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Computational intelligence based designing of microalloyed pipeline steel

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ABSTRACT

Computational intelligence based modeling and optimization techniques are employed primarily to investigate the role of the composition and processing parameters on the mechanical properties of API grade microalloyed pipeline steel and then to design steel having improved performance in respect to its strength, impact toughness and ductility. Artificial Neural Network (ANN) models, capable of prediction and diagnosis in non-linear and complex systems, are used to obtain the relationship of composition and processing parameters with said mechanical properties. Then the models are used as objective functions for the multi-objective genetic algorithms for evolving the tradeoffs between the conflicting objectives of achieving improved strength, ductility and impact toughness. The Pareto optimal solutions are analyzed successfully to study the role of various parameters for designing pipeline steel with such improved performance.

1. Introduction

A large quantity of steel products are being used in the oil and natural gas sector for the production, transportation as well as storage purpose [1]. With the increasing industrial growth and upgraded livelihood of human beings, consumption of petroleum and natural gas has increased considerably for the past few years and it has been increasing continuously [2]. For the last 40 years, due to evolution of improved metallurgical practices and manufacturing techniques there is a demand on higher strength steels for the pipe manufacturing [3]. Along with the higher strength, the most stringent requirement for these steels grades are higher toughness at lower temperatures; which is specifically required for places like Siberia, Alaska as well as at the sea beds which face the extreme situation of operating conditions [4]. Higher strength and higher toughness of the line pipe steels will enable not only high operating pressure leading to economically favoured transportation but also higher safety in pipeline operation.

Ultrahigh strength low carbon microalloyed steels (Ti, Nb, V) have been developed for linepipe application considering the extreme conditions prevailed across the globe. These steels have microstructural constituents which provide an outstanding combination of strength and toughness along with good weldability, resistance to corrosion; lower amount of alloying elements in these steels make them cost effective too [5–8]. To achieve the desired microstructural constituents, these microalloyed steels have been thermomechanically processed and thus the required mechanical properties [9–11]. It is well known that to achieve the desired microstructural features, the thermomechanical processing employed has to be controlled through several processing parameters; namely, the slab reheating temperatures, the finish rolling temperatures and the cooling rate [12].

In case of thermo mechanically controlled processed (TMCP) low carbon microalloyed steels, superior strengths are achieved by modifying the microstructure consisting of low temperature transformation products i.e. acicular ferrite along with precipitation hardening, but the impact toughness is not satisfactory. As toughness of steel could be improved by achieving a good balance between strength and ductility, designing of this genre of microalloyed steel with an optimum combination of strength, ductility and toughness can be approached computationally. Conflicting objectives of this kind can be approached by multi-objective optimization [13] using genetic algorithm [14], which is found to be effective for dealing such materials problems successfully by the previous workers [15–17]. In case of multiple objectives, if they are conflicting in nature, the optimization does not

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Table 1
The minimum, maximum, average value and standard deviation of the input parameters.

Variables	Minimum	Maximum	Average	Standard deviation
C (wt%)	0.016	0.12	0.0574	0.0163
Si (wt%)	0.02	0.62	0.242	0.0963
Mn (wt%)	0.61	3.00	1.912	0.4413
S (wt%)	0.00003	0.0072	0.0013	0.0011
P (wt%)	0.0003	0.028	0.0088	0.0052
Al (wt%)	0	0.086	0.022	0.0157
N (wt%)	0	0.025	0.003	0.0026
Ti (wt%)	0.001	0.036	0.010	0.0075
V (wt%)	0	0.13	0.031	0.0382
Nb (wt%)	0	0.11	0.026	0.0260
Cu (wt%)	0	0.64	0.113	0.0134
Ni (wt%)	0	1.32	0.207	0.2881
Cr (wt%)	0	0.54	0.177	0.1663
Mo (wt%)	0	0.81	0.361	0.2550
Reheating temp (°C)	950	1300	1111.007	64.4779
Start rolling temp (°C)	810	1250	1041.841	67.6251
Finish rolling temp (°C)	698	1006	868.042	69.7742
Cooling start temp (°C)	680	990	833.359	71.8993
Cooling finish temp (°C)	150	764	521.795	104.8106
Cooling rate (°C/S)	1	62	21.915	10.6023

lead to any single solution [18]. Instead it generates multiple solutions, known as Pareto front, which represent the best possible compromise between the objectives. As no ready model for strength and toughness of such steels are available, it was necessary to develop suitable mathematical models, which can be used as objective functions for the above optimization study. Due to highly non-linear and complex relationship between the composition and process parameters along with dynamical microstructural feature, developing a mathematical model to describe the composition–process–structure–property correlation in a steel system like the present case is practically impossible. ANN models [19] have the capability to develop non-linear correlations between the variables of the system from data. Previous workers have successfully used ANN models to describe such complex steel systems [20,21]. In the present work the developed ANN models are also used to find the role of the variables on the final properties of the steels. The Pareto solutions, developed from multiobjective genetic algorithm study using the ANN models as the objective functions, are also used for post-optimization analyses.

2. Database

Around 260 data were collected from the various publications and patents on API grade pipeline steels [22–44]. The alloy composition and the TMCP parameters of the micro-alloyed pipeline steel have been taken as input parameters, the yield strength (YS), tensile strength (UTS), percentage elongation (%El) and impact energy (IE) are designated as the output variables, and are listed in Table 1. Within the alloy chemistry, the concentrations of elements like carbon, manganese, silicon, aluminum, niobium, titanium, boron, sulfur, phosphorous and nitrogen are considered. The inputs and outputs are normalized within the range of −1 to 1 using the following equation

$$X_N = \frac{2(X - X_{min})}{(X_{max} - X_{min})} - 1$$

where X_N represent the normalized value of variable X, where X_{max} and X_{min} are respectively the maximum and minimum values of the variable.

3. Computational process

3.1. Artificial Neural Network (ANN)

Artificial Neural Network is a computational model that is inspired by biologically human brain function. ANN models perform an input–output mapping using a set of interconnected simple processing nodes or neurons. Data enter the network through the input units called input layer; those are then fed forward through the hidden layer in the middle to emerge from the output layer on the right. Minimization of the error/deviation between the observed and the predicted value is the main aim of this modeling. In the present work supervised multilayered feed forward networks are used, which are trained with scaled conjugate gradient algorithms [19]. The input layer consists of fourteenth compositional variables and six process variables and the four property variables are taken as output nodes. As usual there is a hidden layer between the inputs and outputs. The inputs (X_i) are multiplied by weights (W_{ji}), which are summed and added to a bias value (θ_{ji}) to form a hidden node (h_j). The summation is then operated by a highly non-linear transfer function (f). The transfer function used here is *tanh*. The operation can be written as

$$h_j = f(\Sigma W_{ji} X_i + \theta_{ji}) \tag{1}$$

The number of hidden nodes in the hidden layer is varied to find the suitable network architecture. Hidden node values are multiplied with weights, summed up and added to a bias to constitute the output nodes (Y), and can be written as:

$$Y = (\Sigma W_j h_j + \theta') \tag{2}$$

where w_j and θ' are the weights and the bias. The difference between the predicted and actual output is treated as the error, which is back propagated to regulate the weights and biases, known as training or learning of the network. In here separate ANN models have been generated for UTS, YS, %El and IE which were taken as the output. For the four different models the architectures of the networks are selected based on the predictability of the model. The final models for each outputs are chosen from several models with varying number of hidden nodes, varying between 5 and 40 in a single hidden layer. The best scatter plots for the target and achieved output of the trained ANN models are shown in Fig. 1 and the scatter plots are evolved having hidden nodes for YS is 11, UTS is 28, %EL is 25 and IE is 21.

3.2. Genetic algorithm and multi-objective optimization

Genetic algorithms (GAs) (or, more widely, evolutionary algorithms) are non-linear search and optimization methods inspired by the biological processes of natural selection and survival of the fittest [14]. In genetic algorithms a population containing some randomly initiated individuals (chromosomes), each representing a possible solution, is used in the first generation. In the next step a simulated evolution of the population is occurred and a selection operation is done on the population for the survival of the fittest. Next after selection, recombination through crossover followed by a mutation process is occurred to produce the offspring. Finally after these processes a new generation is created having better individuals. The simulation is stopped when a target is reached or after the decided number of iterations.

In presence of multiple conflicting objectives, instead of unique global optimum, a set of solutions known as the Pareto set [13] are generated. As per the definition, no solution is possible to exist having at least the same strength as some member of the Pareto set, and at the same time showing a better Impact Energy. Thus Pareto set propose several equivalent optimum solutions, out of