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Accurately Predicting High Temperature Flow Stress of AZ80 Magnesium Alloy with Particle Swarm Optimization-based Support Vector Regression

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Abstract: An important research trend in metal forming is to predict high temperature flow stress of materials during deformation. In the conventional models, there exist difficulties in the regression analysis based on the experimental results to obtain the model constants. Support vector machine (SVM) is a new technology for solving classification and regression. In this study, a novel accurate and rapid prediction of high temperature flow stress of AZ80 magnesium alloy with particle swarm optimization-based support vector regression (PSOe-SVR) was developed. Datasets were established based on compression tests in the temperature range of 350-450°C and strain rate range of $0.01-50s^{-1}$. Meanwhile, the datasets were corrected for deformation heating and unbalance. The maximum relative errors between the experimental and predicted flow stress with PSOe-SVR, Back propagation neural network (BPNN) and constitutive equation was compared and analyzed. The results show the lower the strain rate, the greater the predicting accuracy of testing samples using PSOe-SVR. Meanwhile, the PSOe-SVR model has the most accurate prediction ability to those of BPNN and constitutive equation. The sample dependence of PSOe-SVR is also lower.

Keywords: AZ80 magnesium, support vector regression, flow stress, prediction, particle swarm optimization

1. Introduction

Magnesium alloys have a great potential for wide application due to their high strength-to-gravity ratios. Recently, Kleiner [1] have shown the high potential of magnesium alloys for lightweight structural components in automotive applications owing to the excellent properties in terms of low density and high specific strength. Unfortunately, magnesium alloys exhibit poor attitude to deformation. Bruni [2] indicated that the low workability of magnesium alloys is as a result of hexagonal crystal structure, and the formability strongly depends on texture and deformation twinning. Therefore, deeper knowledge of the deformation behavior of magnesium alloys, especially the flow stress curves and their dependencies on temperature, strain and strain rate should to be carefully obtained prior to all forming experiments. Among all the wrought magnesium alloys, AZ80 alloy has attractive combination properties such as high strength, high toughness and good plasticity. But AZ80 magnesium alloy is subjected to complex dynamic recrystallization (DRX) in forming processes. Therefore, accurately predict the high temperature flow stress of AZ80 magnesium alloys is always very difficult. Zhou [3] employed the processing map to study the hot deformation behavior of AZ80 alloy so as to optimize its hot workability, and developed a hyperbolic sine constitutive model of the alloy for hot deformation. Quan [4] developed a constitutive model for AZ80 magnesium alloy with considering DRX during hot deformation. Hu [5] developed a novel constitutive equation to investigate influence of dynamic recrystallization on tensile properties of AZ31 magnesium alloy sheet. But in the conventional methods, the regression analysis was carried out based on the experimental results to obtain the constants of the constitutive models. The response of the deformation behaviors of the materials under elevated temperatures is highly nonlinear. Thus, Lin [6] indicated the accuracy of the flow stress predicted by the regression methods is low and the applicable range is limited.

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Nowadays, intelligent theory and method have been used for prediction, estimation and optimization in material engineering. Previous studies showed that artificial neural network (ANN) could obtain satisfied results. Anaraki [7] established a model of high temperature rheological behavior of AZ61 Mg-alloy using ANN, and compared the prediction of flow stress using ANN and using inverse method. Han [8] employed adaptive fuzzy-neural network for prediction of mechanical properties of titanium alloy. Their results show that the maximum relative error is less than 9%. Sun [9] used artificial neural networks successfully to predict the tensile property of hydrogenated Ti600 titanium alloy. However, the serious disadvantage of artificial neural networks is that network training is time-consuming and easy leading to over-fitting. Recently, support vector machines (SVM) has been introduced to solve machine learning tasks such as pattern recognition, regression and estimation. Due to its excellent properties of globally optimal solution and good learning ability for small samples, SVM attracted wide attention. Yoon [10] applied SVM to predict ground water level and stated the overall model performance criteria of SVM are better than those of the ANN in model prediction stage. Chen [11] indicated SVM can be used as a better alternative modeling tool for quantitative structure-property/activity relationship of gas chromatography retention indexes. Shi [12] applied fuzzy SVM on product's KANSEI extraction. However, the biggest problem encountered in constructing the SVM model is how to select the training parameter values. Inappropriate parameter settings lead to poor recreation results. Considering the great influence of the parameters on generalization performance of SVM, particle swarm optimization (PSO) was applied to search the parameters of SVM in global space. The technique was derived from social behavior such as bird flocking and fish schooling, which can efficiently find optimal or near-optimal solutions in search spaces.

In the present study, a novel prediction of high temperature flow stress of AZ80 magnesium with particle swarm optimization-based support vector regression (PSOe-SVR) was developed. The predicted values of flow stress with PSOe-SVR were compared with those obtained with Back propagation neural network (BPNN) and the constitutive equation. The datasets of the flow stress of the AZ80 magnesium to strain, strain rate and the temperature were selected through compression tests.

2. Methods

Support vector regression. Support vector machines (SVM) is a novel statistical learning theory based on machine learning algorithm presented by Vapnik [13]. It is based on the Structural Risk Minimization principle from computational learning theory. It is simple enough to be analyzed mathematically, because it can be shown to correspond to a linear method in a high-dimensional feature space nonlinearly related to input space.

Now e-SVR (support vector regression) has been developed for solving regression. For a given regression problem, the optimization can be expressed as [14]:

$$\min \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{l}\xi_i + C\sum_{i=1}^{l}\xi_i^* \tag{1}$$

$$s.t.(\omega \cdot x_i + b) - y_i \le e + \xi_i \tag{2}$$

$$y_i - (\omega \cdot x_i + b) \le e + \xi_i^* \tag{3}$$

$$\xi_i, \xi_i^* \ge 0, i = 1, 2, \cdots, l. \tag{4}$$

where ω is a column vector with d dimensions, b is the bias term. $x_i \in R^n$ is an input and $y_i \in R^n$ is an target output. $C > 0$ is the penalty factor which controls the equilibrium between the complexity of model and training error, e an insensitive loss parameter that for controlling tube size, namely, errors below e would not be penalized. ξ_i and ξ_i^* are the introducing slack variables guarantee the satisfaction of constraint condition.

For nonlinear regression, the basic idea of e-SVR is to map the input vectors X onto a very high-dimensional space using kernel function K(x, y), and then a nonlinear feature mapping will allow the treatment of non-linear problems in the way similar to that of linear problems. The decision function of this optimal hyperplane is [15]:

$$f(x,y) = \sum_{i=1}^{l}(\alpha_i - \alpha_i^*)K(x,y) + b, 0 \le \alpha_i, \alpha_i^* \le C \tag{5}$$

Where, α_i and α_i^* are Lagrangian multipliers from the quadratic programming (QP) problem. The kernel function $K(x,y)$ can effectively solve the contradiction between high dimension and computing complexity, and is thus a great progress in the development of SVR. There are four possible choices of kernel functions, such as linear, polynomial, sigmoid, and radial basis function. For the regression problems, the radial basis function (RBF) kernel is commonly used, which can be expressed as follows:

$$K(x,y) = \exp(-r \times |x-y|^2) \tag{6}$$

where r is the reciprocal of the property of input data.

Particle swarm optimization. Particle swarm optimization (PSO) is an intuitive and easy-to-implement algorithm, which updates particles based on their individual experience their group experiences and previous movements of the particles, and each particle represents a potential solution within the search space.

Each particle has a position vector (X_i), a velocity vector (V_i), the position at which the best fitness $(pbest)$ encountered by the particle so far, and the best position of all particles $(gbest)$ in current generation. The updating equations of PSO can be expressed as [16]:

$$V_i(t+1) = \omega V_i(t+1) + c_1 r_1 (x_{pbest}(t) \cdots - x_i(t)) + c_2 r_2 (x_{pbest}(t) - x_i(t)) \tag{7}$$

$$x_i(t+1) = x_i(t) + V_i(t+1) \tag{8}$$

The parameters c_1 and c_2 are learning factors, which are set to constant value, r_1 and r_2 are two random values, uniformly distributed in [0, 1], ω is inertia weight which controls the influence of previous velocity on the new velocity, global search performance is good with large inertial weight while a small inertia weight facilitates a local search.

3. Case studies

Date acquisition. The date sets of the flow stress at different strain, strain rate and temperature were acquired through compression tests. The material used in this study was AZ80 magnesium alloy, with a nominal composition of 7.8 Al, 6.5 Zn and a minimum Mn content of 0.3 (wt.%). Cylindrical specimens of 10mm in diameter and 12mm in height were machined from hot extruded bars of 47.2mm in diameter, with the axis along the extrusion direction. Compression tests were performed on Cleeble-3500 machine with strain rates of $0.01s^{-1}$, $0.1s^{-1}$, $1s^{-1}$, $10s^{-1}$ and $50s^{-1}$ and temperatures of 350°C, 400°C and 450°C respectively. The specimen was resistance-heated through a thermocouple sending feedback signals to control the AC-current. In the present study, a very fine, fast-response thermocouple with a diameter of 0.08 mm was used to capture the temperature changes occurring during the tests. Before deformation was initiated, graphite foils were put on the specimen's flat ends as lubricant. Specimens were preheated to the required temperature with a heating rate of 10°C/s and homogenized for 60 seconds, then compressed to 4.4 mm in height, achieving a true strain of 1.0. All the tests were performed in a nitrogen atmosphere.

Date correction for deformation heating during high strain rate deformation. Li [17] indicated that deformation heating is pronounced during deformation at,high strain rates. A correction of flow stress for deformation heating at a high strain rate is a necessity. The temperature increase due to deformation heating may be calculated using the following equation:

$$\triangle T = (\eta(0.9 \sim 0.95)\int \sigma d\varepsilon)/(\rho C_p) \tag{9}$$

$$A[\sinh(\alpha\sigma)] = \varepsilon^{\cdot} \exp[-Q/R(T+\triangle T)] \tag{10}$$

$$Z = \varepsilon^{\cdot} \exp[-Q/R(T+\triangle T)] \tag{11}$$

where $\triangle T$ is the change in temperature, η is the adiabatic factor, $\int \sigma d\varepsilon$ is the mechanical work, ρC_p is the heat capacity and the factor $0.9 \sim 95$ is the fraction of mechanical work transformed to heat. n, α, Q and R are constants, Q is the activation energy of deformation and R is the universal gas constant. Z is Zener-Hollomon parameter.

With both measured and calculated specimen temperatures, flow stress could be corrected for deformation heating according to the procedure described in reference [18]. Fig.1 illustrates the corrected stress-strain curves at various temperatures and strain rates. It can be seen that at high strain rates, the flow stress attains a peak, followed by continuous flow softening till the end of the tests. At low strain rates, the flow curves exhibit gradual softening followed by steady-state flow behavior. The peak stress decreases with increasing temperature or decreasing strain rate. Flow softening is a common characteristic of true strain-true stress curves for many alloys deformed at elevated temperature. It could be caused by deformation heating and by microstructural instabilities inside the material, such as texture formation, dynamic precipitation and dissolution. All the flow stress curves show a single peak implying the occurrence of the DRX during hot deformation.

Date correction for unbalance. Form Fig.1, It can be found that the numbers of data points in different classes are unbalanced. For instance, the numbers of data in stress and strain classes are theoretically infinite, while the correspond numbers of data in strain rate and temperature classes are limited. This will lead to reduced accuracy of SVR. Therefore, linear interpolation is used to increase the number of small data classes, to balance the various types of data.

Assume that y is a function of x, $y = f(x)$, if we have measured the correspond values of x_p and x_q , so $y_p = f(x_p)$,$y_q = f(x_q)$, take a number from x_p to x_q as x, the corresponding value of y is varying linearly along x, then:

$$y = y_p + \frac{x - x_p}{x_q - x_p}(x - x_q) \tag{12}$$

Where x_p, x_q, y_p, y_q is known, x is the interpolated value. Taking different values of x, we can obtain any corresponding value of y .

In this study, according to Fig.1, the temperature range is $[350, 450]$, can be divided into three grades, and strain rate range is $[0.01, 50]s^{-1}$, can be divided into five grades. According to linear interpolation, the temperature is extended to seven grades, strain rate extended to nine grades (shown in Table 1). And then according to (12) and the data in Fig.1, we can obtain values of flow stresses of corresponding unknown data points.

Table 1 Parameters used in interpolation method

Parameters	Numbers of values used	Values of parameters in interpolation method
T(°C)	7	350, 370, 380, 400,420,430, 450
$\varepsilon^{\cdot}(s^{-1})$	9	0.01, 0.05, 0.1, 0.5,1, 5, 10, 30, 50

4. Prediction of high temperature flow stress of AZ80

In this section, a model of high temperature flow stress of AZ80 is developed based on the integration of PSO,

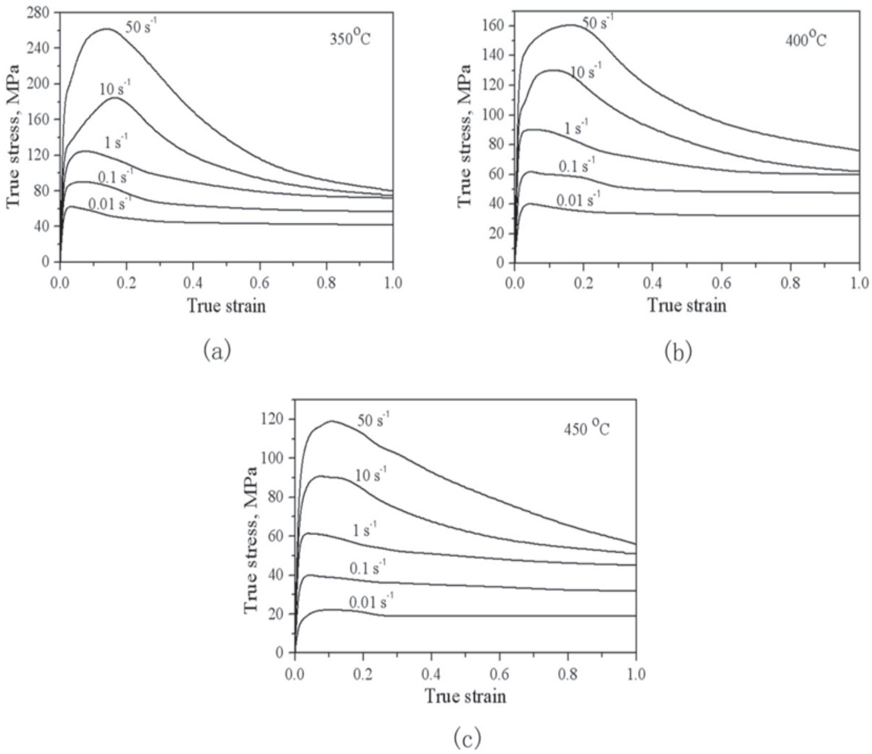

Figure 1 True stress-true strain curve obtained at different strain rates and various temperatures, (a)at 350°C, (b)at 400°C,(c)at 450°C

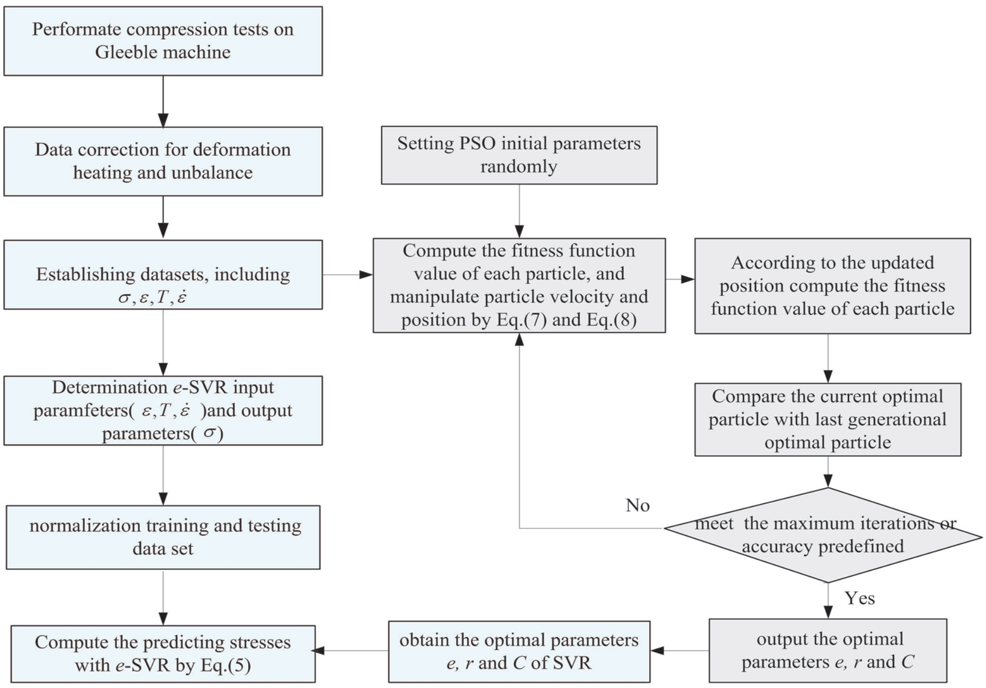

Figure 2 Flow chat presenting model of high temperature flow stress of AZ80

e-SVR, experiments and data correction as shown in Fig.2. The control procedure can be divided into two main sections: the optimal parameters selection of e-SVR based on PSO, and the predicted flow stresses with e-SVR. Meanwhile, mean square error (MSE) was used to qualify the training accuracy.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(\alpha_i - \overline{\alpha}_i)^2 \tag{13}$$

Where, α_i is actual value, $\overline{\alpha}_i$ is predicted value, N is sample number. deformation.

The parameters selection of e-SVR based on PSO. On the basis of the e-SVR model, there are three parameters, e, r and C, to be determined. PSO method was used to optimize the model parameters, to improve the SVR accuracy and generalization. Firstly, with random generate initial particles comprised of, e, r and C. Secondly, set the PSO parameters including number of particles,particle dimension, number of maximal iterations, learn factors and inertia weight for particle velocity. Thirdly compute the fitness function value of each particle, and adopt the mutation operator by (7) and (8) to manipulate particle velocity and position. And then compare the current optimal particle with last generational optimal particle and update global and personal best. Finally, if the maximum iterations and accuracy predefined are met, stop condition checking and output the optimal parameters e, r and C.

Predicting flow stress of AZ80. Three inputs (ε, $\dot{\varepsilon}$ and T) and one output (σ) was used in this study for predicting the high temperature flow stress of AZ80 magnesium alloy with PSOe-SVR. According to (2) and (7), the range of e, r and C were set as $(0,1]$, $(0,500]$ and $(0,1000]$, respectively. The optimal parameters, e, r and C, were obtained when iteration number exceeded 500, or met the predefined accuracy 0.001. So the detailed description steps of predicting flow stresses with PSOe-SVR were as follows:

1. SVR inputs were comprised ε $\dot{\varepsilon}$ of and T, while the flow stress σ was taken as the output obtained from a compression test.
2. Initialize the original data by normalization, and form training and testing data set, respectively.
3. Select the RBF kernel function and obtain the optimal parameters e, r and C based on PSO.
4. Compute the predicting flow stresses by formula (5).
5. Here, MATLAB platform was used to practice the predicting. During the calculating period, the population size of PSO was set as 20, evolutional generation was set as 500, and the learning factors $c_1 = 1.5$,$c_2 = 1.7$. The iterative process was shown in Fig.3. So we can select 0.01, 180 and 726.8036 as the optimal e, r and C value, respectively.

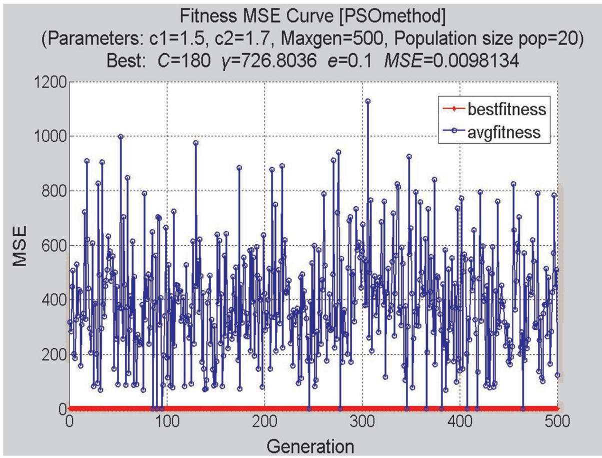

Figure 3 The iterative process

5. Results and discussion

Comparison of predicted and measured stress. Based on the PSOe-SVR approach mentioned in the previous section, 75 sets of flow stress curves were used as the training samples and 3 sets of flow stress curves as the testing samples. Basic parameter values of PSOe-SVR model are shown in Table 2.

Table 2 Parameters used in interpolation method

Parameters	Value
Insensitive loss parameter, e	0.01
Gamma in kernel function, r	180
Penalty factor, C	726.8036
Goal error	0.001
The maximum training number	1000
PSO learning factors c1	1.5
PSO learning factors c2	1.7
PSO population size	20
Training generation	500

The measured and predicted flow stresses between training and testing sets are graphically depicted in Fig.4. It can be found that a very good agreement exits between training predicted results and the measured data. A comparison of the testing samples and measured flow stresses at different temperature and different rates, is presented in Fig.4 too. High correlation also exits between them. The testing predictions are within the acceptable range.

From Fig.5, it can be found that the maximum relative error of training set is very small. They are 0.24, 0.31 and 0.33 at 350°C, 400°C and 450 °C , respectively. In addition, the higher the strain rate, the lower the relative error in flow stress. The reason could be attributed

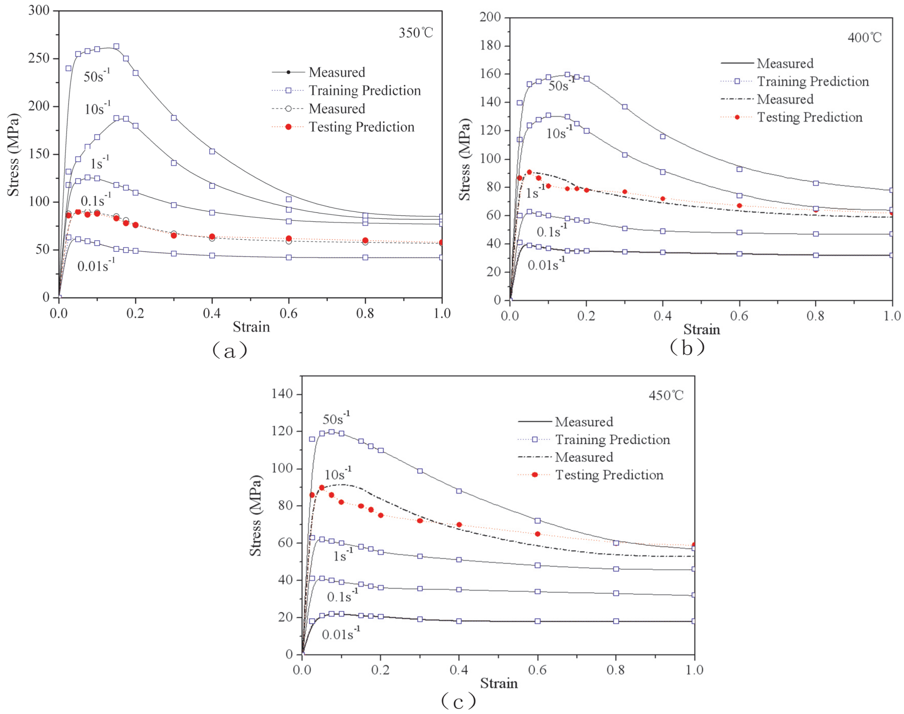

Figure 4 Comparison of measured and predicted flow stresses between training and testing sets at (a)350°C,(b)400°C and (c)450°C

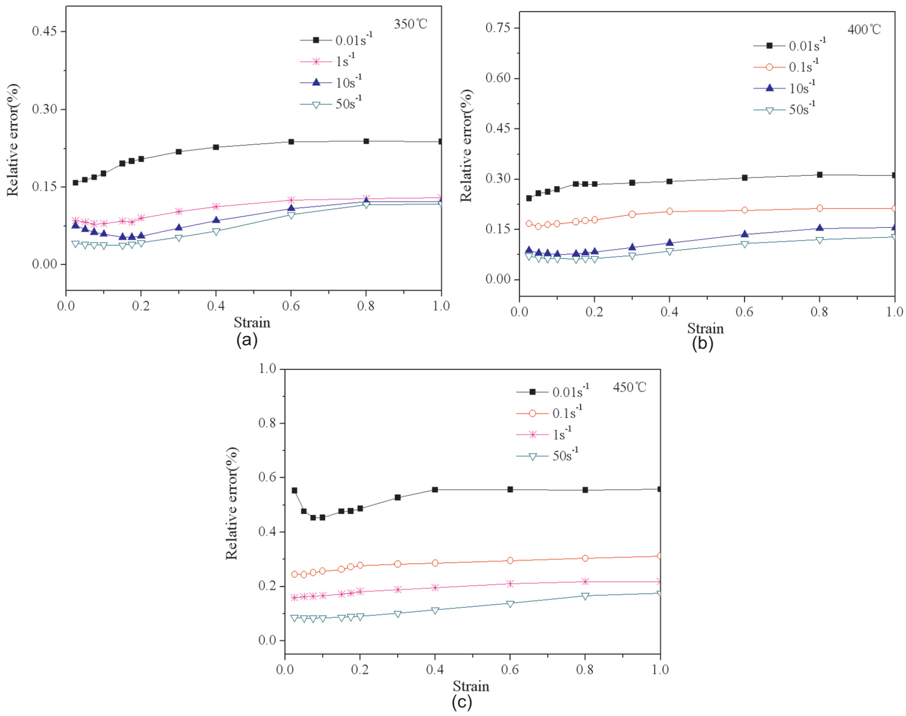

Figure 5 Comparison of stress relative error of training samples obtained at (a)350°C,(b)400°C and (c)450°C

to the sensitivity of flow stress related parameters to experimental factors. At low strain rate, such as at $0.01s^{-1}$ or $0.1s^{-1}$, the strain rate was too small so that could be influences more easily by experimental factors. Chen [19] also pointed out the reason in the estimation of exposed temperature for fire-damaged concrete using support vector machine.

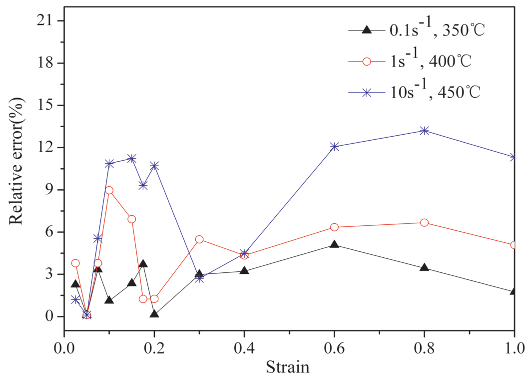

Figure 6 Comparison of stress relative error of testing samples

On the contrary, form Fig.6, it can be found that the lower the strain rate, the lower the relative error of testing samples. Possibly, with the increasing of the model accuracy, the complexity of the model increases, and the accuracy of testing samples decreases. Therefore, the lower the training error, but the higher the testing error [20].

Comparison of the sample dependence between PSOe-SVR and BP-neural network. The performance data of PSOe-SVR model would be changed with the ratio between the number of training sample and testing sample. The changing tendency is shown in Table 3, where TR is the number of training data and TE is the number of testing data.

Table 3 Performance changing tendency of PSOe-SVR model and BPNN model for changed the ratio between the number of training sample and testing sample

TR	TE	PSOe-SVR	PBNN
		MSE	MSE
75	3	0.0098134	0.021567
70	8	0.0098789	0.057862
60	18	0.0099345	0.092343
52	26	0.0099789	0.137645

Given the parameters, e, r and C, it can be found that MSE records very slight variations with the ratio of the numbers of sample number. By contrast, the sample dependence of BP-neural network (BPNN) is relative high. For BPNN, the predicted results depend on all the training samples. However, the predicted results of PSOe-SVR only depend on the key points of the training data, the support vectors. Therefore, its dependence on training samples is relative low. But for both e-SVR and BPNN model, the prediction performance can be improved by increasing the number of training sample.

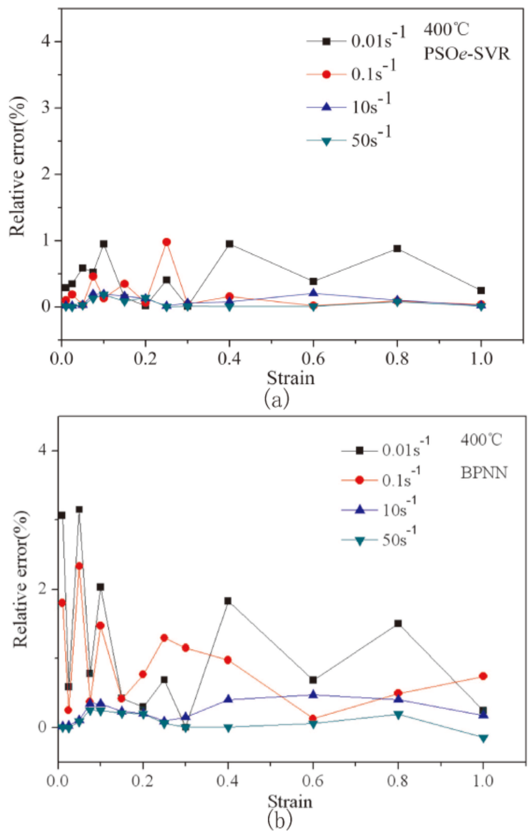

Figure 7 Comparison of stress relative error of training samples obtained at 400°C, $\dot{\varepsilon} = 1s^{-1}$ between (a) PSOe-SVR and (b) BPNN

Comparison of study and generation ability between PSOe-SVR and BPNN. Fig.7 shows that the predicted results for training dataset obtained from Back propagation neural network (BPNN) is worse than those from PSOe-SVR (see Fig.7). The maximum relative error of BPNN at 400°C is 3.1%, which is much higher than that from PSOe-SVR (1.0%). The reason is that excess impact factors lead to over-fitting easily during BPNN modeling [21].

Fig.8 illustrates the scatter plot for the testing dataset with PSOe-SVR and BPNN at 400°C and $\dot{\varepsilon} = 1s^{-1}$. It can be found that the predicted results with PSOe-SVR show smaller scatter than those with BPNN. These results indicate that the training feature of PSOe-SVR from experimental data made this procedure adaptive and exhibiting good learning precision and good generalization. A similar result was also proved by Fei [22], who employed particle swarm optimization-based support vector machine to diagnosis of arrhythmia cords and achieved higher diagnostic accuracy than BP artificial neural network. BPNN builds on the empirical risk minimization principle, and using the gradient descent learning algorithm, BPNN intends to converge local minima. As a result, it suffers from the over-fitting problem. On the other hand, SVM tends to find a global solution during the training as the model is converted into a convex quadratic programming problem. Meanwhile, with the introduction of special loss function, SVR has low model complexity. Consequently, the training results from SVR have better generalization capability than those from BPNN.

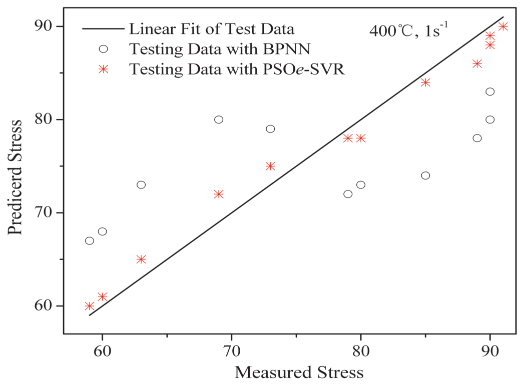

Figure 8 Scatter plot for the testing samples of flow stress at 400°C, $\varepsilon^{\cdot} = 1s^{-1}$

If more data were applied for BPNN training, the study ability and generation ability will be improved. But this improvement will consume more energy and time, in that sense, PSOe-SVR also has certain advantages in a small set of training data.

Comparison of prediction ability among PSOe-SVR, BPNN and constitutive equation. Among many constitutive equations suggested for describing the flow stress in hot metal forming processes, one of the best relationships which exhibit DRX (Dynamic Recrystallization and DRV (Dynamic Recovery) processes is [23]:

$$\begin{cases} \sigma_{DRV} = [\sigma_0^2 e^{-rz} + (\sigma_s^2(1-e^{-rz})]^{0.5} \cdots \\ (\varepsilon < \varepsilon_c) \\ \sigma_{DRX} = \sigma_{DRV} - (\sigma_s - \sigma_{ss})\{1 - \exp \cdots \\ [-k_d(\frac{\varepsilon-\varepsilon_c}{\varepsilon_p-\varepsilon_c})^{n^d}]\}(\varepsilon < \varepsilon_c) \end{cases} \qquad (14)$$

where σ_0 is the initial stress; r is recovery softening parameters; σ_s and σ_{ss} are the saturated stress and the stable stress, respectively; ε_p and ε_c are the strain corresponding to the peak stress and the critical stress, respectively; k_d and n_d are material constants.

With the aim of nonlinear regression, for a given stress and strain, the σ_0, σ_s, σ_{ss} and r can be calculated from the (5). Then we will get the stress dependence of the strain hardening rate $(\theta = d\sigma/d\varepsilon)$. Finally we can obtain the material constants k_d and nd with nonlinear regression. In order to make a direct comparison among three methods, the constitutive equation, BPNN and PSOe-SVR, the same dataset during the BPNN training and the PSOe-SVR training were employed. Fig.9 shows the stress relative error at $450\varepsilon^{\cdot} = 1s^{-1}$ and $\varepsilon^{\cdot} = 1s^{-1}$ using the constitutive equation, BPNN and PSOe-SVR. It can be seen that the PSOe-SVR analysis actually yields the most accurate predictions, and the relative error is the smallest which is lower than 0.6%. The prediction accuracy by using the constitutive equations is the worst. The results also show the PSOe-SVR can learn a parsimonious prediction model from the given data to avoid the data over-fitting problem.

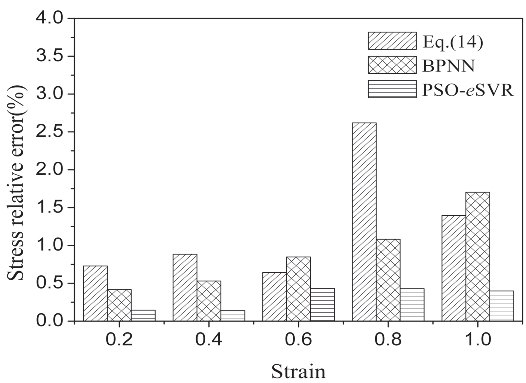

Figure 9 Comparison of stress relative error obtained at 450°C and $\varepsilon^{\cdot} = 1s^{-1}$ using BPNN, PSOe-SVR and the constitutive equations

6. Conclusion

1. The prediction of high temperature flow stress of AZ80 magnesium alloy was developed using a particle swarm optimization-based support vector regression. In this study, e-SVR was used to develop predicting model and PSO was used to optimize model parameters of e-SVR, to avoid the occurrence of over-fitting or under-fitting of the e-SVR model caused by the improper determination of these parameters. Meanwhile, datasets were corrected for deformation heating and unbalance.
2. The PSOe-SVR method could achieve higher predicting accuracy of flow stress as compared with

experiments. The lower the strain rate, the greater the predicting accuracy of testing samples.

3. Compared with BPNN model, the samples dependence of PSOe-SVR model is lower. The study ability and the generation ability of PSOe-SVR model are also better than those of BPNN model. This indicates that the PSOe-SVR can be used as an effective predicting tool for high temperature flow stress studies.
4. Compared with BPNN model and constitutive equation, the prediction accuracy by using PSOe-SVR is the best, and by using the constitutive equations is the worst.

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