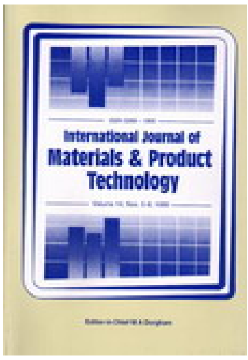

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Analysis of factors affecting core functional competencies in manufacturing industries using fuzzy AHP

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Analysis of factors affecting core functional competencies in manufacturing industries using fuzzy AHP

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Abstract: For firms to be more competitive in the market, core functional abilities are crucial. They give a business the tools it needs to outperform rivals in terms of performance speed, adaptability, and dependability. Many tools and approaches, such as instruments for quantitative and qualitative analysis, are utilised to analyse these elements. This paper deals with the analysis of attributes using Fuzzy AHP technique. During the analysis different factors have been identified and categorised on the priority basis using the Fuzzy AHP which can help the organisation through better insight of core functional competencies.

Keywords: fuzzy AHP; competitiveness; core functional competencies; MCDM; multi-criteria decision-making.

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1 Introduction

Developed nations make excellent use of their organisational resources and have the kind of atmosphere that helps businesses survive in a cutthroat market (Yuvaraj, 2011; Yaşar et al., 2013; Khan et al., 2007).

There are few studies that demonstrate how to manage a core functional competence portfolio in an integrated manner, despite the fact that the concepts of a resource-based view of the firm and core competence as a corporate strategy to obtain competitive advantage have been explored for many decades (Vankireddy and Baral, 2019).

New technological and non-technological knowledge is the source of innovation. Non-technological innovations are those that relate to knowledge, skills, and the organisational working environment. New tools and procedures are connected to technological innovation. And for a company to succeed in the market, both are essential (Bhamra et al., 2011)

This study builds on and extends previous research to provide definitions of the salient characteristics of the key concepts as well as a structured method for the evaluation of the core functional competencies of a company in the process industry. This is done to address the aforementioned problems and to create a more general classification of core competencies so that they can be managed in a more integrated and systematic manner (Foroudi et al., 2019).

The institution's quality has a big impact on competition. The current financial and economic climate calls for the institution's soundness and strength. A country's ability to develop a sector's economic activities depends in large part on its infrastructure. In some nations and areas, a fully working infrastructure connects the domestic and international markets at a minimal cost (Hafeez et al., 2002).

Further study is required to investigate novel performance management strategies in light of the gaps regarding training investment, the goal of ratings, and employees' cognitive processes, as well as the incorporation of a variety of contingency and contextual elements, as was previously mentioned (Walsh and Linton, 2002).

The significance of contextual elements has been emphasised more recently. Studying how context affects how performance appraisal practises are perceived, how people respond, and how they affect outcomes in Chinese public sector enterprises (Wang et al., 2004).

One of the most difficult areas of decision-making that a company's management faces is the choice of technologies. Because there are more technologies and they are more sophisticated than before, it is challenging to identify the best technological options. Nonetheless, in a challenging business environment, the correct technologies could give a company enormous competitive advantages (Greitemann et al., 2014).

For this multi criteria decision making techniques are very helpful to find out the best attributes that may improve the performance of the industries if implemented in good manner. More advanced techniques can play better role than old methods. Many fuzzy techniques are there to work with (Karahoca, 2019).

Given the nature of construction, which is widely viewed as intricate, full of uncertainties, and dependent on changing circumstances, fuzzy membership functions and linguistic variables in particular can be employed to solve challenges encountered in the industry. Furthermore, hybrid fuzzy techniques, including neuro fuzzy and fuzzy neural networks, can be used more broadly since they are better able to address various construction-related issues that fuzzy set/fuzzy logic alone may not be the optimum solution for (Chan et al., 2009).

According to the measured spindle and feed motor currents, wavelet transforms and fuzzy algorithms are employed to monitor tool breakage and wear conditions in real time. In order to successfully detect drill breakage, the continuous and discrete wavelet transforms are first employed to breakdown the spindle and feed ac servo motor current signals. Secondly, under various tool wear conditions, models of the relationships between the present signals and the cutting parameters are created (Li et al., 2000).

By fusing human thinking with learning and connectionist structure, neuro-fuzzy hybridisation seeks to take use of the synergy between neural networks and fuzzy logic in the creation of a tool wear monitoring system. For this case study, a well-known machining technique called turning will be used (Gajate et al., 2012).

Application of fuzzy approaches to the creation of reputation systems that rely on gathering and averaging the opinions of peers. All of the peer opinions are evaluated and synthesised using fuzzy approaches. By contrasting the suggested system's behaviour using probabilistic methods, its behaviour is characterised (Aringhieri et al., 2006).

In publicly financed infrastructure projects with private financing, risk allocation is crucial. Performance of the project depends on whether the risk-allocation technique used can result in effective risk management. A theoretical framework was recently established to simulate the risk allocation decision-making process in privately financed public infrastructure projects. It is based mostly on transaction cost economics (Jin, 2011).

Four feasible factors that were thought to be crucial in the movement of pollutants into and across the soil profile were used to create the Neuro-fuzzy model in Java. These variables include the soil hydrologic group, soil profile depth, soil structure (pedality points), and land usage (Dixon, 2004).

To help radiologists identify breast masses and lesions in different groups of benign and malignant lesions, an intelligent computer-aided diagnostics system may be created. In the current work, we have made an effort to create a computer-assisted treatment planning system that uses neuro-fuzzy genetic algorithms (Das and Bhattacharya, 2008).

Hence fuzzy AHP has been used less in manufacturing industries to properly implement the core functional competencies which can very much change the performance of the manufacturing sector. Therefore this paper deals with the fuzzy AHP technique used in core functional competencies and to know the effect of the same on manufacturing sector directly or indirectly.

2 Literature review

Competence of the Corporation has greatly increased interest in the idea of core functional competencies and skills and helped make The Resource Based Perspective of the Firm, a new school of economic thinking, popular (Gorman et al., 1997; Karami et al., 2004; Yaşar et al., 2013).

The corporation typically begins the planning process by identifying external dangers and opportunities. In order to identify prospective trends and changes and assess their ramifications, it analyses the macro environment as well as the stakeholders, industry, rivals, and customers (Javidan, 1998).

R&D managers, as well as their direct 'clients' and sponsors within the company, are becoming increasingly concerned about having trustworthy mechanisms to drive R&D simultaneously towards successful rapid innovation and accumulation of long-term technological strength (Quelin, 2000).

In order to establish this link between the technological and non-technological aspects of the corporate strategy agenda, the paper examines the parallel literature on the idea of core competencies as a new paradigm in corporate strategy and demonstrates how core competencies can be useful focusing tools (Yuvaraj, 2011).

Core functional Competencies can be conceptualised as bodies of technological expertise (product and process-related) and the organisational capability to successfully use that expertise. As a result, they are organisational in nature as well as technological. They are enhanced and made stronger with continuing usage (or, to put it another way, they are subject to positive returns), and as a result, to some extent, they are firm-specific and non-transferable (Coombs, 1996).

Although there are methods for identifying activities and skills that are useful for students with severe disabilities, these methods offer comparatively little guidance on how to break down functional skills into meaningful subsets that represent the variety of behaviours required in the natural environment (Brown et al., 1987).

It has been observed by Hafeez et al. (2002) that company's core competencies are its greatest assets, so they should be properly fostered and developed. Based on the strengths of their competencies, businesses can choose their future business directions. The lack of a clear explanation of terminology like resource, asset, capability, and competence in relation to competence theory, however, makes it difficult to understand many modern management ideas (Yaşar et al., 2013).

At three stages of professional development – readiness for practicum, readiness for internship, and readiness for entry into practice – the Competence Benchmarks paper specifies fundamental and functional core competencies in professional psychology. The document covers the crucial parts that make up the core competences at each level as well as the behavioural indicators that give the crucial elements operational descriptions (Fouad et al., 2009).

Successful disaster preparedness, response, and recovery require a well-organised, integrated effort with seasoned experts who can use specialised knowledge and abilities in challenging circumstances. While some professionals have the necessary training, others might not have the relevant skills and expertise to function well in a disaster-stricken environment (Walsh et al., 2012).

The corporate rivalry nowadays is tough and well-informed, unlike in the past. In light of this, Henry Ford's maxim, "You may have whatever colour as long as it's black", is no longer a practical way to satisfy customer demands. Businesses now need something unique to compete in the severe market competition (Kawshala, 2017).

The mathematical models known as multi-criteria decision-making (MCDM) approaches assist in making judgements in situations where potential alternatives are weighed against a number of competing criteria. These techniques have a wide range of uses. Examples include supplier selection, technical evaluation of bidders, service quality assessment, and renewable energy (Chatterjee and Chakraborty, 2016).

Making the right judgements can make the difference between success and failure in the field of construction. Also, the majority of the tasks in this sector need taking into account a number of opposing factors, which makes it difficult to manage these activities as a whole (Jato-Espino et al., 2014).

In MCDM challenges, data are frequently ambiguous and subject to change. Thus, running a sensitivity analysis on the input data is a crucial step in many MCDM applications. The decision criterion weights and performance values of the alternatives described in terms of the decision criteria are presented in this work along with a methodology for doing a sensitivity analysis on them (Triantaphyllou and Sánchez, 1997).

Based on a thorough examination of the literature, this study presents an overview of research contributions on multicriteria decision making (MCDM) for forest management and planning. The review emphasises theoretical foundations, debates, and application issues in particular. Additionally, it looks at the nature of the issues raised and how risk is taken into account when making decisions on forest management and planning (Ananda and Herath, 2009).

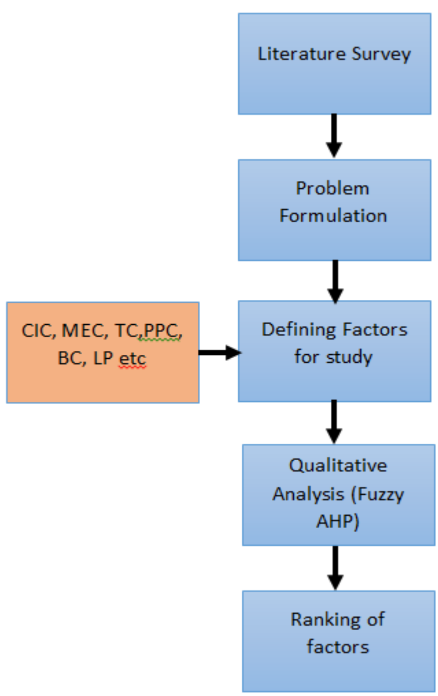
In various MCDM procedures, the issue of determining criteria weights regularly arises. Given that the weights of criteria can have a considerable impact on how a decision is made, it is crucial to pay close attention to the criteria weights' objectivity considerations (Odu, 2019).

Hence from the above literature it has been found that less work has been done on fuzzy techniques. Therefore the paper deals with tha analysis of fuzzy AHP method for the prioritisation of the attributes that have been selected for the concerned study.

3 Procedural frameworks

Figure 1 shows the framework of the study. In the very first step detailed survey of literature was done. Then in the second step problem was formulated which involved various types of consultancy with experts and brainstorming sessions. In the next step various attributes were defined which are concept idea competency, technical competency, material and equipment related competency, behavioural competency, leadership competency, production and control competency and quality competency. After this analysis was done using fuzzy analytical hierarchical process (AHP) which prioritise the factors and given the ranks according to the affecting conditions of the factor on the performance of the manufacturing industry.

Figure 1 Procedural framework (see online version for colours)



4 Fuzzy AHP

One of the widely employed techniques for MCDM is the AHP. The relative ease with which this strategy handles several criteria is one of its key benefits. AHP also handles both qualitative and quantitative data efficiently and is simpler to understand. There is no complex math required to use AHP. Decomposition, pairwise comparisons, priority vector generation, and synthesis are all aspects in AHP. Even if the goal of AHP is to capture expert knowledge, the traditional AHP still cannot capture the way people think (Saaty, 1977).

As a result, fuzzy AHP, a fuzzy addition to AHP, was created to address hierarchical fuzzy issues. The decision-maker can describe their preferences in terms of the weight they assign to each alternative using natural language expressions. The approach mainly uses factor's priority by merging these preferences with current data (collected from survey) and fuzzy-AHP. The pairwise comparisons in the judgement matrix in the fuzzy-AHP technique are fuzzy integers that are altered by the decision maker. The process determines a series of weight vectors that will be used to aggregate the scores for each aspect using fuzzy math (Kahraman et al., 2003; Talib and Asjad, 2019). Linguistic variables generated and their triangular fuzzy numbers are shown in the Table 1.

Table 1 Fuzzy linguistic scale and variables

Fuzzy number	*Fuzzy number scale*	*Linguistic term*
1	1,1,1	No influence
2	1,2,3	Extremely low influence
3	2,3,4	Low influence
4	3,4,5	Moderate influence
5	4,5,6	Good influence
6	5,6,7	Slightly high influence
7	6,7,8	High influence
8	7,8,9	Extremely high influence

4.1 Fuzzy AHP method and analysis

Step 1: In this very first step fuzzy decision matrix is generated by using the crisp values, which are formed by using the weightage triangular scale as described for the preferences given to the alternatives used. Table 2 gives the fuzzy decision matrix.

Step 2: Now calculate fuzzy geometric mean value of the crisp values in the fuzzy decision matrix. This can be calculated by using equation (1). The values of fuzzy geometric mean and sum and reciprocal of the fuzzy geometric mean are shown in Table 3.

$$\text{FGM } (r_i) = \{(l_1 * l_2)^{1/9}, (m_1 * m_2)^{1/9}, (u_1 * u_2)^{1/9} \ldots\ldots)\} \tag{1}$$

where r_i is the fuzzy geometric mean

l, m, u are the lower middle and upper values of fuzzy numbers.

Table 2 Fuzzy decision matrix

	CIC	*DC*	*PC*	*MEC*	*PCC*	*QC*	*BC*	*LC*	*TC*
CIC	(1,1,1)	(1,2,3)	(3,4,5)	(1,2,3)	(5,6,7)	(3,4,5)	(2,3,4)	(3,4,5)	(1/3,1/2,1)
DC	(1/3,1/2,1)	(1,1,1)	(1,1,1)	(1/3,1/2,1)	(1,1,1)	(2,3,4)	(2,3,4)	(1,2,3)	(1/5,1/4,1/3)
PC	(1/5,1/4,1/3)	(1,1,1)	(1,1,1)	(1,1,1)	(1,2,3)	(1,1,1)	(1,2,3)	(1,2,3)	(1/4,1/3,1/2)
MEC	(1/3,1/2,1)	(1,2,3)	(1,1,1)	(1,1,1)	(1,2,3)	(4,5,6)	(5,6,7)	(6,7,8)	(1/3,1/2,1)
PCC	(1/7,1/6,1/5)	(1,1,1)	(1/3,1/2,1)	(1/3,1/2,1)	(1,1,1)	(1,2,3)	(5,6,7)	(6,7,8)	(1/7,1/6,1/5)
QC	(1/5,1/4,1/3)	(1/4,1/3,1/2)	(1,1,1)	(1/6,1/5,1/4)	(1/3,1/2,1)	(1,1,1)	(1,2,3)	(2,3,4)	(1/7,1/6,1/5)
BC	(1/4,1/3,1/2)	(1/4,1/3,1/2)	(1/3,1/2,1)	(1/7,1/6,1/5)	(1/7,1/6,1/5)	(1/3,1/2,1)	(1,1,1)	(1,2,3)	(1/9,1/8,1/7)
LC	(1/5,1/4,1/3)	(1/3,1/2,1)	(1/3,1/2,1)	(1/8,1/7,1/6)	(1/8,1/7,1/6)	(1/4,1/3,1/2)	(1/3,1/2,1)	(1,1,1)	(1/7,1/6,1/5)
TC	(1,2,3)	(3,4,5)	(2,3,4)	(1,2,3)	(5,6,7)	(5,6,7)	(7,8,9)	(5,6,7)	(1,1,1)

Step 3: Now find the values of summation of all the fuzzy numbers and their reciprocal. The lower values are added to lower values middle values to middle and upper values to the upper ones as shown in Table 3.

Step 4: In this step calculate fuzzy weights by using following formula (equation (2)) after which crisp fuzzy values are obtained as shown in Table 4.

$$w_i = r_i * (r_1 + r_2 + \cdots + r_n)^{-1} \tag{2}$$

where w_i is the fuzzy weight

$r_1, r_2, \ldots, r_n$ are the fuzzy geometric means of lower middle and upper values.

Table 3 Fuzzy geometric mean

Factors	*FGM* (r_i)
CIC	1.6468,2.3638,3.1609
DC	0.8615,1.0132,1.3593
PC	0.8099,0.9549,1.1806
MEC	1.5033,1.8114,2.4363
PCC	0.7368,0.946,1.2357
QC	0.4488,0.5881,0.7734
BC	0.2904,0.3857,0.5444
LC	0.2508,0.3192,0.4593
TC	2.5903,3.5199,4.7775
Sum	9.1386,11.9022,15.9274
Reciprocal	1/15.927, 1/11.9022, 1/9.1386

Step 5: Now calculate the centre of area (COA) by taking average of crisp fuzzy numbers calculated for the fuzzy weights and obtain defuzzified weights.

$$\text{COA}\ (\mathrm{d}w_i) = \frac{l+m+u}{3} \tag{3}$$

Step 6: From Table 4 it can be seen that the summation of all the defuzzified weights is more than 1 which is not acceptable. Therefore normalise the weights by dividing each value of the de-fuzzified weight by total of the weights. After that we get the total as 1 which is acceptable and then tanking is done and shown in the Table 4.

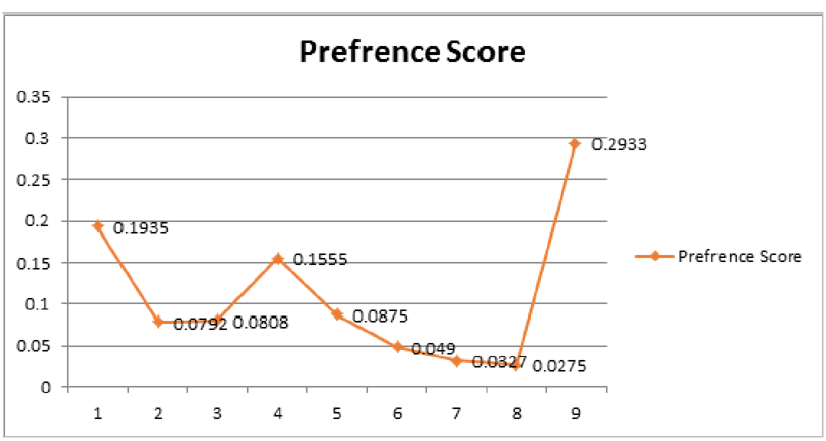
Table 4 Weights, normalised weights and ranks

Factors	w_i	dw_i	nw_i	*Rank*
CIC	0.1034,0.1986,0.3459	0.4173	0.1935	2
DC	0.0541,0.0851,0.1487	0.1709	0.0792	6
PC	0.0509,0.0802,0.1292	0.1742	0.0808	5
MEC	0.0944,0.1522,0.2666	0.3355	0.1555	3
PCC	0.0463,0.0795,0.1352	0.1888	0.0875	4
QC	0.0282,0.0494,0.0846	0.1058	0.049	7
BC	0.0182,0.0324,0.0596	0.0705	0.0327	8
LC	0.0157,0.0268,0.0503	0.0593	0.0275	9
TC	0.1626,0.2957,0.5228	0.6326	0.2933	1
	Sum	2.1549	1	

5 Results and discussions

Factors which affect the performance of manufacturing industry is shown in the Figure 2. The figure shows the preference score of each factor. It can be seen that on highest priority is the factor Technical Competency (TC) and on last is Leadership competency (LC) (TC > CIC > MEC > PCC > PC > DC > QC > BC > LC). Technical competency, concept ides competency, material and equipment related competency and production and control competency are considered as critical factors.

Figure 2 Preference score of factors (see online version for colours)



6 Conclusions

Core functional competencies play a vital role in the performance of manufacturing sector. Some of the competencies under core functional competencies are considered much important. From the study following conclusions has been drawn;

- Technical Competency, concept idea competency, material and equipment related competency and production and control competency are considered as critical competencies.
- This study is done in manufacturing industries based in Northern part of the country.
- Further studies can be done in other parts of the country considering other different factors related to the manufacturing sector.
- Some other analytical tools like fuzzy VIKOR, fuzzy TOPSIS etc. can be used for other research work.

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