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A Hybrid Neural Network - Genetic Algorithm for Prediction of Mechanical Properties of ASS-304 at Elevated Temperatures

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Abstract

In the present work, genetic algorithm is implemented, to optimize the artificial neural networks used, to predict the mechanical properties of Austenitic Stainless Steel 304 (ASS-304) at elevated temperatures. ASS-304 is a very important alloy used in various applications involving high temperatures which make it very important to study the mechanical properties at elevated temperatures. The dynamic neural networks have been employed first for predicting the mechanical properties such as Ultimate Tensile Strength (UTS), Yield Strength (Ys), % elongation, Strain Hardening Exponent (n) and Strength Coefficient (K) at elevated temperatures. Genetic algorithm was then integrated with the neural network model for optimization, to achieve better regression statistics, taking the mean square error as the fitness function. The results show that the proposed hybrid, neural network - genetic model is more accurate and effective method for predicting the mechanical properties of ASS-304 at elevated temperatures.

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Keywords: ASS-304; Material Properties; Artificial Neural Network; Genetic Algorithm

1. Introduction

Austenitic Stainless Steel is very important alloy used in various high temperature applications, include: as fuel cladding, core structural elements in nuclear industries due its high corrosion resistance in seawater environment because of the addition of molybdenum which prevents chloride corrosion[1]. Since it has very less carbon content,

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wear resistance, friction properties are adequate in the heat effected zone and during welding there is very less susceptibility to intergranular corrosion[2]which make it important to study their mechanical properties at elevated temperatures[3].Austenitic stainless steels (300-series), when subjected to high temperatures and loads, there is a martenstic transformation involved plastic deformation which depends on several parameters: chemical composition, mechanical stress and magnetic behavior[4].The martenstic transformation at room and low temperature, which mostly depend on microstructural aspects, influence the drawability of the materials. The drawability of the 304 ASS is very much steady when compared to the 316 ASS. In balance biaxial test, there is a decreased strain hardening rate due to the increase of the volume fraction of the induced martensite when compared to the uniaxial test[5].The ASS 304 material is very much suitable structural element at elevated temperatures and in nuclear reactors the temperature is very high therefore its tensile properties at elevated temperatures needs to be analysed with the knowledge of constitutive modes among which ANN is famous for its simplicity and accuracy.

The trained ANN model gives an excellent correlation coefficient and absolute average error values which represents a good accuracy of the model. The Artificial Neural Network (ANN) to predict the mechanical properties of AZ61 Mg alloy fabricated by equal channel angular pressing (ECAP)[6]. A back-propagation (BP) algorithm is used to train the neural network prediction models. Grain size, yield strength, and tensile strength of the alloy are predicted based on the number of ECAP passes[7]. The ANN predictions are shown to be in excellent agreement with experimental results, and the prediction error is shown to be minimal. These models can also be extended in the future to predict other properties, and possibly characterize other alloys.

Genetic Algorithm (GA) is a search algorithm based on the mechanics of natural selection and genetics and they combine survival of the fittest among string structures to form a search algorithm[8]. GA is particularly suitable for multi-parameter optimization problems with an objective function subject to numerous hard and soft constraints. The main idea of GA is to start with a population of solutions to a problem, and attempt to produce new generations of solutions which are better than the previous ones. GA operates through a simple cycle consisting of the following four stages: initialization, selection, crossover, and mutation. Fig.1. shows the basic steps of the basic genetic algorithm model[9].

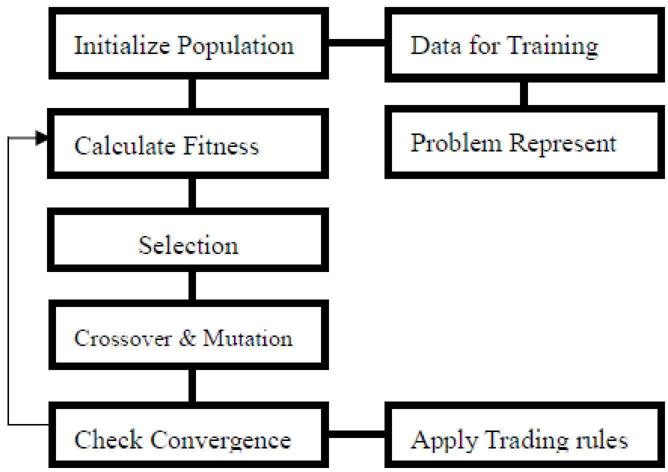

Fig.1. **Basic Steps of the GA Model**

Genetic algorithms are proven, theoretically and empirically, to provide a robust search in complex spaces, thereby offering a valid approach to problems requiring efficient and effective searches. To execute a particular optimization task using GA, it requires to address a genetic representation of candidate solutions, a way to create an initial population of solutions, an evaluation function which describes the quality of each individual, genetic operators that generate new variants during reproduction, and values for the parameters of the GA, such as population size, number of generations and probabilities of applying genetic operators.

In the initialization stage, a population of genetic structures (called chromosomes) that are randomly distributed in the solution space is selected as the starting point of the search. These chromosomes can be encoded using a variety of schemes including binary strings, real numbers or rules. After the initialization stage, each chromosome is evaluated using a user-defined fitness function. The goal of the fitness function is to numerically encode the performance of the chromosome. For real- world applications of optimization methods such as GA, the choice of the fitness function is the most critical step. The mean squarederror (MSE), which is the error between the desired and the predicted outputs as given by the equation (1)[10], is considered as the fitness function in the genetic algorithm.

$$MSE = \frac{1}{N}\sum_{i=1}^{patterns\ number}\left({y_i}^{desired\ output} - {y_i}^{predicted\ output}\right)^2 \qquad (1)$$

In the present study, ANN-GA model is initially trained with one input neuron, representing the temperature and six output neurons, corresponding to the mechanical properties and twenty hidden neurons. The model has been trained with the desired value of MSE using the genetic algorithm for predicted the desired value of the output values.

2. Implementation

2.1. Experimentation on UTM Machine:

In this work, the material tested was Austenitic Stainless Steel 304 (ASS-304). In the previous study of author [“Study the Effect of Temperature on the Properties of ASS-304 Using ANN”, 23rd International Conference on Processing and Fabrication of Advanced Materials, 1186-1192, Dec 2014, IIT Roorkee], the specimens of ASS-304 steels were tested on a 5 ton UTM machine (Fig.2.) to calculate the material properties like Ultimate Tensile Strength (UTS), Yield Strength (YS), % Elongation, Strength Coefficient (K) and Work Hardening Exponent (n). The experiments were conducted from temperature 50^0C to 650^0C in the interval of 50^0C. It was found out that as the temperature increases, there is a decrease in the values of YS, UTS, K and n values. But at 350^0C these values starts increasing again due to blue brittle phenomenon which occurs due to impurities of Cr, Ni and other impurity materials. After 450^0C these properties again starts decreasing due to material being in the plastic region.

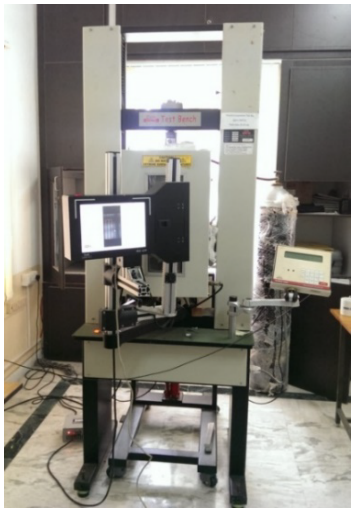

Fig.2. Universal Testing Machine

2.2. Development of ANN- GA Model:

The experimental data (Table 1.) was trained using Artificial Neural Network (ANN) model at unknown temperature with Back Propagation (BP) algorithm. 13 samples of input data i.e. temperature and 13 samples of 6 target data i.e. n, K, UTS, YS, Youngs, %elon were taken to train the network. This training stops when the validation error increased for six iterations, which occurred at 6^{th} iteration. The performance plot which shows the training errors, validation errors and testing errors is shown in Fig.3. The network response is very promising; hence a new input of unknown temperature can be given to the network to predict the properties of the material as the outputs.

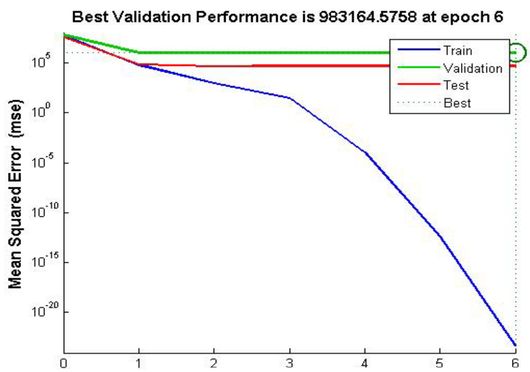

Fig.3. Performance plot

Table 1. Trained data Set

Temperature	N	K	UTS	YS	Youngs	%elon
50^0C	0.3706	1085.925	675	275.36	20652	58.3531
100^0C	0.3394	1029.912	636.6667	299.404	17612	56.93569
150^0C	0.3629	1032.048	578.3333	266.46	17764	42.52202
200^0C	0.3972	1000.691	516.6667	214.3147	20092	37.6805
250^0C	0.4184	1043.758	518.3333	225.72	15048	36.30065
300^0C	0.4474	1159.044	526.6667	221.2	13825	33.25284
350^0C	0.4932	1204.759	520	215.3503	10591	32.8554
400^0C	0.4119	1056.331	471.6667	231.3373	15773	36.96493
450^0C	0.3797	950.3859	500	203.895	22655	32.07232
500^0C	0.3751	848.985	458.3333	193.336	13182	34.00373
550^0C	0.3957	887.9735	440	195.0643	14273	33.90331
600^0C	0.3862	855.6576	395	184.31	15360	37.59177
650^0C	0.3942	675.6161	320	156.144	13012	30.86086

The BP algorithm employed in the training of the neural network derived from the gradient method requires an objective function which is continuously differentiable[11]. This might cause some problems in the learning process, such as the slow convergence, oscillation effect etc., which are due to the random selection of weight and threshold values. Hence, the genetic algorithm is used to optimize the artificial neural network by minimizing the mean squared error which is considered as the fitness function. A function can be written to accept the network, weights and biases, inputs and targets. This function may return the mean squared error based on the outputs and the targets as GA requires a function handle that only returns a scalar value. A basic BP neural network model is created with the definition of a MSE function handle to be passed to GA.

3. Results and Discussion

The concrete steps in implementing the ANN-GA algorithm are as follows:

(i) Create the neural network model.
(ii) Initialize the population.
(iii) Compute the fitness value, MSE of the present population MSE can be considered as the count of fitness value.
(iv) Chromosomes are generated. The encoded chromosomes are searched to minimize the fitness function.

In this phase, GA operates the process of crossover and mutation on initial chromosomes and iterates until the stopping conditions are satisfied. The population size is set to 20 organisms and the crossover and mutation rates are varied to prevent ANN from falling into a local minimum. The range of the crossover rate is set to 0.8 while the mutation rate ranges from 0.05 to 0.1. As the stopping condition, only 50 trials are permitted. The performance plots of the ANN-GA algorithm are shown in Fig.4. and Fig.5.

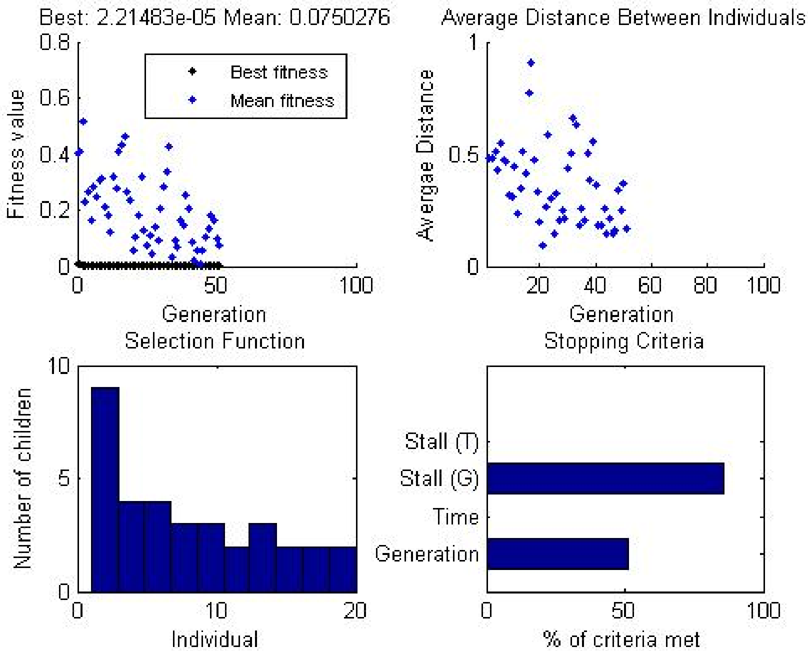

Fig. 4. Performance Plots of the Fitness, Distance, Selection and Stopping

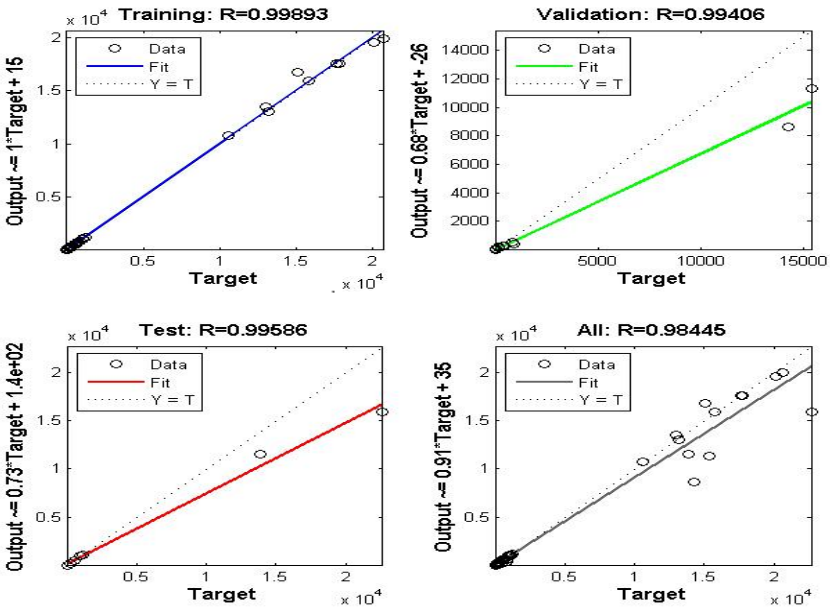

Fig.5. Performance Plots of the ANN-GA Algorithm

The proposed ANN-GA model is tested for new values of the temperature for predicting the mechanical properties of the ASS-304. The test results show that the hybrid ANN-GA model is more accurate, fast and effective method for prediction applications.

4. Conclusions

In this work, the MSE values of the neural network model were minimized using GA. The accurate results show that the proposed ANN-GA model can be considered a robust tool for prediction applications and is an effective mathematical model for assessing the mechanical properties of ASS-304 at elevated temperatures. The hybrid ANN-GA model is validated based on the statistical parameters like the mean square error and the convergence speed.The simulation results show that ANN-GA model gets great improvement in generalization ability, and has higher reliability in prediction when compared to ANN models. The results also show that genetic algorithm can be very good at speeding up convergence speed and solving the problem of local minimum to realize the global search.

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