IMPLEMENTATION OF HYBRID ARTIFICIAL NEURAL NETWORK AND MULTI-CRITERIA DECISION MODEL FOR THE RANKING OF CRITERIA THAT AFFECT PRODUCTIVITY – A CASE STUDY.

J. Vijayanand[1*] & V. Sheshagiri Rao[1]

ARTICLE INFO

Article details
Submitted by authors 31 May 2023
Accepted for publication 6 May 2024
Available online 31 May 2024

Contact details
* Corresponding author
jvanandh@gmail.com

Author affiliations
1 Department of Mechanical Engineering, St Joseph's College Of Engineering, Chennai, India

ORCID® identifiers
J. Vijayanand
https://orcid.org/0000-0002-5042-6136

V. Sheshagiri Rao
https://orcid.org/0000-0002-2972-1464

DOI
http://dx.doi.org//10.7166/35-1-2906

ABSTRACT

This study delves into the often-overlooked factors influencing industrial productivity, focusing on labour and machine maintenance as key drivers. Extensive research was undertaken in a core shop producing automotive components to identify and assess these factors. Using multi-criteria decision models (MCDM) such as analytic hierarchy process (AHP), fuzzy analytic hierarchy process (FAHP), technique for order of preference by similarity to ideal solution (TOPSIS), *viekriterijumsko kompromisno rangiranje* (VIKOR) method, enterprise distributed application service (EDAS), and Entropy TOPSIS, the study ranked various productivity criteria. Artificial neural networks were then employed to validate these rankings. The research emphasised the significance of manufacturing equipment and raw materials, following the prioritisation of the workforce. Implementing material handling systems aimed at reducing errors and enhancing productivity proved pivotal. As a result of these strategies, non-value-added activities (NVA) decreased by 65.56%, process time improved by 61.03%, waiting time reduced significantly by 66.66%, manpower decreased by 35%, and costs decreased by 45%. These outcomes translated into a notable 23% increase in production levels in the core shop. The study underscores the efficacy of innovative work methods and standardised operating procedures in maximising productivity.

OPSOMMING

Hierdie studie ondersoek die faktore wat dikwels oor die hoof gesien word wat industriële produktiwiteit beïnvloed, met die fokus op arbeid en masjienonderhoud as sleuteldrywers. Omvattende navorsing is onderneem in 'n werkswinkel wat motorkomponente vervaardig om hierdie faktore te identifiseer en te evalueer. Deur gebruik te maak van multi-kriteria besluitnemingsmodelle soos analitiese hiërargie proses, vae analitiese hiërargie proses, tegniek vir orde van voorkeur volgens ooreenkoms met ideale oplossing (TOPSIS), *viekriterijumsko kompromisno rangiranje* metode, onderneming verspreide toepassingsdiens, en entropie TOPSIS, het die studie verskeie produktiwiteitskriteria gerangskik. Kunsmatige neurale netwerke is toe aangewend om die rangorde te valideer. Die navorsing het die belangrikheid van vervaardigingstoerusting en rou materiaal beklemtoon, en ook die prioritisering van die arbeidsmag. Die implementering van materiaalhanteringstelsels wat daarop gemik is om foute te verminder en produktiwiteit te verbeter, was deurslaggewend. As gevolg van hierdie strategieë het nie-waardetoegevoegde aktiwiteite met 65,56% afgeneem, prosestyd het met 61,03% verbeter, wagtyd het beduidend met 66.66% verminder, mannekrag het met 35% afgeneem, en koste het met 45% afdaal. Hierdie uitkomste het gelei tot 'n noemenswaardige 23% toename in produksievlakke in die kernwinkel. Die studie beklemtoon die doeltreffendheid van innoverende werkmetodes en gestandaardiseerde bedryfsprosedures om produktiwiteit te maksimeer.

1. INTRODUCTION

Despite extensive research on improving the process of productivity, manufacturing organisations have been encountering setbacks in achieving their expected outcomes. A foundry is a production organisation that produces and supplies metal casts to manufacturing organisations such as the automobile industry, pump industries, and the textile industry, where metallic support structures are of great importance. Productivity in a foundry plant could be enhanced by identifying the influential factors. These factors are grouped into two: internal and external. Product design, materials, and plants are examples of internal elements that can be controlled. External or uncontrollable factors include workforce, materials, environment, and work methods [1]. According to Aggarwal [2], productivity is a process that involves planning, thorough preparation, cautious execution, an extended gestation period, continuous measurement of responses or relations to advancement, and close control of the environments, based on feedback provided by the adaptive control servo systems. Many case studies have shown a partial improvement in productivity after identifying the influential factors [3]. Kabir *et al*. [4], showed that the performance of workers is an influential factor that in turn depends on workers' commitment, motivation, and skills in improving productivity, and concluded that incentive programmes are important in enhancing workers' performance and productivity [4-5]. Heanisch [6] identified the factors affecting the productivity of government workers, and recorded that government workers appreciate freedom and autonomy, teamwork, effective supervision, communication, rewards and recognition, and the elimination of bureaucracy as essential factors in improving overall productivity. According to the study by Saha and Mazumder [7] of organisational behaviour to enhance productivity, the working environment is the most influential factor that affects the performance of workers. The quality of comfort in the working environment is responsible for workers' satisfaction and improved productivity. Based on an extensive literature review, we identified fifteen major factors that enhance productivity. Kumar *et al*. [4], used the analytic hierarchy process (AHP) tool to rank the factors, and found that the top five criteria were management's positive attitude and involvement, proactive employees, good working conditions, suitable tools and equipment, and the availability of water, power, and other input supplies to improve productivity [8]. Piran *et al*. [9], categorised the factors into four perspectives, and concluded that the 'top management' perspective was the most important one. The total factor productivity index (TFPI) for improved product modularity was used in a bus manufacturing company. It was noted that product modularity helps companies to improve the TPFI [9]. To enhance safety and efficiency, it is necessary to adopt a strategic approach that consistently identifies and safeguards against hazardous conditions to ensure the well-being of workers [10]. Salminen *et al*. [11], found that productivity and safety could be integrated. Based on the assessment provided by personnel connected with serious accidents, they confirmed that it was possible to improve both productivity and safety by (i) improving machines and equipment, (ii) initiating better housekeeping, and (iii) creating more spacious work sites.

2. LITERATURE REVIEW

Multi-criteria decision making (MCDM) has emerged as a highly important approach for making decisions in complex situations inside the modern, technologically advanced engineering environment. MCDM is particularly valuable for conducting assessments in situations where the likelihood of conflict is minimal or non-existent. In the current socioeconomic landscape, where decision-making is influenced by multiple aspects, MCDM plays a vital role in these domains. Decisions are influenced by a multitude of circumstances, some of which may or may not have equal importance. The allocation of weights to the criteria is a primary concern in the MCDM problem. Cook [12] and Čančer [13] used the 5Ws and H techniques for this purpose. Several researchers used the cross-entropy method to determine the weighting of criteria when addressing MCDM problems [14-27].

Mihajlovi *et al*. [29] used two MCDM methodologies to select the location for a logistics facility in Serbia: the AHP approach and a hybrid AHP weighted aggregated sum product assessment (WASPAS) method. WASPAS was employed to rank alternatives based on weights derived from the AHP method, while the AHP method was used to determine criteria weights. The rating was almost the same between the two systems, and they concurred on the top and bottom choices. Adali and Tuș [30] used the TOPSIS, enterprise distributed application service (EDAS), and combinative distance-based assessment (CODAS) methodologies to evaluate the suitability of four prospective hospital site locations. The authors noted the simplicity of the TOPSIS and EDAS techniques, finding that all three methods produced identical ratings. Chen *et al*. [31] selected a teahouse site in Lithuania by employing the EDAS method and a modified version of WASPAS. The results indicated that using random weighting methods leads to inconsistent rankings in MCDM approaches [32,33]. Figure 1 shows various MCDM models.

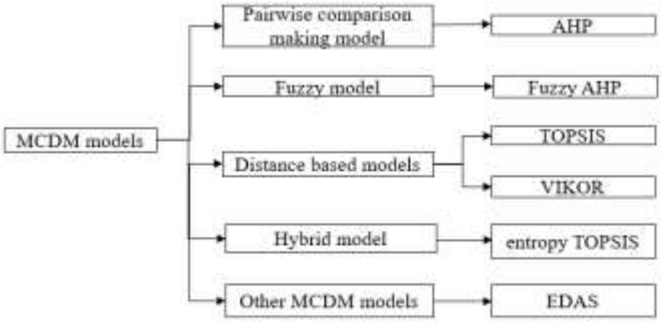

Figure 1: MCDM models

The integration of fuzzy theory with MCDM approaches was largely aimed at addressing the problem of handling linguistic variables in the majority of MCDM systems. Chauhan and Singh [34] employed fuzzy TOPSIS and fuzzy AHP methodologies to choose an appropriate site for the disposal of medical waste. Suman *et al.* [35] investigated the use of AHP and fuzzy AHP methodologies to select a suitable location for the Bangladeshi furniture industry. The ranking of possibilities was mutually agreed upon by the two approaches. The weights emphasised by the two approaches differed, nonetheless. Kieu *et al.* [36,37] employed the CoCoSo technique and hybrid spherical fuzzy AHP to select the location of a distribution facility in Vietnam. Figure 2 shows the proposed model.

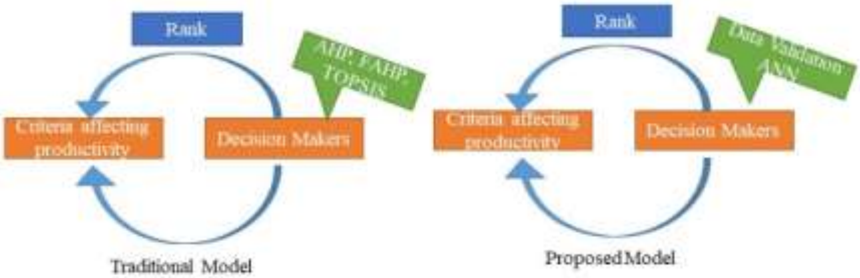

Figure 2: The proposed paradigm differs conceptually from standard techniques

Discovering a suitable neural network architecture for making predictions in nonlinear models proved to be difficult. A genetic algorithm has discovered the optimal network architecture. Au *et al.* [38] conducted experiments on fundamental interconnected neural network models and multiple estimation methods. Chambers and Campbell [39] proposed the use of artificial neural network (ANN) models to represent system components. The ANN meta-models were used to establish connections and model the entire system. The simulation trained the ANNs to function as a unified and centralised processing unit. In 2011, Golmohammadi [40] introduced a mechanism for MCDM using a feed-forward neural network and fuzzy logic. A link between inputs and outputs has been established using neural networks and weights to make assessments based on different criteria. Decision-makers evaluate alternatives to prioritise them. Ciurana *et al.* [41] developed a technique for selecting machine tools in contemporary manufacturing companies. Neural networks were employed to determine the most efficient organising tool. Gutierrez *et al.* [42] developed a demand forecasting model using a neural network that incorporated irregularities. A comparison was made between a neural network and standard time sequence outcomes. Neural networks were discovered to be more effective than traditional methods. Cavalieri *et al.* [43] employed both parametric and ANN techniques to forecast the production costs of a groundbreaking single-disc brake design. ANNs exhibit a superior ability to strike a balance between accuracy and development cost compared with other methodologies. Many academic articles have shown integrated frameworks to prioritise lean technologies in the field of MCDM. Fuzzy AHP, Fuzzy TOPSIS, and the fuzzy decision-making trial and evaluation laboratory (FDEMATEL) are MCDM techniques that are used in the framework model for lean tool selection [44,45]. Triangular fuzzy numbers (TFNs) are used in research because of their straightforwardness [46]. The manufacturing industry is undergoing a significant transformation as it incorporates and is influenced by the implementation of machine-learning techniques [47]. The process mining method presented in this research addresses the drawbacks of conventional mapping techniques [48].

Researchers have long been concerned with how to improve efficiency and productivity. Many types of research in each country have typically used key factors to develop strategies to boost industrial efficiency. Although several studies have been conducted, and the factors that influence productivity have been identified, many productivity issues are still unknown and need to be studied further, even in developed organisations. Based on the previous research and on an extensive literature survey, 38 criteria were found to affect productivity. They were categorised into nine groups, based on their features: 1. workforce [WF] (four criteria); 2. manufacturing equipment [ME] (four criteria); 3. raw material [RW] (five criteria); 4. plant layout [PL] (four criteria); 5. manufacturing process [MP] (four criteria); 6. product design [PD] (four criteria); 7. work method [WM] (four criteria); 8. quality [QT] (four criteria); and 9. environment [EN] (five criteria) (Figure 3). The criteria found in previous research were used as the basis for developing a quantitative model to investigate their impact on core shops in the foundry.

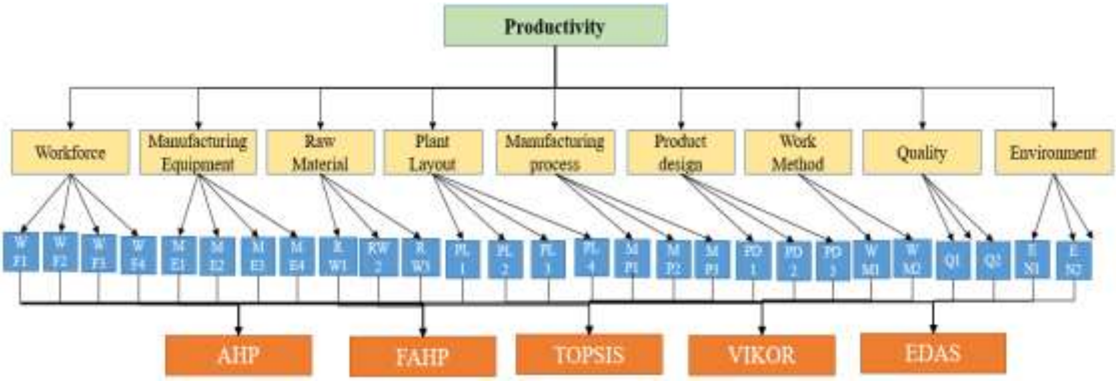

Figure 3: List of criteria and sub-criteria affecting productivity

2.1. KNOWLEDGE GAPS IN THE LITERATURE

While there are potential benefits to combining MCDM techniques with ANNs in analysing productivity factors in manufacturing organisations, there’s a notable lack of extensive research in this area. Previous studies have mainly focused on either MCDM or ANN separately, with limited exploration of their joint application in productivity analysis. Methodological difficulties in combining MCDM and ANN, such as selecting suitable approaches and frameworks, remain inadequately addressed. Moreover, issues surrounding data availability, accuracy, and model verification in diverse industrial settings are significant obstacles. In addition, there’s a dearth of research on implementing integrated MCDM-ANN techniques in real-world manufacturing environments, underscoring the need for more empirical investigations and practical guidelines.

In this study, we propose that using quantitative analysis with MCDM, such as AHP and fuzzy AHP, could help to identify specific factors influencing production at various levels, which could then be managed through standard operating procedures to achieve the predicted productivity. We outline a strategy for enhancing productivity in an Indian foundry, having received approval from the foundry management to begin our research. Our initial focus in the core shop division of the foundry was to identify key productivity-affecting factors with the aim of overcoming the problems that were hindering productivity.

3. MATERIALS AND METHODS

In this paper, the entire ranking of the identified criteria was carried out in a traditional and fuzzy environment following the method of Saaty [49]. The ranking of criteria was understood by using a fuzzy set, which is a more detailed analysis of the research problem [50-52]. All stated criteria were concurrently measured during the ranking process to improve the decision-making process. Figure 4 shows the methodology to rank the criteria and sub-criteria using different MCDM models and validation using ANN.

3.1. TECHNIQUE FOR ORDER OF PREFERENCE BY SIMILARITY TO IDEAL SOLUTION (TOPSIS)

TOPSIS is based on how far the decision matrix's constituent parts are from the ideal best and ideal worst elements for each criterion. First, the decision matrix is normalised to eliminate the impact of using different units of measurement for various criteria. For each criterion, the ideal best and ideal worst elements are determined. Then, using the ideal best and ideal worst values, Euclidian distances are determined between each element of each criterion. These distances are used in the end to calculate the closeness coefficient for each possibility. The closeness coefficients are used to rank the alternatives, with the alternative with the highest closeness coefficient being the most favoured option [53].

3.2. VIKOR (VISEKRITERIJUMSKA OPTIMIZACIJA I KOMPROMISNO RESENJE) method

The optimal element for each criterion in the decision matrix is first determined in VIKOR. They are referred to as the f* and f indices. Then, for each possibility, S and R indices are determined. The aggregate weighted normalised departure from the f* values concerning the separation between the f* and f values is essentially what makes up the S index for each alternative. The highest weighted normalised divergence from the f* values relative to the separation between the f* and f values is essentially what makes up each alternative's R index. Then, using these S and R indices and an assumed strategic weight of between 0 and 1, the VIKOR index for each alternative is produced. Strategic weight is essentially an assumed and modified percentage that is used to incorporate the S and R indices into the VIKOR index calculation. The VIKOR index for the alternatives serves as the basis for the final ranking of the alternatives [54].

3.3. ENTROPY WEIGHT

The identified criteria for TOPSIS computation can be accurately weighted, based on their relative importance, using the entropy weight approach. The entropy weight method's foundation is the amount of data needed to determine the index's weight, which is similar to the fixed weight techniques' primary goal. The TOPSIS approach was used in earlier studies to establish the criteria weight. The findings of this approach to calculating weight are quite subjective, with the result of the evaluation being more adversely affected by the subjective elements. Therefore, the effect of human subjective elements could be reduced by using the entropy approach to generate a real weight within the evaluation indicator system's weighting procedure. This objective weighting approach, which is based purely on neutral data, could eliminate the lack of subjective weighting methods. As a result, the information entropy approach was used in this paper to calculate the weight of the criteria [55].

3.4. EVALUATION BASED ON DISTANCE FROM AVERAGE SOLUTION (EDAS)

In 2015, EDAS, an MCDM process, was proposed and applied to the inventory's classification. An excavator was chosen for a company that builds roads using the EDAS compensation approach, which uses criteria that are independent of one another, and converts qualitative features into quantitative measurements for evaluation. EDAS is well-known because its solution is derived from the average solution, which eliminates the chance of experts treating an alternative unfairly. The EDAS method's simplicity and the need for fewer computations are its most important features. Similar to this, the EDAS method's application is very broad owing to its reliability and simplicity [56].

3.5. ARTIFICIAL NEURAL NETWORK (ANN)

3.5.1. CREATION OF A CONCEPTUAL MODEL FOR NEURAL NETWORK-BASED RANKING

To identify input and target values, historical data was employed. The network was created using MATLAB NNTOOL. Functions and layers tailored to the problem were chosen. The model's weights that were learned from data were accurate. By modelling recent data, the network model was proven to be accurate.

3.5.2. STRUCTURE OF ANN

Based on the ANN's capacity to recognise and maintain complex, non-linear patterns, the leanness index for this study was calculated. However, in the case of ANN, an appropriate conclusion may be reached by combining logic, historical data, and a well-designed neural network model. The NN toolbox in MATLAB was used in this study to train the network. The selection of input variables, network architecture, and volume of training data are only a few design factors that have a big influence on how accurate neural network forecasts are.

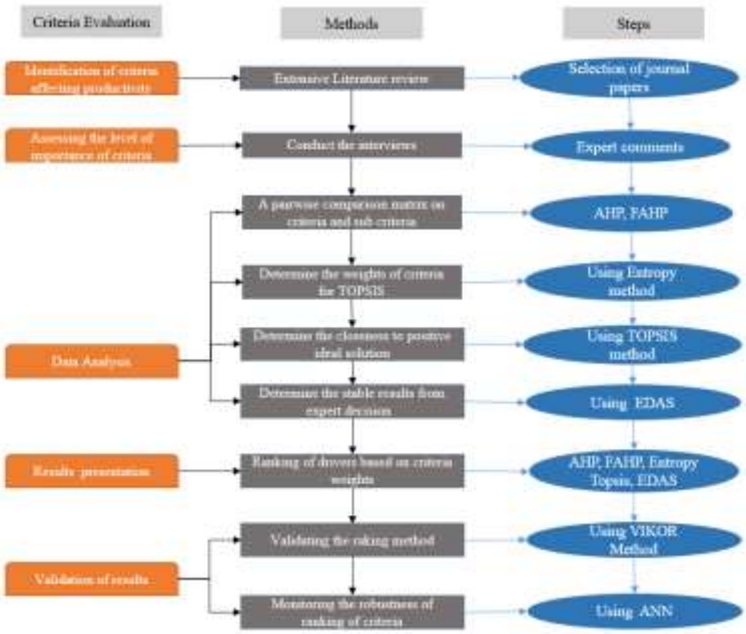

Figure 4: The methodology to rank the criteria using MCDM and ANN

4. APPLICATION OF ANN FOR RANKING CRITERIA THAT AFFECT PRODUCTIVITY

The application stages are presented in the paragraphs below.

4.1. INPUT

The input data for selecting a lean tool was derived from the values obtained by various MCDM models with input from decision-makers. Through trial-and-error or iterations, the optimal combination was determined. The training duration and accuracy depended on the input used. This study's input data determined the ranking of criteria that affected productivity.

4.2. TARGET VALUE

The output was a collection of data that was combined similarly to the input data. The backpropagation algorithm employed both input and output for training. Based on this information, neuronal weights were derived.

4.3. ANN ARCHITECTURE

After determining the input and target values, a network was constructed, after which its parameters had to be provided. Figure 5 illustrates the generated data window, in which variables are specified. In this case, the significant figure variables were network type and layer count. In this situation, there were two strata. The computational effort required to discover the optimal weight combination increased considerably as the number of network parameters and network layers increased. Figure 6 depicts the first stratum of the multi-layered network.

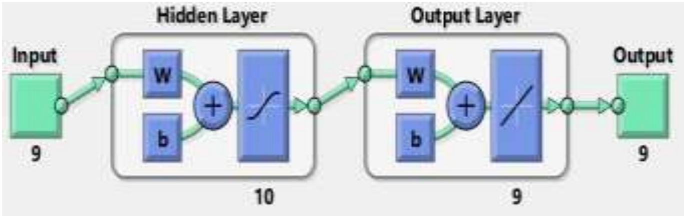

Figure 5: Multi-layered artificial neural network

The choice of the most appropriate learning technique was contingent on the data's characteristics and the problem's intricacy. In scenarios where MCDM and ANNs are integrated, supervised learning methods are commonly used owing to the availability of labelled data from MCDM. Techniques such as backpropagation and variations such as stochastic gradient descent and the Adam optimiser are frequently employed to train neural networks in these contexts. Their effectiveness lies in their ability to minimise the disparity between predicted and actual outcomes.

The model used a feed-forward backpropagation learning approach, employing TRANSLIM as the training function and comprising two layers. The initial layer used TRANSIG to discern patterns, while the subsequent layer used PURELIN to refine the output. Figure 6 shows a comprehensive breakdown of the network parameters, including the allocation of 10 neurons to the hidden layer. This choice of neuron count aimed to strike a balance between model complexity and the mitigation of overfitting, which is particularly beneficial when dealing with limited datasets. This setup ensured the effective handling of tasks that involve multidimensional mapping by tailoring the neural network's architecture to suit the problem's complexity and data characteristics.

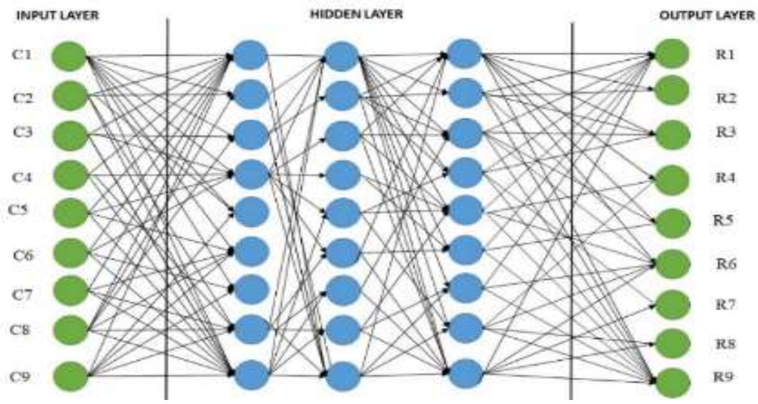

Figure 6: Multi-layered network

4.4. TRAINING AND TESTING

Exploring the intricacies of evolving neural networks frequently involves identifying the ideal training threshold to attain the desired results. Neural networks that are trained to minimise errors on training data sometimes have difficulties in generalising their performance. To ensure efficient functioning, the data was divided into two categories: the training set, which was used to train the network, and the test set, which was used to assess the error rate. The network with the lowest test set error rate was retained. After organising, training continued by incorporating input from decision-makers to generate the linguistic components that formed the training data. Subsequent testing assessed the effectiveness of the network by comparing the results obtained from the data that was not used for training with the ratings awarded by the decision-makers. Validated data plays a crucial role in assessing the effectiveness of an organisation.

4.5. VALIDATION

To evaluate the criterion, the network was simulated over the whole database. To achieve consistent values, the tiny datasets were replicated four times. A total of 180 random samples were selected from the datasets. Eighty per cent of these samples were allocated for training, while the other 20% were evenly divided between validation and testing, with each subset comprising 10% of the total samples.

5. CASE STUDY

The research was carried out at a foundry in Coimbatore, South India. Grey iron and ductile iron casting are two separate casting facilities that are available at the foundry. The research was based on the grey iron foundry plant because it has a very high rejection rate (> 35 per cent). Almost all cast iron components needed for manufacturing are produced by the grey iron foundry, which includes commercial and passenger vehicles, tractors, motors, pumps, textiles, valves, railways, and general engineering. Almost all components require cores of different sizes and shapes to attain the highest design accuracy and to save metal. Therefore, core production is essential in the plant, where the core is shot by the shooter machines with high design accuracy.

As a result, the management's top priority is to preserve the optimal quality level. Management has taken steps to reduce defects in the most important casting in response to persistent customer concerns. In such cases, a team typically uses old techniques to determine the existence of defects and the mechanism of defect creation by manipulating key process variables. However, the foundry in question was under a lot of production pressure, so the planned experiment was not an option for them. Instead, they wanted to look at the best possible improvement based on online production.

Blow holes, cuts and washes, hot tears, runouts, bleeders, misruns, cold shuts, core prints, surface gas defects, and a variety of other defects were found in the casting, resulting in high rejection and rework, lowering overall efficiency and quality by wasting time and money on scrap and rework. The identification of faulty castings happens in two steps. Until machining, the foundry performs a defect screening. After machining, the machine shop performs the second stage of defect detection. The casting had a cumulative defect rate of more than 30%, according to reports. In this case, the organisation intended to reduce the overall defect rate to less than 5% within six months.

This research was solely concerned with the core making process of casting in a grey iron foundry, with a primary emphasis on defect detection and reduction. Other cast objects were not included in this research. Process mapping, which is a visual representation of the process, was the first step in the research. A process map (Figure 7) was created after a detailed examination of the entire core production process to identify the main factors influencing process success. The process map clearly showed that the manufacture of a single casting entailed five major stages: (i) core shooting; (ii) core cleaning and pasting; (iii) core painting; (iv) core baking; and (v) core storage. The process flow diagram of core-making is shown in Figure 7.

Core handling in a foundry is a tough task because human (workforce) handling causes damage to the cores owing to repetitive tasks. An increase in the intensity of work increases absenteeism or lateness in the work area – the result of a lack of diligence on the part of the supervisor. The workforces were not trained properly in a systematic manner, leading to defects in the core product. The cleaning and pasting of the core were done in a separate area, which involved more material handling by the workforce. because of poor work methods, improper cleaning and pasting led to cracks or blows at the time of metal pouring. In painting, the workforce used to dip the core in the paint mixture for 5 to 10 seconds only where the core was not properly coated, which led to core cracks while baking. The electric oven was used for baking the core. The total estimated time for baking was 150 to 180 minutes. The arrangement of the core inside the oven was random in size and shape, and the space was not used properly, and so the energy for baking the core was not properly used. Over-baking and under-baking of the core cause metal penetration during the metal pouring into the mould, and leads to the soft and weak surface of the casting, which in turn results in break-in castings.

Figure 7: Process flow diagram of core shop

6. RESULTS AND DISCUSSION

This work introduced a hybrid MCDM model that used entropy-weighted TOPSIS to determine suitable weights for factors that impact productivity. The entropy-weighted TOPSIS approach showed great potential and effectiveness in ranking the criteria processes. The TOPSIS technology was used to compare the outcomes of two MCDM methods, namely the analytic hierarchy process (AHP) and the fuzzy analytic hierarchy process (FAHP). Subsequently, the Shannon entropy method was used to ascertain the objective weight for each criterion. TOPSIS was used in conjunction with these weights to obtain an unbiased ranking of the alternatives [57].

The methodologies were successfully applied to rank the criteria that would improve efficiency in manufacturing and service organisations. Five experts from industry and academia were asked to rate the criteria, based on their experience. Two of the five experts were professors and each of the professors each had more than a decade in consultation and lecturing operations management. The other three experts were from the industry (one held a top management position and had more than twenty years of experience, and the other two were in the managerial category with experience ranging from nine to 13 years).

6.1. MULTICRITERIA DECISION ANALYSES

The table 1 shows the details of decision makers, and Table 2 shows the ratings given by the decision makers. The random numbers for calculating consistency index are shown in Table 3. The six MCDM techniques considered in this paper (AHP, fuzzy AHP, TOPSIS, entropy TOPSIS, VIKOR, and EDAS) were applied to the decision matrix, the major calculations for these six MCDM techniques are shown in Tables 4, 5, 6, 7, 8, and 9. The rankings obtained from the application of these six MCDM techniques are summarised in Table 10. All MCDM model analyses showed almost similar results for all factors (workforce, manufacturing equipment, raw materials, facilities, work method, methodology, product design, quality, and environment). From the pairwise comparison analysis on the aforementioned factors, we found that the workforce was the most influential factor, affecting productivity by 26.26%. Manufacturing equipment was found to be the second main criterion, affecting productivity by 18.60%. Raw material was the third criterion, contributing 17.09% to productivity loss. Plant layout next, affecting 14.12% of productivity. The manufacturing process scored 07.49% on the scale of influencing productivity. Product design was the next criterion, affecting productivity by 06.40%, while work method affected productivity by 04.40% and poor quality affected productivity by 02.75%. The environment was the last criterion, contributing 03.50% to productivity depletion.

In this study, we used a decision-maker to find nine main criteria and 37 sub-criteria. In the initial findings of the main criteria, workforce (WF) ranked 1 as the most influential factor affecting productivity improvement). Our findings are consistent with the outcomes from previous studies [41-43]. Manufacturing equipment was the second one on the prioritised list of influential factors (ranked 2) followed by raw material (ranked 3), plant layout/facilities (ranked 4), manufacturing process (ranked 5), product design (ranked 6), work method (ranked 7), environment (ranked 8), and quality (ranked 9). The results were similar to all of the MCDM models, which were validated using an artificial neural network.

Table 1: Details of decision-makers

Decision-makers	Designation	Area of expertise	Years of experience
D1	Vice president	Manufacturing - Operations	20
D2	Director	Design and manufacturing	18
D3	Senior manager	Manufacturing and design	15
D4	Professor	Industrial engineering	22
D5	Professor	Manufacturing engineering	20

Table 2: Ratings of criteria given by decision makers

Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9
C1	1	3	1	3	3	5	7	5	7
C2	0.33	1	2	2	3	2	5	5	7
C3	1.00	0.50	1	1	3	4	5	7	3
C4	0.33	0.50	1.00	1	3	3	4	5	5
C5	0.33	0.33	0.33	0.33	1	2	3	3	2
C6	0.20	0.50	0.25	0.33	0.50	1	3	3	2
C7	0.14	0.20	0.20	0.25	0.33	0.33	1	3	3
C8	0.20	0.20	0.14	0.20	0.33	0.33	0.33	1	1
C9	0.14	0.14	0.33	0.20	0.50	0.50	0.33	1	1

Table 3: Random numbers

	1	2	3	4	5	6	7	8	9	10	11
Random No	0.00	0.00	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.51	1.54

Table 4: Weight of criteria using AHP

Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9
Weight	0.2628	0.1860	0.1710	0.1412	0.07474	0.0624	0.0438	0.0274	0.030
Rank	1	2	3	4	5	6	7	8	9

Consistency index = 0.078693; Consistency ratio = 0.054271

Table 5: Pairwise comparison of main criteria using fuzzy AHP

	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**
C1	(1,1,1)	(2,3,4)	(1,1,1)	(2,3,4)	(2,3,4)	(4,5,6)	(6,7,8)	(4,5,6)	(6,7,8)
C2	(0.25,0.33,0.50)	(1,1,1)	(1,2,3)	(1,2,3)	(2,3,4)	(1,2,3)	(4,5,6)	(4,5,6)	(6,7,8)
C3	(1,1,1)	(0.33,0.5,1)	(1,1,1)	(1,1,1)	(2,3,4)	(3,4,5)	(4,5,6)	(6,7,8)	(2,3,4)
C4	(0.25,0.33,0.50)	(0.33,0.5,1)	(1,1,1)	(1,1,1)	(2,3,4)	(2,3,4)	(3,4,5)	(4,5,6)	(4,5,6)
C5	(0.25,0.33,0.50)	(0.25,0.33,0.5)	(0.25,0.33,0.50)	(0.25,0.33,0.50)	(1,1,1)	(1,2,3)	(2,3,4)	(1,2,3)	(1,2,3)
C6	(0.17,0.20,0.25)	(0.33,0.5,1)	(0.20,0.25,0.33)	(0.25,0.33,0.50)	(0.33,0.50,1)	(1,1,1)	(2,3,4)	(2,3,4)	(1,2,3)
C7	(0.13,0.14,0.17)	(0.2,0.2,0.25)	(0.17,0.20,0.25)	(0.20,0.25,0.33)	(0.25,0.33,0.50)	(0.25,0.33,0.50)	(1,1,1)	(2,3,4)	(2,3,4)
C8	(0.17,0.2,0.25)	(0.17,0.2,0.25)	(0.13,0.14,0.17)	(0.17,0.20,0.25)	(0.33,0.50,1)	(0.25,0.33,0.50)	(0.25,0.33,0.50)	(1,1,1)	(1,1,1)
C9	(0.13,0.14,0.17)	(0.13,0.14,0.17)	(0.25,0.33,0.5)	(0.17,0.2,0.25)	(0.33,0.5,1)	(0.33,0.5,1)	(0.25,0.33,0.50)	(1,1,1)	(1.1,1)

Table 6: Ranking of criteria based on TOPSIS

Criteria	D+	D-	CC	Rank
C1	0.062567	0.008759	0.73515	1
C2	0.16206	0.007563	0.45167	2
C3	0.005907	0.084384	0.37876	3
C4	0.11981	0.007988	0.34622	4
C5	0.0551	0.006061	0.31408	8
C6	0.004936	0.074787	0.34401	5
C7	0.059982	0.002828	0.33304	6
C8	0.029394	0.004199	0.33031	7
C9	0.04166	0.005951	0.31106	9

Table 7: Ranking of criteria based on entropy TOPSIS

Criteria	D+	D-	CC	Rank
C1	0.062567	0.008759	0.73515	1
C2	0.16206	0.007563	0.45167	2
C3	0.005907	0.084384	0.37876	3
C4	0.11981	0.007988	0.34622	4
C5	0.0551	0.006061	0.31408	8
C6	0.004936	0.074787	0.34401	5
C7	0.059982	0.002828	0.33304	6
C8	0.029394	0.004199	0.33031	7
C9	0.029224	0.004023	0.30210	9

Table 8: Ranking of criteria based on VIKOR

Criteria	Si	Ri	Qi	Rank
C1	0.1855	0.1153	0.092	1
C2	0.4598	0.1251	0.2048	3
C3	0.4901	0.1563	0.1626	2
C4	0.5495	0.1563	0.2048	3
C5	0.685	0.1669	0.2048	3
C6	0.6806	0.1563	0.2445	6
C7	0.7158	0.1751	0.2629	8
C8	0.7598	0.1751	0.2445	6
C9	0.779	0.1788	0.2629	8

Table 9: Ranking of criteria based on EDAS

Criteria	EDAS	Rank
C1	1	1
C2	0.74015	2
C3	0.68351	3
C4	0.58314	4
C5	0.28262	5
C6	0.2091	6
C7	0.098135	7
C8	0	9
C9	0.016994	8

6.2. COMPARISON OF RESULTS

The final results of the AHP, fuzzy AHP, TOPSIS, entropy TOPSIS, EDAS, VIKOR, and ANN methods were compared, and they are shown in Table 10. It was noted that the ranking results for all these methods are the same for the weights derived by AHP and fuzzy AHP except for VIKOR. Graphical comparisons of the normalised ranking score values of the calculated MCDM methods are given in Figure 8, where the alternatives were ranked according to the decreasing score values. Table 11 shows the ranking of the local weights and the global weights of the sub-criteria using AHP and FAHP. Despite its distinctive inputs and outputs, the neural network has difficulties. Errors may impair training and testing. After nine samples of training and testing, the model's inputs and outputs reduced the mean square error (MSE) values for the training and test outcomes.

Table 10: Ranking of criteria by MCDM (AHP, FAHP, TOPSIS, EDAS, VIKOR, ENTROPY and TOPSIS) and ANN

Criteria	AHP	FAHP	TOPSIS	EDAS	VIKOR	Entropy TOPSIS	ANN
C1	0.262 (#1)	0.257 (#1)	0.798 (#1)	1.000 (#1)	0.092 (#1)	0.842 (#1)	1.627 (#1)
C2	0.185 (#2)	0.185 (#2)	0.479 (#3)	0.740 (#2)	0.204 (#3)	0.516 (#2)	2.597 (#2)
C3	0.170 (#3)	0.168 (#3)	0.492 (#2)	0.683 (#3)	0.162 (#2)	0.411 (#3)	2.683 (#3)
C4	0.141 (#4)	0.146 (#4)	0.291 (#4)	0.583 (#4)	0.204 (#3)	0.350 (#4)	3.896 (#4)
C5	0.074 (#5)	0.075 (#5)	0.146 (#5)	0.282 (#5)	0.204 (#3)	0.165 (#5)	5.321 (#5)
C6	0.062 (#6)	0.065 (#6)	0.098 (#6)	0.209 (#6)	0.244 (#6)	0.138 (#6)	5.917 (#6)
C7	0.043 (#7)	0.040 (#7)	0.032 (#9)	0.098 (#7)	0.262 (#8)	0.065 (#7)	7.387 (#7)
C8	0.027 (#9)	0.029 (#9)	0.038 (#8)	0.000 (#9)	0.244 (#6)	0.020 (#9)	8.978 (#9)
C9	0.030 (#8)	0.031 (#8)	0.043 (#7)	0.016 (#8)	0.262 (#8)	0.036 (#8)	7.634 (#8)

Ranks are indicated within the brackets (#)

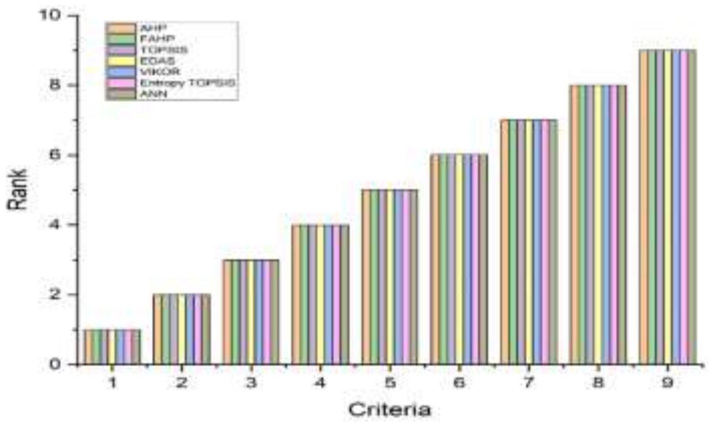

Figure 8: Comparison of other MCDM models with ANN

Table 11: Ranking of local weight and global weight of sub-criteria using AHP and FAHP

AHP			FAHP			AHP			FAHP		
CR	**LW**	**Rank**	**CR**	**LW**	**Rank**	**CR**	**GW**	**Rank**	**CR**	**GW**	**Rank**
MP1	0.58618	1	MP1	0.60400751	1	WF1	0.13499	1	WF1	0.13645	1
WF1	0.51401	2	WF1	0.53071602	2	ME1	0.0829	2	ME1	0.0816	2
PL1	0.49093	3	QT1	0.49938378	3	PL1	0.06932	3	PL1	0.07209	3
Q1	0.47868	4	PL1	0.49229458	4	WF2	0.0684	4	WF2	0.06488	4
ME1	0.4458	5	EN1	0.44154218	5	ME2	0.05686	5	ME2	0.0566	5
WM1	0.43	6	ME1	0.44079553	6	RW2	0.05327	6	RW2	0.05367	6
E1	0.42215	7	PD1	0.42972091	7	RW3	0.04498	7	RW3	0.0459	7
PD1	0.4076	8	WM1	0.41838978	8	MP1	0.04392	8	MP1	0.04537	8
RW2	0.31178	9	PD2	0.33376198	9	PL2	0.04114	9	PL2	0.04247	9
ME2	0.30574	10	RW2	0.31808469	10	WF3	0.03685	10	WF3	0.03589	10
PD2	0.303	11	QT2	0.31065691	11	RW1	0.03231	11	RW1	0.03125	11
Q2	0.29623	12	ME2	0.30572305	12	RW4	0.03033	12	RW4	0.03007	12
PL2	0.29135	13	PL2	0.29003491	13	ME3	0.02873	13	PD1	0.02829	13
RW3	0.26328	14	RW3	0.27202238	14	PD1	0.02545	14	ME3	0.02749	14
WF2	0.26047	15	WF2	0.25236375	15	WF4	0.02238	15	PL3	0.02212	15
WM2	0.25	16	WM2	0.24657031	16	PL3	0.02128	16	PD2	0.02197	16
MP2	0.24607	17	MP2	0.23691781	17	WM1	0.01908	17	WF4	0.01988	17
WM3	0.22	18	WM3	0.22508367	18	PD2	0.01892	18	ME4	0.01943	18
E2	0.22091	19	EN2	0.21864405	19	MP2	0.01844	19	MP2	0.0178	19
RW1	0.18909	20	RW1	0.18518688	20	ME4	0.01748	20	WM1	0.01708	20
RW4	0.17749	21	RW4	0.17817284	21	Q1	0.01318	21	QT1	0.01455	21
E3	0.17267	22	EN3	0.16774408	22	E1	0.01286	22	EN1	0.01399	22
Q3	0.16828	23	PL3	0.15105733	23	WM2	0.01115	23	WM2	0.01007	23

AHP			FAHP			AHP			FAHP		
CR	LW	Rank	CR	LW	Rank	CR	GW	Rank	CR	GW	Rank
PD3	0.16561	24	ME3	0.14849987	24	PD3	0.01034	24	PL4	0.00976	24
ME3	0.15448	25	QT3	0.13998826	25	WM3	0.00977	25	WM3	0.00919	25
PL3	0.15069	26	WF3	0.13958124	26	PL4	0.00947	26	QT2	0.00905	26
WF3	0.1403	27	PD3	0.12229292	27	RW5	0.00855	27	PD3	0.00805	27
PD4	0.12379	28	PD4	0.1142242	28	MP3	0.00848	28	MP3	0.00793	28
E4	0.11506	29	WM4	0.10995624	29	Q2	0.00816	29	RW5	0.00785	29
MP3	0.11317	30	EN4	0.10558351	30	PD4	0.00773	30	PD4	0.00752	30
ME4	0.09398	31	MP3	0.10555133	31	E2	0.00673	31	EN2	0.00693	31
WM4	0.09	32	ME4	0.10498155	32	E3	0.00526	32	EN3	0.00531	32
WF4	0.08522	33	WF4	0.07733898	33	Q3	0.00463	33	WM4	0.00449	33
E5	0.06921	34	PL4	0.06661318	34	MP4	0.00409	34	QT3	0.00408	34
PL4	0.06704	35	EN5	0.06648617	35	WM4	0.00397	35	MP4	0.00402	35
Q4	0.05681	36	MP4	0.05352336	36	E4	0.00351	36	EN4	0.00334	36
MP4	0.05459	37	QT4	0.04997105	37	E5	0.00211	37	EN5	0.00211	37
RW5	0.05003	38	RW5	0.04653321	38	Q4	0.00156	38	QT4	0.00146	38

CR – Criteria, LW – Local weight, GW – Global weight

The collected data were divided into a training dataset and a validation dataset. The training dataset was used to calculate the gradient and to update the connection weights, while the validation dataset was used to assess errors. The training was concluded when the errors for the training dataset decreased and the errors for the validation dataset increased, with the model exhibiting the lowest validation error rate during this time. To achieve a high level of prediction precision, the training dataset was used to train the model. Each iteration's update group size was 10 samples. The number of epochs for an ANN model denoted the number of times the entire training dataset was processed. This investigation examined one thousand epochs. After 53 epochs, the ANN model's prediction accuracy for the training datasets exceeded 99%. The proposed testing set had an overall prediction accuracy of 98%. Figure 9 shows the regression analysis of the network.

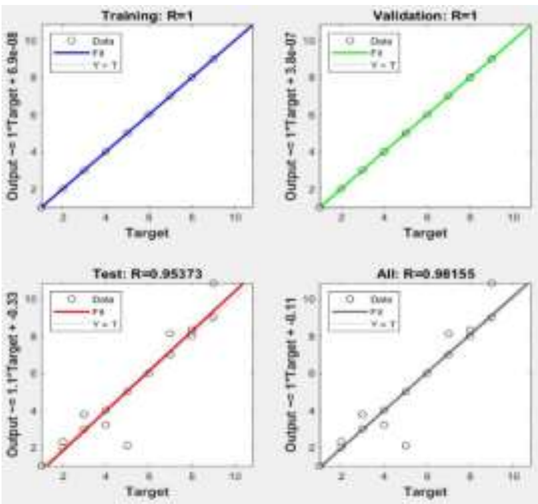

Figure 9: Regression analysis

In the present case study, we have discussed the core defects and the reasons for the defects, which helped us to understand the arrangement of the manufacturing equipment and the workforce involved in the core production shop. AHP and fuzzy AHP were found to be more suitable MCDM models for finding the causes and helping to analyse the productivity improvement [58-61]. Both MCDM models showed almost similar results for all factors. AHP and fuzzy AHP prioritised the factors that needed to be analysed. The highest priorities were given for the highest rank, which invariably affected the other low priority factors. Since the workforce was found to be the most influential factor, we employed a standard operating procedure (SOP) to target primarily the workforce and to employ it productively. In the implementation of the SOP, the core was transported from the production shop to the storage station in a tray. In that way, the workforce involved in carrying the core from one station to another was considerably reduced. In the painting stations, suggestions were given to apply the paint in a controlled flow over the core instead of dipping the core directly into the paint. It also reduced the ergonomic problems experienced by the workforce, thus helping to reduce the absenteeism and lateness of the workforce. These suggestions reduced the core defects and improved the production of the core, which in turn reduced the casting defects.

We also attempted to improve the use of the manufacturing equipment through the Standard Operating Procedure (SOP). To use the oven space fully, we suggested that the workforce arranged the trays and compartmentalised the baking area. This would enable them to place a greater number of cores in the oven and to bake them for a standard time interval. Compartmentalisation of the oven would not only enhance the production volume, but also minimise the consumption of electrical power. A nominal increase in the utility of the equipment would lead to an elevation of the productivity scale because it would improve the quality of the baking of large cores in the shortest time at a lower fuel cost, leading to an improvement in the efficiency of the electric oven. Moreover, the correct baking of the cores would decrease defects such as cuts, washes, and over-baked cores. Therefore, this reduction would improve the output of casting without defects. Later, all cores were moved to the moulding area for further processing. All of the aforementioned suggestions, changes, and arrangements to use the workforce properly and to handle the material would help to increase productivity [52]. After the implementation of these methods and their resultant outcomes, a significant decrease in non-value-added activities (NVA) by 65.56% was revealed, along with a notable enhancement of the process time by 61.03%, a substantial reduction in waiting time by 66.66%, a decrease in manpower by 35%, and a cost reduction by 45%. These findings showed the superior performance achieved in the core shop environment, and productivity was increased by 23%. Figure 10 shows the post implementation of standard operating procedure (SOP).

Figure 10: Changes to SOP: a, b – Before implementing, after implementing in paint shop; c, d – Arrangement in oven

7. CONCLUSION

This paper proposed a very simple and novel method of comparison among the rankings obtained from various MCDM techniques. A number of other different MCDM techniques such as TOPSIS, entropy TOPSIS, VIKOR, and EDAS were selected for the purpose of ranking. The proposed method of comparison analysed the rankings, based on the benefits provided by the rankings. The benefits were determined by the maximum or minimum values of the highest ranked criterion. The reason for choosing the measure of benefit for the analysis was the fact that the primary purpose of any MCDM ranking is to identify the most appropriate alternatives that will produce the maximum benefit.

A case study on core shop in foundry was presented in this paper in order to show the establishment of the associations among the rankings using existing rank correlation methods, and to establish the effectiveness of the proposed method of comparison.

Productivity improvement is an important activity for manufacturing companies, as selecting the wrong criteria can be expensive with respect to product quality, production time, production rate, and resource allocation. It has been suggested that an effective and efficient MCDM tool should be used to address the criteria that could increase productivity.

The manager, along with a team of nine people, examined the criteria for improving productivity in the core shop of a foundry industry (the casting process) [63,64].

- A total of nine major criteria and 38 sub-criteria required pairwise comparisons from the decision-maker in order to establish criteria weights using AHP and fuzzy AHP. The determined criteria weights of the AHP analysis and the fuzzy weights of the fuzzy AHP analysis were compared (Table 10).
- The normalised weights and scores of the analyses were consistent, with AHP and FAHP showing few differences. This could most likely be attributed to the accuracy of the AHP and FAHP selection scales, and the decision-makers' perceptions of the criteria with correct weights had a good impact on the decision results.
- There were significant differences in the results from one method: VIKOR could not provide a conclusive result, indicating that the other methods were better.
- Hybrid neuro-MCDM models could boost criterion weighting and handle uncertainty in the decision environment. The ANN tool is a sophisticated analytical tool for comparing decision-makers' data and criteria ranking. This MCDM study used ANN because fuzzy logic computation is repetitive.
- The comparison of the different MCDM methods directly influenced the core shop in the foundry to make an informed decision to improve productivity in every stage of its processes. By going through this, the team of industrial professionals became more knowledgeable about their decisions and the uncertainty associated with each criterion-related option, directing them to evaluate each criterion-related option before implementing another.

Implementing a material handling system between the stations reduces the handling of the cores by the workforce, and so reduces damage to the cores. The solution that emerged from the research was provided to the plant in order to enhance productivity. The identified factors – the workforce, poor handling of materials and work in progress, and a poor mode of transportation between the stations – directly influenced the core defects that affected productivity. Thus commissioning an effective material handling system at an appropriate place would minimise the adverse role played by the prioritised sub-criteria. As a result they would have a positive impact on the major criteria and so produce better levels of productivity.

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