Proposing a Model for Predicting Flow Stress of Aluminium Alloy in Tensile Test

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Abstract
To obtain materials with desired properties, traditional approaches use experiments, while modern approaches use computer simulation. There is no doubt that computer simulation is cheaper and faster than experiments. By using appropriate computer models, simulation results are in the same accuracy with experiments. In this paper we use genetic algorithm to predict the flow stress of aluminum alloy during tensile test. Experimental results prove the success of our model.
Streszczenie.

Keywords: Genetic Algorithm, Aluminum Alloy, Flow Stress, Tensile Test.
Słowa kluczowe:

Introduction
The reaction of solid materials against forces, torques, or generally any type of external stress, whether it be static or dynamic, under working or testing condition is called mechanical behavior or property. The quality of materials used in industrial design depends more than anything else on their mechanical properties. One way to determine mechanical properties of material is using standard laboratory methods [1].

One of the most important tests in determining mechanical properties of materials is tensile test that gives us the degree of hardness and softness of materials. The specification of this test is stress - strain curve where the changes of stress are measured by raising the strain or deformation. Holman equation [1] expresses the relationship between stress and strain. The main issue with Holman equation is varying the constants within a specific range instead of having a fixed value. Obtaining proper value for Holman equation constants helps us to predict flow stress of aluminum alloy in tensile test. The broad range of aluminum alloy usage in industry increases the importance of solving this problem [1-7].

In [8] a combination of fuzzy modelling and PSO has been proposed for designing multi-purpose optimum alloy which was used in steel alloy heat–treatment design. Experimental results showed that this algorithm could provide fully optimized solutions under appropriate pressure to help researchers to find effective and useful designs for steel alloy.

Artificial Neural Networks was used to predict the tensile strength, hardening behavior and density of particles of aluminum oxide [9]. In [10] the artificial intelligence network was used in order to predict the kinetic friction welding of AA7039 aluminum alloy.

The rest of the paper is organized as follows. In Section 2 we review the genetic algorithm. In Section 3 we briefly explain the flow stress of Aluminium alloy in tensile test. In Section 4 we explain the proposed model. Finally Section 5 concludes the paper.

Genetic Algorithm
Genetic algorithm is a statistical method for optimization and search which is a branch of evolutionary computation [11]. Evolutionary computation is itself a part of artificial intelligence. Genetic algorithm is based on natural genetics and is inspired by Darwin's evolutionary theory [12-15]. Figure 1 depicts the steps of the algorithm.

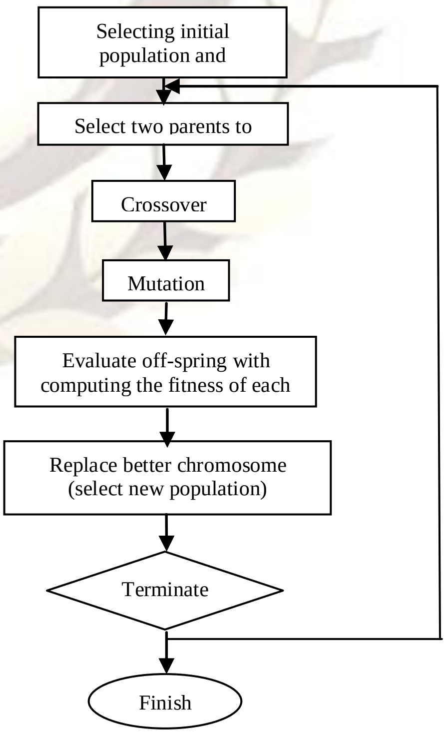

Fig.1. The steps of genetic algorithm [13].

The algorithm starts with a set of (random) chromosomes as the initial population. A fitness function is used to evaluate the quality of each chromosome. In each iteration high quality chromosomes are selected as parents to produce new off-spring which form the new population. Of course, to diversify the new population from the previous one, the mutation operator is used to gain off-springs with different properties from their parents.

Better chromosomes from off-springs and parents are selected as the new population. The algorithm continues with the same steps for the new population until it finds the solution.

Flow stress of Aluminium alloy in tensile test

For many metals and alloys, stress and strain changes in the range of uniform plastic deformation are obtained from the Holman equation as follows:

$$\sigma = K\varepsilon^n \qquad (1)$$

where K is a constant which depends on a variety of factors such as temperature and the type of sample. The vale of K is between 50 to 700 (Mpa) [1, 7, 16]. n is called work hardening rate in cold plastic deformation. The value of n is important for items that are used in deep stretch. This relation is valid only from the yield point up to the maximum stress point. n is between 0.1 and 0.5 for most metals, zero for an ideal plastic material, and 0.05 to 0.5 for aluminum alloy between. Variables ε and σ are respectively strain (dimensionless) and stress (MPa).

We used genetic algorithm to obtain optimal value for the constants in the above equation. After solving the equation, we can predict the behavior of the material or to optimize its function without using expensive and time consuming experiments.

The proposed model

We used Holman equation's constants (n and k) as chromosomes' genes. For crossover, we used a linear combination of genes as follows [11]:

$$P_{new\,1} = 0.5P_m + 0.5P_f \qquad (1)$$
$$P_{new\,2} = 1.5P_m - 0.5P_f$$
$$P_{new\,3} = -0.5P_m + 1.5P_f$$

where Pnew1 ‹Pnew2 and Pnew3 are offspring and Pm and Pf are parents. We used monotonic mutation (Equation 2) using the values in Table1 as limits.

$$P_n' = P_n + \gamma N_n(0,1) \qquad (2)$$

Pn and P'n are offsprings before and after mutation respectively. γ is the distance between the upper bound and the lower bound of the offspring's domain. Nn(0,1) is a random value between 0 and 1.

To determine the algorithm termination we used the following conditions [11]:

- when the error function is less than a desired value
- when the error function remains constant for a specific number of generations
- when a specific number of generations are examined

Table 1. The domain of Holman equation's constants

Constant	Lower Bound	Higher Bound
k	0.05	0.5
n	50	700

Several factors affect the speed and accuracy of the genetic algorithm including the initial population, crossover and mutation operators, fitness function and type of the error function. The proper values of these parameters vary from one problem to another and are usually determined through experiment. This combination of settings is called optimal combination and is shown in Table 2 for our problem.

We examined three error functions in the fitness function as follows [11] (in the following equations yi is the value obtained from experiments and y'i is the output of the proposed model:

$$1\text{- } error^2 = \sum_{i=1}^{n}(y_i - y_i')^2 \qquad (4)$$

$$2\text{- } error = \frac{\sum_{i=1}^{n}|y_i - y_i'|}{n} \qquad (5)$$

$$3\text{- } error = \prod_{i=1}^{n}|y_i - y_i'| \qquad (6)$$

Table 2. The optimal setting for genetic algorithm

Parameter	Value
Npop	400
X_{rate}	0.2
$Mutation_{rate}$	0.1
Itration	300
Error Type	2

Figure 2 compares the stress - strain obtained from the model with experimental data. As can be seen from the figure, the output of the model is very close to the data obtained through experiments.

Figure 3 depicts the difference of the strain obtained from the model from the strain obtained through the strain test. As can be seen from the figure, the difference is very close to 0 which means the model mach with the strain test.

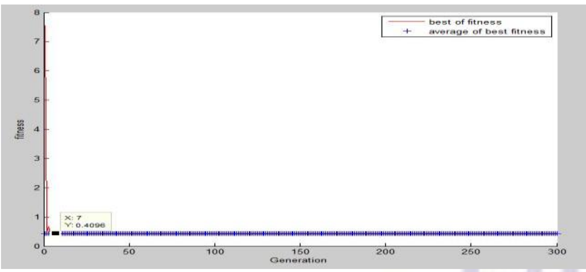

Fig.2. Comparing the stress - strain obtained from the model
with experimental data

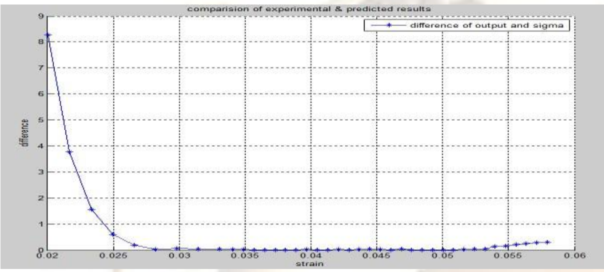

Figure 3. The difference between the stress obtained from the model with the stress obtained from stress test using error type 2.

The average and the best value of the fitness function for different number of generations are shown in Figure 4.

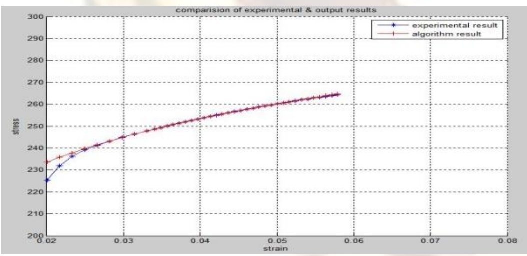

Figure 4. Average and the best value for function in generation

All experiments were performed with 40 data. The remaining 16 data were used to check the accuracy of the algorithm. The output data obtained from 40 data were given to the system model as input and the output of the modeled system was compared with the output of our system. The result is shown in Table 3.

Table 3. The final values for Holman equation's constant

Number of data	Best Fitness	Generation	n	K(MPa)
40	0.4096	7	0.1178	370.3072
56	0.4431	5	0.1175	369.8983

Conclusion

We proposed a model to predict the values of constants in Holman equation using genetic algorithm. The results show that the output of the proposed model is very close to the values obtained in experiments. We are currently working on employing other algorithms such as PSO to see which one is more suitable for predicting flow stress of aluminum alloy during tensile test. For the future, we intend to propose models for other properties of materials.

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