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Predictive Model for Material Behavior Prediction

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Abstract: Predictive modeling is playing a major role in the manufacturing fields. In this paper a predictive model is demonstrated to predict composite materials behaviors in materials manufacturing industries. In recent times, the problem of prediction of properties of composite materials has attracted enormous attention from different communities such as statistics, soft computing, and engineering. This is due to prospective benefits of reduction in testing and inventory cost increase in the finding the properties of composite materials.

Keywords: Predictive Modeling, Composite material, Regression, Solidification

I. INTRODUCTION

Basic technique solidification is used to solidify the materials in material manufacturing industry. The commercial and technological importance of this solidification process comes from the growing importance of the materials being processed. Once materials are process to solidify, the behaviors are determined by materials testing methods. This is done to check the mechanical behavior and physical nature of the that materials is analyzed when it influenced both by outside force and surroundings which are considered as the main basis of defining engineering design parameters. Manufacturers must minimize cost and testing time, and additionally, the product must comply with the required dimensions and quality criteria for a better competition [9].

In the daily life of human each and every material he/she use in any type of work whether inside or outside the home he/she opt for light weighted materials. This requirement introduces manufacture to manufacturing such type of materials. This leads increased in manufacturing the composite materials at a much faster rate than of metals or ceramics during the last 10 years [4]. Indeed, many parts previously made of metals are today being made of plastic and plastic composites. In most of the engineering applications, metals are being replaced with polymer composite materials [1]. The property of the composite material is enhanced by different combination of reinforcements and process technologies [5]. It is well known that mechanical behaviours are the most significant properties considered by the designer for engineering application [11]. Hence, the manufacturer tries to enhance these properties by using different combinations of external parameters in the solidification process [9][12]. Adjusting appropriate measures of external parameters makes it possible to obtain maximum mechanical strength of the materials [2]. It is complicated process to fix suitable measures for the required mechanical strength due to lack of experts in the field of composite materials manufacturing process. Hence, there is a need to repeat the experiments until the requirements are met. This results in wastage of resources like time, cost and human power.

If the predictive models are found in this stage, certain extent we can decrease times, test cost and increase efficiency of manufacturing process. Usually statistic model are found in predicting the mechanical properties providing with few information [7]. Besides, we can mine more useful information from the test data using the advanced data mining models.

Recently many advanced data mining predictive models are being used in real time applications [6]. These predictive techniques are preferred depending on the nature of data [10]. Few data mining predictive models are present in the literature which is used for predicting materials life time, mechanical property of steel strips using, and mechanical properties of friction stir welded AA6351 aluminum[3][13] etc.

In this paper a data mining predictive model to predict the mechanical properties of wheat straw reinforcement polypropylene composite material from the external parameters like temperature, mold pressure, fibre content and mold time. Multi linear regression is employed in predicting the mechanical properties.

II. MULTIPLE REGRESSION MODELLING

Multiple regressions is a technique that allows us to determine the correlation between a continuous dependent variable and two or more continuous or discrete independent variables. It can be used for a variety of purposes such as analyzing of experimental, ordinal, or categorical data. Thus, it can be considered to be helpful in predicting the properties of materials. In order to predict the mechanical properties of materials, non-linear polynomial degree 2 equations are preferred based on the nature of the wheat straw reinforcement polypropylene composite material data and it is expressed as:

$$\mathbf{Y = P_0 + P_1X + P_2X^2 + \ldots\ldots\ldots\ldots + P_nX^n + \varepsilon}$$

The coefficients $P_0, P_1, \ldots, P_n$ are to be estimated using suitable methods.

Thereafter, the analysis of variance is used to seek the relationship between a response variable (output parameter) and two or more continuous or discrete independent variables. The performance criterion is given by the coefficient of determinant (R^2) and the sum of square error (SSE).

III. PROPOSED MODEL

A predictive model is proposed to predict mechanical behaviour using external manufacturing process parameters data. Tensile strength and toughness are mechanical properties influenced by manufacturing process parameters like fibre content, time, mold pressure, and mold temperature. An effective approach has been developed based on multiple regression to predict the mechanical properties of composite materials in order to minimize cost and time of the manufacturing process. Model is implemented for wheat straw reinforcement polypropylene composite material data and

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model is evaluated based on the prediction accuracy. The architecture of proposed model is shown in Figure1.

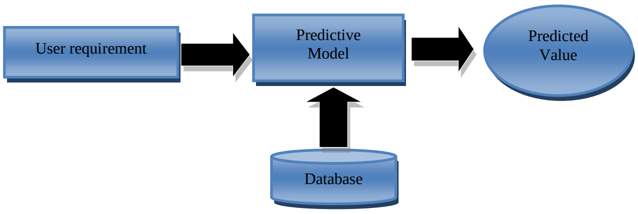

Fig 1: Schematic architecture of proposed prediction model

The proposed model involves different phases; each phase performs intricate tasks in predicting the mechanical properties of wheat straw reinforcement polypropylene composite materials. The involved phases of the model are user interface, database, and predictive model phases. The steps involved in each phase are described concisely in the following sections.

User Interface Phase

A graphical user interface is designed to provide an interface between user and functional components of the proposed model. GUI provides contemporary controls to select the dataset from the database and displays the computed performance of the model in the customised area. Based on the constructed model, the user is requested to enter the measure of the process parameters to predict the corresponding mechanical behaviours.

Database

Standard wheat straw reinforcement polypropylene composite material datasets are considered in this model. These datasets consist of 6 attributes, of each material. Four attributes represent the different process parameter values. Generally, in Materials Science this type of data is collected by conducting experiments in manufacturing industries [12]. These data are used to study the influence of external parameters on the mechanical behaviour of the composite materials. This helps in adjusting the processing parameters to enhance the mechanical strength of the composite materials. Using this data, the mechanical properties of the composite materials are predicted from the proposed model.

Multiple Regression Model

Multiple regression is a technique that allows us to determine the correlation between a continuous dependent variable and two or more continuous or discrete independent variables. It can be used for a variety of purposes such as analysing of experimental, ordinal, or categorical data (Myers, R. H, 1990). Thus, it can be considered to be helpful in predicting the properties of materials. In order to predict the mechanical properties of materials, non-linear polynomial degree 2 equations are consider and it can be expressed as:

$$Y = P_0 + P_1 X + P_2 X^2 + \dots\dots\dots + P_n X^n + \varepsilon$$

Where, Y (Toughness and Tensile strength) is the estimated variable and X (Fibre content, Time, Mold Pressure, and Temperature) is the response variables. The coefficients $P_0, P_1 \dots, P_n$ is estimated using least squared method.

IV. EXPERIMENTAL RESULTS

In this section, the results of the experiment conducted to demonstrate the performance of the proposed predictive models to predict the mechanical properties of composite materials are presented. Wheat straw reinforcement polypropylene composite materials datasets are considered for the experiments. These datasets are collected from the experiments conducted by [12] to study the influences of the manufacturing process parameters on materials mechanical behaviour. He carried out 30 experiments to collect datasets. From each experiment, the readings are collected and published in brochures. Using these datasets, the proposed models are evaluated for predicting the mechanical properties of composite materials. The results obtained from the model are discussed below.

A multiple regression model is constructed to the given datasets. While constructing the model, for each process parameter, a polynomial line is fitted to study the relationship between independent variables and response variable. The fitted polynomial lines for independent variables corresponding to their response variable are plotted in the scatter plot and it is represented in Figure 2:

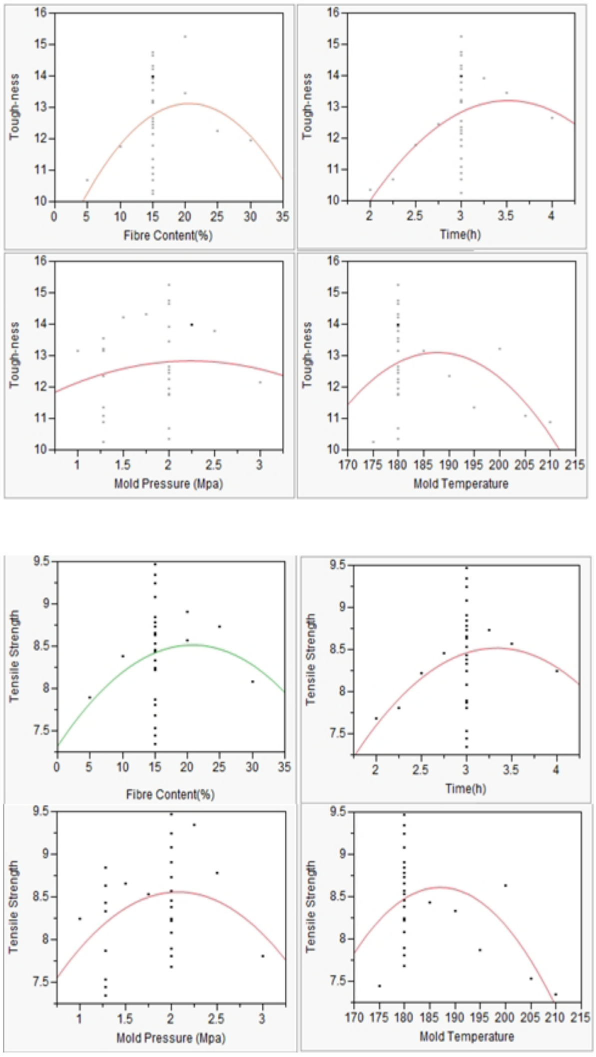

Figure 2: (a) and (b) show the non-linear fitted line on and parameters

The obtained coefficients from the least square method for the model are shown in tables 1.

Table 1: Coefficients estimated by least square method for tensile strength and toughness.

Parameter	Tensile Strength	Toughness
P1	10.724	-99.493
P2	0.050	0.000

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P3	-0.372	5.401
P4	0.017	0.475
P5	-0.010	1.050
P6	-0.006	0.000
P7	0.147	-0.840
P8	-0.373	0.007
P9	0.000	-0.003
P10	0.060	0.000
P11	0.047	0.000
P12	-0.001	0.000
P13	0.071	-1.168
P14	-0.003	-0.706
P15	0.002	-0.318

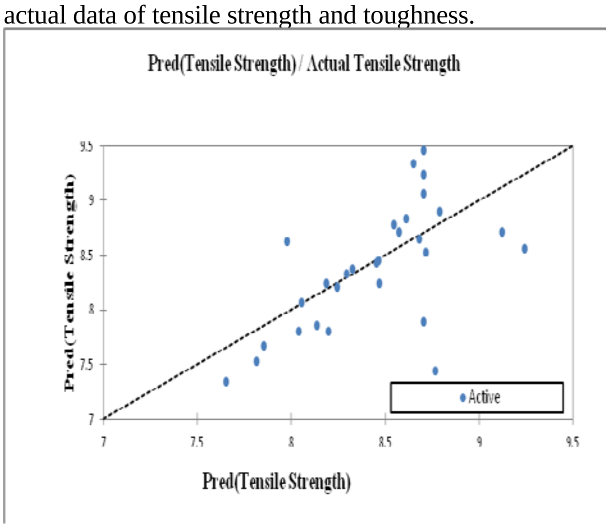
The second order polynomial equation of the model for Tensile strength and Toughness is given as:

$$\begin{aligned} \mathit{Tensile\ Strength} &= 10.724 + 0.0496 * Fibre + -0.372 * Time + 1.673E-02 * MoldPR + -9.864E-03 \\ &* MoldTemp + -5.98E-03 * Fibre^2 + 0.147 * Time^2 + -0.373 * MoldPR^2 + -1.889E-05 \\ &* MoldTemp^2 + 6.026E-02 * Fibre * Time + 4.746E-02 * Fibre * X3 + -5.534E-04 * Fibre \\ &* MoldTemp + 7.141E-02 * Time * MoldPR + -3.103E-03 * Time * MoldTemp + 2.299E \\ &- 03 * MoldPR * MoldTemp \end{aligned}$$

And

$$\begin{aligned} Toughness = {} & 14.956 + 0.141 * Fibre + -0.679 * Time + -6.491E-03 * MoldPR + -1.016E-02 \\ &* MoldTemp + -1.299E-02 * Fibre^2 + 0.282 * Time^2 + -0.249 * MoldPR^2 + -1.431E-04 \\ &* MoldTemp^2 + 0.188 * Fibre * Time + -0.0536 * Fibre * MoldPR + -5.946E-04 * Fibre \\ &* MoldTemp + -0.103 * Time * MoldPR + -3.292E-03 * Time * MoldTemp + 0.932E-03 \\ &* MoldPR * MoldTemp \end{aligned}$$

Figure 3 (a) & (b) shows the comparison of actual measured values with model predicted values which is represented using the scatter plot indicating the predicted line passing between the actual data of tensile strength and toughness.



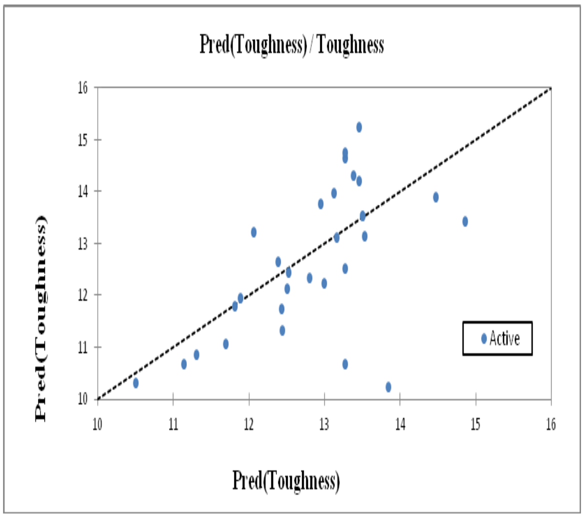
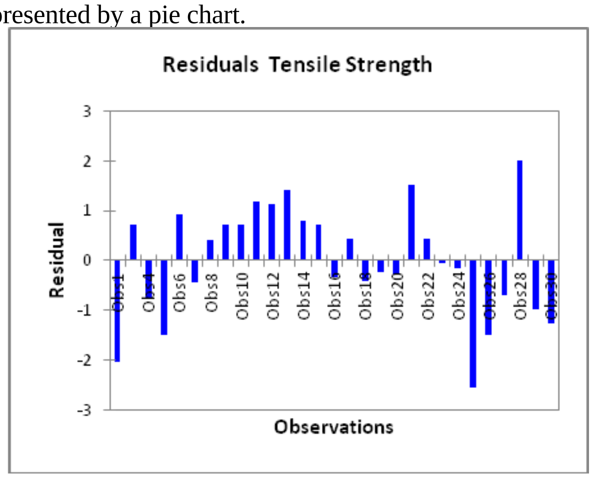


Figure 3: (a) & (b) Representing the predicted values with actual values

Figure 4 (a) & (b) shows the difference of actual and predicted values of toughness and tensile strength. Here residuals error between actual and predicted values is represented by a pie chart.



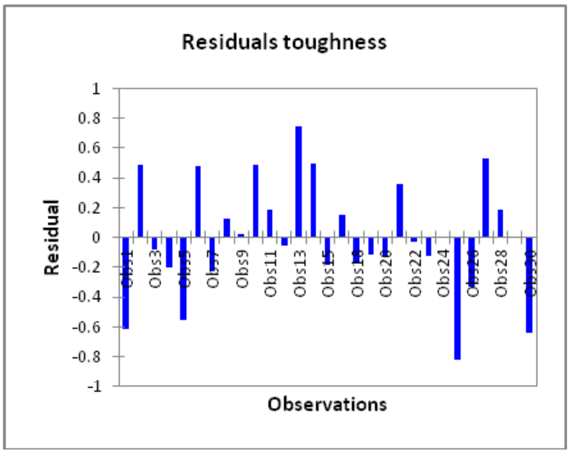


Figure 4: (a) & (b) Represents difference of predicted value with actual values

The performance of the fitted least square equation is measured by coefficient of determination R^2 and it is represented as:

$$R^2 = 1 - \frac{SSE}{SS_{yy}}$$

The SSE measures the deviation of observations from their predicted values:

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$$SSE = \sum_i (y_i - \hat{y}_i)^2$$

The SS_{yy} measures the deviation of the observation from their mean:

$$SS_{yy} = \sum_i (y_i - \bar{y}_i)^2$$

The performance of the constructed model to predict the tensile strength and toughness is given by statistical measures like coefficient of determination and with sum of square error are presented in Table 2.

Table 2: The coefficient of determination and the sum of square error

Mechanical Behaviours	R^2	**SSE**
Tensile strength	0.907	-5.181
Toughness	0.914	-4.621

The obtained result shows that the model predicts the tensile strength and toughness with an accuracy of 90 %, and 91 %, respectively, from the solidification process parameter.

V. CONCLUSION

In this paper, we proposed a data mining predictive model to predict mechanical behaviours of composite materials from the external parameters of the manufacturing process. This model helps by minimizing the cost and time of the manufacturing process. In order to predict the mechanical behaviour multiple regression techniques is considered. We employed a multilayer perceptron (MLP) network in order to establish a non-linear regression model that can be used to directly predict the mechanical behaviour of composite materials. The overall performance of the model is measured by mean square error (MES) and coefficient of determination (R^2).

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