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Prediction of titanium content in alloys for Aircraft applications

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Abstract

Titanium alloys find huge application in the aircraft industry for their excellent strength to weight ratio and corrosion resistance. New alloys developed have to undergo an elaborate process of testing and evaluation, subject to which further research is perceived. Applications of Neural Networks are regaining interest for their versatility on computational feasibility wherein the system is designed to learn from data in a manner emulating the learning pattern in the human brain. An effort has been made in this project to utilize the potent tools like ANN for mechanical property prediction. While, titanium alloy IMI834 is chosen for the project work for its excellent response to the heat treatments the ANN package from MATLAB is chosen for developing the network. The interplay of various parameters on mechanical properties and their interdependencies offer an excellent scope to setup an ANN to predict their behavior. IMI 834 is basically near alpha titanium alloy of medium strength (typically 1050 MPa) and Al, Sn, Zr, Nb, Mo, Si, C, O (Ti-5.8Al-4Sn-3.5Zr-0.7Nb-0.5Mo-0.35Si-0.06C-0.1O) is alloying elements.

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1. TITANIUM ALLOYS:

1.1 Origin & introduction of Titanium Alloys:

Titanium is widely distributed throughout the universe .It has been discovered in the stars. Its concentration within the earth's crust of about 0.6% makes it the fourth most abundant of the structural metals (after Aluminum, iron, and Magnesium)[1] .It is 20 times more than copper, 100 times more than tungsten, and 600 times more than molybdenum . This abundance is to some extent illusory, however, in that, titanium is not so found in economically extractable concentrations .Concentrated sources of the metal are the minerals limonite, titan magnetite, anatine, and brookite. At one time or another practically, all aerospace structures (air frames, skin and Engine components) have benefited from the introduction of titanium. Titanium (titanium and its alloys) has two principle virtues:

1.2 Titanium 834 (IMI 834) Alloy:

1.2.1 Near α Alloy

It is near alpha alloy [1], these alloys contain 1 to 2 wt. % of beta stabilizers, which are added to improve their strength and workability. The alpha phase is predominant in these alloys, which are a good compromise between high-strength α+β alloys and creep resistant alpha alloys. IMI 834 (TI-5.8Al-4Sn-3.5Zr-0.7Nb-0.5Mo-0.35Si-0.06C-0.1O) is the most advanced alloy of this class and of medium strength (typically 1050 MPa) and temperature capability up to 600^{o} C combined with good fatigue resistance. The alloy derives its properties from solid – solution strengthening, and heat treatment high in the α+β phase field. The addition of carbon facilitates treatment by widening the heat treatment window.

This alloy heat treated high in the α+β phase field to achieve 5 to 10 % primaryα, and it offers a good combination of fatigue and creep resistance. The solution treatment that determines the primary alpha volume fraction has an influence on the properties. A study of IMI 834 alloy, heat treated at different temperatures and creep-tested at 220 MPa and 650^{o} C, shows the variation of dimple size with the increase from 22h to 22 h when the solution treatment temperature was increased from 970^{o} C (70 % alpha) to 1080^{o} C (0 % alpha).

LITERATURE SURVEY

A study on the prediction of the mechanical properties of a ceramic tool based on an artificial neural network. Application of Artificial Neural Network for prediction of time-temperature-transformation diagram in titanium alloys. Application of Bayesian ANN for modeling and prediction of ferrite number in austenitic stainless steel welds. Comparison of analysis of two methods for the analysis of composite material Heat treatment techniques optimization for 7175 aluminum alloy by an ANN and Genetic Algorithm. A neural network approach for solution of the inverse problem for selection of powder metallurgy materials. Prediction of Nickel-base Super alloy rheological behavior under hot forging condition using ANN. Parameter identification by neural network for intelligent deep drawing of axi-symmetric work-pieces. Comparison of neural network models on material removal rate in Electric discharge machining. Corrosion prediction in aging aircraft materials using Neural Networks Collected literature related to Titanium alloys, IMI834 ALLOY, Artificial Neural Network (ANNs).

2. EXPERIMENTAL WORK

2.1 Generation and study of Microstructures of IMI 834:

2.1.1 Heat treatment of IMI 834:

Heat treatment for IMI834
Solution treatment 1025°C\2 hrs.\AC
Ageing treatment 700°C\2 hrs.\AC

Different types of heat treatments were carried out with combinations of cooling rate, step heat treatment, ageing temperature to obtain microstructures as per 2.1.1.

Quantification Data for primary alpha:

TABLE 1: Quantification Data for primary alpha

Sl. No.	Heat treatment	Primary alpha size, micro-meter	Std. Dev.	Vol. % of primary alpha
1	1025/2h/OQ	18.57	12.80	18.76
2	1025/10h/OQ	20.99	15.58	19.42
3	1025/24h/OQ	24.28	14.26	21.12
4	1025/2h/OQ	18.57	12.80	18.76
5	1030/1h/0.01C/s FC-1025/1h/OQ	20.34	15.92	17.93
6	1040/1h/0.01C/s FC-1025/1h/OQ	21.98	13.20	19.11
7	1050/1h/0.01C/s FC-1025/1h/OQ	26.85	14.28	18.52
8	1000/2h/OQ	29.36	18.04	38.51
9	1010/1h/0.01C/s FC-1000/1h/OQ	29.58	17.75	37.02
10	1030/1h/0.01C/s FC-1000/1h/OQ	21.90	12.54	34.87
11	1050/1h/0.01C/s FC-1000/1h/OQ	27.58	16.28	34.38
12	1025/2h/WQ	18.51	11.92	19.42
13	1025/2h/OQ	18.57	12.80	18.76
14	1035/2h/AC	17.14	12.27	12.53
15	1040/2h/0.1C/s FC	29.07	18.46	53.38
16	Rolled IMI834-1025/2h/OQ	15		18
17	Forged IMI 834-1025/2h/OQ	24		20
18	Rolled IMI834-950/2h/OQ			75
19	Forged IMI 834-950/2h/OQ			67
20	Rolled IMI834-1040/1h/0.01C/s FC- 950/2h/OQ	32.87		71
21	Forged IMI 834-1040/1h/0.01C/s FC-950/2h/OQ	38.53		74

Sl. No.	Heat treatment	Avg. Lath size, micro-meter	Std. Dev.	Smallest lath, micro-meter
22	1060/2h/WQ + 650/2h/AC			
23	1060/2h/OQ + 650/2h/AC	1.53	1.53	1.53
24	1060/2h/AQ + 650/2h/AC	4	4	4
25	1060/2h/0.1C/s FC + 650/2h/AC	11.45	4.51	6.45

The MATLAB Tool Box and the training parameters I got the good convergence with target values to the ANN Predicted values after training the network. The Network was trained well. Comparison of NN modal output with target values figure we can see below.

From the figure below

The red color was target values
The cyan color was output value

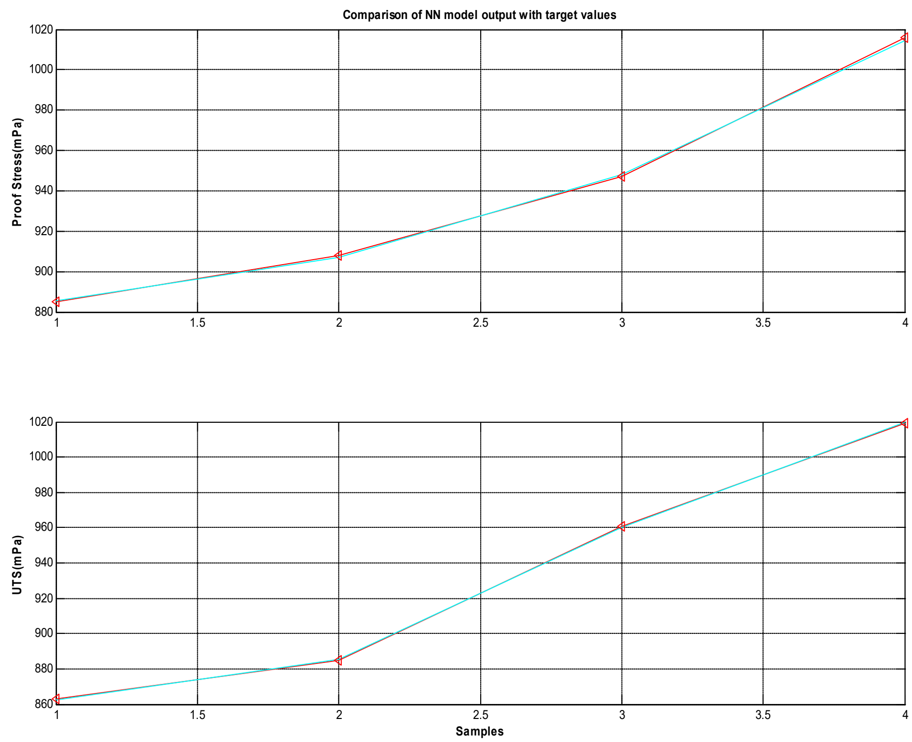

FIGURE 2: Comparison of ANN modal output with target value

3. Predicted Properties:

TABLE 2: Training data set before normalizing

Sl No:	Input parameters		Target parameters		Output values			
	Primary α size	Primary α vol.	Proof stress(MPa)	UTS(MPa)	Proof stress(MPa)	UTS(MPa)	Proof stress (MPa) Error	UTS(MPa) Error
1	32	97	885	963	885.62	862.62		
2	23.22	77	908	985	907.09	885.44		
3	11.3	24	947	1061	948.13	960.31		
4	10.83	18	1016	1119	1014.6	1019.8		

TABLE 3: Training data set after normalizing

Sl No:	Input parameters		Target parameters		Output values			
	Primary α size	Primary α vol.	Proof stress(MPa)	UTS (MPa)	Proof stress(MPa)	UTS (MPa)	Proof stress (MPa) Error	UTS(MPa) Error
1	0.73333	0.96667	0.34	0.21	0.34249	0.20875		
2	0.44067	0.74444	0.432	0.28333	0.42837	0.2848		
3	0.043333	0.15556	0.588	0.53667	0.59252	0.53437		
4	0.027667	0.088889	0.864	0.73	0.85836	0.73262		

TABLE 4: Predicted properties after normalization:

Sl. No:	Input parameters		Output values	
	Primary α size	Primary α vol.	Proof stress (MPa)	UTS (MPa)
1	18.57	18.76	918.81	941.17
2	20.99	19.42	898.81	925.57
3	24.28	21.12	880.92	909.44
4	18.57	18.76	918.81	941.17
5	20.34	17.93	909.29	934.43
6	21.98	19.11	894.28	922.1
7	26.85	18.52	874.08	904.99
8	29.36	38.51	871.9	885.31
9	29.58	37.02	870.57	885.39
10	21.9	34.87	886.49	902.89
11	27.58	34.38	874.04	891.16
12	18.51	19.42	915.46	938.36
13	18.57	18.76	918.81	941.17
14	17.14	12.53	997.85	1004.8
15	29.07	53.38	880.51	880.51
16	15	18	963.69	974.62

4. RESULTS DISCUSSION

Following various heat treatments the microstructures were generated for variety of alpha sizes and vol. fractions. The quantification of these microstructures is shown in Table 1. Few of the specimens with varying primary alpha size and vol. fraction were tensile tested and the same is shown in Table 2. These were normalized (Table 3) so as use for the neural network for data prediction. The network (Feed Forward Back Propagation) is trained using the data set as per Table 3. The convergence of the same i.e. the output values and the target values is shown in Fig. 2. The same trained network is utilized for predicting the data for test data i.e. quantified parameters. The results for the same are shown in Table 4. Based on the heat treatment followed the microstructure varied and in turn the strength properties. The neural network is used as a tool for predicting the strength properties based on the quantification of the micro-structural parameters. IMI 834 typically has 15 % primary alpha vol. fraction with primary alpha size of 25 µm. This 15% vol. fraction provided the pinning effect and increase in the strength properties. By observing the minimum and maximum values of alpha size and volume percentage, we should have less proof stress and UTS values for the high alpha size and alpha volume fractions, on the other hand, for the less alpha size and alpha volume fractions, the proof stress and UTS values should be more. In this project work the predicted mechanical properties appears to be in relevance to the desired properties. The mechanical property (proof stress, UTS) at below 15 μm of primary alpha size and alpha volume fractions attains saturation as shown in figure 3. Predicted mechanical properties by neural networks are correlated satisfactorily with the target values (experimental values). These two parameters (alpha size and alpha volume fractions) are not just sufficient to predict the mechanical properties of an alloy (IMI 834), but an attempt has been made vide this project to use the neural network as the tool for strength property predication. Various parameters are still needed to be studied for data forecasting.

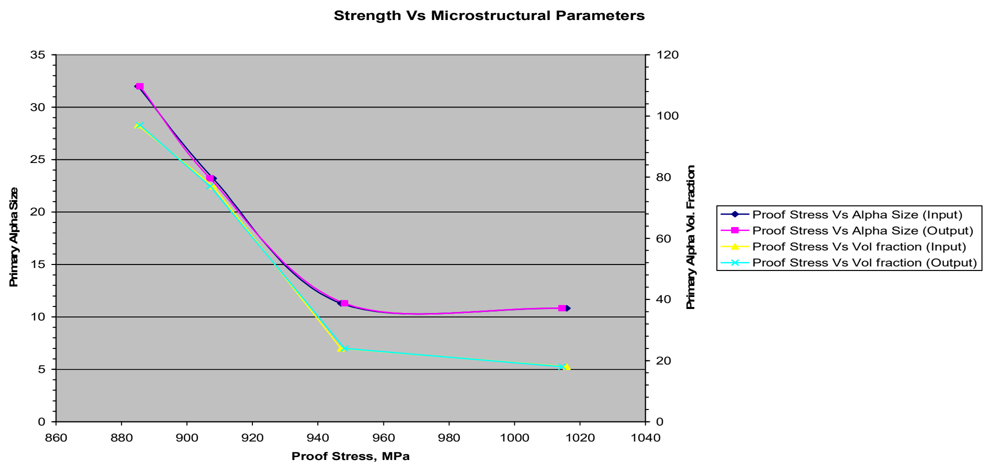

FIGURE 3: Comparison between strength Vs Micro-structural parameters

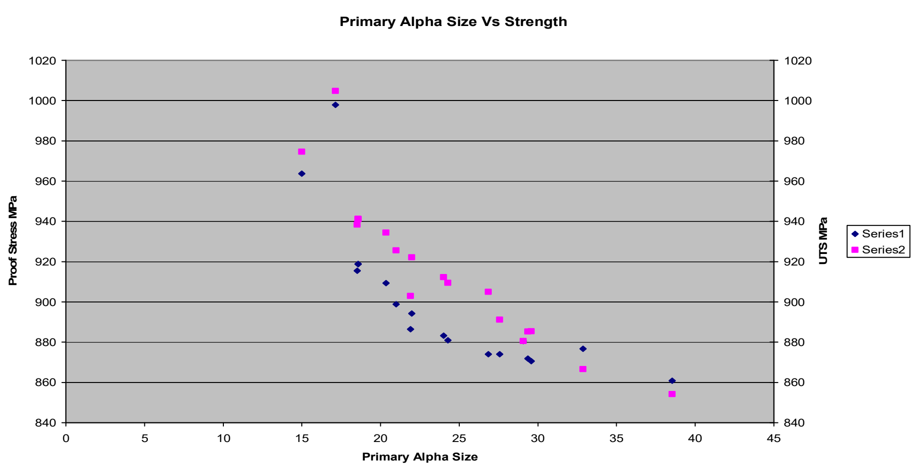

FIGURE 4: Comparison of primary alpha size Vs strength

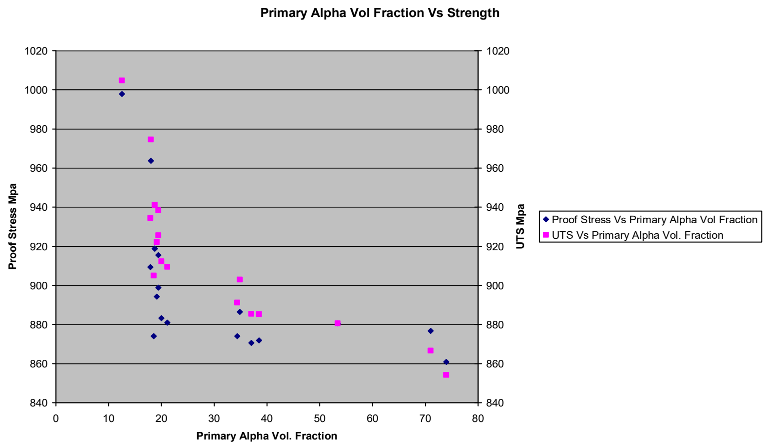

FIGURE 5: Comparison of primary alpha vol. fraction Vs strength

From this study we can predict the mechanical properties of the structure. Also, the same prediction technology can be extended and applied to know the microstructure for a given properties. Thus for a particular alloy the properties could be predicted before processing the alloy and even the processing route can be planned to attain the desired microstructure. In case of any failure of a component wherein the material is in use, the micro-structural quantification can be performed to predict the properties and the service temperatures under the service environment. We can apply the same approach to forecast the properties of newly developed materials or alloys.

5. CONCLUSIONS

The Non-linear mapping relationship among the alpha size, volume faction of titanium 834 (IMI 834) alloy at different heat treatment conditions, proof strength, and ultimate tensile strength (UTS) of IMI 834 alloy has been established, and the ANN model for predicting the proof stress ultimate tensile strength (UTS) of IMI 834 has been well trained and built by using the training sample.

The established neural network model has been used to predict the mechanical properties of (proof stress and ultimate tensile strength (UTS)) IMI 834 alloy. It has been shown that the predicted results are well in agreement with training set, it has given reasonable expected properties.

The trained results are in good agreement with experimental data. The test cases are in reasonable agreement with the experimental data.

Due to less data points of the training set, the ANN training takes less time and the number of neurons used are less in number.

With the availability of more data points the neural network will be more useful for parallel processing of the data and predicting the properties.

The approach presented will be helpful to predict the mechanical properties of some other alloys, so as to minimize the overall mechanical testing.

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