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Implementation of Genetic Programming Technique for Simulating the Material Properties of Sintered Al-Fe Composite

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Abstract: *The variation of sintered aluminium iron composites with respect to parameters of load, density ratio, aspect ratio and percentage of iron are analyzed. The material properties analyzed are axial stress, axial strain, hoop stress, hoop strain, Poisson's ratio and hydrostatic stress. Symbolic regression equations were generated to accurately predict the effect of parameters on the material properties. The limitations of conventional parametric equation fitting were overcome with the use of symbolic multivariate regression fitting. To achieve this objective, the novel approach of Genetic Programming has been used. The data sets have been taken from the Hydraulic Testing Machine using the sintered component. Data for aspect ratios of 0.25, 0.5, 0.75, 1.00; density ratios from 0.8-0.96 and % of iron from 0-8 have been included to find the effect of each parameter on the material properties. The predicted values using Genetic Programming coincided well with the experimental results. The results indicate the efficacy of GP to predict the effect of multiple input parameters on material properties. Further GP can be extended to predict the effect of variation of input parameters on the properties of any composite. The computational model developed will be used to predict the material properties for various iron composition by simple substitution without conducting experiments.*

Keywords*: GP-Genetic Programming, Al-Fe composite, P/M-Powder Metallurgy, computational model*

I. Introduction

Metal powders are used in a variety of applications which include dietary supplements in food processing, additives in paints and other coatings. Powder Metallurgy is a highly evolved method of manufacturing reliable net shaped components by blending elemental or pre-alloyed powders together, compacting this blend in a die, and sintering or heating the pressed part in a controlled atmosphere furnace to bond the particles metallurgically.

The P/M process is a unique part fabrication method that is highly cost effective in producing simple or complex parts at, or close to, final dimensions. Physical and mechanical properties of components can be tailored through close control of starting materials and process parameters [1]. Particular properties can be improved through secondary processing operations such as heat treating and cold/hot forming. Production of complex shapes to very close dimensional tolerances, with minimum scrap loss and fewer secondary machining operations. Increased demand for light weight components, primarily driven by the need to reduce energy consumption in a variety of societal and structural components, has led to increased use of aluminium.

Additionally, the cost of fabrication coupled with a need to improve part recovery has led to significant growth in the net-shaped component manufacturing processes. Aluminium Powder Metallurgy (P/M) offers components with exceptional mechanical and fatigue properties, low density, corrosion resistance, high thermal and electrical conductivity, excellent machinability, good response to a variety of finishing processes, and which are competitive on a cost per unit volume basis [2]. In addition, aluminium P/M parts can be further processed to eliminate porosity and improve bonding yielding properties that compare favourably to those of conventional wrought aluminium products.

II. Experimental procedure

Separately aluminium and iron powders were purchased and their individual properties were identified. Atomized aluminium and iron powder was mixed thoroughly. The green compacts of different height to diameter ratios (aspect ratio) namely 0.25, 0.50, 0.75 and 1.00 were prepared [3] from the aforesaid powder on a hydraulic testing machine of 1.8 MN capacity at a different pressure range in order to obtain the proper initial green compaction densities. The densities and the initial aspect ratios were maintained by precisely controlling the powder mass and accurately monitoring the compacting pressures. Different lubricants were used to lubricate the punch, die and the bottom insert while preparing the compacts. Sintering of these compacts was carried out in an electric muffle furnace at 525-540°C for a holding period of one hour in a dry fine silica sand pack container. Immediately after the completion of sintering schedule, the sintered compacts were allowed to cool to room temperature. Once the sintered compacts attained room temperature, the residual ceramic coatings was removed by using the various grades of emery paper. Immediately after cleaning the sintered performs, the initial heights, the diameters and the fractional densities were measured. During the axial compression tests, the die set was well lubricated by MoS_2 lubricant, in order to create a situation for almost ideal deformation. In general, each compact was subjected to compressive loading in steps of 0.03 MN until fine cracks appeared on its free surface. Immediately after the completion of each step of loading, the height, the contact diameters, the bulged diameter and the density were measured for each of the deformed compacts.

III. Genetic Programming

GP is better than a random search process. The symbolic regression function may be just too complicated to have been figured out by human trial and error functions. We might as well consider using Microsoft Excel 2003 with its data analysis Add-In. The problem is that such software and other specialised software merely fit in the co-efficient for a pre-determined polynomial or transcendental function. Symbolic regression is the process of discovering both the functional form of a target function and all of its necessary coefficient, or at least an approximation to these. This is distinct from other forms of regression such as polynomial regression in which you are merely trying to find the coefficients of a polynomial of a pre specified order. GP is one of the most useful, general purpose problem solving techniques available to developers. It has been used to solve a wide range of problems, such as symbolic regression, data mining, optimization, and emergent behaviour in biological communities. GP is one instance of the class of techniques called evolutionary algorithms, which are based on insights from the study of natural selection and evolution [4]. Living things are extraordinarily complex; far more so than even the most advanced systems designed by humans. Evolutionary algorithms solve problems not by explicit design and analysis, but by a process akin to natural selection. An evolutionary algorithm solves a problem by first generating a large number of random problem solvers (programs). Each problem solver is executed and rated according to a fitness metric defined by the developer. In the same way that evolution in nature results from natural selection, an evolutionary algorithm selects the best problem solvers in each generation and breeds them [5,6].

IV. Methodology of GP

Data sets from the experiments were taken for the analysis. Material properties for the variation of iron composition from 0-8%, density ratio from 0.82-0.96 and aspect ratio of 0.25, 0.50, 0.75 and 1.00 were taken. The data samples were randomized manually using Microsoft Excel software. The randomized data sets were fed into the software by initially splitting them into three sets viz., training, validation and applied testing [7]. DISCIPULUS™ self configures itself to accept the last column always as the expected output. Trial runs to find out the best parameters that generated optimal solution in the minimum possible time. Initially the runs were performed with the default settings. One by one the parameters such as population size, crossover rate, DSS sub set size, and FPU registers used were varied to find optimum values [7]. The trials showed the following results. Population size of 800 was optimum rather than the default setting of 500. A higher crossover rate {75% non-homologous and 25% homologous} was found to be optimum. A smaller DSS subset size {60} was more optimal than the default 100. The above factors favourably affected result generation.

IV.1.1. Regression

Regression analysis is any statistical method where the mean of one or more random variables is predicted based on other measured random variables. Symbolic regression is the process of discovering both the functional form of a target function and all of its necessary coefficients, or at least an approximation to these.

IV.1.2. Fitness Measurement

Fitness is nothing but how far the data value predicted by the GP coincides with the experimental value

IV.1.3. Correlation Coefficient, r/R

The quantity r, called the linear correlation coefficient, measures the strength and the direction of a linear relationship between two variables. The mathematical formula for computing r is

$$r = \frac{n\sum xy - (\sum x)(\sum y)}{\sqrt{n(\sum x^2) - (\sum x)^2}\sqrt{n(\sum y^2) - (\sum y)^2}} \qquad (1)$$

Where n is the number of pairs of data.

The value of r is such that $-1 < r < +1$. The + and – signs are used for positive linear correlations and negative linear correlations, respectively. If x and y have a strong positive linear correlation, r is close to +1. An r value of exactly +1 indicates a perfect positive fit. Positive values indicate a relationship between x and y such that as values for x increase, values for y also increase. . If x and y have a strong positive linear correlation, r is close to -1. An r value of exactly -1 indicates a perfect negative fit. Negative values indicate a relationship between x and y such that as values for x increase, values for y also decrease. If there is no linear correlation or a weak linear correlation, r is close to 0. A value near zero means that there is a random, nonlinear relationship between the two variables. The square of the correlation coefficient gives the coefficient of determination. The coefficient of determination, r^2, is useful because it gives the proportion of the variance (fluctuation) of one variable that is predictable from the other variable. It is a measure that allows us to determine how certain one can be in making predictions from a certain model/graph. The coefficient of determination is the ratio of the explained variation to the total variation [8, 9]. The coefficient of determination is such that $0< r^2 < 1$, and denotes the strength of the linear association between x and y. The coefficient of determination represents the percent of the data that is the closest to the line of best fit. If r =0.922, then r^2 =0.850, which means that 85% of the total variation in y can be explained by the linear relationship between x and y. the other 15% of the variation in y remains unexplained.

IV.1.4. Parameters in GP

Table 1: Various parameters used in GP

Terminal Set	T={X, Random-Constants}
Functional Set	F={+,-,*,%,sqrt} Note: The protected division function % returns a value of 1 when division by 0 is attempted
Fitness	The square root of the sum of the square of absolute value of the differences (errors), between the program's output and the observed data.
Termination	An individual emerges whose sum of absolute errors is less than specified Required number of runs are completed Required Correlation Coefficient is obtained
Parameters	Population Size Homologous Crossover Rate Mutation Rate DSS Subset Size

V. Results and Discussion

In Genetic programming modelling, it is necessary to select suitable terminal from set *F* and available terminal genes from set *f (0)* [10,11]. From these, the evolutionary process will try to build as fit an organism (i.e. mathematical model) as possible for material characteristics prediction. The organisms consist of both terminal and function genes, having the nature of computer programs which differ in form and size [12, 13]. Three independent data sets were obtained on the basis of measurement: training, validation, applied data sets. Load, Density ratio, Aspect ratio and the percentage of iron were used as independent input variables and the hoop strain as dependent output variable. On the basis of training data set, different models for hoop strain were developed by the genetic programming [14, 15, and 16]. Using GP simulation, the best mathematical model for hoop strain is given by,

$$\textbf{Hoop strain} = V_0\,[(B_0\,V_1^2+0.02857)*(0.0377*V_0)]^2 \qquad (2)$$

Where,

$\mathbf{B_0} = [(\mathbf{A_0}+0.02857)*(-0.0133*\mathbf{V_0})] + 0.02857$; $\mathbf{A_0} = -\,0.8732\,V_2\,\mathbf{(}0.053113 - 0.003649\,V_3\mathbf{)^2}$

And, $\mathbf{V_0}$= Load (in KN); $\mathbf{V_1}$= Density Ratio; $\mathbf{V_2}$= Aspect Ratio; $\mathbf{V_3}$= %Fe

Table 1: Comparison between experimental and predicted values of hoop strain

Load(V_0) (in KN)	Density Ratio(V_1)	Aspect Ratio(V_2)	% Fe(V_3)	Hoopstrain (Exp. Output)	Hoopstrain (GP Output)	Error %
70	0.9	1	8	0.47	0.45	0.05
60	0.9	0.5	6	0.34	0.33	0.03
60	0.97	0.75	0	0.39	0.38	0.02
45	0.9	1	4	0.2	0.21	-0.03
10	0.91	0.5	0	0	0.00	0.00
40	0.95	0.5	0	0.15	0.16	-0.07
61	0.91	1	4	0.38	0.38	0.01
40	0.95	0.75	0	0.17	0.17	0.01
45	0.95	0.5	2	0.19	0.20	-0.06

15	0.91	1	2	0.01	0.01	0.16
80	0.93	0.5	4	0.51	0.54	-0.07
85	0.98	0.75	0	0.66	0.64	0.04
60	0.97	0.75	0	0.37	0.38	-0.03
20.5	0.87	1	8	0.02	0.02	0.08
75	0.98	0.75	0	0.56	0.54	0.03
70	0.97	0.5	0	0.45	0.47	-0.05
50	0.89	0.5	8	0.21	0.22	-0.06
20	0.85	0.5	6	0.02	0.02	0.23
20	0.85	0.75	8	0.01	0.01	-0.50
60	0.97	1	0	0.4	0.39	0.02
20	0.87	1	4	0.02	0.02	-0.13
70	0.99	0.75	0	0.48	0.49	-0.02
70	0.92	1	4	0.47	0.47	-0.01
40	0.9	0.75	4	0.13	0.15	-0.17
40	0.95	0.75	0	0.17	0.17	0.01
45	0.9	1	4	0.22	0.21	0.07
70	0.92	0.5	4	0.45	0.44	0.01
45	0.92	0.5	2	0.19	0.20	-0.05
85	0.97	0.75	0	0.66	0.63	0.04
40	0.9	0.5	4	0.14	0.14	-0.03
80	0.98	0.5	0	0.55	0.57	-0.04
40	0.94	0.75	0	0.18	0.17	0.06
60	0.97	0.75	0	0.39	0.38	0.02
40	0.88	1	4	0.15	0.16	-0.04
25.5	0.85	1	6	0.04	0.04	-0.11
90	0.9	0.5	6	0.61	0.62	-0.01
45	0.91	0.75	4	0.19	0.20	-0.05
10	0.89	0.75	4	0	0.00	0.00
50	0.93	0.5	2	0.26	0.25	0.03
50	0.9	1	8	0.23	0.24	-0.05
110	0.88	0.5	8	0.72	0.72	0.00

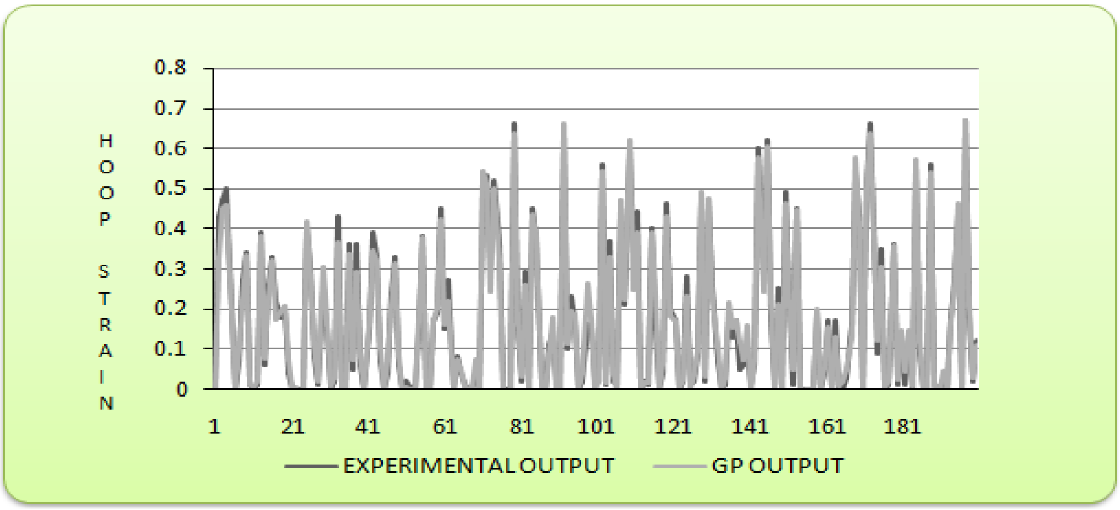

Fig I: Experimental output vs. GP output

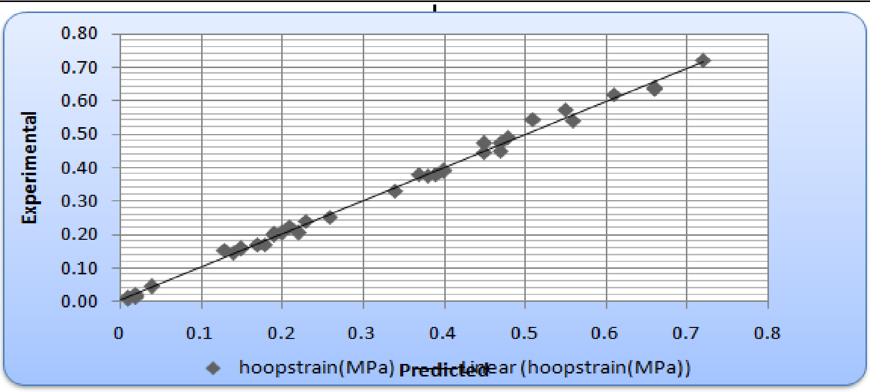

Fig II: The relationship between experimental and predicted hoop strain

VI. Conclusion

Using the above computational model we will predict the material properties for various iron composition by simple substitution without conducting any experiments.Genetic programming (GP) has proved to be a highly versatile and useful tool for identifying relationships in data for which a more precise theoretical construct is unavailable [17,18]. The experimental data in this research were in fact the environment to which the population of models had to be adapted as much as possible. The models presented are a result of the self-organization and stochastic processes taking place during simulated evolution. The accuracies of solutions obtained by *GP* depend on applied evolutionary parameters and also on the number of measurements and the accuracy of measurement. In general, more measurements supply more information to evolution which improves the structures of models. In the proposed concept the mathematical models for verifying the experimental results of mechanical characteristics are subject to adaptation. Its reliability is about 99.26%. In the testing phase, the genetically produced model gives the same result as actually found out during the experiment, thereby with the reliability of cent percent. It is inferred from our research findings that the genetic programming approach could be well used for the prediction of mechanical characteristics of sintered aluminium iron composites without conducting the experiments. This helps to establish efficient planning and optimizing of process for the quality production of composite materials depending upon the functional requirements.

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