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A SVM Model to Predict the Hot Deformation Flow Curves of AZ91 Magnesium Alloy

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Abstract: In this work, a support vector machine (SVM) model was developed to predict the hot deformation flow curves of AZ91 magnesium alloy. The experimental stress-strain curves, obtained from hot compression testing at different deformation conditions, were sampled. Consequently, a data base with the input variables of the deformation temperature, strain rate and strain and the output variable of flow stress was prepared. To develop the support vector machine (SVM) model, the overall data was divided into two subsets of training and testing (randomly selected). Root mean square error (RMSE) criterion was used to evaluate the prediction performance of the developed model. The low RMSE value calculated for the developed model showed the robustness of it to predict the hot deformation flow curves of tested alloy. Also, the performance of the SVM model was compared with the performance of some previously used constitutive equations. The overall results showed the better performance of the SVM model over them.

Keywords: Support Vector Machine, Radial Basis Function, Hot compression, Flow stress.

1. Introduction

Low density, high strength to weight ratio and excellent castability are the main characteristics of magnesium alloys that make them good candidates for transportation industries applications [1-3]. However, because of low workability of these alloys at room temperature (that is the result of their HCP crystal structure); almost all manufacturing processes of them are conducted at elevated temperatures [1, 4]. Finite element simulation is an efficient way to analyze and control the metal forming processes. To develop a finite element simulation (especially, at hot working condition) it is needed to describe the flow stress of under studied material through a constitutive model. As explained by Lin and Chen [5], the constitutive models can be divided into three categories including phenomenological models, physical-based models and artificial neural network (ANN) models [5].

Phenomenological models are models which are used to fit a mathematical function on the experimental flow curves obtained at different deformation conditions (usually, through the hot compression testing). Johnson-Cook and Arrhenius-type equations are the most famous models of this category that have ever been used to describe the flow stress behavior of different materials [6, 7]. As a case study, the predictability of Johnson-Cook and Arrhenius-type equations for modeling the hot deformation behavior of Mg-6Al-1Zn has been evaluated by Abbasi-Bani et al. [8].

On the other hand, physical-based models are models which are developed based on physical aspects of the material behaviors such as thermally activated dislocation movement and kinetics of slips.

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Zerilli–Armstrong (ZA) model [9], dynamic recrystallization (DRX) model [10] and Preston–Tonks–Wallace (PTW) model [11] are some examples of this category.

Also, ANN models have widely been used for flow stress modeling. Mirzadeh et al. [12] developed a neural network model to predict the flow curves of three different steel types. They showed the higher accuracy of developed model over the two other phenomenological constitutive equations. Though, the neural network models act as a black box, a trained neural network that is developed based on the experimental data can be used as a lateral module accompanying with a FEM code to simulate the hot deformation processing of different materials.

Besides the three main categories of phenomenological models, physical-based models and artificial neural network (ANN) models (categorized by Lin and Chen [5]), the ability of support vector machine (SVM) technique to predict the flow stress of austenitic stainless steel 304 has been investigated by Desu et al. [13], in a recent work. According to the literature survey, this is the only work conducted to examine the capability of SVM for flow stress modeling. This technique acts as a black box and, in a way similar to the ANN models, can be used as a lateral module accompanying with a FEM code for flow stress description of the materials.

The main contribution of the present study is to evaluate the capability of the SVM model to predict the hot deformation flow curves of AZ91 magnesium alloy. For this reason, the experimental flow curves of tested alloy, obtained from hot compression testing (at different deformation temperatures and strain rates), were sampled for different strains with a predefined interval. Thus, a data base with the input variables of the deformation temperature, strain rate and strain and the output variable of flow stress was prepared. To develop the support vector machine (SVM) model, the overall data was divided into two subsets of training and testing (randomly selected). The training data set was used to establish the SVM model. Scatter diagrams together with the root mean square error (RMSE) criterion were used to compare the results of modeled flow curves with the experimental ones for both training and testing data sets. Also, the performance of the developed SVM model was compared with the performances of three previously examined constitutive equations on the same experimental flow curves [14].

2. Experimental Flow Curves

The experimental flow curves of the tested alloy were obtained from the hot compression tests conducted on a 250 kN Zwick tensile/compression testing machine equipped with a radiant furnace with the temperature accuracy of ±5 °C [15]. More details about the hot compression testing of the tested alloy have been reported in Ref. [15]. The obtained flow curves that have been used to develop the SVM model for the tested AZ91 magnesium alloy are presented in Fig. 1. As can be seen, the flow stress increases to a peak value and then gradually falls to a steady state stress which is an indication of the occurrence of dynamic recrystallization (DRX) and precipitate coarsening [16, 17]. However, as it can be seen in Fig. 1, at highest strain rates of 1 s^{-1} and different temperatures, steady state can hardly be seen that means in such conditions flow curves reach to the steady sate stress at strains beyond the tested strains (i.e. after the strain of 0.5). Moreover, as expected, the flow stress increases with an increase in strain rate and a decrease in deformation temperature.

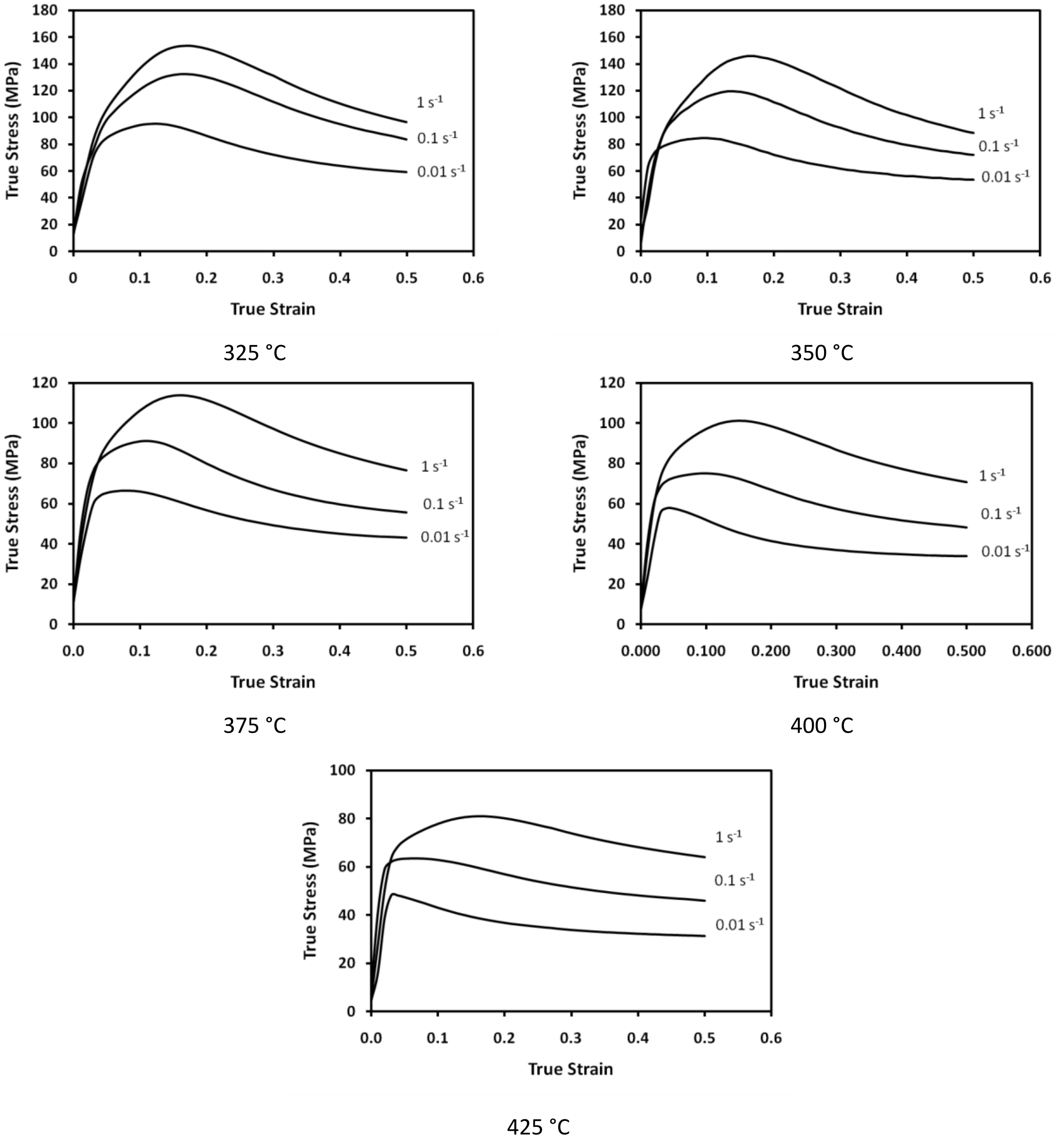

Fig. 1. Experimental flow curves of AZ91 magnesium alloy obtained at different deformation conditions [15].

3. Phenomenological Models

In this section, the results of previously used phenomenological constitutive models to describe the hot deformation flow curves of AZ91 magnesium alloy are presented from the literature (previous work of the Author(s)) [14]. These include the Arrhenius equation with strain dependent constants, the exponential equation with strain dependent constants and a recently developed simple model (developed based on a power function of Zener-Hollomon parameter and a third order polynomial function of ε power a constant number). The overall results are as follows:

3.1. Arrhenius-type equation

Using the Arrhenius equation with strain dependent constants the hot deformation flow stress of AZ91 magnesium alloy can be described through the following equation:

$$\sigma = \frac{1}{\alpha} ln\left\{(Z/A)^{1/n} + \left[(Z/A)^{2/n} + 1\right]^{1/2}\right\} \quad (1)$$

while the strain dependent constants of this equation can be calculated using the following relations [14]:

$$\alpha = 0.518\varepsilon^4 - 0.746\varepsilon^3 + 0.375\varepsilon^2 - 0.062\varepsilon + 0.015 \quad (2)$$

$$n = -293.0\varepsilon^3 + 310.5\varepsilon^2 - 100.1\varepsilon + 14.49 \quad (3)$$

$$Q = 11479887\varepsilon^4 - 14{,}137{,}096\varepsilon^3 + 6358104\varepsilon^2 - 1339535\varepsilon + 286328 \quad (4)$$

$$lnA = 2281.237\varepsilon^4 - 2760.780\varepsilon^3 + 1206.529\varepsilon^2 - 243.762\varepsilon + 48.668 \quad (5)$$

3.2. Exponential-type equation

Using the exponential equation with strain dependent constants the hot deformation flow stress of AZ91 magnesium alloy can be described through the following equation:

$$\sigma = (ln\dot{\varepsilon} + \frac{Q}{RT} - lnA'')/\beta \quad (6)$$

while the strain dependent constants of this equation can be calculated using the following relations [14]:

$$\beta = -5.913\varepsilon^3 + 6.204\varepsilon^2 - 1.886\varepsilon + 0.251 \quad (7)$$

$$Q = -937464.653\varepsilon^3 + 1181186.145\varepsilon^2 - 564241.074\varepsilon + 258298.730 \quad (8)$$

$$lnA'' = 181.5\varepsilon^3 - 161.9\varepsilon^2 + 21.02\varepsilon + 26.16 \quad (9)$$

3.3. The equation developed based on a power function of Zener-Hollomon parameter and a third order polynomial function of ε power a constant number

Using the developed model based on a power function of Zener-Hollomon parameter and a third order polynomial function of ε power a constant number, the hot deformation flow stress of AZ91 magnesium alloy can be described as follows [14]:

$$\sigma = \dot{\varepsilon}^{\,0.122} exp(\frac{0.122\times144998}{RT}) \times (-3.333 + 41.335\varepsilon^{0.4} - 74.551\varepsilon^{0.8} + 41.322\varepsilon^{1.2}) \quad (10)$$

4. Support Vector Machine

As mentioned before, SVM can be used for applications such as classification and regression. In SVM method for regression, using N training data ($\{(x_i, y_i) \mid i = 1, ..., N\}$) the input space x is transferred into a higher dimensional feature space (applying the kernel functions) at the first; then, a linear machine is constructed in the feature space [18, 19]:

$$f(x) = W^T \emptyset(x) + b \quad (11)$$

where $W = [w_1, \dots, w_N]^T$ is the weight vector that controls the smoothness of the model, $\emptyset(x)$ is the transformation function (kernel function) and b is the bias. In the relation above, the values of weights and bias vectors are calculated by minimizing the regularized risk function [14]:

$$R(f) = \frac{1}{2}\|W\|^2 + C\sum_{i=1}^{N} L(y_i, f(x_i)) \quad (12)$$

where $L(y_i, f(x_i))$ is the epsilon sensitive loss function:

$$L(y_i, f(x_i)) = \begin{cases} 0 & if\ |y_i - f(x_i)| < \varepsilon \\ |y_i - f(x_i)| - \varepsilon & otherwise \end{cases} \quad (13)$$

According to the ε value, the data points inside the ε tube ($|y_i - f(x_i)| < \varepsilon$) are considered as zero loss; while, the data points out of the ε tube, called the support vectors, participate in training error loss. Hence, the size of ε insensitive zone controls the number of support vectors. Increasing in the ε insensitive zone controls the number of support vectors [20].

Two nonnegative slack variables ξ_i and ξ_i^* are introduced to measure the deviation of training data points outside the ε insensitive zone. So, in SVM, the optimization problem is to minimize the following function [21, 22]:

$$\min \ \frac{1}{2}\|W\|^2 + C\sum_{i=1}^{N}\xi_i + \xi_i^* \tag{14}$$

subject to

$$y_i - W^T\emptyset(x_i) - b \leq \varepsilon + \xi_i \qquad i = 1, \dots, N \tag{15}$$

$$-y_i + W^T\emptyset(x_i) + b \leq \varepsilon + \xi_i^* \qquad i = 1, \dots, N \tag{16}$$

$$\xi_i, \xi_i^* \geq 0 \qquad i = 1, \dots, N \tag{17}$$

Using Lagrange multiplier, the dual form of this optimization problem can be solved as in the follow:

$$\max -\frac{1}{2}\sum_{i,j=1}^{N}(\alpha_i - \alpha_i^*)\,(\alpha_j - \alpha_j^*)K(x_i, x_j) - \varepsilon\sum_{i=1}^{N}(\alpha_i + \alpha_i^*) + \sum_{i=1}^{N} y_i(\alpha_i - \alpha_i^*) \tag{18}$$

subject to

$$\sum_{i=1}^{N}(\alpha_i - \alpha_i^*) = 0, \ \ \alpha_i, \alpha_i^* \in [0, C] \tag{19}$$

where α and α^* are Lagrangian multipliers and $K(x_i, x_j) = \emptyset(x_i)^T\emptyset(x_j)$ is the kernel matrix. In addition to the latter constraints, Karush-Kuhn-Tucker conditions should also be satisfied [22, 23]. Usually, a Gaussian radial basis function is used as the kernel function:

$$K(x_i, x_j) = exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right) \tag{20}$$

Thus, the final form of the function $f(x)$ is given by:

$$f(x) = \sum_{i=1}^{N}(\alpha_i - \alpha_i^*)\,K(x_i, x) + b \tag{21}$$

It is obvious that the prediction performance of a SVM model, depends on the proper selection of its parameters including: kernel parameter σ, the capacity C and the parameter of ε.

5. Results and Discussion

The experimental flow curves obtained from hot compression tests at different deformation temperatures and strain rates [15] were sampled for the strains in the range of 0.05 to 0.5 with step size of 0.01. Thus, a data base with the input variables of the deformation temperature, strain rate and strain and the output variable of flow stress with 690 patterns was prepared. The prepared data base was divided into two subsets of training and testing. Two third of the overall data (i.e. 460 randomly selected patterns) was used as training data to develop the SVM model and the rest was used to test the developed SVM model for unseen data. The online SVR toolbox for MATLAB application developed by Parrella [23] was applied to predict the flow stress of tested alloy. The RMSE criterion was used to assess the prediction performance of the developed model:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - f(x)_i)} \tag{22}$$

where y_i is the target output, $f(x)_i$ is the model output and *n* is the number of data patterns. After some trial and error, the values of kernel parameter σ, the capacity C and the parameter of ε were selected as 30, 10 and 0.01, respectively. Using the scatter diagrams, the results obtained for training, testing and overall data patterns experimental flow stresses are shown in Fig. 2.

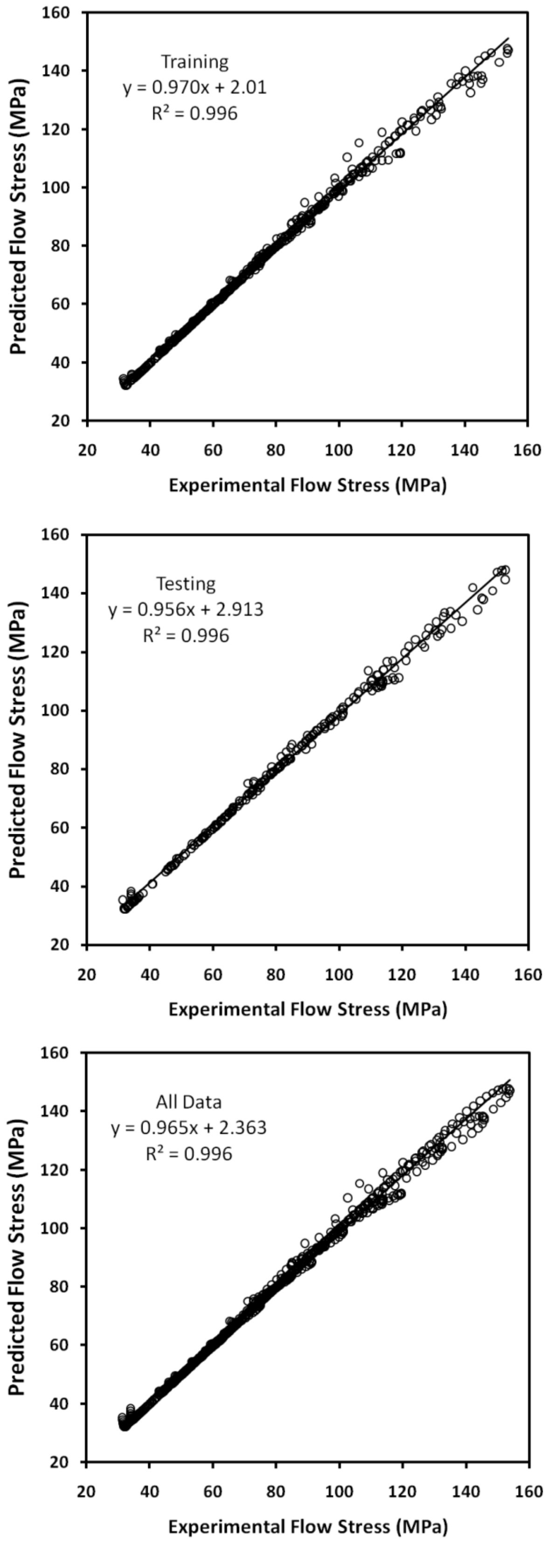

Fig. 2. The comparison between the experimental and modeled flow curves (using the SVM model) for training, testing and overall data patterns.

As can be seen there is a good agreement between the experimental flow stresses and the modeled ones. These, together with low RMSE value, obtained for training, testing and overall data (see table 1) shows the robustness of the SVM model to predict the hot deformation flow curves of tested alloy.

Table 1. RMSE values obtained for training, testing and overall data patterns.

	Training data patterns	Testing data patterns	Overall data patterns
RMSE criterion (MPa)	1.83	2.28	1.99

Also, a comparison between the experimental and calculated flow curves (using the SVM model) at deformation conditions with two temperatures of 375 and 400 °C with different strain rates are presented in Figs. 3a and 3b, respectively.

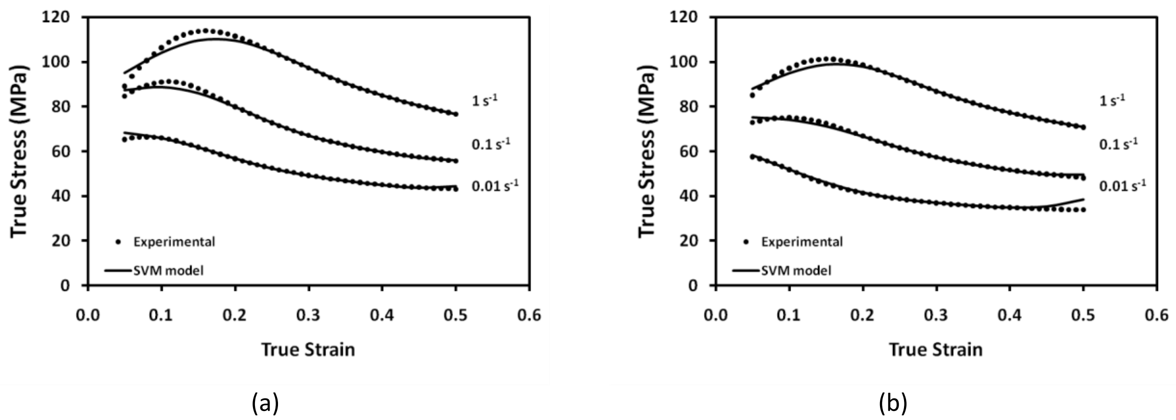

Fig. 3. The comparison between the experimental and modeled flow curves (using the SVM model) at deformation conditions with two temperatures of (a) 375 and (b) 400 °C with different strain rates.

As can be seen, there is a good consistency between the modeled and experimental flow curves. Moreover, as can be seen the strain hardening and work softening stages appeared in DRX flow curves of tested alloy can be modeled, simultaneously. These together with the low RMSE value of 1.99 MPa obtained for overall data shows the high performance of the developed SVM model in modeling the hot deformation flow curves of the tested alloy. In Table 2, the RMSE value obtained for the developed SVM model is compared with the RMSE values of the other previously examined constitutive equations [14].

Table 2. RMSE values obtained for the SVM model and previously examined constitutive models.

Examined model	RMSE criterion (MPa)
SVM model (current study)	1.99
Arrhenius equation with strain dependent constants [14]	4.96
exponential equation with strain dependent constants [14]	5.88
simple model developed based on a power function of Zener-Hollomon parameter and a third order polynomial function of ε power a constant number [14]	10.51

As presented in Table 2, the RMSE value obtained for the developed SVM model shows the better performance of it over the other investigated constitutive models.

6. Conclusion

A support vector machine (SVM) model was applied to predict the hot deformation flow curves of AZ91 magnesium alloy. The experimental flow curves of tested alloy, obtained from hot compression testing (at different deformation temperatures and strain rates) were sampled for different strains with a predefined interval. Therefore, a data base with the input variables of the deformation temperature, strain rate and strain and the output variable of flow stress was provided. Two thirds of the overall data (randomly selected) was used as training data to develop the SVM model and the rest was used to test the developed model. Root mean square error (RMSE) criterion was used to evaluate the prediction performance of the developed model. The low RMSE value of 1.99 MPa, obtained from SVM showed the robustness of the developed model to predict the hot deformation flow curves of tested alloy. Moreover, the performance of the SVM model was compared with the performance of some previously used constitutive equations. The overall results showed the better performance of the SVM model over them.

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استفاده از مدل SVM جهت پیش بینی منحنی های سیلان کارگرم آلیاژ منیزیمی AZ91

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چکیده: در مطالعه حاضر، از مدل ماشین بردار پشتیبان (SVM) جهت پیش بینی منحنی های سیلان کارگرم آلیاژ منیزیمی AZ91 استفاده شد. نمودار های تنش-کرنش حاصل از آزمون فشار گرم در شرایط تغییر شکل متفاوت نمونه برداری شدند. بدین ترتیب، پایگاه داده‌ای با متغیر های ورودی دمای تغییر شکل گرم، کرنش و نرخ کرنش فراهم شد. به منظور توسعه مدل ماشین بردار پشتیبان پایگاه داده فراهم شده به دو زیرمجموعه داده های آموزش و آزمون (با انتخاب تصادفی) تقسیم شد. از معیار ریشه میانگین مربعات خطا جهت ارزیابی عملکرد مدل توسعه داده شده استفاده شد. همچنین، عملکرد مدل ماشین بردار پشتیبان توسعه داده شده با عملکرد چند مدل جامع توسعه داده شده قبلی مقایسه گردید. با توجه به نتایج بدست آمده، نشان داده شد که مدل ماشین بردار پشتیبان عملکرد بهتری نسبت به سایر مدل‌های مورد مطالعه دارد.

واژه های کلیدی: ماشین بردار پشتیبان (SVM، تابع پایه شعاعی، فشار گرم، تنش سیلان.