Fatigue Behavior of Microalloy Steel

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Abstract

Microalloy steels are potentially used for applications in earthmoving equipments and automobile components. Their excellent combination of strength and ductility/formability at lower costs are the distinct advantages over similar high strength low alloy steels. In the present investigation, fatigue behavior/fracture toughness of microalloy steel was studied to evaluate their influence on microstructure. It was found that the fatigue properties (in terms of fracture toughness) as well as the tensile properties (in terms of 0.2% proof stress) of microalloy steels increased with increase in martensite content. Artificial neural network (ANN) based theoretical prediction model was developed and was found to exhibit excellent matching with the experimental results. This simultaneous increase in fatigue and strength properties of microalloy steels makes them potential materials for various engineering applications.

1. Introduction

The normal approach for avoiding premature material failure is by designing stresses well below the yield strength of the material. However, many of the new high strength and/or high elastic materials under extreme conditions, when the same approach was used leading to catastrophic failures. The fractures occurred in a brittle manner and the materials did not exhibit their typical ductility even at lower stress levels. Design criteria have been subsequently developed for the safe use of materials on the basis of fracture toughness. Fracture toughness is a fundamental material property that depends on many factors, the most influential of which is microstructure of the material. The influence of microstructure on fatigue crack growth behavior in steels has been a subject of considerable research interest for many years. Some of the recent research finding of the current authors in this direction have been highly encouraging [1-5]. Evaluation of newer materials with improved combinations of strength, ductility and toughness has led to the emergence of microalloy steels in recent years. Microalloy steels were developed to satisfy an increasing need, primarily in the automobile industry, for new high strength steels that permit weight reduction with neither sacrificing formability nor dramatically increasing costs.

Artificial Neural Network (ANN) can be effectively used to develop models to analyze and predict mechanical properties of materials. Neural computing is a relatively new field of artificial intelligence (AI), which tries to mimic the structure and operation of biological neural systems, such as the human brain, by creating an Artificial Neural Network (ANN) on a computer. These ANNs are modeling techniques that are especially useful to address problems where solutions are not clearly formulated [6] or where the relationships between inputs and outputs are not sufficiently known. ANNs have the ability to learn by example. Patterns in a series of input and output values of example cases are recognized. This acquired "knowledge" can then be used by ANN to predict unknown output values for a given set of input values. Alternatively, ANNs can also be used for classification. In this case, the artificial neural networks' output is a discrete category to which the item described by the input values belongs. ANN are composed of simple interconnected elements called processing elements (PEs) or artificial neurons that act as microprocessors. Each PE has an input and an output side. The connections on the input side correspond to the dendrites of the biological original and provide the input from other PEs while the connections on the output side correspond to the axon and transmit the output. Synapses are mimicked by providing connection weights between the various PEs and transfer functions or thresholds within the PEs. Figure 1 illustrates a simple processing element of an ANN with three arbitrary numbers of inputs and outputs [4]. The activation of the PE results from the sum of the weighted inputs and can be negative, zero, or positive. This is due to the synaptic weights, which represent excitatory synapses when positive ($w_i>0$) or inhibitory ones when negative ($w_i<0$). The PEs output is computed by applying the transfer function to the activation, which as a result of the synaptic weights, can be negative, zero, or positive. The type of transfer function to be used depends on the type of ANN to be designed.

One of the most popular neural network models is the back-propagation network. Currently, back-propagation is the most popular, effective and easy to learn model for complex networks. To develop a back-propagation neural network, a developer inputs known information, assigns weight to the connections within the network architecture, and runs in the networks repeatedly until the output is satisfactorily accurate. The weighted matrix of interconnections allows the neural networks to learn and remember [7].

2. Material and heat treatment

Commercial microalloyed steel (hot rolled condition) was used in the present investigation. The composition of this steel is given in Table 1. Half size compact tension (CT) specimens were used for the evaluation of fracture toughness as per ASTM E399 standard. All the machined CT specimens were austenitized at 920^{o}C in a muffle furnace, homogenized for 30 min and then quenched in 9% brine solution to get a fully martensitic structure. This was to ensure the same starting microstructure in all the cases. The individual CT specimens were intercritically annealed between 730^{o}C and 850^{o}C to get ferrite+martensite structure with martensite content varying between 32 and 76%.

Table 1 Chemical composition of microalloy steel.

Element	C	Mn	Si	S	P	Cr	Mo	V	B
Weight %	0.14	1.36	0.50	0.007	0.028	0.042	0.115	0.062	0.002

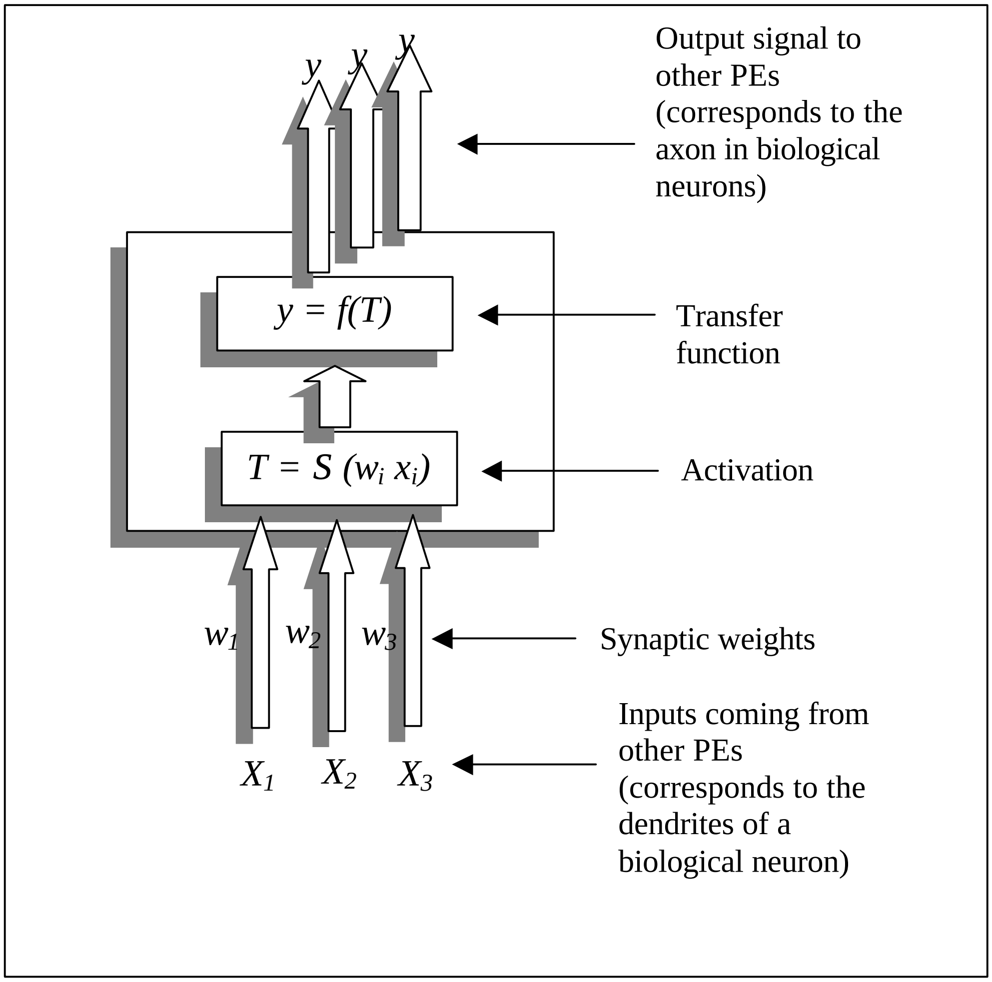

Figure 1 Processing element of an ANN model with three arbitrary numbers of inputs and outputs

3. Fracture toughness test

Half-size compact tension (CT) specimens were used as per the ASTM E399 standard. Fatigue precracking was carried out as per ASTM E647 standard using INSTRON-UTM (Model 8032 servohydraulic closed loop test system of capacity 100 kN) machine. Load shedding technique was used to develop the crack growth at different stress/ΔK values. Crack growth was monitored using a traveling microscope (with a resolution of 0.01mm) on optically polished surfaces. About 0.05-mm crack extension was monitored at each load decrement, keeping the load ratio (0.1) constant. Tests were terminated when the crack size was about half the size of the width (0.5W) of the sample.

The precracked specimens were subjected to load-displacement test under stroke control mode at a displacement rate of 2 mm/min, till fracture. Using the test program (software) the load corresponding to a 2% apparent increment in crack extension(P_Q)was established. From this value of P_Q, apparent value of fracture toughness (K_Q) was calculated as per ASTM standard E399.

4. Influence of microstructure

Typical microstructures are presented in Figure 2(a) and 2(d). Martensite is platelet in type in most of the microstructures except blocky in type at higher volume content of martensite. Detailed microscopic examination was carried out for the microalloy steel samples containing martensite from 32% to 76%. The morphology of martensite in microalloy is known to cause significant differences in crack propagation thereby affecting the fracture toughness. In the present investigated microstructure, a martensite envelope surrounds the crack growing in ferrite. It has been shown that the martensite in the present microstructure constrains the plastic deformation in the ferrite phase. The constraining effect in the present type of microstructure increases with the increase in the volume fraction of martensite having a continuous network enclosing ferrite phase.

Typical fatigue fracture surface features for the microalloy steel at near threshold regions are given in Figure 2(b), 2(c), 2(e) and 2(f). At near thresholds, they are characterized by transgranular/intergranular cleavage resulting from the coexistence of main crack and the branched cracks. At the near threshold region, wherein the size of the crack becomes equal to or less than that of the grains, the fracture features are governed by the crystallography of individual grains as evident in these figures. The secondary cracks are responsible for the deceleration of crack growth.

5. ANN back-propagation model

The major property that deems ANNs superiority to algorithmic and other network based systems is their ability to be trained on historical information as well as real-time data. Training is the act of continuously adjusting their connection weights until they reach unique values that allow the network to produce outputs that are close enough to the desired outputs. The accuracy of the developed model, therefore, depends on these weights. Once optimum weights are reached, the weights and biased values encode the network's state of knowledge. Thereafter, using the network on new cases is merely a matter of simple mathematical manipulation of these values.

The neural network used for the proposed model was developed with NeuroShell 2 software by Ward Systems Group, Inc., using a back-propagation architecture with multi- layers jump connections, where every layer (slab) is linked to every previous layer. In model-1, the network was trained for yield strength. The inputs were the annealing temperature (T), and volume percent of martensite content (%M), and outputs were the yield strength (0.2% Y.S.). In model-2, the network was trained for Charpy Toughness and Fracture Toughness. The inputs for the model-2 were the annealing temperature (T), volume percent of martensite content (%M), and yield strength (0.2% Y.S.), and outputs were Charpy Toughness and Fracture Toughness. The number of hidden neurons, for which the logistic activation function, $f(x)=1/\{1+ exp(-x)\}$ was used, was determined according to the following formula [8]:

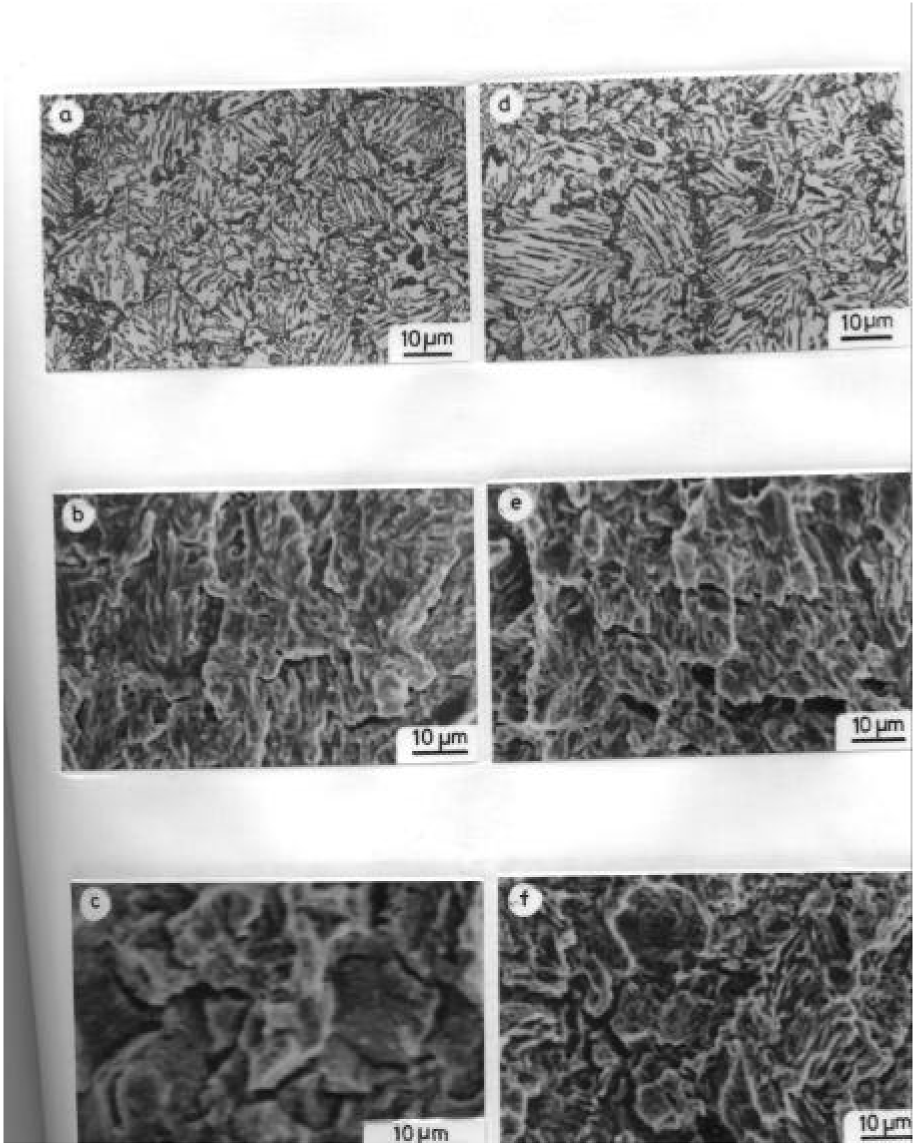

Figure 2 Typical microstructures and fractographic features of microalloy steel

Number of hidden neurons = 0.5(Inputs + Outputs) + √(Number of training patterns)

In the present research, several different ANN back-propagation trial models with different layers/slabs connections, weights and activation functions (including linear, Tanh, Tanh15, Sine, Symmetric Logistic, Gaussian, Gaussian Complement, etc.) were trained. In addition, pattern selections including "Rotation" and "Random" were used with weight updates using Vanilla, Momentum and TurboProp. The presented ANN back-propagation model with logistic activation function, "Rotation" for pattern selection, and "TurboProp" for weight updates was the best one among all other trials, which converges very rapidly to reach the excellent statistical performance with the coefficient of multiple determination, $R^2 = 0.999$, and squared of coefficient of correlation, $r^2 = 0.998$.

The training models are presented in Figures 3 through 5 for the variation of yield strength, charpy toughness and fracture toughness with intercritical annealing temperature respectively. The ANN based training model and the experimental results show excellent matching as evident in all these figures.

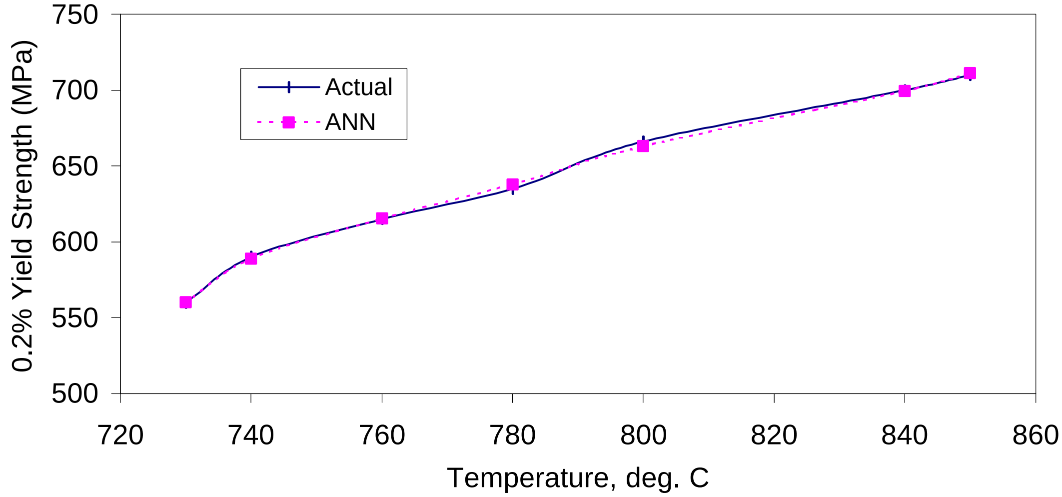

Figure 3 Annealing Temperature vs. 0.2 % Yield Strength – Actual and ANN Prediction during Training

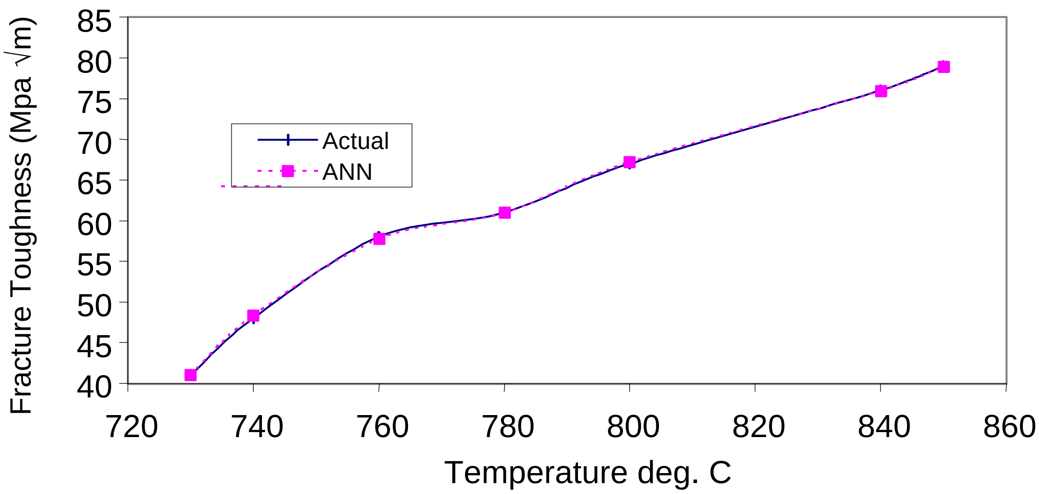

Figure 4 Annealing Temperature vs. Fracture Toughness – Actual and ANN Prediction during Training

6. Prediction models

6.1. Prediction model for fracture toughness as a function of temperature

The prediction model for the above is presented in Figure 5. Generally, both fracture toughness and charpy toughness increased with increase in temperature of intercritical annealing. Also, it is evident that the microalloy steel can be annealed above 850^0C to further enhance the toughness properties. However, the toughness properties seem to reach the saturation point around 930^0C.

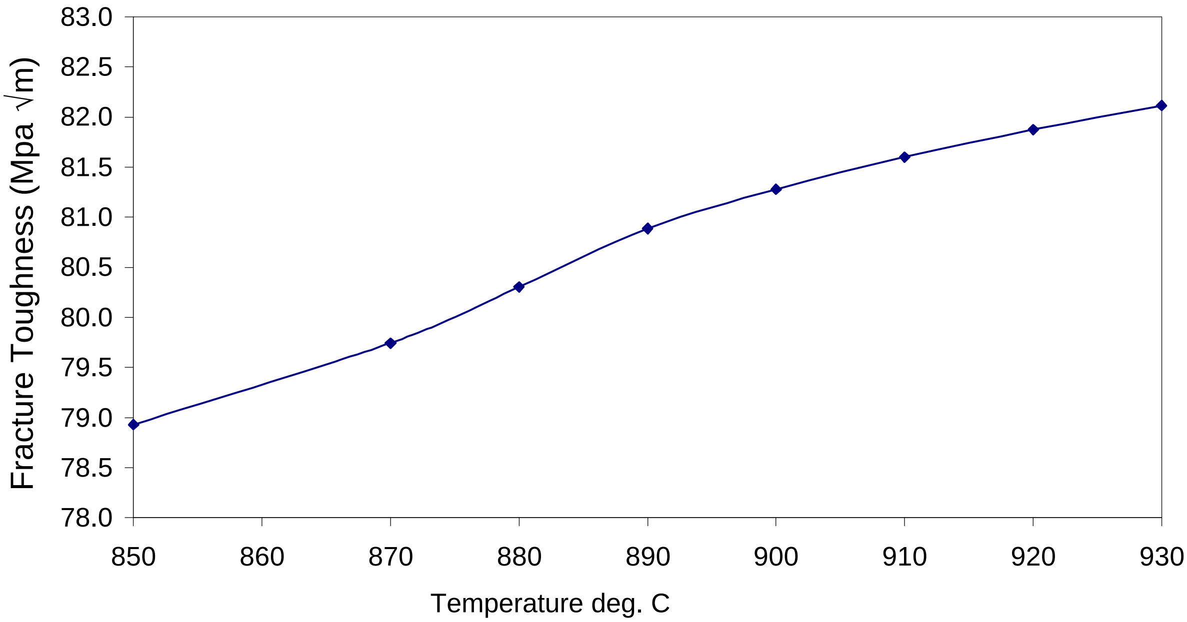

Figure 5 ANN Prediction for Fracture Toughness as a function of heat treatment

6.2. Prediction model for fracture toughness as a function of martensite content

Figure 6 demonstrates the prediction model for the toughness properties as a function of martensite content. As in the previous case, both fracture toughness and charpy toughness showed a general increasing trend with increase in vol% of martensite. Furthermore, the toughness properties reached maximum for the microalloy steel at about 97% martensite. From this prediction model, it is clear that the optimization of toughness properties would occur for the microalloy steel containing 97 vol% martensite.

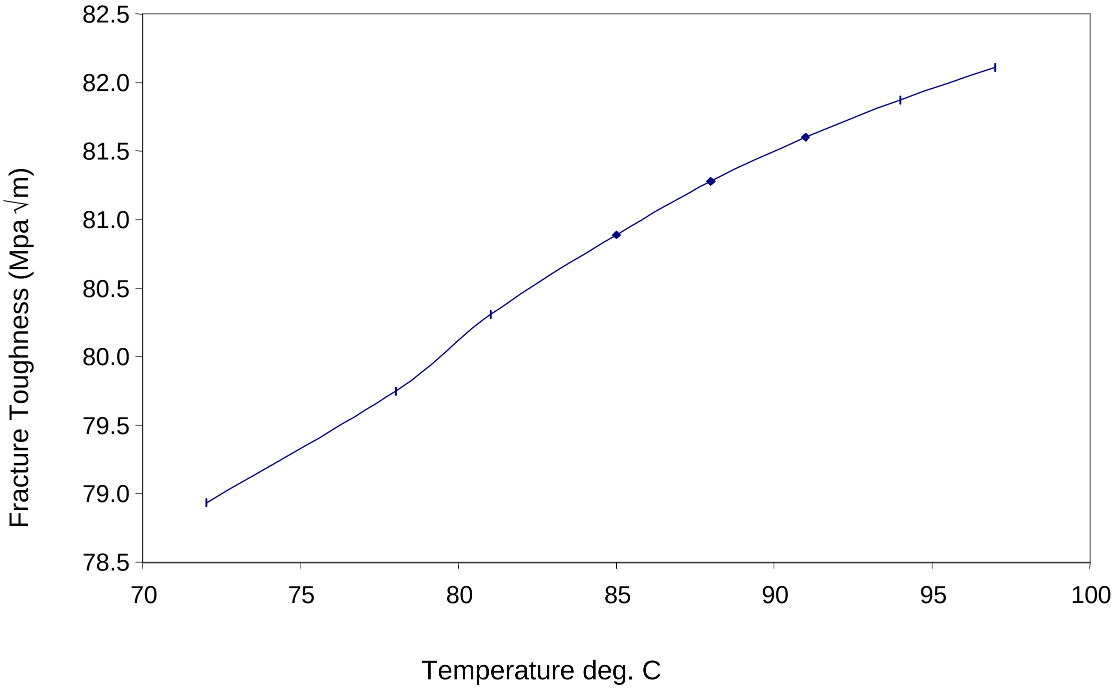

Figure 6 ANN Prediction for Fracture Toughness as a function of % Martensite content

7. Conclusions

The simultaneous improvement and the best combination of strength and fracture toughness were observed for the microalloy steel containing 76% martensite. Furthermore, based on the ANN prediction models, the fracture toughness properties showed maximum values at 930^0C and at about 97% martensite. ANN based prediction model demonstrated the best statistical performance with the experimental results. These predicted fracture toughness values can be reliably used in any engineering application substituting the complexity and the higher cost involved in fracture toughness testing.

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