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Study on Process Parameters of Centrifugal Cast Al17 wt% Si and Predicting the Mechanical and Tribological Properties using Machine Learning Algorithms

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Abstract

Aluminum alloys are the most widely utilized metal in today's world for manufacturing all industrial applications that demand lightweight characteristics as well as mechanical and tribological capabilities. As a requirement for obtaining quality products, it is critical that the manufacturing process is also optimized. As a replace to the conventional methods of manufacturing, this article presents the development of machine learning (ML) models for Al-17wt% Si taking into account process parameters such as different teeming temperatures and rotation speeds of molds. In addition, the properties of hardness and wear are taken into account in the construction of the data base and the models are formed for the same. In this work, machine learning techniques such as Linear Regression (LR) and Artificial Neural Networks (ANN) algorithms are used to predict tensile and wear properties. ANN and LR models show similar results, but ANN can handle many more complexities, making the model reliable. This method of predicting the properties will lead to the definition of the optimized process parameters, minimizing the efforts on conventional manufacturing and testing processes.

Keywords: *Al17wt%Si, Mechanical properties, Tribological properties, Prediction models, Machine learning algorithm.*

1.0 Introduction

In recent years machine learning techniques has been evolved with all possible applications. In the early days, it was assumed that these types of program-based models or predictions should be restricted to a few engineering fields or specific fields. But these kinds of newer materials will have an impact on developing the process for manufacturing and followed by much experimentation for optimization which will be based time which is an indefinable parameter. In this type of scenario, program-based models play a significant role in

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predicting required parameters and characteristics in the field of materials science.

The research focuses on the horizontal centrifugal casting process, which can be used to create a wear-resistant material with high strength. A heterogeneous micro structured material with a high-volume proportion of hard particles scattered on the inner surface, where better wear qualities are required, and a gradually decreasing lower volume fraction of hard particles on the outer surface, where better wear properties are required. Hence, focuses are on the preparation of cylinder liners for Al-17wt% Si utilizing centrifugal casting. Microstructure, hardness, tensile strength, and wear are all characteristics of these cylinder liners.

In this work the author has approached to study the behaviour of aluminum alloys with different reinforcement and their strength properties with the help of machine learning techniques like LR, ANN and KNN and predicting the performance of the same, in which ANN shows a better result than other models[1].

Ultimate tensile strength (UTS) being another significant mechanical property in foundry technology[2] supports the same argument of ML models in predicting mechanical properties during the production process. Hence, ANN and K-Nearest-Neighbour algorithms are used for predictions and a Bayesian-based approach was developed for the same ones.

Artificial Intelligence (AI)-ML based approach is also seen in welding technology where AI algorithms are used for analysis in mechanical property in Friction Stir Welded Joints using python programming, in which ANN and regression models like Decision Trees was selected for predicting ultimate tensile strength. The ANN algorithm gives a better and more accurate result than the decision tree regression algorithm[3].

The use of artificial neural networks in conjunction with big data availability to describe the plastic behaviour of aluminium alloys[4] is based on the features of numerous commercially relevant materials. Furthermore, an artificial neural network is used to train a database of materials to produce predictions with a confidence level of greater than 95%. It’s also clear that the approach achieves a higher value of outcome, comparable to empirical equations for a certain material; as a result, it gives a better picture since it can approximate the attributes of any aluminium alloy. For optimal application in the design of structures and components, the ability to accurately forecast the characteristics of a given metal is the study made with aluminium alloys[5].

Artificial Neural Network (ANN) is utilised for prediction and analysis of mechanical characteristics for A413 aluminium alloy made by squeeze casting technique along the line of thought process towards machine learning. A secondary goal of this study is to conduct a quantitative and statistical analysis to assess the influence on mechanical characteristics due to parameters that are submitted during casting[6]. Machine-learning-assisted prediction of the mechanical properties of Cu-Al alloys[7,8] investigated the machine-learning method to predict the mechanical performance of Cu-Al alloys manufactured using the powder metallurgy technique to increase the rate of production, improve the characterization of new materials, and provide insights into their properties. Six fundamental methods using chemical composition and porosity as descriptors are used to estimate the performance of composites. In this paper, an effort is made to prepare Al-17wt% Si hollow cylinder castings using a horizontal centrifugal casting process with teeming temperature and rpm as variables. The castings are then tested, and ML models are used to predict mechanical properties by building a database based on varying teeming temperature and mould rotational speeds. Hollow cylinders are cast at 650°C, 750°C, and 850°C, respectively, with mould rotating rates of 400, 600 and 800 rpm. In all, 9 castings were created for each teeming temperature and rpm stated, and two sets of casting samples, totaling 18 samples, were generated for stable comparison. Each casting was subjected to the creation of a specimens for mechanical testing.

In addition, hardness is measured at various points along the thickness of the cylinder (ID, MID, and OD), as well as tensile and wear properties, by preparing tensile specimens along the length of the cylinder according to ASTM E8 standards and wear specimens according to ASTMG99 standards, respectively. Sample data is generated with series of test as shown in Table 1

Table 1: Sample dataset

RPM	Temp	H-ID	H-MD	H-OD	Tensile	Wear
400	650	30	22	28	135	12
600	650	33	32	27	146	10
800	650	36	33	31	160	6
400	750	45	42	31	158	9
600	750	50	46	38	175	8
800	750	54	52	28	180	7
400	850	58	56	30	185	8
600	850	64	61	28	197	7
800	850	68	66	26	208	6

In this work, LR and ANN machine learning algorithms are used to forecast mechanical characteristics for the stated aluminum alloy, utilising teeming temperature and mould rotation rates as inputs, as shown in Fig.1.

2.0 Problem Description

In industries, establishing the optimized process of manufacturing with state-of-the-art technologies is the new

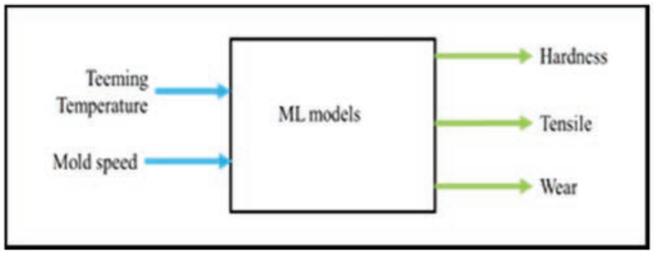

Figure 1: ML model for mechanical properties prediction

trend. As a result, R&D organisations take the lead in developing strategies to overcome the challenges of trial-and-error approaches. As a result, modern approaches like AI-ML might be used to define material composition, process parameters, rejection rates, time optimization, and many other things. Therefore, in this study, machine learning models are used to predict the mechanical and tribological properties of horizontal centrifugal castings made with Al-17wt per cent Si. Studied by by Bonollo referred to cylinder liner matrix[9]

The goal of this research is to address the aforementioned issues while also bolstering current trends by:

1. Developing machine learning models to predict mechanical and tribological qualities based on process input factors
2. Extending the research to include other materials and using machine learning algorithms to discover a solution for application-based property prediction.
3. To use ML models to handle material science in a time efficient manner utilising a technology neutral approach.

2.1 Methodology

The methodology of the study is explained using flowchart as shown in the Fig.2, which consists of two major steps and its listed below.

1. Casting and Characterization
2. Machine Learning models and validation

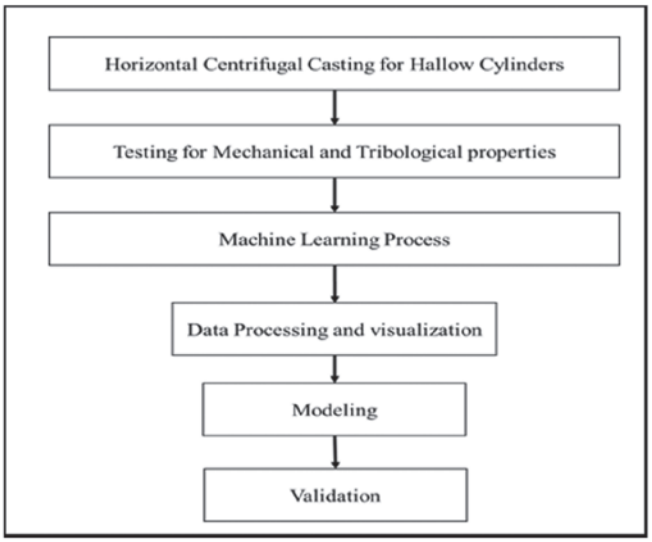

Figure 2: Flow chart for methodology of the work

2.2 Casting and Characterization

In this work, Al-17wt% Si is obtained as a raw material in the form of ingots and processed with a horizontal centrifugal casting machine to build hollow cylinders as illustrated in Fig.3. Castings require two important factors, such as teeming temperature and rotating speed. Same as studied in characterization of Al-17wt% Si paper in[10].

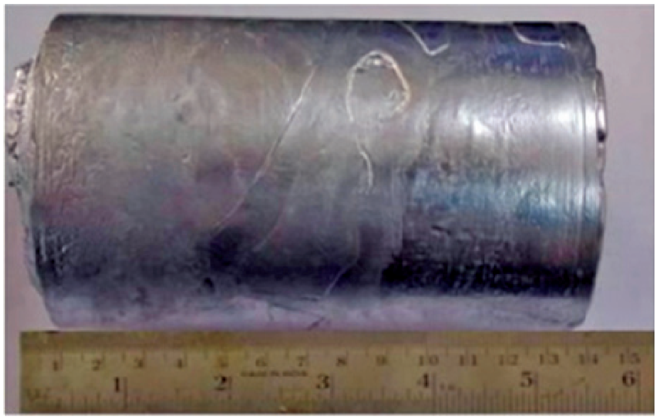

Figure 3: Actual Size of the casting

According to the literature review, teeming temperature is defined as a temperature that is just above melting point and ranges from 650°C to 850°C in 100°C increments. To study the consequences of the lowest to maximum change in parameter speed is varied from 400 to 800 rpm. The best teeming temperature is 850°C, since the Si particles are free to travel in the molten state of metal, at 800 rpm the Si particles settle at the inner diameter of the aluminium, which will move towards the outer diameter owing to centrifugal force which helps for better strength along the radius of the liner.

As a result, cast samples were rigorously evaluated for hardness, tensile strength, and wear in this regard. As a consequence, these findings were tabulated in order to create Machine Learning models and estimate their accuracy levels using various test sizes for model validation.

2.3 Machine Learning Models and Validation

Machine learning models and validation will have the mentioned steps below.

Step 1: Data Processing and visualization

Step 2: Modelling and tuning

Step 3: Validation

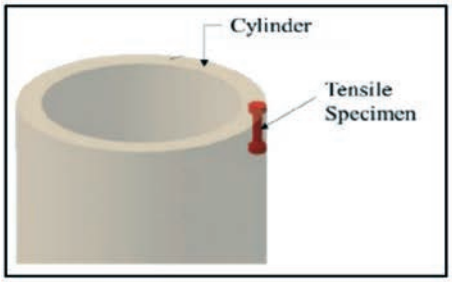

Figure 4: Tensile specimen

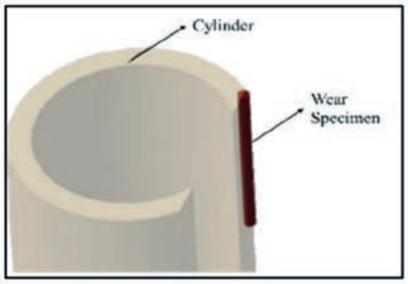

Figure 5: Wear specimen

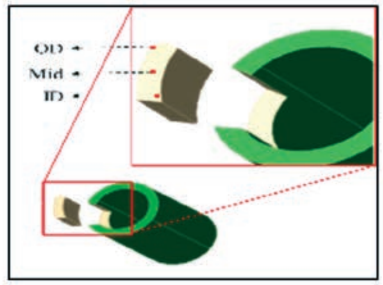

Figure 6: Hardness test specimen

Data Processing and visualization

Data processing is the cornerstone of the Machine Learning process; during the analysis stage, it's critical to do exploratory data analysis and get a bird's eye perspective of the data's patterns. It is also a must to have the data shown before moving on to the next phase. There will be two phases in the data processing process.

Data collection: samples were produced, tested, and tabulated for tensile, hardness and wear samples taken along the length of the cylinders as shown in Figs.4 to 6. Table 2, display the composition of material chosen.

Feature Engineering: Feature engineering is the process of extracting traits, qualities, and attributes from raw data and utilizing them in predictive models to investigate their effects. In this study, ML models are created to forecast the performance of the algorithms by considering specific material, process factors, hardness, tensile, and wear qualities.

Table 2: Composition of material for Al-17Si

Alloy	Composition (wt%)					
	Si	Fe	Sr	Ti	B	Al
Al-Si	17	0.1	-	-	-	Balance

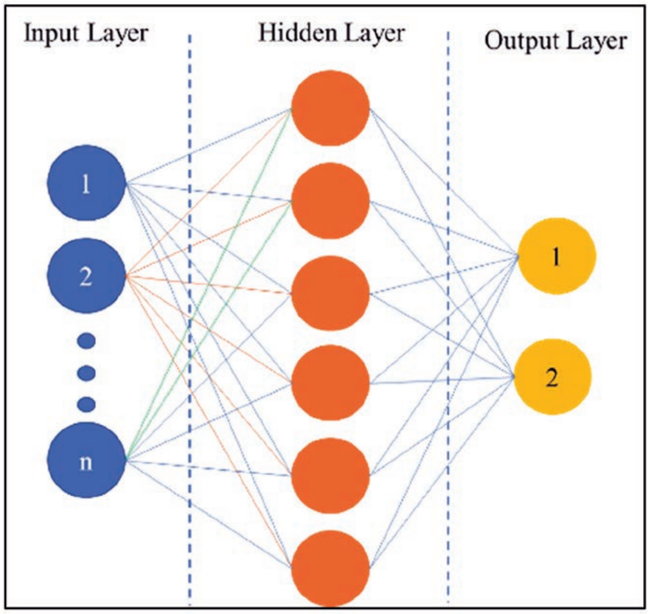

Figure 7: Schematic of ANN model

2.4 Modelling and Tuning

After the data has been pre-processed, the analysis phase is followed by modelling and tweaking. Coding methods, selecting train and test data sizes, training the data set, testing the data set for small size, and lastly determining the model's correctness are the primary phases involved in modelling.

Linear regression is a supervised learning-based machine learning technique. Forecasting and analyzing the relationship between the variables and their relevance in the composites are done using regression models. An artificial neural network, also known as a neural network learning algorithm, is a computer learning system in which the input data is understood and translated into the intended output as illustrated in Fig.7.

2.5 Validation of model

The input data is separated into a size of high entries train data and lower entries of test data during validation.

LR stands for supervised learning, and ANN stands for a network-based method for model prediction. Data may be validated by accuracy levels using these two methods, and predictions can be more accurate. This will also enable for agree upon for any other models for validations.

3.0 Results and Discussions

The current research focuses on the construction of machine learning models based on process factors such as teeming temperature and mold rotating speed, with the goals of hardness (ID, Mid, OD), tensile, and wear as inputs. In Jupyter Notebook with python3, the given input parameters and targets are trained using LR and ANN algorithms. RMSE (Root Mean Square Error) plots, which illustrate the

Table 3: Co-relation Matrix

	A	B	C	D	E	F	G
A	1	0.43	0.23	0.30	0.35	0.82	0.39
B	0.43	1	0.96	0.94	0.55	0.89	0.57
C	0.23	0.96	1	0.99	0.43	0.96	0.65
D	0.30	0.94	0.99	1	0.42	0.97	0.63
E	0.35	0.55	0.43	0.42	1	0.84	0.43
F	0.82	0.89	0.96	0.97	0.84	1	0.60
G	0.39	0.57	0.65	0.63	0.43	0.60	1

distribution of data points focused along the line of best fit, are used to assess the model's correctness. As a result, the model's accuracy is demonstrated using varying training data. In addition, the R-Squared score is a critical indicator for assessing the success of a regression-based machine learning model. The R-Squared number explains the model's accuracy. If the model is good, the R-squared score is one (1). If the model is bad, the R-squared score is zero (0). The data is prepared in a stereo and schematic method for the ML models approach, where the prepared samples are tested and tabulated for three temperatures and three rpm. As a result, there are nine different cylinder combinations. Similarly, 15 sets of data were created for this method, and the accuracy was compared to the percentage of trained data. The best approach for defining the link between the parameters is to look at a correlation matrix. This matrix clearly indicates a relationship level that is heading towards one (1) and can provide a bird's eye perspective of correlation across parameters. There will be the least relationship across if it is negative or zero (0), as illustrated in Table 3. RPM and teeming temperature have a favourable impact on the characteristics.

A: RPM, B: Temp, C: H-ID, D: H-MD, E: H-OD, F: Tensile, G: Wear

The correlation matrix helps us understand the relationship between mechanical and tribological properties by defining the hardness at ID and wear, with 0.65 defining the highest correlation where the Si particles are deposited the most. Similarly, tensile to wear has a value of 0.60, temperature has a value of 0.5, and rpm has a value of 0.39. It is obvious that the hardness is substantially connected with the wear characteristics.

3.1 Hardness Prediction

Both algorithms, LR and ANN, are applied to the data set with the sole purpose of predicting hardness at ID. Because this is a cylinder liner application, it necessitates a higher level of hardness on the inner surface as well as the deposition of Si particles to decrease wear. As a result, the prediction model is based solely on ID. However, data from OD and Mid is utilised to train the dataset. As shown in Fig.8, ANN has an accuracy level of 0.92 and a superior RMSE score of 16.16, indicating that the ANN model has greater accuracy levels. As shown in Table 3, the R-Squared and RMSE values of the LR model are likewise comparable.

3.2 Tensile Strength Prediction

It was discovered that ANN holds up well in tensile data prediction, with a lower RMSE score of 35.64 and a higher R-Squared value of 0.94. This depicts model behaviour, and tweaking the model aids in anticipating the values of the needed properties in relation to the intended anticipations. This also shows that RPM and teeming temperature have an impact on tensile characteristics.

3.3 Wear Strength Prediction

Because wear is a tribological feature of a material, the ANN model outperforms the LR model, with an R-Squared data of 0.89 and an RMSE of 5.86. The lower the RMSE score, the better the model, since the distribution of residuals around the best fit line narrows. This demonstrates that when the percentage of train data grows, the model's accuracy grows as well, indicating that the prediction model's dependability grows.

The input variables have a stronger impact on the model's prediction and performance. Table 4 shows a performance tabulation of the same.

Table 4: Performance Tabulation

		R-Square	RMSE
Hardness	LR	0.88	25.21
	ANN	0.92	16.16
Tensile	LR	0.91	39.64
	ANN	0.94	35.64
Wear	LR	0.85	9.64
	ANN	0.89	5.86

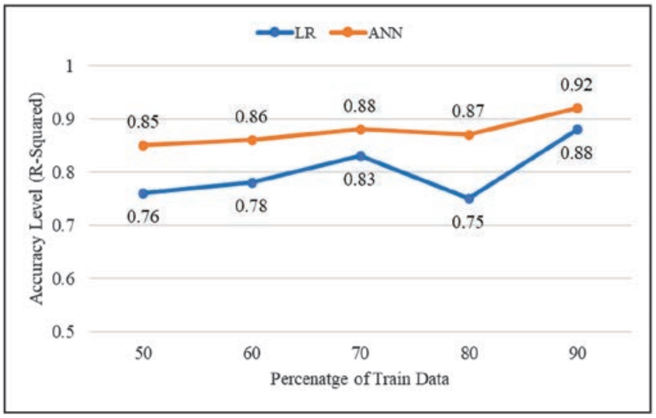

Figure 8: ML models for Hardness prediction accuracy

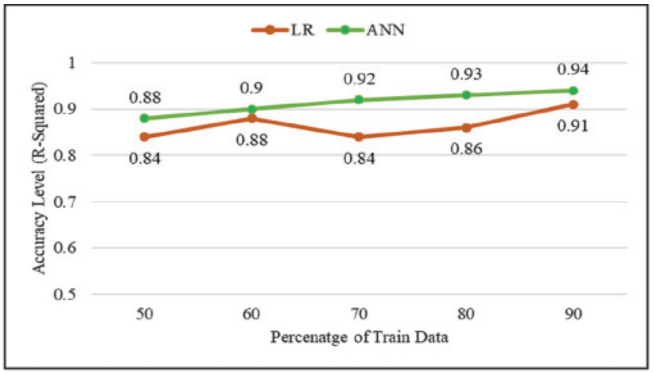

Figure 9: ML models for tensile prediction accuracy

Figure 10: ML models for wear Prediction accuracy

4.0 Conclusion

In this research, an attempt is made to develop ML models in order to investigate the impact of input process parameters on mechanical and tribological features in horizontal centrifugal casting with aluminum alloy Al-17wt% Si. LR and ANN models were used to forecast the influence of tempering temperatures of 650°C, 750°C, and 850°C on hardness, tensile, and wear characteristics of an aluminium alloy with tempering temperatures of 650°C, 750°C, and 850°C with mould rotation speeds of 400,600,800 RPM. The correlation matrix depicts the impact of input process factors on the expected mechanical and tribological qualities of the final product. Positive numbers and values that trend towards one (1) have a stronger effect, as seen by the findings. Models are trained by expanding the training dataset from 50% to 90%; this has a good impact on machine learning models, which have a tendency to provide correct results. In all three instances, ANN achieves superior outcomes, indicating that the R-Squared value is trending towards one (1) and the RMSE score is lower in comparison, which is a measure of residual data distribution and data concentration around the best fit line. The data point with a lower RMSE score is closer to the best fit line.

5.0 Scope for Future Work and Limitation

1. The investigation of dynamic qualities such as fatigue strength and vibration analysis can be considered as a part of future study. Depending on the applications, the percentage of Si optimization can be chosen.
2. This model also expands the scope of research and optimization of the scientific approach to different combinations of alloy. With extended research and support of data science, characterises of casting can be predicted when nano materials are included.
3. To obtain the practical test results and data set generation relevant to application are challenging.
4. Test samples prepared for mechanical and tribological examinations may contain casting defects which may lead to incorrect dataset with low accuracy levels and predictions.

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