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Application of Neural Network for Material Selection: A Review

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Abstract - *The growing material demand due to technological advancement has motivated material engineers to develop a large variety of materials as a substitute to conventional materials. However, little attention has been given to the tools and methods that aid material selection processes. This work reviews the principle of material selection as well as other multi-criteria decision-making (MCDM) techniques used in material selection. MCDM is considered a complex decision-making tool involving both qualitative and quantitative factors. Recently, several MCDM techniques and approaches have been suggested and developed to aid the decision-making process. The main aim of this research is to systematically review the application of neural networks as MCDM technique either used individually or integrated with other MCDM techniques. With numerous developed individual and integrated approaches for material selection problems, this systematic review identified two important themes that are important, i.e., screening and ranking.*

Keywords: *decision making, neural network, material selection, MCDM.*

I. INTRODUCTION

The ever-increasing innovation in materials science and technology reveals diversified materials presently available for the manufacturing process and design engineering, thereby making the selection of a material for a given component a difficult and challenging task [1], [2]. Ashby [3] reported that there are over 80,000 materials of choice for engineers. Materials utilization was totally a selection process that involved deciding from a given, rather unlimited set of materials the one best suited for an application by virtue of its characteristics. Therefore, material selection can be defined as a process of selecting the most suitable material from a group of possible candidate materials by setting selection criteria after the intended design has been finalized [4].

Generally, there is not always a single criterion of selection in choosing the right material. Design engineers are usually faced with a large number of material selection criteria/ factors [5]. These criteria range from mechanical to physical properties, electrical properties, and possibly corrosion resistance [6], [1]. Therefore, each material selection criterion offers a wide range of material properties and performance attributes that can be considered [7]. The selection of optimal composite material for engineering design is a Multiple Criteria Decision Making (MCDM) problem as every property of each material influences the selection. Usually, manufacturers and design engineers do not rely on single material for their production/ design, and they mostly focus on the development of composite and the possible reinforcing material to improve the overall material property [8].

A variety of quantitative selection methods, algorithms, and software tools have been developed for materials performance selection [2]. Over a decade ago, material selection and decision-making in the field of manufacturing were implemented by a variety of computer-based commercial software systems. In recent years, artificial neural network (ANN) models have been reported to provide a practical solution for pattern recognition, classification, and optimization problems [9]. Additionally, it has the capacity to eliminate the need for expensive experimental investigation in various areas of the manufacturing process. It is a non-linear statistical analysis tool, which is suitable for the simulation of data that are hard to be described by physical models. It has been reportedly employed to study diverse problems in material selection, development of new composite material processing, and applications [10].

The application of ANN offers a potentially powerful means for companies to achieve the required cost and lead time reduction through the incorporation of timely material selection-related advice. A neural network can be used to model the often non-linear empirical data held by manufacturers. Researchers have used neural networks to develop models for a variety of decision-making and material selection cases. This paper reviewed and presented the basics of material selection, artificial neural networks, and a survey of published work that focuses on the use of ANN in the material selection process.

II. ARTIFICIAL NEURAL NETWORK

Inspired by the biological human nervous system, the neural network is a series of distributed information consisting of processing elements interconnected together and can transmit information to another. The neural network is capable of enabling the employment of multiple-input and generation of multiple recommendations of suitable material composition and processes.

An artificial neural network can be defined as a computer system that emulates the neurons of a biological nervous system or computational models of a brain [11], [4]. They are a group of models developed to achieve estimation functions that depend on a large number of inputs. ANNs have been well acknowledged as useful and cost-effective tools to solve complex tasks. Neural networks consist of simple processors, which are called neurons linked by weighted connections. The neuron forms the basis for designing neural networks. Each neuron has inputs and generates an output that can be seen as the reflection of local information stored in connections [12].

A neural network consists of an input unit, weights, an activation function, and an output unit [13]. The most common activation function is a sigmoid function. ANN's are inherently nonlinear models that recognize patterns and make classifications accordingly. Feed Forward Multilayer Networks are the ANN models reported to have the most success in classification problems [14].

One of the advantages of the application of neural networks in material science research is that neural networks have the ability to extract meaningful outputs from complicated and complex data. The trained neural network is an expert for given information given to analyze and provides new projections, predictions, and possibilities in any situation of interest. Neural networks have a large number of properties and capabilities like nonlinearity, input-output mapping, adaptivity, evidential response, contextual information, and fault tolerance via redundant information coding.

III. PRINCIPLES OF MATERIAL SELECTION

Material selection is a process aimed at the identification of materials that, after manufacturing, will have the dimension, shape, and properties necessary for the product or component to demonstrate its required function at the lowest cost [15]. Generally, material selection aims to minimize cost while meeting the customer requirement and performance goals [16]. The selection of proper material is one of the vital and important aspects of engineering design and manufacturing [17], [18]. Proper material selection can be accomplished by creating a balance or compromise between function, material, shape, and process [16]. However, an inappropriate choice of material can adversely affect the reputation of a manufacturing organization as well as its productivity and profitability [19], [20]. It requires information about the type of loading, operating condition, manufacturing process, and cost [21]. However, environmental constraints, economical demands, and performance enhancement are the main issues for material selection [22].

A framework that consists of initial screening, comparing, and selection of the best material would be desirable in guiding the process [23]. Ashby *et al.* [24] reported that this framework could be achieved through four fundamental steps such as a means of translating requirements, screening methods, ranking methods, and searching approaches. Screening and ranking are two vital steps in material selection. A variety of quantitative selection methods have been developed to analyze the data in the selection processes so that a systematic evaluation can be made.

The different materials selection methods, including knowledge-based systems (KBS), Questionnaire/guideline method, computer-aided materials selection systems, and neural networks, are used for material screening, but these techniques do not provide any ranking order. The cost per unit property method only considers one material property as the most critical and ignores other material properties. The chart (Ashby) method, which is the most popular screening method, limits the decisions in materials selection to only two or three criteria. Therefore, the traditional screening approaches cannot guarantee the selection of the best material. MCDM can be used to supplement the use of material screening methods, particularly for the chart method, when selecting materials for new product design.

A. Material Screening Methods

Screening is an effective way to eliminate candidates that are not suitable for selection and to establish a potential set of suitable alternatives from a readily available large data set that consists of material properties. This is a stage where all materials available are screened and narrowed down on the basis of rigid properties for subsequent detailed evaluation by using the critical requirements of each part to define its performance requirement [25]. These material performance requirements are divided into five broad categories such as functional requirements, processability requirements, cost, reliability, and resistance to service conditions [23].

Material screening methods are classified into cost per unit property method, Ashby (chart) method, digital logic method, questionnaire method, knowledge-based systems, materials in product selection tools, and artificial intelligence methods [1], [16]. These artificial intelligence methods can be subdivided into computer-aided materials selection systems, case-based reasoning, knowledge-based systems, and neural networks. This is illustrated in Figure 1 below

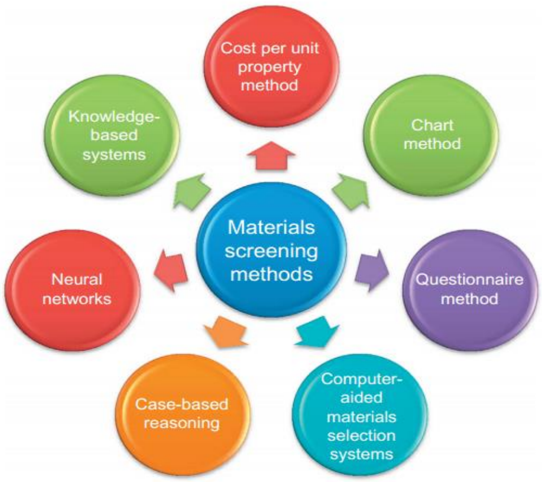

Figure1: Screening methods in material selection [26]

Sapuan S. M. [27] conducted research on a knowledge-based system (KBS) for materials selection in mechanical engineering design. They studied various works on the development of computerized material selection systems and showed that KBS is a very appropriate tool in the material selection process. However, they concluded that the materials selection process using a material database is not very reliable.

a) Neural Network: A Material Screening Method

Neural networks have been reportedly applied in the screening of material by analyzing a large amount of data stored in an expert system, thereby narrowing down the choices to a manageable number for subsequent detailed evaluation. Goel and Chen [16] developed an intelligent hybrid expert network for material selection. In their approach, they stored the knowledge in a neural network in the form of weights associated with links. The neural network was then incorporated with an expert system to provide simple consistency checks and to interpret the numerical output of the network neural network to make a final prediction. The developed model was reported to handle a vast amount of information in a very short time, with the decisions made by the system are consistent.

Similarly, Amoiralis et al. [28] proposed the use of ANN for the selection of winding material in power transformers. They used a supervised trained, fully connected three-layer feed-forward network with the error backpropagation algorithm with 13-13-1 topology (13 input neurons, 13 neurons in 1 hidden layer, and 1 neuron in the output layer) and reported a 94.7% classification success rate on the test set. They concluded that the performance of the ANN is exceptional and very suitable for industrial use.

Sapuan and Mujtaba[11] presented the development of a 2 stage neural network-based material selection system for natural fiber polymer composites. In the first stage, they implemented a fully connected four-layer (one input, two hidden, and one output) feed-forward network with a sigmoid function to screen and predict the correlation between the inputs and select the materials whose output properties are very close to the predicted output property. They adopted a method called multi-attribute ranking to decide which material is the most suitable for the second stage. They concluded that the developed system enables designers to select appropriate composites based on predefined criteria.

B. Material Ranking Methods

The selection of a suitable material demands a great amount of comparing, and often several candidates or alternatives exist for a specific application after employing one or more screening methods to narrow down all the potential candidate materials as discussed in section 2 above. Ranking methods can be used to further narrow and rank the remaining possible materials to a few optimum candidate materials. In literature, Multi-Criteria Decision Making (MCDM) methods and optimization approaches have been applied in this regard. The complexity of materials selection makes multi-criteria analysis an invaluable tool in the engineering design process. However, the application of various multi-criteria decision-making (MCDM) methods has been reported to yield different results, especially when alternatives lead to similar performance [20]. Therefore, MCDM is used to help design engineers to select materials based on several material characteristics [29]. MCDM methods divide into two main categories. Namely, Multiple Objective Decision Making (MODM) and Multiple Attribute Decision Making (MADM) approaches. MCDM techniques usually produce different outcomes for selecting or ranking a set of an alternative decisions involving multiple criteria. Considerable effort has been reported on the development of numerous MCDN models. However, in spite of these efforts, no best approach and no single multi-criteria analysis that is inherently better than others. These numerous existing methods do not simplify the decision-making problem but make it relatively complicated [19]. There are several methods in each of the above categories. Each technique has its own characteristics, and the methods can combine with each other or fuzzy methods [1].

a) Multi-Attribute Decision-Making Methods

The multi-attribute decision can best be explained as the selection of an optimal material for an engineering design or manufacturing process from among two or more alternative materials on the basis of two or more attributes [30]. This selection is a demanding intellectual process that takes a lot of time and experience. After identifying the material selection attributes and creating a shortlist of materials in a given engineering application, the MADM methods can be used to rank and select the optimum material. The decision variables can be quantitative or qualitative. These methods include the Analytical Hierarchy Process (AHP), Technique of ranking Preferences by Similarity to the Ideal Solution (TOPSIS), ELimination and Choice Expressing the Reality (ELECTRE), limits on properties method, and individual methods [26]. AHP was the commonly used MCDM technique, followed by TOPSIS and ANP. The lowest applied MCDM tool was MAUT [29].

A lot of research has been conducted and reported on the use of MCDM methods in materials selection. Some research reported the use of the hybrid (more than one method) MCDM method for material selection. For example, Singh *et al.*[31] presented a fuzzy-AHP and M-TOPSIS based approach for the selection of composite material. The first stage involves the calculation of the weight of each criterion using the Fuzzy AHP technique, whereas the M-TOPSIS technique was used to calculate and rank each alternative in the second stage. They concluded that the method emerges as a simple and reliable technique to select the best alternatives.

Research by Patnaik *et al.*[32] reported the selection of composites materials for structural applications through MCDM approaches. They applied the AHP-TOPSIS method in selecting good wear resistance material. AHP was used to obtain the weightage, and TOPSIS was used to rank the materials. Similarly, Patnaik *et al.*[33] used hybrid MCDM approach for composite material selection. In the first stage, the AHP method approach was used to obtain the weights of different properties of materials, whereas the MOORA method was used to provide the ranking of the materials. They observed that these methods are very simple to understand, easy to implement for assigning rankings to the materials alternatives.

Al-Oqla*et al.*[34] presented a decision-making model for evaluating, selecting, and ranking the appropriateness of different polymer types. The model was developed to rank different polymers using the analytical hierarchy process (AHP). They reported that the developed model used consistent, systematic expert judgment and helps in establishing a road map for the selection of the best polymer characteristics and parameters.

b) Multi-Objective Decision-Making Methods

Materials selection usually deals with choosing the best material from various material databases that suit a specific product design requirement by considering multiple requirements and goals. Materials selection generally contains two important stages [1]. Engineering designers have to consider many different objectives, including material design, when necessary for new product development. For such design problems, different MODM methods, as well as MADM methods, are available in the literature. Therefore, the application of multi-objective optimization in materials engineering and design is emphasized rather than explaining MODM methods. Some of these MODM methods include Multi-Attribute Utility Analysis (MAUA), Goal programming, Genetic Algorithm, and Neural Network

c) Neural Network: A Material Ranking Method

Artificial neural network (ANN) provides a practical solution for a wide range of applications. These applications include pattern recognition, classification, and optimization problems. It is also used in signal processing, speech recognition, condition monitoring, and functional approximation [4]. Recently, there is an increase in the number of reports (in literature) on the use of ANN as a material selection tool for a variety of materials.

Smith *et al.* [35] identified that the neural network approach is suitable for powder metallurgy (PM) modeling for material selection purposes. They used a Matlab back-propagation neural network toolbox to develop a material selector for Ferrous PM materials. The system employs the required mechanical properties in order to recommend the material density and percentage carbon needed to attain the properties through P/M manufacture. Similarly, they reported that the technique had improved the accuracy of the material selection by reducing the standard deviation of the errors associated with the inverse solution by 36%.

Research by Yang *et al.* [36] developed a genetically optimized neural network system (GONNS) for the selection of optimum composite material and operating conditions. They evaluated the performance of the package using three case studies and reported that the error of GONNS was found to be less than 1% and concluded that GONNS is very promising for many complex optimization problems. Equally, they concluded that the approach is very convenient for many applications, including material selection.

Another research by Yang *et al.* [37] on the development of an automated procedure to select optimum material and processing conditions for composite materials (CoMaSA) is proposed and reported. The package uses three separate programs. These programs train the neural networks to represent the characteristics of the parts, estimate complexity from the /STL files, and optimum material and process parameters are selected by using multiple neural networks and genetic algorithms. The programs require minimum user input as almost all the critical values are obtained automatically. They concluded that the procedure is very convenient also to model and optimize other complex systems.

Zhou *et al.* [5] proposed the combination of a back-propagation neural network with a genetic algorithm for the development of a multi-objective optimization model of material selection when developing sustainable products. The problem of material selection for drink containers was used as a case study. They concluded that the selection of the final material should be a consideration of all these factors but not the particular one. The result from their model shows that the system can calculate and harmonize different factors and select suitable material, rightly and efficiently.

Henafizadeh*et al.*[38] developed a neural network-based expert system for perfume selection. Factors of perfume customer's decision were recognized using the Fuzzy Delphi method, and a back-propagation neural network classification model was developed and trained with 2303 data of customers. The results recommended from the developed expert system that the prediction accuracy is satisfactory. They concluded that the model can provide benefits to both the buyer and seller of perfume.

A research by Somkuwar*et al.*[2] used ANN technique to demonstrate its robustness and generalisation capability in material selection for product design. The coding for algorithms is implemented using NN toolbox in Matlab environment. The networks were trained with material properties as input and material identity as output. They concluded that NN can be used as a tool for predicting of most suitable material for specific product design. The performance indices of the networks are up to standard range. Similarly, Somkuwar*et al.*[39] integrated expert network, developed using visual C++ with radial basis neural network tool box of Matlab for material selection. Their consideration for selection focused on sensorial properties and cost of steel.

Golmohammadi[40] developed a fuzzy multi-criteria decision making model based on a feed forward artificial neural network. The model was developed to use historical data and update the database information for alternatives over time for future decision. They reported that their model is applicable for a wide variety of multi-attribute decision making problems and can be used for future ranking or selection without manager s' judgment effort.

Ahmed Ali *et al*.[9] reported the integration of artificial neural network and expert system for material classification of natural fibre reinforced polymer composites. The computational tool Matlab was used for the classification. Levenberg-Marquardt training algorithm, which provides faster rate of convergence, is applied for training the feed forward network. The system proves to be consistent with 93.3% classification accuracy with 15 neurons in the hidden layer. From the findings of the research, they concluded that ANN can be integrated with expert system, can handle huge data and can be implemented in material selection.

Cherian*et al.*[41] employed a neural network approach for selection of powder metallurgy materials and process parameters. Three mechanical property combination (tensile strength, elongation and hardness) were chosen as the input to network whereas the network output are sintered density, compaction pressure, sintering temperature, sintering atmosphere. They reported that powder metallurgy material selection is particularly well suited to application of neural network methods.

Lastly,Asthana and Gupta [42] developed a decision making model by integrating genetic algorithm (GA) with ANN to select the best and optimal supplier. The developed model consists of two parts: the first part applies GA to find the optimal value of function of quality, delay time, unit cost, quantity, and service. The second part uses the optimum value of the function in the ANN model to determine the supplier score. They reported that the result of the study proves that the model can be used to select and rank the best supplier from the available potential suppliers.

IV. CONCLUSION

The traditional material selection techniques such as KBS, questionnaire, Ashby method, and computer aided material selection system are reportedly used for material screening, but these techniques do not provide any ranking order. As such these traditional screening approaches do not guarantee the selection of optimum material. It can be concluded that though a number of researches.

From this review, it was found and can be concluded that numerous individual and integrated approaches were proposed to solve the material selection problem. However, only few publications have been reported on the application of NNs in in material screening processes, and very limited literature has been found in the area of application of NN integrated approaches for materials selection.

REFERENCES

[1] Jahan A., Ismail M. Y., Sapuan S. M., Mustapha F., Material screening and choosing methods – A review. Materials and Design, (2010)696-705.

[2] Somkuwar A. K., Khaira H. K., Somkuwar V., Materials Selection For Product Design Using Artificial Neural Network Technique. Journal of Engineering, Science and Management Education, (2010) 51-54.

[3] Ashby M. F., Brechet Y. J. M., Cebon D., Selection Strategies for Materials and Processes. Mater Des, (2004) 51-67.

[4] Sapuan S. M., Materials Selection for Composites: Concurrent Engineering Perspective. In Composite Materials(2017) 209-265. http://dx.doi.org/10.1016/B978-0-12-802507-9.00006-4.

[5] Zhou C-C., Yin G-F., Hu X-B., Multi-objective optimization of material selection for sustainable products: Artificial neural networks and genetic algorithm approach. Materials and Design, (2009)1209-1215.

[6] Abali R.,Development of Material Selection Software for Non-Ferrous Metals. Kano: BUK Dissertation., (2017).

[7] Shanian A., Savadogo O., A material selection model based on the concept of multiple attribute decision making. Material and Design,(2006) 329-337.

[8] Ahmed Ali B. A., Sapuan S. M., Zainudin E. S., Othman M., Java based expert system for selection of natural fibre composite materials. Journal of Food, Agriculture & Environment, (2013)1871-1877.

[9] Ahmed Ali B. A., Sapuan S. M., Zainudin E. S., Othman M., Integration of Artificial Neural Network and Expert System for Material Classification of Natural Fibre Reinforced Polymer Composites. American Journal of Applied Sciences, (2015)174-184.

[10] Shabani M. O., Mazahery A., Bahmani A. Davami P., Varahram N., Solidification of A356 Al alloy: experimental study and modeling. Kovove Mater., 49(2011)253-258.

[11] Sapuan S. M., Mujtaba I. M., Development of a Prototype Computational Framework for Selection of Natural Fiber Reinforced Polymer Composite Materials Using Neural Network. Composite Materials Technology: Neural Network Applications, (2010)317-340.

[12] Kröse B., Van der Smagt P.,An introduction to neural networks. Amsterdam: The University of Amsterdam., (1996).

[13] Yegnanarayana B., Artificial neural networks. PHI Learning Pvt. Ltd.,(2009).

[14] Heaton J.,Introduction to neural networks with Java. Heaton Research, Inc., (2008).

[15] Ermolaeva N. S.,Kaveline K. G., Spoormaker J. L., Materials selection combined with optimal structural design: concept and some results. Materials and Design ,(2002) 459–470.

[16] Rahim A. A. A., Musa S. N., Ramesh S., Lim M. K., A Systematic Review on Material Selection Methods. Journal of Materials: Design and Application, (2020)1-28.

[17] Goel V., Chen J., Application of Expert Network for Material

Selection in Engineering Design. Computers in Industry, (1996)87-101.

[18] Ipek M., Selvi I. H., Findik F., Torkul O., Cedimoglu I. H., An expert system based material selection approach to manufacturing. Materials and Design, (2012)1-32 http://dx.doi.org/10.1016/j.matdes.2012.11.060.

[19] Chatterjee P., Athawale V. M., Chakraborty S. ,Materials selection using complex proportional assessment and evaluation of mixed data methods. Mater Des, (2011)851-860.

[20] Jahan A., Ismail Md. Y., Shuib S., Norfazidah D., Edwards K. L., An aggregation technique for optimal decision-making in materials selection. Materials and Design, (2011)4918-4924.

[21] Davoodi M. M., Sapuan S. M., Aidy A., Abu Osman N. A., Oshkour A. A., Wan Abas W. A. B., Development process of new bumper beam for passenger car: A review. Materials and Design, (2012)304-313.

[22] Edwards K. L., Strategic substitution of new materials for old: Applications in automotive product development. Materials and Design, (2004)529-533.

[23] Faraq M. M. (1997). Materials Selection for Engineering Design. London: Prentice-Hall.

[24] Ashby M. F., Brechet Y. J. M., Cebon D., Selection Strategies for Materials and Processes. Mater Des, (2004) 51-67.

[25] Faraq M. M., Quantitative Methods of Materials Selection. Cairo, Egypt: Mechanical Engineers Handbook, Fourth Edition, edited by Myer Kutz., (2015).

[26] Jahan A., Edwards K. L., Bahraminasab M.,Multi-criteria Decision Analysis for Supporting the Selection of Engineering Materials in Product Design. Oxford, United Kingdom: Butterworth-Heinemann, DOI: https://doi.org/10.1016/C2014-0-03347-3.(2016).

[27] Sapuan S. M., A knowledge-based system for materials selection in mechanical engineering design. Materials and Design, (2001) 687-695.

[28] Amoiralis E. I., Georgilakis P. S., Gioulekas A. T., An Artificial Neural Network for the Selection of Winding Material in Power Transformers. Conference Paper, (2006) 465-468.

[29] Noryani M., Sapuan S. M., Mastura M. T., Multi-criteria decision-making tools for material selection of natural fibre composite: A review. Journal of Mechanical Engineering and Sciences, (2018)3330-3353.

[30] Rao R.V., Davim J.P., A decision-making framework model for material selection using a combined multiple attribute decision-making method. Int. J. Adv. Manuf. Technol, (2008)751-760.

[31] Singh A. K., Avikal S., Nithin Kumar K. C., Manish K., Thakura P., A fuzzy-AHP and M- TOPSIS based approach for selection of composite materials used in structural applications. Materials Today: Proceedings, (2020)1-5 https://doi.org/10.1016/j.matpr.2020.02.644.

[32] Patnaik P. K., Swain P. T. R., Purohit A., Selection of composite materials for structural applications through. Materials Today: Proceedings, (2019) 3454–3461.

[33] Patnaik P. M., Swain P. T. R., Mishra S. K., Purohit A., Biswas S., Composite material selection for structural applications based on AHP-MOORA approach. Materials Today: Proceedings, (2020)1-5 https://doi.org/10.1016/j.matpr.2020.04.063.

[34] AL-Oqla F. M., Sapuan S. M., Ishak M. R., Nuraini A. A.., A Model for Evaluating and Determining the Most Appropriate Polymer Matrix Type for Natural Fiber Composites. International Journal of Polymer Analysis and Characterization, (2015) 191-205.

[35] Smith L. N., German R. M., Smith M. L., A neural network approach for solution of the inverse problem for selection of powder metallurgy materials. Journals of materials Processing Technology, (2002) 419-425.

[36] Yang S. Y., Tansel I. N., Kropas-Hughes C. V., Selection of optimal material and operating conditions in composite manufacturing. Part I: computational tool. International Journal of Machine Tools & Manufacture, (2003) 169-173.

[37] Yang S. Y., Girivasan V., Singh N. R., Tansel I. N., Kropas-Hughes C. V., Selection of optimal material and operating conditions in composite manufacturing. Part II: complexity, representation of characteristics and decision making. International Journal of Machine Tools & Manufacture, (2003)175-184.

[38] Hanafizadeh P., Ravasan A. Z., Khaki H. R., An expert system for perfume selection using artificial neural network. Expert Systems with Applications, (2010)8879-8887.

[39] Somkuwar V., Bhagoriya J. L., Khaira H. K., An expert system for aid in material selection process using artificial neural network. International Journal of Advance Engineering Application, (2011)169-171.

[40] Golmohammadi D., Neural network application for fuzzy multi-criteria decision making problems. Int. J. Production Economics, (2011) 490-504.

[41] Cherian R., Smith L. N., Midha P. S., A Neural Network Approach for Selection of Powder Metallurgy Materials and Process Parameters. Artificial Intelligence in Engineering ,(2000) 1-8.

[42] Asthana N., Gupta M., Supplier selection using artificial neural network and genetic algorithm. Int. J. Indian Culture and Business Management,(2015) 457-472.