

Exploring the Relationship Between Tensile Strength and Alloy Composition

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Abstract: Aluminium alloys are used in a variety of applications and their tensile strength is a key property in determining their suitability for various engineering applications. Understanding the factors affecting tensile strength can help in designing more efficient alloys. In this study, a linear regression model is used to predict the tensile strength of aluminium alloys based on their chemical composition and processing conditions. A large number of different types of aluminium alloys were used in the experiments while two algorithmic linear regression models were developed and the model with accurate predictions was used as the result. The models reveal significant predictors between alloying elements and processing parameters, thus providing insights into optimising alloy properties and providing directions for future research. The final linear regression model developed experimentally successfully predicted the properties of aluminium alloys. The results of the study show that different compositional contents and processing temperatures in aluminium alloys also affect the tensile strength. This model found that different metal contents in different aluminium alloys and processing temperatures affect the tensile properties of the final alloy.

Keywords: Aluminium alloys, tensile strength, linear regression model

1. Introduction

Aluminium alloys have a wide range of applications in many fields such as aerospace, automotive and construction due to their excellent physical, chemical and mechanical properties. At the same time, aluminium alloys are ideal for many engineering and experimental purposes due to their low density, high strength and excellent corrosion resistance. Tensile strength is one of the very important mechanical properties of aluminium alloys, which directly affects their application performance and safety. Therefore, accurate prediction of the tensile strength of aluminium alloys is important for material design and application.

Aluminium alloys are divided into 1000 series, 2000 series and other kinds of aluminium alloys due to their different compositions, of which 35 are chosen in this paper to be used more in daily life and industrial activities. Due to the different processing and trace element ratios, this paper has searched for specific information on these 35 alloys in different websites, journals and papers.

As there are many factors that affect the tensile strength of aluminium alloys including chemical composition, processing temperature, strain rate, defect rate and microstructure of the material. At

the same time this paper chooses two aspects that have a greater influence: chemical composition and processing temperature.

The traditional experimental methods can obtain accurate data, but they are time consuming, labour intensive and costly. In order to improve efficiency, researchers have started to apply various regression prediction models to predict material properties. Among them, linear regression model has become a common method to predict material properties because of its simplicity and efficiency. At the same time, the existing research in building models to summarise and generalise the existing alloys, it is difficult to predict the properties of new alloys.

To provide an effective method for the prediction of the tensile strength of aluminum alloys, linear regression model is used to analyse the effects of composition, processing temperature and other factors on the tensile strength of aluminium alloys, and to verify the validity of the regression model. The regression coefficients of the model can be used to quantitatively assess the influence of each factor on the tensile strength, which can further provide a scientific basis for the design and optimisation of aluminium alloy materials.

2. Literature review

The tensile strength of aluminium alloys is a very important part of materials science and is influenced by alloy composition, microstructure and processing. The StaCast project in Europe has shown that optimising the microstructure through tool design and process management can effectively improve the properties of aluminium-silicon alloys beyond the standards of conventional processes. It is also vital to understand the effect of alloy composition on the ultimate tensile strength (UTS), which is further investigated through the 7000 series of alloys. Machine learning (ML) is becoming a key tool for alloy property exploration, which can simplify the prediction of important properties such as tensile strength.[1][2]

3. Methods

3.1. Data Collection and Preprocessing

The data for this study was collected from various sources including online databases and journals such as MatWeb, Material Properties, Aluminium and Aluminium Alloys. After thorough collation and analysis, a dataset has been compiled in this paper that includes the chemical composition, processing conditions and tensile strength of 35 different series of aluminium alloys. According to Table 1, The dataset contains some key variables such as percentage composition of key metals like aluminium, magnesium, copper, silicon, iron, manganese and zinc. In addition, the processing temperatures associated with these alloys were recorded and analysed in this dataset. Lastly, this dataset also records the tensile strengths of the various alloys to expedite the subsequent steps.

Table 1: of Aluminium alloy content, processing temperature and tensile strength of each model

Alloy Type	Aluminium(%)	Magnesium(%)	Copper(%)	Silicon(%)	Iron (metal)(%)	Manganese(%)	Zinc(%)	Processing temperature(°C)	Tensile strength(MPa)
1050	99.5	0.05	0.05	0.25	0.4	0.05	0.05	350	70-100
1060	99.6	0.05	0.05	0.3	0.35	0.05	0.05	350	75-110
1070	99.7	0.03	0.04	0.2	0.25	0.03	0.04	350	70-120
1100	99	0.03	0.125	0.2	0.35	0.03	0.1	350	70-120
1200	99	0.05	0.05	0.2	0.05	0.05	0.1	350	70-121
2024	92.7	1.5	4.35	0.5	0.50	0.6	0.25	492.5	450-530
2014	90.25	0.5	4.45	0.85	0.50	0.8	0.25	492.5	455-515
2219	92.5	0.02	6.3	0.2	0.30	0.3	0.1	520	470-540
2017	92.5	0.6	4	0.5	0.70	0.7	0.25	492.5	440-490
2036	92.5	0.675	4.6	0.5	0.5	0.6	0.25	492.5	440-490
3003	97.85	0.05	0.05	0.6	0.7	1.25	0.1	375	110-170
3105	96.9	0.5	0.3	0.60	0.7	0.55	0.4	375	120-185
3004	96.8	1.05	0.25	0.3	0.7	1.25	0.25	375	120-180
3005	96.6	0.5	0.3	0.6	0.7	1.25	0.4	375	120-185

Table 1: (continued).

3104	96.8	1.05	0.2	0.6	0.7	1.05	0.4	425	120-180
4032	85	1.05	0.75	12.25	1	0.1	0.25	425	315-380
4045	88.75	0.05	0.3	11.25	0.8	0.05	0.1	425	250-310
4145	88.5	0.05	3.5	10	0.8	0.1	0.1	425	300-360
4047	89	0.1	0.3	12	0.8	0.1	0.2	425	270-330
4035	86	0.9	0.75	11	0.8	0.05	0.25	425	300-370
5052	95.6	2.5	0.1	0.25	0.4	0.1	0.1	355	190-260
5083	93.25	4.45	0.1	0.4	0.4	0.7	0.25	355	275-350
5754	95.8	3.1	0.1	0.4	0.4	3.1	0.2	355	190-270
5454	96.3	2.7	0.1	0.25	0.4	0.75	0.25	355	210-280
5056	95.8	5.5	0.1	0.3	0.4	0.125	0.1	355	250-315
6061	97.9	1	0.275	0.6	0.7	0.15	0.25	540	260-310
6082	94.7	0.9	0.1	1	0.5	0.55	0.25	540	300-350
6063	97.9	0.675	0.1	0.4	0.35	0.1	0.1	515	160-210
6005A	97.9	0.75	0.1	0.75	0.5	0.55	0.25	540	200-250
6101	97.9	0.75	0.1	0.55	0.35	0.1	0.35	515	150-200
7075	89.25	2.5	1.6	0.4	0.5	0.3	5.6	475	510-590
7050	89.3	3.25	2.3	0.12	0.15	0.1	6.2	470	510-590
7020	95.7	1.2	0.2	0.3	0.35	0.3	4.5	482.5	380-480
7072	99.4	0.1	0.1	0.08	0.1	0.01	1.05	375	220-270
7010	88.7	2.4	2	0.12	0.15	0.1	6.3	482.5	500-580

The first step is initial data preprocessing, which consists of processing the range values and converting them to mean values. For example, an alloy with a magnesium content range of 1.2-1.8 per cent was expressed as an average value of 1.5 per cent. In the graphs, data preprocessing and averaging were performed for different metal contents and processing temperatures (this table is after data preprocessing). In order to ensure the accuracy of the experiments, the tensile strengths have not been converted to average values. In this way, in the subsequent process, in order to facilitate the establishment of linear regression model and linear regression calculation, and simplify the operation of the code.

3.2. Linear Regression Model

Linear regression models are simple, efficient, and highly accurate. So I choose the linear regression model for the next step of model building.[3]

A multivariate linear regression model was developed to predict the tensile strength of aluminium alloys using the following predictors: percentage of Aluminium, Magnesium, Copper, Silicon, Iron, Manganese, Zinc, and processing temperature.[3] The mathematical expression of the model is

$$\text{TensileStrength} = \beta_0 + \beta_1(\text{Aluminum}) + \beta_2(\text{Magnesium}) + \beta_3(\text{Copper}) + \beta_4(\text{Silicon}) + \beta_5(\text{Iron}) + \beta_6(\text{Manganese}) + \beta_7(\text{Zinc}) + \beta_8(\text{ProcessingTemperature})$$

Formulas 2 of Linear regression equation

In addition, R^2 (coefficient of determination) was calculated, which represents the percentage of variation in the target variable (in this case tensile strength) that can be explained by the model, and the closer R^2 is to 1, the higher the predictive power and reliability of the model. the mathematical expression for R^2 is

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}$$

4. Results and discussion

Table 2 shows that the linear regression model's final R-value is 0.80, meaning that the model predictors account for 80% of the variation in tensile strength[4] This high R^2 value is very close to 1, which indicates that alloy composition and processing temperature have a significant effect on the tensile strength of aluminium alloys, confirming the validity of the model. At the same time, the mean square error (MSE) of 1102.75 corresponds to a root mean square error (RMSE) of about 33 MPa. Considering that tensile strengths are typically in the range of 100 to 400 MPa, this level of error (approximately 10% of the total error range) is acceptable for material property prediction. This indicates that the model was very successful and provided reasonably reliable predictions.

Intercept (β_0): 926.6684684224529

Table 2: Feature and Coefficient

n	Feature	Coefficient(β_n)
1	Aluminium (%)	-10.293616
2	Magnesium (%)	22.655196
3	Copper (%)	39.158482
4	Silicon (%)	0.294549
5	Iron (%)	-27.017101
6	Manganese (%)	2.145949
7	Zinc (%)	23.527363
8	Processing Temp (°C)	0.596080

4.1. Relationship between composition and tensile strength

From the analysis, it can be seen that for every 1% increase in aluminium content, the tensile strength of the alloy decreases by about 10 MPa. On the contrary, for every 1 per cent increase in magnesium content, the tensile strength increases by about 22 MPa. Similarly, for every 1% increase in copper, silicon, manganese and zinc content, the tensile strength increases by about 39 MPa, 0.3 MPa, 2 MPa and 23 MPa, respectively. On the other hand, according to the linear regression model, the tensile strength decreases by about 27 MPa for every 1 per cent increase in iron content. In contrast, copper, iron, magnesium and zinc came to have the greatest effect on the tensile strength, while silicon and manganese had a lower relevance for the tensile strength of the alloys. Future studies should focus on the impact of the more influential metal components on tensile strength.

4.2. Effect of processing temperature

For every 100°C increase in processing temperature, the tensile strength of the alloy increases by about 59 MPa, which indicates that temperature plays an important role in increasing the strength of the material.

Finally, based on the results of the linear regression, the tensile strength of aluminium alloys can be predicted more accurately on the basis of alloy composition and processing temperature, which will help in the subsequent study of the properties of aluminium alloys, and a better understanding of the influence of each component on aluminium alloys.

4.3. Prediction of tensile strength

Figure 1 represents the predicted tensile strength, the X-axis represents the actual data, the Y-axis represents the predicted data, the red dotted line represents the actual and predicted values being equal,

and the blue dots are the predicted data values. The image shows that the predicted data values are basically around the red line, indicating the feasibility and success of the modelling

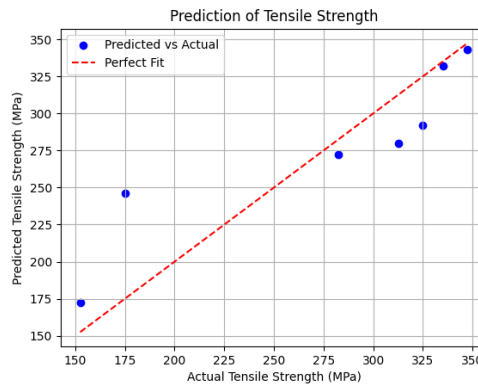


Figure 1: Actual Tensile Strength vs. Predicted Tensile Strength

Although the linear regression model constructed in this paper can effectively predict the tensile strength of aluminium alloys, it still has some limitations. This is due to the fact that this study solely concentrates on the composition of the alloy and the temperature at which it is processed, neglecting other factors that also influence tensile strength. In industry for example strain rate, defect density, cooling rate and microstructural features (e.g. grain size, precipitation distribution) also affect tensile strength but were not included in the model in this simulation. Consideration of these variables would have been effective in improving the accuracy of the predictions and would have provided more comprehensive data for future studies. This dataset includes only 35 aluminium alloys and is not representative of aluminium alloys used in industrial, domestic and experimental applications. A larger and more diverse dataset for this simulation would allow the model to be better optimised and simulated, and could effectively improve performance on alloys outside of its training set.

Future research could explore additional models for prediction, such as nonlinear regression, neural networks, or hybrid models, which would better capture the relationship between input variables and tensile strength.[5] In contrast to linear regression, these models effectively take into account non-linear effects and interactions of variable rainfall results. It is also possible to add microstructural parameters, such as grain size, phase distribution or dislocation density, to improve the predictive power of the model. Advanced techniques and equipment, such as electron microscopy or X-ray diffraction, are also used to assist the simulation.

5. Conclusion

This study highlights the practicality and validity of using linear regression models to predict the tensile strength of aluminium alloys, which is an important step forward in the field of materials science and engineering. By analysing the data, this paper identifies the composition of different alloying elements (e.g., magnesium, copper and silicon) as well as the processing temperature as the main factors affecting the tensile strength. Models developed on the basis of this research clearly reveal the interactions between these variables, allowing for more accurate prediction of material properties.

The results of this study not only provide insight into the complex relationship between alloy composition and mechanical properties, but also offer valuable insights into the practical application of aluminium alloys. These findings can help to design and optimise alloy compositions to meet specific industrial needs. For example, by adjusting the proportions of certain elements or changing

processing conditions, engineers can increase tensile strength to meet the needs of a wide range of engineering applications, from automotive components to aerospace structures.

In addition, this research highlights the potential to further advance predictive modelling. While linear regression modelling has proven to be a reliable tool for initial analysis, it provides an opportunity to explore more sophisticated machine learning techniques in the future. Techniques such as neural networks, decision trees or clustering methods can capture the more complex non-linear relationships in data to make more accurate and reliable predictions.

At the same time, this study has some limitations, such as using too small a sample, constructing too simple a model, etc.

The importance of this research goes far beyond tensile strength prediction, as contributions from the wider field of materials science pave the way for future research. It also encourages the exploration of advanced computational methods and their application to materials design, ultimately creating stronger, more durable, and more efficient materials.

In conclusion, this study not only validates the application of linear regression in material property prediction, but also lays the foundation for future innovations. It is hoped that as machine learning techniques continue to evolve, they will be able to predict the behaviour of complex materials more accurately, further advancing the design and application of aluminium alloys and other important materials

References

- [1] Pfeiffer, O.P., Liu, H., Montanelli, L. et al. Aluminum alloy compositions and properties extracted from a corpus of scientific manuscripts and US patents. *Sci Data* 9, 128 (2022). <https://doi.org/10.1038/s41597-022-01215-7>
- [2] AR Anilchandra 1,*, Lars Arnberg 2, Franco Bonollo 3, Elena Fiorese 3, Giulio Timelli Evaluating the Tensile Properties of Aluminum Foundry Alloys through Reference Castings—A Review *Materials (Basel)*. 2017 Aug 30;10(9):1011. doi: 10.3390/ma10091011
- [3] Keya Fu,Dexin Zhu,Yuqi Zhang,Cheng Zhang,Xiaodong Wang,Changji Wang,Tao Jiang,Feng Mao,Cheng Zhang,Xiaobo Meng,Hua Yu(2023) Predictive Modeling of Tensile Strength in Aluminum Alloys via Machine Learning.*Materials* 2023, 16(22), 7236
- [4] Mohamed A. Shaheen, Rebecca Presswood, Sheida Afshan Application of Machine Learning to predict the mechanical properties of high strength steel at elevated temperatures based on the chemical composition *Structures* Volume 52, June 2023, <https://doi.org/10.1016/j.istruc.2023.03.085>
- [5] Xincheng Chen, Jingyu Zhong, Huanyue Lin, Xianfeng Ma, Jishen Jiang, Yaojun Li. High precision modeling with stacked neural network to predict the mechanical property of aluminum alloy *Materials Letters* Volume 375, 15 November 2024 <https://doi.org/10.1016/j.matlet.2024.137187>
- [6] Fuse, K., Venkata, P., Reddy, R.M. et al. Machine learning classification approach for predicting tensile strength in aluminium alloy during friction stir welding. *Int J Interact Des Manuf* (2024). <https://doi.org/10.1007/s12008-024-01999-5>
- [7] Lu, Z.; Kapoor, I.; Li, Y.; Liu, Y.; Zeng, X.; Wang, L. Machine learning driven design of high-performance Al alloys. *J. Mater. Inf.* 2024, 4, 19. <http://dx.doi.org/10.20517/jmi.2024.21>