$

Then, the calculation of *Gm* is used to perform in the AHP matrix model. Assuming n attributes, the pairwise comparison of attribute *i* with attribute *j* yields a square matrix $A_{n\times n}$ where a_{ij} denotes the comparative importance of attribute *i* with respect to attribute *j*. In the matrix, $a_{ij} = 1$ when $i = j$ and $a_{ji} = 1/a_{ij}$ (Valentina et al., 2015).

$$A_{n\times n} = \begin{pmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{pmatrix}$$

Process 3: Once the pairwise matrix is done, it should be normalized using rule number (2).

$$C_{ij} = \frac{a_{ij}}{\sum_{j=1}^{n} a_{parameters}} \quad \text{Where } i, j = 1\ldots n \tag{2}$$

Process 4: Calculate the weighted normalized decision matrix.

$$W_i = \sum_{j=1}^{n} C_{ij} \quad \text{Where } i = 1\ldots n \tag{3}$$

Process 5: Calculate the Eigenvector and row matrix.

$$E = N^{th} rootvalue/\Sigma N^{th} \tag{4}$$

$$Row\ Matrix = \sum_{j=1}^{n} a_{ij} \times e_{j1} \tag{5}$$

Process 6: Calculate the Eigenvalue λ_{max}

$$\lambda_{max} = Row\ Matrix \tag{6}$$

Process 7: Calculate the consistency index and consistency ration.

$$CI = (\lambda_{max}-1)/(n-1) \tag{7}$$

$$CR = CI/RI \tag{8}$$

Where *n* and *RI* denote the order of the matrix.

<u>Step 3:</u> Evaluate the LPDC machine alternatives with the TOPSIS method to achieve the final ranking results. TOPSIS is one of the numerical methods for multi-criteria decision-making (on the history of TOPSIS see (Hwang & Yoon, 1981; Hwang et al., 1993; Zaltako & Novoselac, 2013). This is a broadly applicable method with a simple mathematical model. The standard TOPSIS methodology aims to select the alternatives which have the shortest distance from the positive ideal solution and the longest distance from the negative ideal solution at the same time. The positive ideal solution maximizes the benefit attributes and minimizes the cost attributes, whereas the negative ideal solution maximizes the cost attributes and minimizes the benefit attributes. The TOPSIS methodology has been applied extensively in the MCDM field, such as by Khalili-Damghani et al. (2013); Rubayet and Karmaker (2016); Wisetla and Ransikarbum (2020); Warapoj and Nitidetch (2019).

The stepwise procedure for implementing TOPSIS is presented as follows:

Process 1: Construct the normalized decision matrix of beneficial and non-beneficial criteria.

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_j^J x_{ij}^2}} \quad \text{Where } j = 1\ldots J,\ i = 1\ldots n \tag{9}$$

x_{ij} and r_{ij} are the original and normalized scores of the decision matrix, respectively.

Process 2: Construct the weighted normalized decision matrix.

$$V_{ij} = w_i \times r_{ij} \quad \text{where } j = 1\ldots J,\ i = 1\ldots n \tag{10}$$

Process 3: Determine the positive ideal solution (PIS) and the negative ideal solution (NIS).

$$A^{+} = \{V_1^{+}, V_2^{+}, \ldots, V_n^{+}\}\ max\ values \tag{11}$$

$$V_i^{+} = \{max(V_{ij}) if\ j \in J; min(V_{ij}) if\ j \in J'\} \tag{12}$$

$$A^{-} = \{V_1^{-}, V_2^{-}, \ldots, V_n^{-}\}\ min\ values \tag{13}$$

$$V_i^{-} = \{min(V_{ij}) if\ j \in J; max(V_{ij}) if\ j \in J'\} \tag{14}$$

Process 4: Calculate the Euclidian distance of each alternative from PIIS and NIS.

$$d_i^{+} = \sqrt{\sum_{j=1}^{n}\left(V_{ij}-V_j^{+}\right)^2} \quad \text{Where } j = 1,2,\ldots J \qquad (15)$$

$$d_i^{-} = \sqrt{\sum_{j=1}^{n}\left(V_{ij}-V_j^{-}\right)^2} \quad \text{Where } j = 1,2,\ldots J \qquad (16)$$

Process 5: Calculate the relative closeness coefficient to the ideal solution of each alternative CC_i

$$CC_i = \frac{d_i}{d_i^{+}-d_i^{+}} \quad \text{Where } j = 1,2,\ldots J \qquad (16)$$

Process 6: Based on the decreasing values of the closeness coefficient, alternatives are ranked from the most valuable to the worst. The alternative having the highest closeness coefficient (CC_i) is selected.

Step 4: Evaluating Outcomes: the objective of evaluating outcomes is for the decision-maker to develop insight into the decision. Many of the lessons developed in this stage come from examining the implications of the decision. Insight can be obtained by referencing key business metrics, such as increased revenue, lower costs, larger market share, or greater consumer awareness. Once the outcome of a decision is known, the results may imply a need to revise the decision and try again. When decision outcomes are immeasurable or ambiguous, data deliberation and a measure to deal with negative attitudes are considered.

Maintaining self-esteem may also cause decision-makers to attribute good outcomes to their actions and bad outcomes to factors outside their control. This type of bias can limit the honest assessment of what went right and what did not, thus reducing what could be learned by carefully evaluating outcomes. Hence, a case study of this research is to highlight the result supporting the proposed decision, which contributes to the research outcome.

4. CASE STUDY

The case study in this research was performed at the medium-sized manufacturing factory located in Samut Prakarn Province, Thailand. It manufactures and distributes water valves, ball taps, and ball valves. The company also offers water meters, brass rods, valves, and related fittings. According to the proposed model in Figure 2, Step 1 has been performed by determining the goal, constructing a decision-making team, and determining the machine decision alternative. Over many years, the company has continued to focus on the development of production processes to be more efficient, while reducing costs and improving quality, especially in the die casting production process of the sand-casting department, which is the most important process for water valve production.

The production process starts at the sand-casting department where the sand and core are prepared for a jolt and squeeze operations to obtain the sand mold. In the melting process, pouring operations are considered in the next step. When this operation is completed, the sprue will be removed to be used as a water meter. Then, the product is grounded and undergoes shot blasting operations. The process of the case study is explained in detail in Figure 3.

According to Figure 3, a case study of the die casting production process, defects can cause rework or even worse; they can lead to scraps for many reasons, such as lack of quality control, the absence of a maintenance schedule, lack of skills, lack of standard machine, absence of communication, uncontrollable sand quality, light insufficient, a lack of work rules, and a high rate of downtime. In this case study, the defect ratio has been analyzed by the engineering team and it has been discerned that the majority of defective work is found in the casting process.

The chief executive officer subsequently ordered changes in the current casting production process from the gravity sand casting process; the alloy is poured into a mold made of sand that must be destroyed to reveal the manufactured component, to the LPDC method with its advantage of strength and the ability to form complex geometries whilst maximizing material usage and controlling die cavity filling at the same time.

There are many advantages of LPDC compared to the current casting process. For example, it guarantees high yields greater than 90 percent. The production costs are lower than for high-pressure die casting, and it has improved linear tolerance than gravity casting. It is also possible to obtain parts with thin walls. However, this manufacturing technique has certain main disadvantages, e.g. the tooling costs being slightly higher than other casting technologies such as gravity casting. It also requires complex machinery that may be expensive.

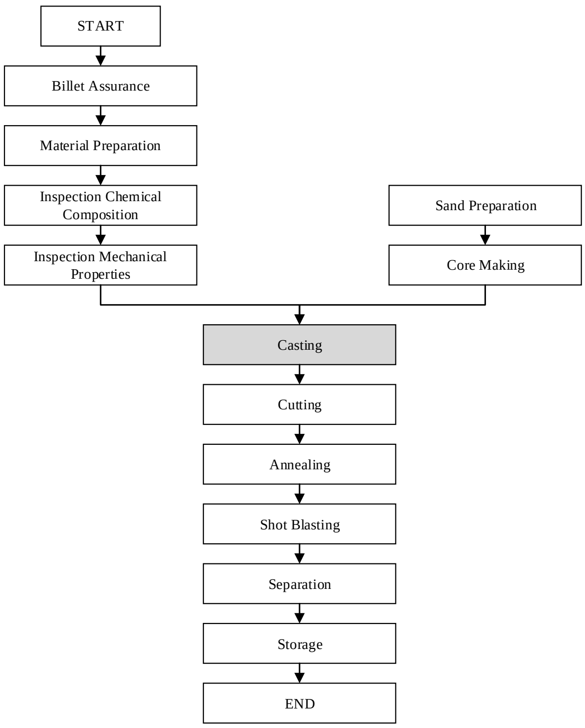

Figure 3 A case study of the die-casting production process

As mentioned earlier, the quality of LPDC parts is mostly influenced by the process technology and conditions, which are highly impacted by the casting machine. Thus, choosing the right die casting machine is an important consideration because it impacts the process flexibility, involves a high degree of reproducibility and precision, energy-saving, and maximum productivity and efficiency. Many decision parameters must be involved such as the ton capacity, injection and ejection system, the die locking mechanism, the electrical systems, etc. In this case study, the current process is adapted by three low pressures die casting machine alternatives; each machine has certain advantages and disadvantages to decide from multiple perspectives. The characteristics of these machines are illustrated in Figure 4 and described in the next section.

Figure 4 LPDC alternatives machines

4.1 LPDC Machine A

LPDC machine A in the selection list is a compact system with an integrated induction melting furnace, two manipulator units for the two die halves, a coating or cooling bath, and an electronic control unit with a touch panel. The control panel of the system is divided into two logical areas: one for controlling the furnace and the other for controlling the casting machine. However, both control areas are monitored by a Programmable Logic Control (PLC) and visualization.

The power for the inductors is supplied via a thyristor controller. There is one thyristor module available for each of the three inductors that are controlled by a control unit. At the beginning of the casting cycle, the manipulator starts from the park position. The manipulator swivels so that the opened die halves are in front of the core insertion window, which must be opened before the core is inserted. The sand core is then inserted into the mobile die half.

In the following, reference will always be made to the mobile and the fixed die, where the mobile die represents the side of the mobile die half. The fixed die or the fixed die half is mounted rigidly to the manipulator arm and can be swiveled, but not traversed. After the sand core is inserted by hand, the core insertion window must be closed, and the casting cycle starts automatically. The manipulator moves to the furnace and the freely programmable pressure curve is executed at the same time. After the die touches down on the riser tube, the molten metal is filled into the die from below by a controlled pressure build-up.

This procedure guarantees the laminar flow in die without turbulence. After the casting process, the die is lifted automatically from the furnace, and the manipulator moves to the parts removal position. The die opens and the casting part is ejected. It drops automatically into the vertically adjustable removal device. The table registers the finished casting by an initiator and moves back to its original position. In this position, the casting is tilted from the table through the removal window out of the work zone.

An additional collecting container is recommended for this procedure. After the casting part is ejected, the manipulator traverses to the split coating/cooling bath. The die halves dip into the respective bath half. By the individually adjustable dip time, the die halves are cooled and coated with a layer of graphite. The manipulator then moves back to the core insertion position. At this point, the cycle can be repeated, as described above, or it can be ended. The second manipulator works during production equally. When both manipulators are in production, the manipulators always traverse clockwise.

If only one manipulator is in production and another is in park position for die change or is in a special function i.e. sandblasting, the manipulator is moved counterclockwise to the furnace. The entire system with its area of movements is enclosed by a safety fence and safety doors that may not be opened during the running operation. In addition, there is a safety barrier between the parking position for die change and the rest of the machine. This allows the operator to work on one manipulator, e.g. maintenance or die changing, while the second manipulator is working.

4.2 LPDC Machine B

The LPDC machine B is specially designed to work with an operator for each machine. Its task is to place the sand-cores and to supervise quality. The machine is composed of a furnace and a manipulator that controls all the die movements. The operator is positioned in front of the core placing area. Once the head is placed in the right position, the working cycle is ready to start. The automatic cycle can be started by pushing the relevant button, and it will be completely automatic.

The manipulator closes the two half-dies, places them horizontally, and rotates the furnace. Next, the furnace raises, and the molten metal is injected into the die. When the furnace lowers, the manipulator rotates and places itself in the core-placing area. The half dies open themselves and the operator picks up the cast with appropriate pliers. Then, the dies dip into the tank filled with liquid graphite and return to the starting position. After that, the bench tilts and gets ready for the positioning of another core.

The operator will repeat the operation previously described. The machine positions the dies on the furnace and low-pressure casts automatically; it waits till the melted metal gets solid and opens the half-dies to allow the casting extraction.

4.3 LPDC Machine C

LPDC Machine C can be used for casting all kinds of small components of zinc alloy and copper alloy. This

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technology greatly reduces the internal porosity in products and improves the quality of products, so it has been welcomed by many manufactures. This machine has a similar technology as Machine A, but is made by another brand in another country.

According to the information for three machines, Step 2 of the proposed model has been performed. The criteria were separated to calculate AHP (Underlining character is the best parameter), as illustrated in Table 2.

Table 2 Characteristics of Machines A, B, and C

	Criteria	Values Machine		
		A	B	C
C1	Melting rate	500 kg/h	410 kg/h	350kg/h
C2	Cycle time	35s	50s	70s
C3	Maximal production/ Day	822 pieces	576 pieces	411 pieces
C4	Capacity of the furnace	1800 Kg	1000 Kg	1800kg
C5	Charging mode	Manual	Automatic	Manual
C6	Control system	PLC S7	PC477b	PC477b
C7	Hydraulic pressure	90 bar / 7.5 kW	90 bar / 7.5 kW	80bar/ 7.5 kW
C8	Electrical feed	400 V	410 V	380V
C9	Energy during melting	150 kW	80kw	125KW
C10	Scrap percentage	3%	1%	2%
C11	Number of workers	2	1	2

The LPDC machine selection hierarchy structure is presented in Figure 5. It consists of eleven decision criteria and three machine alternatives. However, the cost of each LPDC machine was not considered because the distributors offered the same price level, and the top management aimed to pay more attention to machine efficiency than the economic perspective.

Eleven attributes were chosen as comparison criteria by the decision-making team (experts), including a production manager, general manager, and production engineer. The experts' team profile includes: the production manager possesses a master's degree in industrial engineering; the general manager possesses a master's in economics; the senior production engineer possesses a master's degree in electrical engineering. Moreover, years of experience in the water valves industry among the experts were 20, 24, and 15 years, respectively.

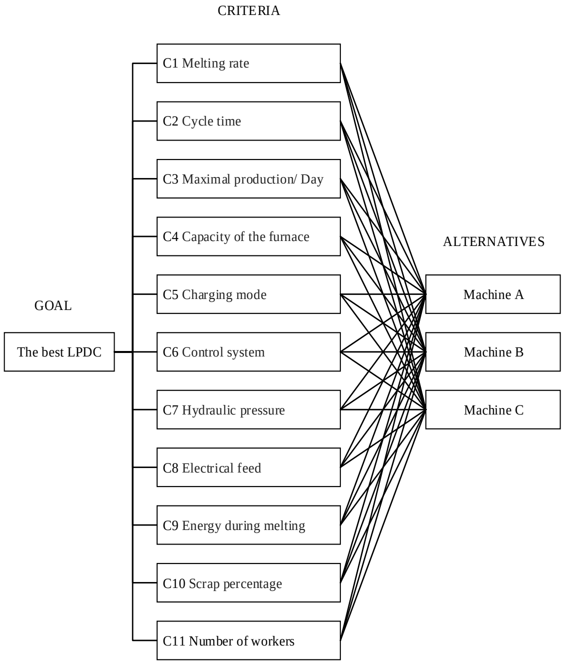

Figure 5 Hierarchy structure for the LPDC machine selections

The analysis and calculation of eleven criteria were performed based on the proposed methodology in Step 2. It is important to consider the weight of important criteria, and the comparison using pairwise comparison from the decision rating of the decision-maker. The Gm from Equation (1) was retrieved from the expert group that compared each pair using the primary criteria following the AHP. The calculation methods are as follows.

The first expert has given a score of 5, while the second expert has given a score of 7, and the third expert has given a score of 3; the results are as follows:

$$C2 = \sqrt[3]{5\times7\times3}$$
$$C2 = 4.72$$

The pairwise comparison matrix is presented in Table 3 and the formula (3), the result criteria weight calculation is presented in Tables 4-5.

Table 3 Pair-wise comparison matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
C1	1.00	0.21	0.16	3.00	2.00	0.25	0.33	0.20	0.14	0.12	0.20
C2	4.72	1.00	0.71	5.00	8.00	3.00	5.00	3.00	4.00	2.00	3.00
C3	6.25	1.40	1.00	6.00	9.00	3.00	5.00	4.00	3.00	2.00	3.00
C4	0.33	0.20	0.17	1.00	3.00	0.20	0.62	0.50	0.20	0.14	0.76
C5	0.50	0.13	0.11	0.33	1.00	0.14	0.33	0.14	0.11	0.11	0.28
C6	4.00	0.33	0.33	5.00	7.00	1.00	3.00	2.00	1.00	0.66	2.00
C7	3.00	0.20	0.20	1.61	3.00	0.33	1.00	0.76	0.25	0.27	1.00
C8	5.00	0.33	0.25	2.00	7.00	0.50	1.32	1.00	0.45	0.33	1.50
C9	7.00	0.25	0.33	5.00	9.00	1.00	4.00	2.22	1.00	2.00	2.00
C10	8.33	0.50	0.50	7.00	9.00	1.52	3.70	3.00	0.50	1.00	2.50
C11	5.00	0.33	0.33	1.32	3.57	0.50	1.00	0.67	0.50	0.40	1.00
Sum	**45.13**	**4.89**	**4.10**	**37.26**	**61.57**	**11.44**	**25.31**	**17.49**	**11.15**	**9.04**	**17.24**

Table 4 Criteria weight table

C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
0.03	0.19	**0.21**	0.03	0.01	0.10	0.04	0.07	0.12	0.14	0.06

Table 5 Consistency matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	WSV*	CrW*
C1	0.03	0.04	0.03	0.09	0.03	0.02	0.01	0.01	0.02	0.02	0.01	0.31	0.03
C2	0.13	0.19	0.15	0.14	0.12	0.30	0.21	0.20	0.50	0.27	0.17	2.38	0.19
C3	0.17	0.27	0.21	0.17	0.13	0.30	0.21	0.26	0.37	0.27	0.17	2.54	0.21
C4	0.01	0.04	0.04	0.03	0.04	0.02	0.03	0.03	0.02	0.02	0.04	0.32	0.03
C5	0.01	0.02	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.17	0.01
C6	0.11	0.06	0.07	0.14	0.10	0.10	0.13	0.13	0.12	0.09	0.11	1.18	0.10
C7	0.08	0.04	0.04	0.05	0.04	0.03	0.04	0.05	0.03	0.04	0.06	0.50	0.04
C8	0.14	0.06	0.05	0.06	0.10	0.05	0.06	0.07	0.06	0.05	0.08	0.77	0.07
C9	0.19	0.05	0.07	0.14	0.13	0.10	0.17	0.15	0.12	0.27	0.11	1.51	0.12
C10	0.23	0.10	0.11	0.20	0.13	0.15	0.16	0.20	0.06	0.14	0.14	1.61	0.14
C11*	0.14	0.06	0.07	0.04	0.05	0.05	0.04	0.04	0.06	0.05	0.06	0.67	0.06

*Remarks: (WSV = weighted sum value, CrW = criteria weight, CR = Consistency Ratio) In this study, n = 11, as a result, RI = 1.51, λ_{max} = 11.80, CI = (11.80-11)/(11-1) = 0.08, CR = 0.053 (If the Consistency Ratio is lower than 10%, the inconsistency is acceptable).

Table 6 Pre-Normalized decision matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
MC A	500	35	822	1800	2	3	90	400	150	3	2
MC B	410	50	576	1000	5	5	90	410	80	1	1
MC C	350	70	411	1800	2	1	80	380	125	2	2
$\sqrt{\sum_{i}^{n} x_{ij}^2}$	735.26	92.87	1,084.61	2,734.96	5.74	5.92	150.33	687.39	211.01	3.74	3.00

Table 7 Normalized decision matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
MC A	0.68	0.38	0.76	0.66	0.35	0.51	0.60	0.58	0.71	0.80	0.67
MC B	0.56	0.54	0.53	0.37	0.87	0.85	0.60	0.60	0.38	0.27	0.33
MC C	0.48	0.75	0.38	0.66	0.35	0.17	0.53	0.55	0.59	0.53	0.67

Table 8 Weighted normalized decision matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
MC A	0.02	0.07	0.16	0.02	0.01	0.05	0.03	0.04	0.09	0.11	0.04
MC B	0.02	0.10	0.11	0.01	0.01	0.08	0.03	0.04	0.05	0.04	0.02
MC C	0.01	0.15	0.08	0.02	0.01	0.02	0.02	0.04	0.07	0.07	0.04

Table 9 Ideal solutions and Euclidian distances values

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	d_i^+	d_i^-
MC A	0.02	0.07	0.16	0.02	0.01	0.05	0.03	0.04	0.09	0.11	0.04	0.08	0.12
MC B	0.02	0.10	0.11	0.01	0.01	0.08	0.03	0.04	0.05	0.04	0.02	0.11	0.08
MC C	0.01	0.15	0.08	0.02	0.01	0.02	0.02	0.04	0.07	0.07	0.04	0.11	0.09
V_i^+	0.02	0.15	0.16	0.02	0.01	0.08	0.03	0.04	0.09	0.11	0.04		
V_i^-	0.01	0.07	0.08	0.01	0.01	0.02	0.02	0.04	0.05	0.04	0.02		

In the next step, the decision result from AHP is calculated to ranking and estimations of the three machines by using the TOPSIS method, as proposed in Step 3 (Figure 2). Consequently, equation numbers 9-16 are applied in Tables 6-9. The pre-normalized decision matrix of the TOPSIS method is presented in Table 6. It is initiated by creating an evaluation matrix consisting of three alternatives and eleven criteria, with the normalized value of each alternative and criteria. After that, the matrix is normalized for the decision matrix of beneficial and non-beneficial criteria, as depicted in Table 7. Then, the LPDC machine alternatives with the TOPSIS method in Step 3 are evaluated using the criteria weight from Table 4. The weighted norm decision matrix is presented in Table 8, while ideal solutions and Euclidean distances values are presented in Table 9.

Step 4, as proposed in Figure 2, involves selecting the best alternative and evaluating the decision output after MCDM methods are used to rank the potential alternatives by considering the weights of all criteria obtained by AHP. A decision matrix using three decision-makers' opinions is developed using numerical values. The decision matrix of the TOPSIS method is shown in Table 10.

The aggregated values of each criterion are then calculated by using the average technique in the TOPSIS method. Focusing on the values of closeness coefficients of three suitable machines, Machine A becomes the most dominating alternative that has the highest closeness coefficient (CC_i) of 0.60. As a result, Machine A should be selected as the best machine among the three alternatives, followed by Machine C (0.44) and Machine B (0.43), respectively.

Table 10 Rank of machines based on CC_i

Machine	d_i^+	d_i^-	$d_i^+ + d_i^-$	CC_i	Rank
MC A	**0.08**	**0.12**	**0.20**	**0.60**	**1**
MC B	0.11	0.08	0.19	0.43	3
MC C	0.11	0.09	0.20	0.44	2

5. Results and Discussion

The MCDM evaluation procedure for supporting LPDC machine selection by using the AHP and TOPSIS is presented in this paper. It consists of four main steps for selecting the best LPDC machine. In this case study, eleven criteria are analyzed including Melting rate, Cycle time, Maximal production per Day, Capacity of the furnace, Charging mode, Control system, Hydraulic pressure, Electrical feed, Energy during melting, Scrap percentage, and Number of workers. Top ranking criteria are Maximal production rate (C3), Cycle time (C2), and scrap percentage (C10). A variety of decision-making factors and different opinions from experts can be resolved and consented logically by this method. Machine A becomes the most dominating alternative, which has the highest closeness coefficient score. The result of the final decision-making is fulfilled with involved parties. Therefore, the results from the application of this methodology can offer the water valve manufacturer case study with valuable insight into the criteria that reflect the business assessment of machine selection.

This framework will act as a guide for the decision-makers to select the most suitable LPDC machine via an integrated approach of AHP and TOPSIS. The anticipated methods in this research consist of four steps at its core, starting from determining the goal and constructing a decision-making team, then determining the machine alternative with the criteria of the existing problem, and finally, inspection and identification. The calculation method is carried out by using AHP and TOPSIS. The final decision is made by selecting the best alternative and evaluating the decision output.

6. Conclusions and Recommendations

Selecting the right machine is an important issue for business improvement and supporting the industry 4.0 development direction. This paper presents a methodology for selecting the LPDC machine based on a hybrid multi-criteria decision-making process. However, there are several criteria that need to be considered in the machine selection process, which involves multiple consideration parameters based on the requirement of decision-makers, such as production rate, waste ratio, and energy consumption, etc.

According to the research question, selecting an appropriate manufacturing machine is an especially important and complex problem for firms, usually dealing with many criteria. The contribution of this research is the comprehensive decision-making methodology for selecting LPDC machine production. The approach presented in this paper applies the AHP and TOPSIS methods for selecting the most beneficial variant among three machine structures. Moreover, a large matrix with eleven criteria was used for pairwise comparisons and presented. The closeness coefficient values are used in decision making; the best machine alternative with the highest rate is selected. In this research, the results from the present method were calculated using Microsoft Excel. In conclusion, the utilization of the machine after installation and operation was achieved as anticipated. Therefore, it is not optional, but essential to implement this method for dealing with a variety of multi-criteria decision-making problems due to its flexibility. The proposed method is effective in a group decision environment and can also solve the problem of complex individual decision-making.

In addition to suggestions for future research, some other MCDM methods, such as ELECTRE; PROMETHEE, etc. and other decision-making criteria such as environmental or economic perspectives can be integrated and applied to increase the ability for decision making.

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