

## Prediction Tensile Stress of AA6061 Using Particle Swarm Optimization Algorithm

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### Abstract:

Mechanical properties of materials are conventionally evaluated by experimental tests such as tensile test. However these experiments are almost expensive and time consuming. It is desirable to predict material properties through computer simulations and modeling. Artificial intelligence models can be used successfully in this field. In this paper, the particle swarm optimization algorithm was utilized to predict flow stress of AA6061 aluminum alloy during tensile test. The material constants in Hollomon's equation were determined as well. The simulation results show good agreement with experimental data.

**Keywords:** Particle swarm optimization, Al Alloy, Flow Stress, Tensile Test

### 1. Introduction

In recent years, optimization has an important role in various scientific fields [1]. Optimization implies that how the best solution of a problem is accomplished.

Behavior of engineering materials against force, torque, or generally, any external stress either static or dynamic on the specific circumstances of work environment or test environment, called mechanical properties. Quality of materials used in industrial components depends on their mechanical properties. There are several experimental tests such as tensile test, hardness, impact test to study mechanical properties of materials [2].

A tensile test also known as tension test is the most common test in evaluating mechanical properties of materials. This test is used to determine behavior of a sample while an axial stretching load is applied. The test characteristic is stress - strain curve.

It is desirable for engineers to predict tensile properties of material without doing experiments. Hollomon's equation is extensively used to study tensile properties of alloys in various applications [3-6]. That is power law relationship between the stress and amount of plastic strain [2, 7]:

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

where  $\sigma$  is the stress,  $\varepsilon$  is the plastic strain,  $K$  and  $n$  are material constants.  $K$  is the strength index, and  $n$  is the strain hardening exponent.

Mahfouf and Linkens [8] used an integrated fuzzy model and Particle Swarm Optimization (PSO) to address optimum alloy in multi criteria designing making. They developed prediction models of optimization fuzzy algorithm to design heat treatment cycles of steels. Altinkok [9] studied tensile properties and hardness of aluminum base composite using artificial neural network. Behavior of 7039 aluminum alloy joints in friction stir welded investigated by Lakshminarayanan and Balasubramanian [10]. They used artificial intelligence network to predict tensile properties of alloy in different process conditions.

PSO is one of the most algorithms utilized in the field of collective intelligence. This algorithm, developed by Eberhart and Kennedy in 1995 and inspired by the social behavior of animals such as fish and birds that is designed live together in small groups and large [11-13]. In PSO, there are several solutions that can simultaneously work together. The potential solutions called particles. They brows in the search space to reach the optimal position. Speed and position of each particle is randomly initialized in the problem space. Then all the particles will gradually move to achieve the best solutions [1, 14].

Assume that our search space is  $d$ -dimensional, and the  $i$ th particle of the swarm can be represented by a  $d$ -dimensional position vector  $X_i = [x_{i1}, x_{i2}, x_{i3}, \dots, x_{id}]$ . The velocity of the particle is denoted by  $v_i = [v_{i1}, v_{i2}, v_{i3}, \dots, v_{id}]$ . In addition consider that the best visited position for the particle is  $P_{ibest} = [P_{i1}, P_{i2}, P_{i3}, \dots, P_{id}]$  and also the best position has been explored so far is  $P_{gbest} = [P_{g1}, P_{g2}, P_{g3}, \dots, P_{gd}]$ . Therefore the position of the particle and its velocity is being updated by using the following equations [14]:

$$V_i^{k+1} = wV_i^k + c_1r_1(P_{ibest} - x_i^k) + c_2r_2(P_{gbest} - x_i^k) \quad (2)$$

$$x_i^{k+1} = x_i^k + V_i^{k+1} \quad (3)$$

where  $V_i^k$  is the velocity of  $i$ th particle at the  $k$ th iteration,  $x_i^k$  is current the solution (or position) of the  $i$ th particle.  $c_1$  is the self-confidence (cognitive)

factor and  $c_2$  is the swarm confidence (social) factor.  $r_1$  and  $r_2$  are random numbers generated uniformly between 0 and 1.  $w$  is inertia weight that control influence components of current speed on their next speed and balance the ability of the algorithm in the search is local and global search. So it is reasonable  $w$  decreases gradually. Meanwhile the first global search has to be done and gradually goes towards local search. Several methods have been proposed to determine the value of inertia weight [15, 16].

In this paper, the PSO algorithm developed to predict flow stress of 6061 aluminum alloy during tensile test. The material constants in Hollomon's equation of alloy can be obtained from this algorithm as well.

## 2. Algorithm, Model and Experiment

In order to improve the PSO algorithm performance, in prediction of tensile stress; a matrix for constants in Hollomon's equation was considered. In this matrix,  $n$  and  $K$  are the first and second elements respectively.

It is essential to define initially a suitable cost function for solving the problem. Three types of error criteria used in study [16]:

Sum of squares error between the output model and experimental data:

$$errortype_1^2 = \sum_{i=1}^m (y_i - y'_i)^2 \quad (4)$$

1- The mean error between model output and measurements:

$$errortype_2 = \frac{\sum_{i=1}^m |y_i - y'_i|}{m} \quad (5)$$

2- The product of all the errors between model output and experimental values:

$$errortype_3 = \prod_{i=1}^m |y_i - y'_i| \quad (6)$$

In equations 1-3,  $m$  is number of particles,  $y_i$  is actual system output and  $y'_i$  is the model output. In order to validate the mode and to compare the model output white the actual data, tensile test was carried out on the AA6061 samples. The detail of material and experimental procedures has been presented in reference [17].

## 3. Result and Discussion

Several factors affect the on convergence speed and accuracy including population size, learning factor, inertia weight, fitness function and the type of error [14]. The influences of these factors on the speed and accuracy of PSO algorithm depends on the specific problem. In this study, different sets of these factors were implied in the program and the results were evaluated from computation time and error rate point of view. The combination of settings, which led to optimum results is presented in Table 1. output of the program implementation for 40 and 56 data are shown in table 2. The results show that the maximum error 1.4601833 and average error of is 0.74464.

Table 1: The optimum PSO algorithm factors

factors	values
Pop <sub>size</sub>	100
$c_1$	1
$c_2$	3
Iteration	300
Error Type	2

Table 2: The final values obtained for the Hollomon's equation constants

Number of data	Best Fitness	Iteration	n	K(MPa)
40	0.4096	204	0.1178	370.3072
56	0.4433	167	0.1154	367.3247

Fig.1 shows the average and the best value of cost function to obtain materials constants in Hollomon's equation. As illustrated in this figure, the cost function value decreases when the number of iteration increases. After 50 iterations it remains nearly constant. When the iteration reaches to 204, the best value of cost function is achieved.

In fig.2, the difference between the stress values obtained from model and measurements is demonstrated. In this figure, the data obtained according to error type2 in Eq.5. The fig.2 shows that for a small plastic strain, the contrast between the model output and actual values is more sensible. While deformation proceeds, the magnitude of difference becomes negligible.

The difference between the data predicted by the model and experimental data is shown in Fig.3. It is clear that a good agreement between the model output and actual value has been obtained. For strain value less than 0.025, the predicted curve deviates from experimental data. This is due to that this part of curve is reprehensive of onset of plastic deformation and material behavior transfers from elastic to plastic deformation. It has to be mentioned that Hollomon's equation is merely applicable for uniform plastic deformation of material.

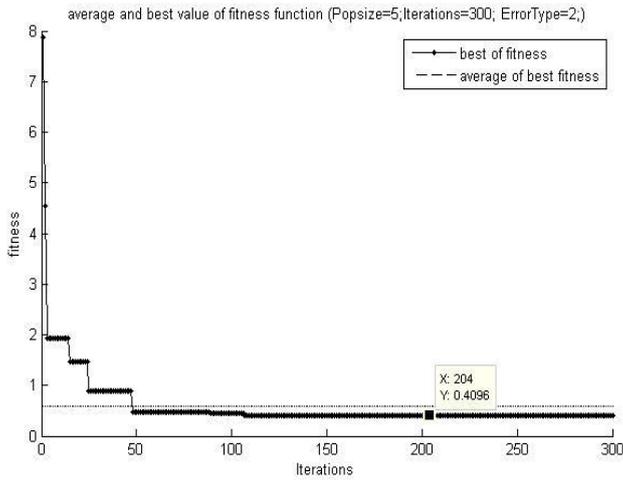


Fig. 1: Average and the best value of cost function of the problem

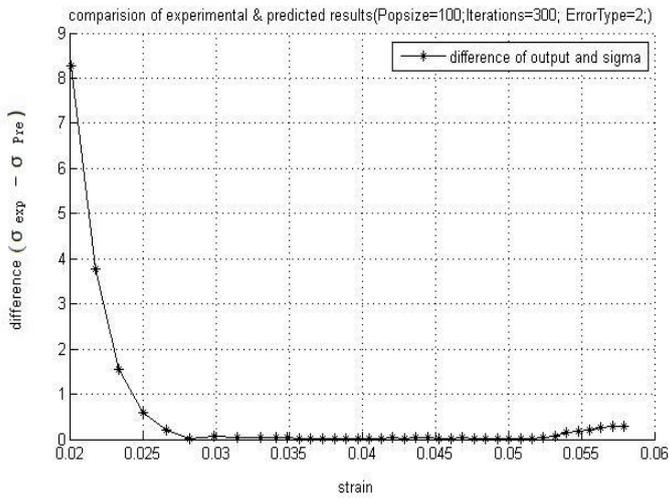


Fig. 2: The difference between the theoretical stress values and experimental stress for error type 2

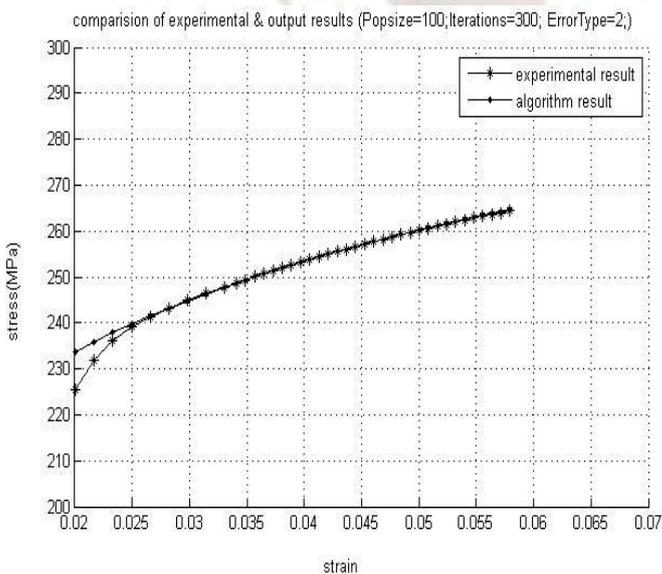


Fig. 3: Comparison of the stress - strain obtained from the model and experimental data

Fig. 4 compares the stress-strain curves for various error types and experimental data. It is clear that all error types predict the same result and have a good agreement with practical curve. In addition, the material constants in Hollomon's equation are identical in different error types; however the cost functions are different as presented in table3.

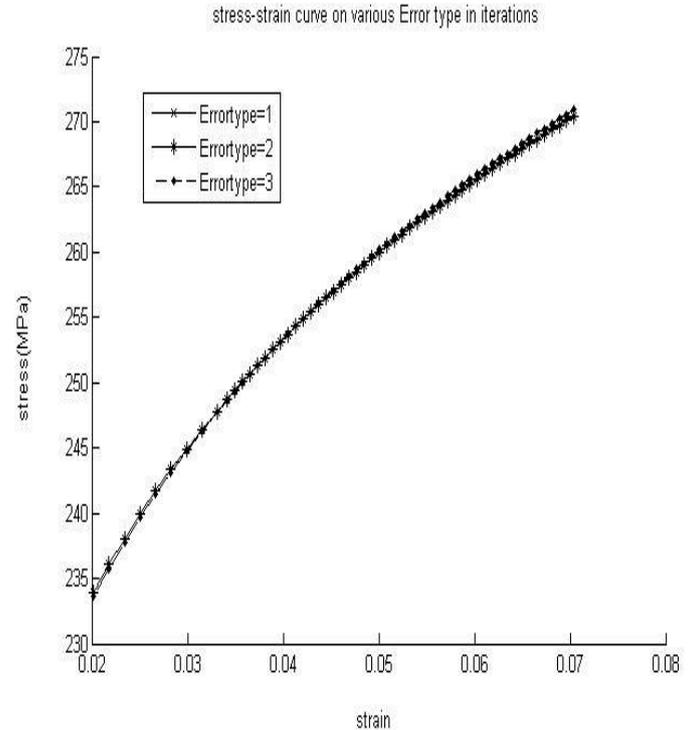


Fig. 4: stress-strain curve obtain for various error type

Table 3: Material constants in Hollomon's equation and cost functions for different error types

Error type	n	K(MPa)	best value of cost function
1	0.1178	370.3072	16.3837
2	0.1178	370.3072	0.4096
3	0.1172	369.5283	9.1417e-065

#### 4. Conclusion

The PSO algorithm developed to predict tensile Stress of 606 aluminum alloy. The optimum material constants in Hollomon's equation; i.e n= 0.1178 and K= 370.3072MPa obtained. Choosing a suitable choice operator of population size, inertia weight and learning factors lead to valuable result with minimal cost. Finally, the particle swarm optimization algorithm has a good potential to use in mechanical and materials engineering problems. The comparison of stress data of model with experimental results indicated a good agreement.

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