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Tribological Properties of Polymer Composites Using Non Traditional Optimization Technique: a review

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Abstract

Specific wear rate of composite materials plays a significant role in industry. The processes to measure it are both time and cost consuming. It is essential to suggest a modeling method to predict and analyze the effectiveness of parameters of specific wear rate. Nowadays, computational methods such as Grey Relational Analysis (GRA), Artificial Neural Network (ANN), Fuzzy Inference System (FIS) and adaptive neuro-fuzzy inference system (ANFIS) are mainly considered as applicable tools from modeling point of view. The objective of using ANN, ANFIS is also to apply this tool for systematic parameter studies in the optimum design of composite materials for specific applications. In the present review, various principles of the neural network approach for predicting certain properties of polymer composite materials are discussed. The aim of this review is to promote more consideration of using GRA, ANN and ANFIS in the field of polymer composite property prediction and design.

Keywords: Grey relational analysis (GRA), Artificial neural network (ANN), Fuzzy Inference System (FIS), Specific wear rate, Polymer, Composites

1. Introduction

Nowadays, polymers and polymer based composites are used commonly in situations where a good tribological property is required. Homopolymers alone cannot satisfy the required properties for the tribological applications such as cams, brakes, bearings, gears etc., Thus to improve properties and to lower the cost of polymer products, fillers are employed. The fillers can be in micro and nano sizes of inorganic fillers, organic fillers and metallic particulate materials. The tribological behavior of polymers with the addition of fillers is of great interests in recent years to improve the friction coefficient and wear rate.

Wear of the material is an inevitable result of the metal cutting process. Since undesirable effects of tool wear include: (1) a loss in the dimensional accuracy of the finished product and (2) possible damage to the workpiece, the on-line prediction of cutting tool wear becomes crucial. To date, it remains one of the major obstacles in the optimization of the metal cutting process and in the full implementation of unmanned machining. It is especially important for precision flexible manufacturing systems (PFMS).Thus, developing an intelligent estimation system for tool wear is important. Artificial neural networks (ANNs), fuzzy logic, and genetic systems constitute three independent research fields regarding sixth generation systems (SGS). Motivated by the results in each of these areas and the potential for mutual progress in computational modeling, an integration of these concepts is very important. ANNs and the fuzzy model have been used in many application areas, and each pairing has its own advantages and disadvantages. Therefore, how to success- fully integrate these two approaches, ANNs and fuzzy modeling, for the machining systems is the main focus of this research.

2. Grey relational analysis

Grey relational theory is very much applicable to a system in which the model is unsure or the information is incomplete. The process of preprocessing of all the data is called as Grey relational generating. Wear factor corresponds to lower-the-higher criterion [1].

Normalized value $X_k(k)$ criterion can be expressed as:

$$X_k(k) = \frac{\max Yi(k) - Yi(k)}{\max Yi(k) - \min Yi(k)} \qquad (1)$$

The grey relational coefficient $\xi_i(k)$ can be expressed as follows:

$$\xi_i(k) = \frac{\Delta \min + \xi * \Delta max}{\Delta oi(k) - \xi * \Delta max} \qquad (2)$$

After averaging grey relational coefficient, the grey relational grade Yi is computed as:

$$Yi = \frac{1}{n}\sum_1^n \xi i(k) \qquad (3)$$

Optimization of the complicated multiple process responses is converted into optimization of single grey relational grade.

3. Artificial Neural Networks

3.1 What are Artificial Neural Network

Artificial neural networks are computational systems that simulate the microstructure (neurons) of a biological nervous system. The most basic components of ANNs are modeled after the structure of the brain, and therefore even the terminology is borrowed from neuroscience. The most basic element of the human brain is a specific type of cell, which provides us with the abilities to remember, think, and apply previous experiences to our every action. These cells are known as neurons, and each of these neurons can connect with up to 200,000 other neurons. The power of the brain comes from the numbers of these basic components and the multiple connections between them. All natural neurons have four basic components, which are dendrites, soma, axons, and synapses. Basically, a biological neuron receives input from other sources, combines them in some way, performs a generally nonlinear operation on the result, and then output the final result. Biological neural networks are constructed in a three-dimensional way from microscopic components. These biological neurons seem capable of almost unlimited inter-connections. Inspired by biological neurons, ANNs are composed of simple elements operating in parallel, i.e. ANNs are the simple clustering of the primitive artificial neurons. This clustering occurs by creating layers, which are then connected to one another. How these layers connect may also vary. Basically, all ANNs have a similar topological structure. Some of the neurons interface with the real world to receive its input, and other neurons provide the real world with the network's output. All the rest of the neurons are hidden from view. As in nature, the network function is determined largely by the interconnections between neurons, which are not simple connections, but some non-linear functions. Each input to a neuron has a weight factor of the function that determines the strength of the interconnection and thus the contribution of that interconnection to the following neurons. ANNs can be trained to perform a particular function by adjusting the values of these weight factors between the neurons, either from the information from outside the network or by the neurons themselves in response to the input. This is the key to the ability of ANNs to achieve learning and memory. ANNs are widely used in many applications such as forecasting, control, data compression, pattern recognition, speech, vision, medicine, and power systems. Neural network models provide an alternative approach to analyze the data, because they can deduce patterns in the data. A simple process element of the ANN is shown in Figure 1. The network has three layers; the input, hidden, and output layers. The input and output layers are defined as nodes, and the hidden layer provides a relation between the input and output layers. Initially, the weights of the nodes are random and the network has not any knowledge. For a given input pattern, the network produces an associated output pattern. Its learning and update procedure is based on a relatively simple concept: the network is provided with both a set of patterns to be learned and the desired system response for each pattern. If the network generates the wrong answer, then the weights are updated to be less error. Finally, future responses of the network are more likely to be correct.

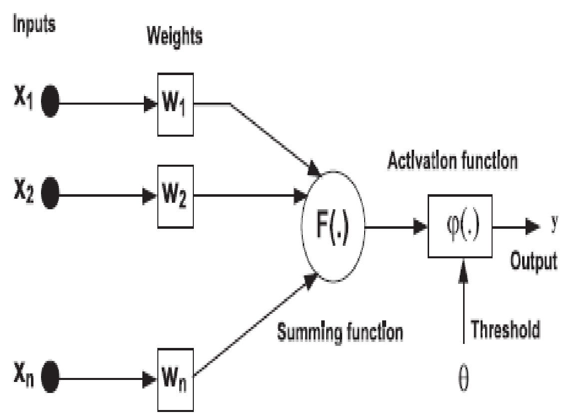

Figure 1: Mathematical model of neural network

3.2 Evaluation of the ANN Method

A dataset of measurement results will usually be divided into a training dataset and a test dataset. The training dataset is used to adjust the weights of all the connecting nodes until the desired error level is reached. Thereafter, the network performance is evaluated by using the test dataset. The quality of the prediction can normally be characterized by the root mean square error (RMSE) of the predicted values from the real measured data. Smaller the RMSE of the test dataset higher is the predictive quality. As an improvement, the coefficient of determination B (also called R^2 coefficient in some publications) has been introduced to evaluate ANNs quality, defined by

$$\text{MAPE}=\left(\frac{1}{N}\sum_i \left|\frac{t_i-t_0}{t_i}\right| \times 100\right) \quad \ldots (1)$$

$$R^2=1-\left(\frac{\sum_i (t_i-t_0)^2}{\sum_i (O)^2}\right) \quad \ldots (2)$$

4. Neuro-Fuzzy Inference Systems

Neuro-fuzzy inference techniques combine the paradigms of fuzzy logic and neural networks in order to take advantage of both techniques, achieving the simplicity of modeling (neural networks), while providing knowledge explicitly expressed in a set of *if*-then rules. Neuro-fuzzy systems have been widely used in modeling, identification and monitoring of complex systems. Since its origin in the early nineties, neuro-fuzzy systems have undergone various changes over the years, giving rise to various trends in research. For example, depending on the type of inference that the neuro-fuzzy system uses, or according to the structure of the neuro-fuzzy system, it can distinguish various sub-groups within the neuro-fuzzy approaches. In terms of learning procedures (type of inference), most evolutionary neuro-fuzzy strategies apply inductive reasoning systems. In inductive reasoning the key issue is to find a general model (function) drawn from the entire set of input/output data representing the whole system. The model is later used for designing the required control system. In contrast, there are transductive reasoning methods that generate a model at a single point of the workspace, giving rise to transductive neuro-fuzzy inference systems. According to the structure, an evolving neuro-fuzzy system is able to update its knowledge and refine the model through interaction with the environment. The main advantage in the use of these systems for modeling and monitoring process is that the structure of the evolving neuro-fuzzy system changes depending on what the process demands, unlike the current neuro-fuzzy systems which have fixed structure. Transductive methods have some advantages over inductive methods, because sometimes creating a valid model for the entire space or region of operation is a difficult task, yielding inadequate performance in some cases. The dynamic generation of local models enables the knowledge represented as the set of known data facilitating incremental on-line learning to be expanded easily. In addition, these strategies are capable of functioning correctly with a small training set.

5. Review of Literature

J. Sudeepana et.al, reported on the tribological properties of acrylonitrile-butadiene-styrene (ABS) polymer filled with micron-sized calcium carbonate (CaCO3). Filler content, normal load and sliding speed are considered as design parameters and coefficient of friction (COF) and specific wear rate are considered as the response parameters. Friction and wear rate experiments are conducted in a multi-tribo-tester using block-on-roller configuration in dry sliding conditions for a time of 300 seconds with three different levels of filler content, load and speed. Optimization of friction and wear rate test parameters are done with the help of grey Taguchi design of experiments. From the combination of analysis, both the responses are combined into a single response of grey relational grade. The optimum design parameter combination for minimum coefficient of friction and specific wear rate are found using grey relational analysis (GRA). It can be found that the 5% of filler content, 35 N of load and 120 rpm of speed (A1B3C3) gives the optimum values of grey relational grade for ABS / CaCO3composites. Analysis of variance (ANOVA) is also used to find out the most influential factor which affects the tribological properties. The most influential factor is normal load followed by sliding speed and filler content. Further, a confirmation test is carried out to validate the result. It is seen that the grey relational grade is increased about 72.56% from the initial to the optimum condition. Finally, surface morphology is studied using scanning electron microscopy (SEM). It can be concluded from this study that with the addition of micron-sized CaCO3 at the right combination of design parameters, the tribological properties get improved.

Chin-Ping Fung reported work on the optimization of injection molding process parameters using the grey relational analysis method. Nine experimental runs based on the Taguchi method of orthogonal arrays were performed to determine the best factor level condition. The wear volume losses of fiber-reinforced polybutylene terephthalate in different sliding directions were selected to be the quality targets. Volume losses were obtained using a Schwingum Reibung Verschleiss (SRV) "ball-on-plane" wear tester. The factor levels were assessed according to two chosen wear volume losses. The degree of influence that the controllable process factors exert on the wear volume losses was studied by investigating the correlation between them. By analyzing the grey relational grade matrix, the most influential process factor and the most easily influenced wear property could be found. Melt temperature was found to be the most influential factor in both wear volume losses of different sliding directions. From the response table of the average grey relational grade, it was found that the largest value of grey relational grade for filling time, melt temperature, mold temperature, and ram speed was 2 s, 260◦C, 90◦C, and 100%, respectively. These are therefore the recommended levels of controllable injection molding process factors when both the wear volume losses of P-type and AP-type, in which the two directions of sliding wear are different, are simultaneously considered. The wear volume loss of AP-type demonstrated the strongest reference sequence. The wear volume loss of sliding direction perpendicular to injection flow was more easily influenced by process factors than was the wear volume loss of the sliding direction parallel to the injection flow. The importance of the controllable factors to wear volume loss of AP-type is in the sequence of melt temperature, ram speed, mold temperature, and filling time. On the other hand, the importance of the controllable factors to wear volume loss of P-type is in the sequence of melt temperature, mold temperature, ram speed, and filling time. The sequences of the importance to the wear volume loss in the controllable factors were slightly different for the two sliding directions, but the melt temperature was still the most important factor. It means that the melt temperature had the strongest correlation to wear volume losses of both P-type and AP-type. Therefore, the melt temperature was the most influential factor to the wear properties of fiber-reinforced PBT products among the four injection molding process factors investigated in this study.

R. Singh et.al, reported a work on the optimization of carburization process parameters for mild steel by using the Grey based Taguchi method. Design of experiments was done on the basis of an orthogonal array L9 (3^4). Nine experiments were performed and mechanical & wear properties were selected as the quality target. An optimized parameter combination of the carburizing process was obtained via Grey relational analysis.The optimized parameters were the largest value of average Grey relational grade for carburization temperature of 960^0C, carburization sock time of 4 hr., tempering temperature of 260^0C, and tempering sock time of 0.6 hr. By analyzing the Grey relational grade we find the degree of influence of each factor on the quality target. By this study we found that carburizing temperature was the most dominated factor 84.921 %, which mostly influences the mechanical and wear properties of carburized mild steel followed by tempering temperature 8.297 %, Carburization sock time 6.051 %, tempering sock time 0.731 %. At last, a confirmation test was conducted according to predicted optimal parameter setting and it shows that the sequence of identified optimal parameters is suitable for carburization process of mild steel.

A. Dhinakar et.al, reported a work on optimization of sliding wear parameters for Mg/Grp composites by grey relational analysis. Composite materials are generally made up of two constituents-matrix and reinforcement. The matrix material is stable and provides support to the reinforcement material. A variety of moulding methods can be used to prepare composites based on the type of application. The objective of manufacturing a new composite material is to improve the mechanical properties such as strength, stiffness, toughness and high temperature performance. The size of the reinforcement determines its potential of contributing its properties to the composite. As magnesium is being the one of the most abundant and lightest of all metals, it can be the best replacement for the material used in aerospace and automotive industry as composite material. Wear characteristic of magnesium is poor, but wear resistant is an important property for the industrial metals. As graphite is being soft and lubricant material, it is mixed in the proportion of 5%, 10%, and 15% with magnesium, processed by powder metallurgy technique, then extruded and machined to conduct pin-on-disc test by Taguchi L9 orthogonal array design. Wear test is carried out on Standard C45 steel disc. The response parameters wear loss and coefficients of friction were observed during the test. Grey Relational Analysis is used to optimize the wear reducing parameters and Analysis of Variance is performed to identify the significance of the parameters. By using grey relational analysis the recommended levels of parameters for an optimum grey relational grade is 5% volume fraction with grey relational grade of 0.5142 and 10 N load with grey relational grade of 0.5431 and 0.8 m/s of grey relational grade of 0.5851. From ANOVA for grey relational grade states that contribution on grey relational grade by Normal load is about 70 % and by volume fraction is just less than 10% but contribution of disc speed is lesser than contributions of interaction effects. Increase in volume fraction of Graphite shows good property of the composite materials against wear.

V. Kumar et.al, reported a work on Optimization of tribological performance parameters of Al-6061T6 alloy reinforced with SiC, (Al2O3) 15% and graphite particulates of weight percentage of 10%. The wear and frictional properties of the hybrid metal matrix composites was studied by performing dry sliding wear test using pin-on-disc wear tester based on Taguchi method and Grey relational analysis. A L27 orthogonal array was selected for analysis of the data. From the Taguchi analysis the optimal combination of process parameter for minimum wear and friction is found to be L2S2D3, i.e., the highest level of applied load and sliding distance along with highest level of sliding speed. From the tests result, it is observed from ANOVA that parameter Applied Load (30.23%) has the highest influence on tribological behavior followed by sliding distance (29.6147%) and sliding speed (9.5430%). The interaction set the parameters have slightly influence on friction and wear property of hybrid composite. Incorporation of SiC, Al2O3 and Gr particulate increase the wear resistance of hybrid composites by performing a protective layer between pin and counterface has a significant effect on the friction and wear depth. Confirmation experiment was carried out and made a comparison between initial and optimal experimental parameters values which shows wear depth is reduced by (61.5%) and friction is decreased by (33.5%).

A.K. Singh et.al, reported that the present work deals with drill wear monitoring using an artificial neural network. A radial drilling machine (Batliboi Limited, BR618 model) is used for the drilling operation. HSS drill bits with different diameters were used for drilling in a copper workpiece under different cutting conditions. In our study, spindle speed varied in the range from 315 rpm to 1000 rpm in six increments. Similarly, federate was also varied from 0.13 to 0.71 mm/rpm, in six steps. HSS drill bits of three different diameters have been used for drilling holes in a copper plate. Various combinations of spindle speed, feedrate and drill diameters were used to perform 49 different drilling operations. For each of these operations, thrust force and torque were measured using the data acquisition system, and was stored in the computer. Also, corresponding to each cutting condition, maximum flank wear was measured using a digital microscope with a Carl–Zeiss software interface. A back propagation neural network (BPNN) has been used to predict the flank wear of high speed steel (HSS) drill bits for drilling holes on copper workpiece. Experiments have been carried out over a wide range of cutting conditions and the effect of various process parameters like feed rate, spindle speed, and drill diameter on thrust force and torque has been studied. The data thus obtained from the experiments have been used to train a BPNN for wear prediction. From the 49 datasets obtained in the experiment, 34 were selected at random for training the network and remaining 15 were used for testing. The normalized datasets were used for training the network. The optimal network for our case was selected to be 5-4-1, with a momentum coefficient (α) of 0.3 and a learning rate (β) of 0.3. The performance of the trained neural network has been tested with the experimental data, and has been found to be satisfactory.

A. Mesbahi et.al, reported that specific wear rate of composite materials plays a significant role in industry. The processes to measure it are both time and cost consuming. It is essential to suggest a modeling method to predict and analyze the effectiveness of parameters of specific wear rate. Nowadays, computational methods such as Artificial Neural Network (ANN), Fuzzy Inference System (FIS) and adaptive neuro-fuzzy inference system (ANFIS) are mainly considered as applicable tools from modeling point of view. ANFIS present integrate performance of neural network (NN) and fuzzy system (FS). Present paper investigates performance prediction of a specific wear rate of epoxy composites with various compositions using ANFIS. In this present paper, data has been extracted from Zhang et al. including inputs: 1- Matrix (epoxy) (volume percent) 2- polytetrafluoroethylen (PTFE) (volume percent) 3- Graphite (volume percent) 4- Short-CF (volume percent) 5- Nano-TiO2 (volume percent). And Specific wear rate has been considered as output. Table 3 shows these data (Zhang et al.). Multi-Layer Perceptron (MLP) was selected as a powerful tool in ANN. In this method neurons are used in multi-layer with back propagation (BP) algorithm for adjusting weights. Different learning method in BP algorithm presented for adjusting weights. Data sets 1 and 2 have been applied to the MLP networks three times more than other data. Thirty sets of data for training and 6 sets for testing sets were used for ANN networks in random selection algorithm. Six set of data have been used for validation MLP networks. ANFIS has been chosen Genfis3 with specification. Data sets 1 and 2 have been applied to the ANFIS (GENFIS3) networks three times more than other data. The obtained results showed that ANFIS is a powerful tool in modeling specific wear rate. The obtained mean of squared error (MSE) for testing sets in present paper obtained 0.0071.

T. B. Asafa et.al., report the development of a predictive model based on artificial neural network (ANN) for the estimation of flank and nose wear of uncoated carbide inserts during orthogonal turning of NST (Nigerian steel) 37.2. Turning experiments were conducted at different cutting conditions on a M300 Harrison lathe using Sandvic Coromant uncoated carbide inserts with ISO designations SNMA 120406 using full factorial design. Samples of fully annealed NST 37.2 steel bars with 25 mm diameter were obtained from Delta Steel Company (DSC). Straight turning was done on M300 Harrison-type lathe driven by 3.0 Hp Kapak inductions motor with speed range of 40-2500 rpm. Cutting speed (v), feed rate (f), depth of cut (d), spindle power (W), and length of cut (l) were the input parameters to both the machining experiments as well as the ANN prediction model while the flank wear (*VB*) and nose wear (*NC*) were the output variables. Nine different structures of multi-layer perceptron neural networks with feed-forward and back-propagation learning algorithms were designed using the MATLAB Neural Network Toolbox. An optimal ANN architecture of 5-$[12]_4$-2 with the Levenberg-Marquardt training algorithm and a learning rate of 0.1 was obtained using Taguchi method of experimental design. The results of ANN prediction show that the model generalized well with root mean square errors (RMSE) of 3.6% and 4.7% for flank and nose wear, respectively. With the optimized ANN architecture, parametric study was conducted to relate the effect of each turning parameters on the tool wear. The ANN predictive model captures the dynamic behavior of the tool wear and can be deployed effectively for online monitoring process.

M. Hazza et.al, reported that predicting and modeling flank wear length in high speed hard turning by using ceramic cutting tools with negative rake angle was conducted using two different techniques. Regression model is developed by using design of expert 7.1.6 and neural network technique model was built by using MATLAB 2009b. A set of experimental data for high speed hard turning of hardened AISI 4340 steel was obtained with different cutting speeds, feed rate and negative rake angle. Experimental works were carried out on CNC turning machine type Power Path 15 HS – High Speed Version (spindle ASA A 2-5") and the insert chosen for this study was a mixed ceramic (Al_2O_3+TiC).Under dry cutting conditions with a 0.15 mm constant depth of cut a full factorial for three cutting parameters (cutting speed, negative rake angle and feed rate) after 1000 mm of cutting. Flank wear length was measured to train the neural network models and to develop mathematical model by using regression analysis. The flank wear length has a pred R-squared of 0.9887 is in reasonable agreement with the adj R-squared of 0.9917. Adeq Precision measures the signal to noise ratio. The ratio of 95.352 indicates an adequate signal. The results were compared with the measured values of the flank wear length; the error was approximately equal to 5.57 %. ANN method was employed with three inputs (cutting speed, feed rate and rake angle) and 20 hidden layers and after eight iterations the final prediction comes out .The deviation from the measured values equal to 4%. Predictive neural network models are found to be capable of better predictions tool flank wear within the range that they had been trained. The experiment analysis and modeling highlight that the machining criteria such as the flank wear length influenced by different cutting parameters. The results show that the cutting speed has the most effect of the flank wear as illustrate from the analysis of variance table. From the results it was found that the artificial neural network gives more accurate predicting than the regression analysis model. It is shown also that ANNs can be used as an alternative method for the experimental studies when the mathematical model cannot be formed.

M. Lei et.al, reported that the geometric accuracy and surface roughness are mainly affected by the flank wear at the minor cutting edge in finish machining. A genetic algorithm-based fuzzy estimator obtained by a fuzzy inference algorithm to evaluate the minor flank wear length in finish milling is introduced. The fuzzy inference rules are trained by genetic algorithms (GA) through practice. Fuzzy membership functions and rules are usually decided upon subjectively. In this paper, the performance of the fuzzy estimator may be improved if the fuzzy inference model is supplemented by a genetic-based learning mechanism. A single-point fly-cutting was adopted in order to reduce the run-out and positioning accuracy problem among inserts in finish machining. A rectangular workpiece (60 mm 3 70 mm) made of 45# steel was replaced after each cutting experiment performed under a given group cutting condition. Cutting conditions, such as cutting speed, feed rate and depth of cut were varied in the ranges 350–1100 r.p.m., 20–40 mm min21 and 0.3–0.8 mm, respectively, and they are grouped into eight categories for rule generation and verification tests for estimation. The features sensitive to minor flank wear are extracted from the dispersion analysis of a time series AR model of the feed directional acceleration of the spindle housing. Linguistic rules for fuzzy estimation are constructed using these features, and then fuzzy inferences are carried out with test data sets under various cutting conditions. The proposed system turns out to be effective for estimating minor flank wear length, and its mean error is less than 13%.

6. Conclusions

The following conclusions could be drawn from the present review:

1. We observed that most of the researcher has taken input parameters (controllable factors) as a load, sliding distance, speed and material and few researcher taken input parameter: Tempering time, Tempering temperature, Sock Time etc. and output parameters as a specific wear rate, coefficient of friction etc. for grey relational analysis.
2. We also found that for wear the most significant parameters are load, sliding distance, sliding speed.
3. From Grey relational analysis the optimum set parameters were found and from the confirmation test it is concluded that the optimum set parameters were acceptable.
4. An ANN is ideally suited for simulating complex polymer composite problems because, like its biological counterparts, it can learn, and therefore can be trained to find solutions. In contrast to classical approaches in composite modeling, neural networks require no explicit mechanistic model or restrictive assumptions of normality or linearity.
5. It is ideal in polymer composite design when only material compositions and testing conditions serve as ANN input data. A well trained ANN is expected to be very helpful to predict the material properties before manufacturing/testing the real composites.
6. There are many parameters in the manufacturing processes that control the final qualities of the polymer composites. ANN and ANFIS could be of help to simulate the relationships between these manufacturing parameters and the material performance, which can be used as the basis for a computer based processing optimization.
7. The analysis of relationships between some simple properties and other complex properties will be of additional help in the design of new composite materials. The simple properties are normally easier to obtain than complex ones, and therefore successful prediction could be of benefit to reduce the number of more complex experiments.
8. The required number of training data can be reduced by optimizing the neural network architecture and by choosing suitable input parameters. However, the more complex the nonlinear relation between input and output is, the more training data are required.
9.

REFERENCES

- *J Sudeepan, K Kumar, T K Barman and P Sahoo (2014), Study of Tribological Behavior of ABS/ Caco3 Composite Using Grey Relational Analysis, 3rd International Conference on Materials Processing and Characterisation, Procedia Materials Science 6, 682 – 691*
- *Chin-Ping Fung (2003), 'Manufacturing Process Optimization for Wear Property of Fiber-Reinforced Polybutylene Terephthalate Composites with Grey Relational Analysis', Wear 254, 298–306*
- *R. Singh, V. Chaturvedi and J. Vimal (2012), Optimization of Control Parameters for Mechanical and Wear Properties of Carburized Mild Steel Using Grey Relational Analysis, International Journal of Engineering Research and Applications (IJERA) ISSN: 2248-9622, Vol. 2, Issue 3, pp.2047-2052*
  - *Dhinakar, T. Panneer Selvam and S. Raghuraman (April 2014), Optimization of Sliding Wear Parameters for Mg/Grp Composites by Grey Relational Analysis, International Journal of Advances in Materials Science and Engineering (IJAMSE) Vol.3, No.2*
- *V. Kumar, S. Sharma and A. Verma (4- Feb 2014), Optimization of Tribological Performance of Al6061T6/15% SiC/15% Al2O3/10% Graphite HMMC using Taguchi Method and Grey Relational Analysis, International Journal of Engineering Trends and Technology (IJETT), Volume 8*
- *A.K. Singh, S.S. Panda, S.K. Pal, D. Chakraborty (2006), Predicting Drill Wear Using an Artificial Neural Network, Int J Adv Manuf Technol, DOI 10.1007/s00170-004-2376-0, 28: 456–462*
- *Ali Haghighat Mesbahi, Dariush Semnani, Saeid Nouri Khorasani (2012), Performance prediction of a specific wear rate in epoxy nanocomposites with various composition content of polytetrafluoroethylen (PTFE), graphite, short carbon fibers (CF) and nano-TiO2 using adaptive neuro-fuzzy inference system (ANFIS), Composites: Part B 43 549–558*
- *T. B. Asafa and D. A. Fadare April 2012, Artificial neural network predictive modeling of uncoated carbide tool wear when turning nst 37.2 steel, ARPN Journal of engineering and applied sciences, ISSN 1819-6608, vol. 7, no. 4*
- *Muataz Al Hazza1, Erry Y.T. Adesta (2011), Flank wear modeling in high speed hard turning by using artificial neural network and regression analysis, Advanced materials research vols. 264-265 pp 1097-1101*
- *Ming Lei, Yang Xiaohong and Yang Shuzi (1999), Tool wear length estimation with a self-learning fuzzy inference algorithm in finish milling, Int J Adv Manuf Technol 15:537–545*