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Chapter

Decision-Making in Real-Life Industrial Environment through Graph Theory Approach

Ravi Pratap Singh, Ravinder Kataria and Sandeep Singhal

Abstract

The approach called as "graph theory and matrix approach" has been well employed in numerous research studies with a view to perform the decision-making while the situation is becoming perplexed type or where there is a very strong relative importance of one parameter over another. In such cases, the said graph theory and matrix method provides very suitable and fruitful solutions to make the decision to its final effective extent. The further improvements and the outcome enhancement can also be revealed through the use of combined practice of graph theory results along with some artificial intelligence-inspired logics and practices such as fuzzy logic, artificial neural network, etc. The significance and applicability of said method in vast fields of science, engineering, and research are also proved. Nowadays, our manufacturing sectors are getting up to date through the applications of artificial intelligence and several software-based directions. This is all to enhance the overall machine system performance with a view to improve desired performance characteristics of the process under the study. Few sections of this chapter has also elaborated the utility of the artificial intelligence-inspired fuzzy logic-based decision system which has already been a part of previous researches.

Keywords: diagraph, computer systems, artificial intelligence, matrix, industries, fuzzy logic, artificial neural network

1. Basic overview of graph theory

The decision-making has now been developed and practiced with the use of several recently emerged methodologies to make the traditionally employed practices more effective and impressive [1–3]. The behavior of humans has been mimicked out in an effective and limited way through artificial intelligence models. Artificial neural networks, evolutionary computing, fuzzy logic, probabilistic analysis models, intelligent agents, etc. are some major tools which usually define the basic artificial intelligence system. Wren and Jain [4] have explored the application of artificial intelligence (AI) while practicing a healthy decision-making in practical industry-based problems. There are so many AI techniques which have been investigated in past researches for the purpose of decision-making [5, 6]. These methodologies are, namely, data trend analyzing, coordinating the data delivery, forecast providing, data consistency development, uncertainty quantification, etc. The well-known decision-making method, called *graph theory*, is a systematic and

logical approach which also has proven to be useful for analyzing and modeling a wide range of applications in engineering and numerous other areas. This methodology is particularly based on the advanced theory of graphs, and therefore its applications are very well renowned. The demonstration through graph "or" digraph model has proven to be useful for modeling and analyzing numerous varieties of systems and problems in numerous fields of science and technology [7–9]. The approach based on the matrix method is useful in analyzing the graph/digraph models expeditiously to derive the system function and index to meet the objectives.

Graph theory is a subject of combinatorial mathematics and draws a lot from matrix theory. The matrix representation of the graph molds the problem to make use of computers for various complex operations. The graph theory and matrix methods (GTMM) consist of the digraph representation, the matrix representation, and the mathematical representation, i.e., a permanent function. The digraph is the visual representation of the variables and their interdependencies. The matrix converts the digraph into mathematical form, and the permanent function is a mathematical representation that helps to determine the numerical index [10, 11]. The graph theory approach is a systematic approach for conversion of qualitative factors to quantitative values, and mathematical modeling gives an edge to the proposed technique over conventional methods like cause-effect diagrams, flow charts, etc. These method outcomes can now be settled into some artificial intelligence-based tools and steps to generate some more fruitful and smart solutions. More specifically, the fuzzy logic-based approach can be implemented further to utilize the human thoughts regarding the problem under consideration. The logic generation will be based on the pure human experiences which help to implement the artificial intelligence-based graph theory approach more reasonable and practicable. The AI, generally described as the discipline of developing machines performing things that would entail human astuteness, is often perplexed with robotics, particularly humanoid robotics, as they are contiguous to "human" intellect. Graph theory has a wide range of applications in engineering and numerous other areas. The essential steps for executing the abovesaid methodology are as follows.

2. Selection of attributes

In this chief step, various characteristics which affect the outcome under study are identified, and the experimental design that gratifies the operation requirements is finalized. The trait values (T_i) and relative importance (u_{ij}) are obtained using **Tables 1** and **2**.

2.1 Machinability attribute digraph representation

A digraph is exploited to illustrate the aspects which affect the machinability and interdependencies among them in terms of *edges* and *nodes*. A cluster of directed edges $R = \{u_{ij}\}$ and a cluster of nodes $Q = \{T_i\}$, with $i = 1, 2, ..., X$, consist in a digraph. A node *Ti* signifies the *i*th machinability attribute, and edges epitomize their relative importance. The number of nodes (X) reflected is the same as the number of machinability attributes considered for the machining operation. For example, three vital attributes, viz., material removal rate (1), tool wear rate (2), and surface roughness (3), are designated for the assessment of machinability work considered. The machinability characteristic diagraph is represented as shown in **Figure 1**.

S. no.	Qualitative measure of factors affecting machinability of titanium	Assigned value of machinability factors (T_i)
1.	Exceptionally low	0
2.	Extremely low	1
3.	Very low	2
4.	Below average	3
5.	Average	4
6.	Above average	5
7.	Moderate	6
8.	High	7
9.	Very high	8
10.	Extremely high	9
11.	Exceptionally high	10

Table 1.
Quantification of factors affecting machinability of titanium [12].

S. no.	Category description	Interdependencies of attributes	
		u_{ij}	$u_{ji} = 10\text{-}u_{ij}$
1.	Two attributes are of equal importance	5	5
2.	One attribute is slightly more important than the other	6	4
3.	One attribute is more important than the other	7	3
4.	One attribute is much more important than the other	8	2
5.	One attribute is extremely more important than the other	9	1
6.	One attribute is exceptionally more important than the other	10	0

Table 2.
Relative importance of machinability attributes (u_{ij}) [12].

2.2 Matrix representation of the machinability attribute digraph

The digraph is needed to be characterized in matrix form (H) called a variable permanent matrix for permanent machinability index (VPM_M). This is $X \times X$ matrix which deliberates all of the attributes (i.e., T_i) with their relative importance (i.e., u_{ij}). The matrix shown in Eq. (1) is articulated as per the machinability estimation digraph (**Figure 1**).

The tradition of the three imperative attributes is embodied by diagonal elements T1, T2, and T3, and interdependencies between them are revealed by off-diagonal elements of the matrix for individual attributes [12, 13].

For the deliberated machinability attribute digraph, the matrix H is illustrated as

$$VPM_M = H = \begin{array}{c} \text{Attributes} \\ 1 \\ 2 \\ 3 \\ 4 \\ \cdots \\ \cdots \\ X \end{array} \begin{bmatrix} 1 & 2 & 3 & 4 & \cdots & \cdots & X \\ T_1 & u_{12} & u_{13} & u_{14} & \cdots & \cdots & u_{1X} \\ u_{21} & T_2 & u_{23} & u_{24} & \cdots & \cdots & u_{2X} \\ u_{31} & u_{32} & T_3 & u_{34} & \cdots & \cdots & u_{3X} \\ u_{41} & u_{42} & u_{43} & T_4 & \cdots & \cdots & u_{4X} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ u_{X1} & u_{X2} & u_{X3} & u_{X4} & \cdots & \cdots & T_X \end{bmatrix} \quad (1)$$

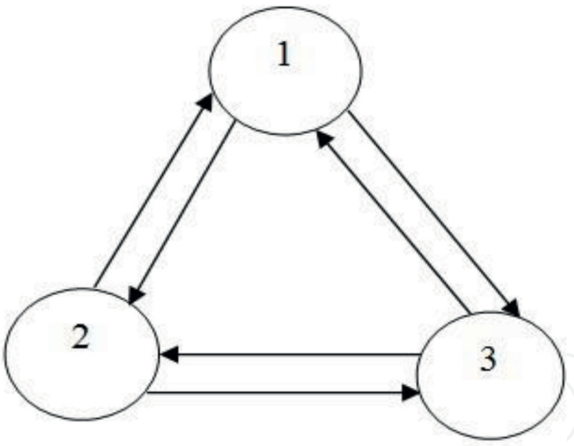


Figure 1.
Machinability attribute digraph representation.

Representation of this variable permanent matrix for VPM_M for the considered machinability attribute digraph (shown in **Figure 1**) is given below:

$$VPM_M = H = \begin{array}{c} \\ \text{MRR} \\ \text{TWR} \\ \text{SR} \end{array} \begin{array}{c} \begin{array}{ccc} \text{MRR} & \text{TWR} & \text{SR} \end{array} \\ \begin{bmatrix} T_1 & u_{ij} & u_{ik} \\ u_{ji} & T_2 & u_{jk} \\ u_{ki} & u_{kj} & T_3 \end{bmatrix} \end{array} \tag{2}$$

2.3 Variable permanent function representation

The permanent of this matrix *H*, i.e., per (*H*), is distinct as the permanent machinability function. Machinability estimation signifies machinability traits of various experimental runs as measured. Furthermore, this tactic leads to avoid any loss of data as it does not carry any negative sign in the expression [12].

The "variable permanent machinability function" is expressed in sigma form as

$$\begin{aligned} \text{x per (H)} = {} & \prod_{i=1} T_i + \sum_{i,j,\ldots,X}(u_{ij}u_{ji})\, T_k T_l \ldots T_X + \sum_{i,j,\ldots X}(u_{ij}u_{jk}u_{ki} + u_{ik}u_{kj}u_{ji}) T_l T_m \ldots T_X \\ & + \left\{ \sum_{i,j,\ldots X}(u_{ij}u_{ji})(u_{kl}u_{lk})\, T_m T_n \ldots T_X + \sum_{i,j,\ldots X}(u_{ij}u_{jk}u_{kl}u_{li} + u_{il}u_{lk}u_{kj}u_{ji})\, T_m T_n \ldots T_X \right\} \\ & + \left[\sum_{i,j,\ldots X}(u_{lm}u_{ml})(u_{ij}u_{jk}u_{ki} + u_{ik}u_{kj}u_{ji}) T_n T_o \ldots T_X + \sum_{i,j,\ldots X}(u_{ij}u_{jk}u_{kl}u_{lm}u_{mi} + u_{im}u_{ml}u_{lk}u_{kj}u_{ji}) T_n T_o \ldots T_X \right] \\ & + [(\sum_{i,j,\ldots X}(u_{mn}u_{nm})(u_{ij}u_{jk}u_{kl}u_{li} + u_{il}u_{lk}u_{kj}u_{ji}) T_o \ldots T_X + \sum_{i,j,\ldots X}(u_{ij}u_{jk}u_{ki} + u_{ik}u_{kj}u_{ji})\, (u_{lm}u_{mn}u_{nl} + \\ & u_{ln}u_{nm}u_{ml})\, T_o \ldots T_X + \sum_{i,j,\ldots X}(u_{ij}u_{ji})(u_{kl}u_{lk})(u_{mn}u_{nm})\, T_o \ldots T_X \\ & + \sum_{i,j,\ldots X}(u_{ij}u_{jk}u_{kl}u_{lm}u_{mn}u_{ni} + u_{in}u_{nm}u_{ml}u_{lk}u_{kj}u_{ji})\, T_o \ldots T_X) \end{aligned} \tag{3}$$

2.4 Evaluation of permanent machinability index

The permanent machinability function defined in Eq. (3) is engaged for appraisal of the permanent machinability index. The *permanent machinability index* is articulated as the arithmetical value of permanent machinability function.

All the assessable values of T_i are needed to be normalized on the similar scale as qualitative values, i.e., 0 to 10. For *beneficial machinability attributes*, the obligation of 0 and 10 is for smaller range value (T_{is}) and bigger range value (T_{ib}), respectively. Other midway values T_{ii} of the traits could also be dispensed in the scale from 0 to 10, as in Eq. (4):

$$\begin{aligned} T_i &= \{10/T_{ib}\} \times T_{ii} \quad \text{for } T_{is} = 0 \\ T_i &= \{10/(T_{ib} - T_{is})\} \times (T_{ii} - T_{is}) \quad \text{for } T_{is}>0 \end{aligned} \tag{4}$$

For *non-beneficial machinability attributes*, assignment of 0 and 10 is for bigger range value (T_{is}) and smaller range value (T_{ib}), respectively. Other intermediate values T_{ii} of the attributes could also be assigned in the scale from 0 to 10, as shown in Eq. (5):

$$\begin{aligned} T_i &= 10\{\,1 - (T_{ii}/T_{ib})\} \text{ for } T_{is} = 0 \\ T_i &= \{10/(T_{ib} - T_{is})\} \times\ (T_{ib} - T_{ii}) \text{ for } T_{is}>0 \end{aligned} \tag{5}$$

Relative interdependency amid two traits (i.e., u_{ij}) for the considered project is also allotted as a value over the range from 0 to 10 and is arranged into six categories. The interdependency between two attributes can be distributed on the scale 0 to 10 as given below:

$$u_{ij} = 10 - u_{ji} \tag{6}$$

The investigational runs are then arranged in down/rising order as per the calculated values of permanent machinability index. The investigational run having the *highest value* of permanent machinability index is chosen as the *best alternative* for the task under deliberation.

2.5 Identification and comparison of different available alternatives

Let V_{ij} signify the total assessment of the terms of *j*th sub-clustering of the *i*th clustering of the variable permanent machinability function. For the case of no sub-grouping, then the situation will be $V_{ij} = V_i$, i.e., total assessment of terms of the *i*th clustering. The identification set for an experimental run for the considered machining process is

$$/V_1/V_2/V_3/V_4/V_{51} + V_{52}/V_{61} + V_{62}/ \tag{7}$$

A contrast between any two investigational runs can also be made by using Eq. (8). On the basis of divergence of performance, the dissimilarity coefficient (C_d) for any two investigational runs is proposed as

$$C_d = (1/B)\sum\Phi_{ij},\ i,\ j \tag{8}$$

where B = max. of $[\sum |V_{ij}|$ and $\sum |V'_{ij}|]$, i,j i,j

The assessments of the terms for the variable permanent machinability function (V_{ij} and V'_{ij}) for two investigational run under the estimation and contrast, and $\Phi_{ij} = |V_{ij} - V'_{ij}|$. The similarity coefficient is also expressed as

$$C_s = 1 - C_d \tag{9}$$

2.6 Coefficients of similarity and dissimilarity

The calculation is being performed for similarity and dissimilarity coefficients as per Eqs. (8) and (9).

3. Case studies on graph theory: a view on real-life problem solving

There are so many investigations that have been carried out by the numerous researchers throughout the globe in the domain of graph theory and its allied approaches to study and analyze the method's applicability and reliability. The further optimization of the process under the study can also help the investigator to attain better and effective research outcomes [1, 14]. The discussion has also been explored by incorporating the possibilities to use the artificial intelligence-inspired logics in collaboration with the established graph theory approach. In this way, some case studies are reviewed and presented below to provide an overview which can explore about the major findings of the researches persuaded and the state-of-the-art representation of past investigations in the best conclusive manner. The selected case studies are as follows.

3.1 Machinability evaluation of work materials

Rao and Gandhi [8, 9] have presented a graph theory-based methodology with a view to evaluate the machinability of work materials for a given machining operation. They have proposed a universal machinability index that evaluates and ranks work materials for a given machining operation. The development of a digraph was also conducted to reflect the machinability attributes and their relative importance for the operation considered. The coefficients of similarity and dissimilarity and the identification sets have also been proposed. Disparate the traditional methods which adopt only one of the machinability assessment criteria, their proposed method has considered all of the criteria simultaneously and gives the correct and complete evaluation of the machinability of work materials. They have concluded that their proposed universal machinability index evaluates and ranks work materials for the considered machining operation. When it comes to taking the combined advantages of the features of artificial intelligence with the graph theory approach, the process moderation always becomes more crucial to consider. The requirements of the end customer regarding the produced goods further become extensively vital.

3.2 Selection of industrial robot

Rao and Padmanabhan [15] have conducted a research study based on graph theory method for the evaluation of alternative industrial robots. They have attained a robot selection index that evaluates and ranks robots for a considered industrial application. The calculated index was obtained from a robot selection attribute function, obtained from the robot selection attribute digraph. They have reported that the obtained similarity index from robot selection attribute function which was quite useful for easy storage and retrieval of the data. The proposed study was a general methodology, and there can be any number of quantitative and qualitative robot selection attributes simultaneously and offers a more objective, simple, and consistent robot selection approach. Their proposed robot selection index has been utilized to evaluate and rank the robots for the selected robot selection problem. In addition, the expectation of the end user of the robotic system

can also be provided perfectly by properly understanding and practicing the modeling and simulation methodologies related to the artificial intelligence. Furthermore, the decision support system also helps to gather, analyze, and trend forming of the existing demands of the customer or end product user [16, 17].

3.3 Failure cause analysis of machine tools

Rao and Gandhi [8, 9] have analyzed the failure reasons of a machine tool by means of digraph and matrix approaches. The machine tool failure causation digraph has been modeled a failure reason taking into deliberation its failure-backing actions and their contact in terms of the reason—consequence relationship. After that, they have determined machine tool failure causation function from the machine tool failure causation matrix. The said matrix was attained through the digraph, which is distinctive of the failure root. The obtained function was not only convenient for failure reason analysis but likewise for comparison and appraisal of the failure reason. In addition, the machine tool failure causality index, derived from the machine tool failure causality function, had also been proposed, which evaluated and ranked the failure causes of a machine tool.

The attained machine tool failure causation function has identified the backing failure occasions of a machine tool that were decisive for minimization of the failure root and also supports in contrast and assessment of the failure source of a machine tool. The arithmetical value of the machine tool failure causation function has also been computed and named as *the machine tool failure cause index*. This index has been concluded as a measure of the severity of the failure cause. Furthermore, an artificial intelligence-inspired fuzzy logic-based system can properly help to make the problem more realistic, and the causes of the tool failures can be resolved out or eliminated [18, 19]. The AI-based process optimization is another domain where the failure reduction and the overall performance improvement can be settled out.

3.4 Selection of rapid prototyping process

Rao and Padmanabhan [20] have employed a graph theory-based methodology for selection of a rapid prototyping (RP) process that best suits the end use of a given product or part. The "rapid prototyping process selection index" has been also anticipated to estimate and rank the RP progressions for constructing a given product. The index was gained from an RP procedure assortment attribute function, acquired from the RP course selection attribute digraph. The digraph is established considering RP method assortment attributes and their relative importance for the deliberated application. The projected process reflects RP process variety attributes and their interrelations, and the RP process assortment index evaluates and ranks RP processes for a given RP procedure collection problem. The projected method was observed as a broad technique and capable to deliberate any number of measurable and qualitative RP course assortment attributes concurrently and proposes a more objective and modest RP method selection approach.

3.5 Performance evaluation of carbide compacting die

Jangra et al. [21, 22] conducted a study to assess the concert of carbide compacting die by means of graph theory approach (GTA). Factors influencing the die performance and their relations were analyzed by evolving a mathematical model by employing the digraph-based matrix method. The die performance index was attained through the matrix model established from the developed digraphs. This index value has compared and ranked the factors distressing the die

performance. They have considered several process output errors such as dimensional inaccuracy, large surface craters, deep recast layers, etc. that have been minimized during die manufacturing which further helps to achieve better die performance. They have formed a group of factors upsetting the presentation of carbide compacting die into major five factors, viz., machine tool, work material, the geometry of die, tool electrode, and processing operation. The GTA procedure revealed that the machine tool had the maximum value of the index. Consequently, they have considered it as the utmost persuading factor influencing the die performance. Furthermore, they have also reported that in the event of die material, low cobalt concentration and lesser grain size harvest decent surface finish, while in machine tool, low discharge energy and high dielectric flow rate yield good surface finish. In the case of die geometry, large workpiece thickness and small taper angles result in lesser geometrical deviations.

Through this methodology, they have quantified the weak and strong factors which help in efficient process planning during die manufacturing, consequently. The GTA practice revealed that the machine tool had an uppermost value of the computed index. Therefore, it was considered as the most influencing parameter affecting the die performance.

While in respect of the die material, small grain size and low cobalt concentration yielded decent surface finish; however, in the case of the machine tool, low discharge energy and high dielectric flow rate yielded good surface finish and hence favors the good die performance. In the case of die geometry, large workpiece thickness and small taper angles reported in slighter geometrical deviances hence aid to attain better die performance. Die performance was articulated in terms of an index. This index value was depending on the inheritance of main factors which was further depending on their sub-factors. Therefore, a suitable combination of the sub-system and their sub-factors could easily be selected for the required die performance.

Singh et al. [23] have reported the optimization of the process inputs while processing composite material using ultrasonic machining using fuzzy logic-based smart decision- and rule making. The overall fuzzy system possesses the basic elements particularly fuzzy sets, fuzzy rulings, fuzzy inference, membership functions, and defuzzification [24–26]. The basic fuzzy logic system is illustrated in **Figure 2**. They have also explored the utility of the fuzzy logic-based ruling for the proper implementation of the human neural system logics. **Figure 3** is describing the employed triangular membership functions for the composite problem [23].

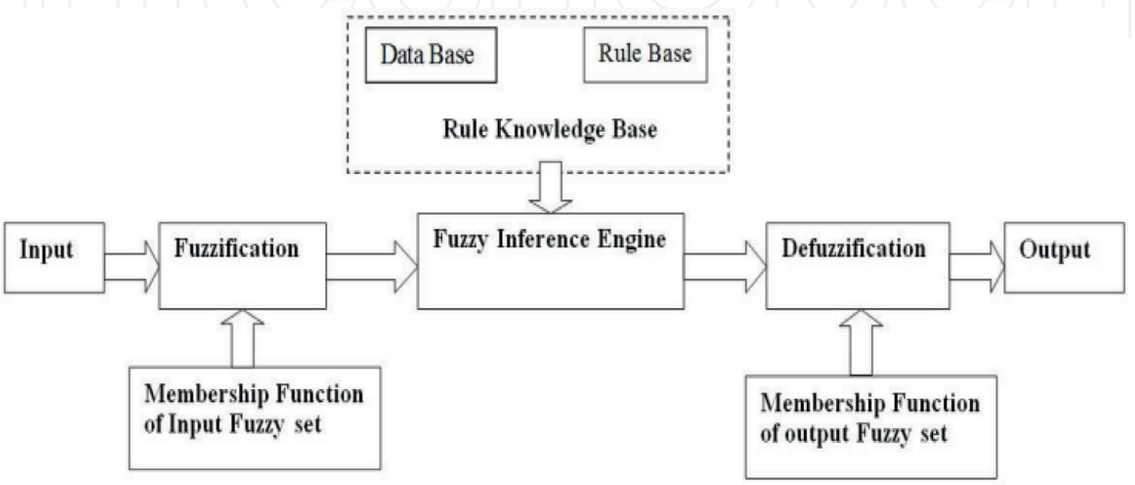


Figure 2.
The fuzzy logic system.

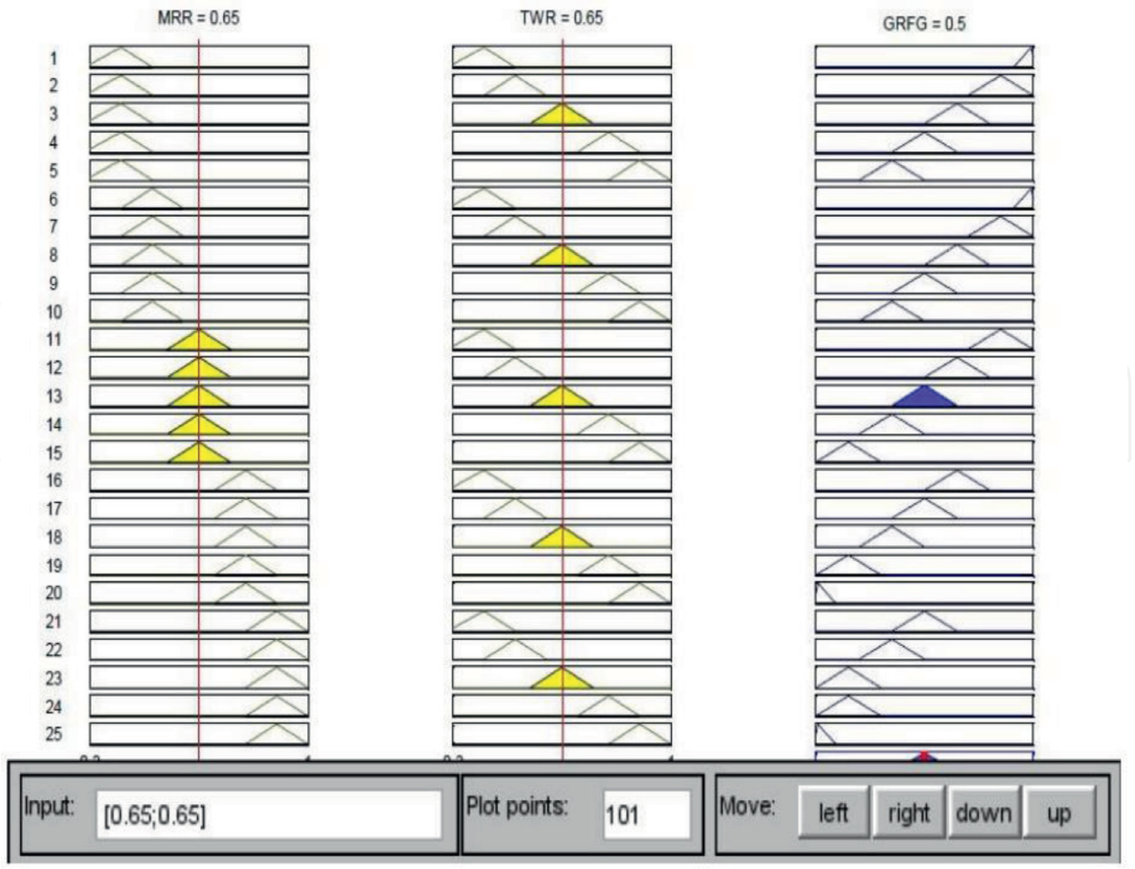


Figure 3.
Triangular membership functions of fuzzy system.

3.6 Analysis and evaluation of product design

Paramasivam and Senthil [1] have explored that the product design evaluation is essential for all manufacturing industries to explore the soundness and effectiveness of the product design. In their study, they presented a mathematical model for evaluating and analyzing the product design alternatives using graph theory and matrix approach. The different contributing factors were identified, and their relative importance was considered. A digraph model was constructed to represent the abstract information of the product design which takes into account all the factors. The digraph model was then transformed into a matrix form, which further was employed for computer processing. A permanent index was attained from the product design appraisal function, consequent from the matrix for all product design substitutes, and it showed the effectiveness of the product design. The indices were also deliberated for all the alternatives under study, and they were graded in rising order, and the product design analogous to the first rank was selected as the finest one.

Their proposed practice was quite adaptable from the opinion that it incorporates all factors of the product design. The GTM method was explored as pertinent to any product design entailing of any number of variables. The utility of matrix algebra was found to be expedient both for pictorial and computer analysis. The product design assessment index has represented the product design features and was useful in positioning the several product models based on the design facets. It was also concluded that the GTM method can be applicable to various problems of incompatible nature and to the problems, where the measurable data are not obtainable, i.e., machine cell layout analysis, material handling system evaluation, vehicle routing optimization, supplier selection problem, etc. Furthermore, the

results obtained through the graph theory approach can easily be modeled through the collaborative practice through artificial neural network methodology which is inspired from the AI. The artificial neural network (ANN) can be defined as an interconnected group of nodes, similar to the vast network of neurons in a human brain. Duan and Yeh [27] have practiced and explored artificial intelligence-based decision-making. They have implemented the said approach to make the decision for accounting choice evaluation and selection through an intelligent system-based methodology. The basic illustration of an ANN model has been represented in **Figure 4**.

3.7 Selection of appropriate equipment for industrial purpose

Safari et al. [28] have explained out that proper equipment selection is a very important activity for manufacturing systems due to the fact that improper equipment selection can negatively affect the overall performance and productivity of a manufacturing system. They have further implemented a two-step fuzzy-analytical hierarchy process (AHP) and graph theory matrix approach (GTMA) methodology, i.e., GTMA uses fuzzy-AHP result weights as input weights.

They have presented a real-life study to reflect the applicability and performance of the proposed methodology. It was concluded that using linguistic variables, the evaluation process can become more realistic. The usage of fuzzy-AHP weights in GTMA has made the application more realistic and reliable. The proposed model was only implemented on an equipment selection problem in the company. They have further suggested the possibilities to employ other

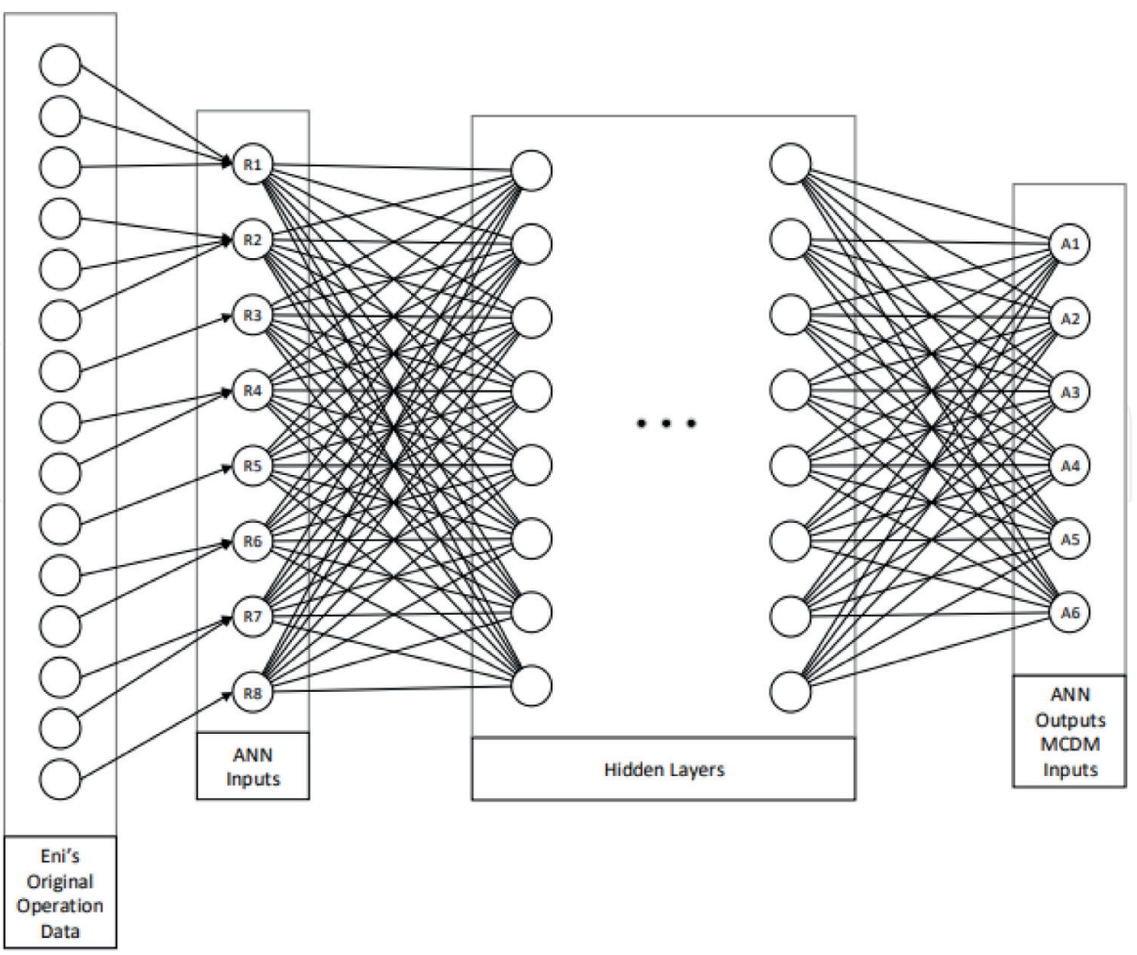


Figure 4.
Illustration of an artificial neural network (ANN) model.

decision-making methods such as fuzzy ELECTRE, fuzzy GTMA, and interval GTMA as a future direction.

3.8 Machinability study of commercial pure titanium

Singh et al. [10] have utilized the graph theory-based matrix method for the study of machinability of commercially pure titanium. In general, the single and multiple response optimization of any machining processes gives a different shape to the problem to elaborate it in the most better way and further makes the system more reliable and productive [29, 30]. They further said that any type of processing method is well subjective by the machinability of the work material under study. They have proposed a GTMM-based practice for the valuation of machinability of titanium workpiece in ultrasonic drilling.

Identification of numerous process attributes along with their relative prominence was undertaken and analyzed by mounting a mathematical function by engaging GTMM. Furthermore, an attribute digraph was also established, which has provided them with a visual image of reflected attributes with their relative connections. The developed digraph was further embodied by using matrix relation. A permanent machinability index for all the investigational runs was also attained from matrix form demonstration built on attribute digraph. The blend of all the attributes for any processing approach has made the proposed method quite versatile. The results have revealed that an experimental run having the combination consisting tool material of titanium, grit size of 500, and a power supply of 300 W yielded optimized results for machinability.

4. Conclusions

The application and the capability of artificial intelligence-inspired fuzzy logic-based decision-making have been discussed. The graph theory-based decision-making method has also been explored to employ in practical industrial situations. The following major inferences can be drawn from the proposed chapter. These are:

- The discussed methodology, namely, graph theory, is capable enough to handle the versatile real-life situation as this method includes the several input factors and their sub-factors too.

- The graph theory and matrix methods consist of the digraph representation, the matrix representation, and the mathematical representation, i.e., a permanent function. The digraph is the visual representation of the variables and their interdependencies.

- From the domain of AI, there are some observed major practices, namely, artificial neural networks, evolutionary computing, fuzzy logic, probabilistic analysis models, intelligent agents, etc., which usually define the basic artificial intelligence system.

- The artificial intelligence-inspired logics and practices can make the traditional decision-making more effective and versatile too. The fuzzy logic-based decision-making has emerged as one of the basic collaborative exercise conducted to offer viable solutions to any domain of real-life practical problems. The computation involved in these methods is simple, effective, and moreover quite friendly for the decision-makers.

- The triangular and the trapezoidal membership function of a fuzzy-based logic can also offer the conceptual-based rule making and decision-making.

- The demonstrated case studies from the different past researches explored about the applicability of the suggested method in numerous industries ranging from the manufacturing, service industries, robotic industries, die-making firms, automobiles, etc.

Conflict of interest

There is no conflict of interest.

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References

[1] Singh RP, Singhal S. Rotary ultrasonic machining: A review. Materials and Manufacturing Processes. 2016;**31**:1795-1824

[2] Pomerol JC. Artificial intelligence and human decision making. European Journal of Operational Research. 1996; **99**:3-25

[3] Hertz L, Krogh A, Palmer RG. Introduction to the Theory of Neural Computing. Addison Wesley; 1991

[4] Wren GP, Jain L. Artificial intelligence for decision making. Springer Publications. 2006;**LNCS-4252**:531-536

[5] Fodor J, Roubens M. Fuzzy Preference Modelling and Multicriteria Decision Support. Kluwer; 1994

[6] Nowicki R, Slowinski R, Stefanowski J. Evaluation of vibroacoustic diagnostic symptoms by means of the rough sets theory. Computers in Industry. 1992;**20**: 141-152

[7] Singh RP, Singhal S. Experimental investigation of machining characteristics in rotary ultrasonic machining of quartz ceramic. Proceedings of the Institution of Mechanical Engineers, Part L: Journal of Materials Design and Applications. 2016;**232**:870-889

[8] Rao RV, Gandhi OP. Digraph and matrix methods for the machinability evaluation of work materials. International Journal of Machine Tools & Manufacture. 2002;**42**:321-330

[9] Rao RV, Gandhi OP. Failure cause analysis of machine tools using digraph and matrix methods. International Journal of Machine Tools & Manufacture. 2002;**42**:521-528

[10] Singh RP, Kumar J, Kataria R, Singhal S. Investigation of the machinability of commercially pure titanium in ultrasonic machining using graph theory and matrix method. Journal of Engineering Research. 2015;**3**: 75-94

[11] Singh RP, Singhal S. Rotary ultrasonic machining of macor ceramic: An experimental investigation and microstructure analysis. Materials and Manufacturing Processes. 2016;**32**: 927-939

[12] Rao RV. Decision Making in Manufacturing Environment. Springer Publications; 2007

[13] Paramasivam V, Senthil V. Analysis and evaluation of product design through design aspects using digraph and matrix approach. International Journal on Interactive Design and Manufacturing. 2009;**3**:13-23

[14] Singh RP, Singhal S. Investigation of machining characteristics in rotary ultrasonic machining of alumina ceramic. Materials and Manufacturing Processes. 2016;**32**:309-326

[15] Rao RV, Padmanabhan KK. Selection, identification and comparison of industrial robots using digraph and matrix methods. Robotics and Computer-Integrated Manufacturing. 2006;**22**:373-383

[16] Pomerol JC, Roy B, Sabroux CR, Saad A. An intelligent DSS for the multicriteria evaluation of railway timetables. Foundations of Computer and Decision Science. 1995;**20**:219-238

[17] Rasmussen J. Skills, rules and knowledge, signals, signs and symbols and other distinctions in human performance models. IEEE Transactions SMC. 1983;**13**:257-266

[18] Dubois D, Prade H. Fuzzy Sets and Systems: Theory and Applications. Academic Press; 1980

[19] Rasmussen J. The Human as a System Component—Human Interaction with Computer. Academic Press; 1980

[20] Rao RV, Padmanabhan KK. Rapid prototyping process selection using graph theory and matrix approach. Journal of Materials Processing Technology. 2007;**194**:81-88

[21] Jangra K, Grover S, Chan FTS, Aggrawal A. Digraph and matrix method to evaluate the machinability of tungsten carbide composite with wire EDM. International Journal of Advanced Manufacturing Technology. 2011;**56**: 959-974

[22] Jangra K, Grover S, Aggrawal A. Digraph and matrix method for the performance evaluation of carbide compacting die manufactured by wire EDM. International Journal of Advanced Manufacturing Technology. 2011;**54**: 579-591

[23] Singh RP, Kataria R, Kumar J, Verma J. Multi-response optimization of machining characteristics in ultrasonic machining of WC-Co composite through Taguchi method and grey fuzzy logic. AIMS Material Science. 2018;**5**: 75-92

[24] Newell A. The knowledge level. Artificial Intelligence. 1982;**18**:87-127

[25] Nilsson JJ. Principles of Artificial Intelligence. TIOGA Publishing Company; 1980

[26] Zadeh LA. Fuzzy sets as a basis for a theory of possibility. Fuzzy Sets and Systems. 1978;**1**:3-28

[27] Duan Y, Yeh CH. An intelligent system based approach to accounting choices evaluation and selection. In: Proceedings of Pacific Asia Conference on Information Systems (PACIS). 2018

[28] Safari H, Faghih A, Fathi MR. Integration of graph theory and matrix approach with fuzzy AHP for equipment selection. Journal of Industrial Engineering and Management. 2013;**6**:477-494

[29] Singh RP, Singhal S. Experimental study on rotary ultrasonic machining of alumina ceramic: Microstructure analysis and multi-response optimization. Proceedings of the Institution of Mechanical Engineers, Part L: Journal of Materials Design and Applications. 2016. DOI: 10.1177/1464420716657370

[30] Singh RP, Singhal S. An experimental study on rotary ultrasonic machining of macor ceramic. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture doi. 2016. DOI: 10.1177/0954405416666897