A Hybrid Model Used to Predict Flow Stress and its Application

Wang Yanping[1], Wu Bing[2]

1.School of Electric and Electronic Engineering ,Shandong University of Technology,Zibo 255049,China

2.School of Science , Shandong University of Technology, Zibo 255049,China

E-mail:yanping_wang_yue@163.com

Abstract : To improved the prediction accuracy of the flow stress, a hybrid model based on the Hybrid Least Squares Support Vector Machine (HLS-SVM) and Mathematical Models (MM) was proposed. In HLS-SVM model, the optimal parameters of LS-SVM were obtained by self-adaptive Particle Swarm Optimization (PSO)based on Simulated Annealing (SA). Simulation experiment results revealed that this model could correctly recur to the flow stress in the sample data and accurately predict the non-sample data. The efficiency and accuracy of the predicted flow stress achiieved by the proposed model were better than the methods used in most literature.

Key word: least square support vector machine ;particle swarm optimization; simulated annealing;flow stress

1 Introduction

In the steel industry , establishing a reasonable order of rolling is the key to high-quality products, and the rule to determine the different flow strees of metal under the conditions of deformation resistance is necessary to develope a reasonable order of rolling. For the certain metal flow stress, the early studies [1-3] mainly focused on the improvement and optimization of the mathematical model, but in metal's thermal stress process, there are many factors that affect the flow stress. These effects are extremely complex, most are non-linear, and therefore, by using mathematical models to predict the flow stress are less precise, the application is restricted. Later, the artificial intelligence methods of large-scale parallel computing and strong non-linear data simulation capabilities, are widely used in the prediction of the flow stress, to a large extent increased the accuracy and efficiency of the flow stress prediction. In the prediction of the flow stress, the most widely method is Back Propagation (BP) network [4-5], however, a BP network is also easy to fall into local maximum point, the slow convergence rate and the presence of overfitting phenomena such as the defects can not be ignored.

In recent years, Support Vector Machines attracted widespread attention and made a lot of results. However, the SVM in the area of the flow stress prediction is a relatively new technology. The main purpose of this study is to verify the feasibility and effectiveness of the hybrid model in the prediction of the flow stress and attempt to practice the method.

2. Problem Description

The prediction of flow stress can be described as : a variety of conditions known to the stress rate, stress degree and stress temperature, to establish a model to predict the flow stress . In the study, first of all, through the thermal simulation experiment to obtain a variety of flow stress under the conditions of deformation resistance; and then to these data, the establishment of prediction model, using known data to validate the model's feasibility and effectiveness. Typically, the thermal simulation test results as the actual value, and the prediction model built to predict the results as the predicted value.

In this study, to choose the Root Mean Square Error (RMSE) between the actual value and predictive value of the flow stress as an evaluation function:

$$RMSE = \sqrt{\frac{1}{n} * \sum_{i=1}^{n} (y_i - f(x_i))^2} \qquad (1)$$

In which : y_i is the actual value , $f(x_i)$ is predictive value, n is the number of samples.

The smaller the *RMSE* is, the prediction performance of the builed model is better, the accuracy is higher. Therefore, the establishment of predictive model is designed to minimize the deviation between the actual value and the predicted value and improve the model's generalization performance.

3. Method Description

3. 1 the Hybrid Least Squares Support Vector Machine (HLS-SVM)

1999, Suykens and Vandewalle proposed the Least Square Support Vector Machines (LS-SVM) method.

Given training data set $\{x_i, y_i\}^n{}_{i=1}$, x_i is the input data, y_i is the output data. The function estimation problem in w space can be described as solving the following problem:

$$\min J = \frac{1}{2} w^T w + \frac{1}{2} r \sum_{i=1}^{n} e_i^2 \tag{2}$$

s.t. $y_i = w^T \phi(x_i) + b + e_i, i = 1,2,\cdots,n.$

in which : e_i is the error variable, r is the ultra-adjustable parameters.The optimization problem can be transformed into the following linear equation:

$$\begin{bmatrix} 0 & 1^T \\ 1 & \Omega + r^{-1} 1 \end{bmatrix} \begin{bmatrix} b \\ a \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix} \tag{3}$$

In which:

$y_i = [y_1, \cdots, y_n]^T, 1 = [1, \cdots, 1]^T, a = [\alpha_1, \cdots, \alpha_n]^T$

$, \Omega_{ij} = \phi(x_i)^T \bullet \phi(x_i) \quad = K(x_i, x_j), K(x_i, x_j)$

is the Kernel function.

The estimatation of LS-SVM can be expressed as:

$$f(x) = \sum_{i=1}^{n} \alpha_i K(x, x_i) + b \tag{4}$$

The function of $K(x_i, x_j) = \exp(-\frac{1}{2\lambda^2} \|x_i - x_j\|^2)$ because of its good performance, to be used as the kernel function of LS-SVM. the optimal parameters of λ and r were obtained by self-adaptive Particle Swarm Optimization (PSO)based on Simulated Annealing (SA).

Particle Swarm Optimization(PSO) is a population-based optimization techniques. At present, most widely used model is by the Shi and Eberhart in 1999, the global optimization model:

$$V_{id} = W * V_{id} + C_1 \times Rand \times (P_{best} - X_{id}) + C_2 \times rand \times (G_{best} - X_{id}); \tag{5}$$

$$X_{id} = X_{id} + V_{id}. \tag{6}$$

in which: v_{id} is the speed of particles i, X_{id} is the position of particles i, w is Inertia weight, C_1 and C_2 are the acceleration constants, *Rand* and *rand* are the random function changed in the scope of *[0,1]* , P_{best} is the best location of particles experience .

Adaptive function is the performance evaluation of particle standards. Flow stress prediction model objective is to minimize the deviation between the actual value and the predicted value. Therefore, you can choose (1) as a type of adaptive function.

Inertia weight is the impact of optimizing the performance of POS as an important factor. In this paper, the inertia weight is set based on the objective function of particles. Adaptive weighted factor, described as follows:

$$W = \begin{cases} W_{max}, & f > f_{avg} \\ W_{min} + \dfrac{(W_{max} - W_{min})(f - f_{min})}{f_{avg} - f_{min}}, & f \le f_{avg} \end{cases} \tag{7}$$

in which: w_{max} is the initial weight, w_{min} is the final weight, f is the current objective function of particles, f_{avg} and f_{min}, respectively, the objective function for all particles of average and minimum values.

Simulated annealing algorithm is a heuristic algorithm to solve the combinatorial optimization problem, which, through repetition of an initial solution for local improvements, and to accept the almost certain probability to avoid falling into local optimum, thus get a better solution.

In the operation of PSO projects, the simulated annealing algorithm is used to deal with particles. $\Delta = f(P_{best}) - f(G_{best})$, if $\Delta < 0$,and accept $G_{best} = P_{best}$ at the probability 1; if $\Delta \ge 0$,and accept $G_{best} = P_{best}$ at the probability *prob*,

$$prob = \exp(- \Delta / temp). \tag{8}$$

Where, P_{best} is the best location of the first particle, G_{best} is the best location of all particles in Stocks , *temp* is the present tempture.

In this paper,using the adaptive PSO algorithm based on the simulated annealing strategy to automatically select the LS-SVM parameters.The adaptive PSO algorithm based on the annealing strategy uses adaptive inertia weighted PSO factor to balance the global search and local search capabilities, uses simulated annealing algorithm to improve PSO's ability to escape from local optimum. Algorithm processes as follows:

Start

the first step: setting parameters

initialized stocks size, maximum algebra, precision, $W_{max}, W_{min}, C_1, C_2$;

Current algebra $G = 0$;

the second step: the calculation and prediction candomly generated for each particle location and initial velocity;

input the training sample set and test sample sets; LS-SVM model for learning and prediction; calculated for each particle's adaptation; initialized for G_{best} *based on the smallest adaptive*

978-1-935068-01-3 © 2009 SciRes.

particle in stocks; initialized for P_{best} based on the location of each particle current algebra does not meet the set algebra of the largest model accuracy or precision does not meet requirements{G=G+1; With (5) and (6) produce the next generation of stocks; LS_SVM model learning and prediction; Calculated for each particle's adaptation; For each particle to the simulated annealing strategy; By comparing to find new G_{best} and P_{best} ;}The third step: the output Save the model parameters, validate the promotion of capacity; End

3. 2 The Support vector machine hybrid model

The traditional flow stress models are actually the theory - experiment model, they only considered the degree, the rate and the temperatureof deformation and other major factor. Therefore, the use of Mathematical Models(MM) to predict the flow stress of the lower precision, and the limited scope of application.

Hybrid LS-SVM(HLS-SVM) considered apart from the above major factors, also considered the chemical composition and other factors, use it to correct the deviation of flow stress. MM reflects the main directions of flow stress,which can be used to predict the main value of the flow stress. SupportVector Machine hybrid preditive model can be described as follows:

$$\sigma = \sigma_{MM} + D_{HLS-SVM} . \tag{9}$$

Where: σ_{MM} for the calculated values of the flow stress's mathematical model; $D_{HLS\text{-}SVM}$ for the HLS-SVM output, it is the deviation between the actual value and mathematical models.

The equation of the mathematical model used to predict flow stress can be chosed as follows:

$$\begin{aligned}\sigma_{MM} &= \sigma_0 \exp(\alpha_1 + \alpha_2 T)(\dot{\varepsilon}/\dot{\varepsilon}_0)\alpha^{3+\alpha_4 T} \\ &\times [\alpha_5(\varepsilon/\varepsilon_0)^{\alpha_6} + (1-\alpha_5)(\varepsilon/\varepsilon_0)].\end{aligned} \tag{10}$$

In which:T=(t+273)/1 000, the unit of K, σ_0 -based flow stress, units of MPa, that is, the flow stress when t=1000^{o}C, $\varepsilon_0 = 0.4, \dot{\varepsilon}_0 = 10s^{-1}$, α_1 ~ α_6 are the regression coefficient.

4. Test and results

The Gleeble-1500 thermal simulation test machine is used to test 45$^{\#}$ steel. The Pattern size is $\phi 8mm \times 15\,mm$. The chemical composition of steel 45$^{\#}$ shows as Table 1, the flow conditions as shown in table 2.

In the thermal simulation experiments, for each sample tested, obtained flow stress, and stored them in the

Table 1 The chemical composition of steel 45$^{\#}$

C	Si	Mn	P	S	Cr	Ni
0.480	*0.190*	*0.610*	*0.023*	*0.019*	*0.100*	*0.010*

Table 2 The flow conditions of thermal simulation test

t/^{o}C (flow tempture)	750	800	850	900	950	1000
$\dot{\varepsilon}$ /s^{-1} *(flow velocity)*	*0.5*	*1*	*5*	*10*	*15*	*20*
ε (flow degree)			*0.05~0.6*			

sample database as sample datas. From the sample database to extract datas, in accordance with the measured values of flow stress model and mathematical calculations of the absolute relative error of *x* to calculate the standard deviation of all samples δ , if a data exists $\delta|x-\bar{x}| \geq 3\delta$, is that the data errors, to delete . Ultimately, 180 sets of data patterns are selected, they were randomly divided into two subsets: training subset, test subset, of which 70 sets of data as a training sample used to train the network, 110 sets of data as the test samples used to test the network generalization performance.

Before the application of HSNM-MM, standardization of data is very important. Each attribute of the datas can be standardized by by following formula:

$$x_i' = \frac{(x_i - \mu)}{\rho} \tag{11}$$

Where: x_i is the input parameter, μ is the average value of input parameters, ρ is the standard deviation of the input1 parameters.

The inputs of Hybrid LS-SVM were determined by considering mathematical models and thermal simulation experiments . Inputs were C, Si, Mn, P, S, Cr and Ni content, flow degree, flow rate and flow temperature, the outputs were flow stress's value.

During the study process, through a number of simulation experiments, l the parameters of the model are choiced as follows: stocks size 50, the largest Algebra 200, W_{max} = 1.2, W_{min} = 0.4, C_1 = 2.0, C_2 = 2.0, each initialized particle is parameters set of LS -SVM. through

20 times simulation experiments, LS-SVM parameters were identified, when $\lambda = 0.8028, r = 113.26$, the model had the best generalization performance. And with the increase in the number of iteration, the optimized effect was getting better and better.the actual number of iterations should be determined based on the specific accuracy requirements and the time requirements.

For evaluating the model's performance, we compare the HLS-SVM with support vector machine model and mathematical model. As shown in Table 3.

Table 3 Comparisons of various algorithms

Datas	HLS-SVM		LS-SVM		MM
	AveR	BestR	AveR	BestR	
Relative RMSE	3.0297	2.8931	4.5416	3.8240	7.9860
Error $\beta \le 0.01$	43.37%	44.64%	19.82%	25.33%	13.93%
Rate $0.01 < \beta \le 0.05$	49.84%	51.91%	59.38%	61.52%	36.32%
$0.05 < \beta \le 0.10$	6.79%	3.45%	12.46%	10.67%	38.96%
$\beta > 0.10$	0	0	8.34%	2.78%	10.79%

From Table 3 ,we can see that RMSE value of HLS-SVM is smaller than other methods, indicating the precision and fitting to the actual value achieved from HLS-SVM are better than other methods. By comparing HLS-SVM and LS-SVM ,we can find HLS-SVM's performance are better than LS-SVM's. This shows that the mathematical model for the prediction of flow stress is also essential. However, only the mathematical model prediction result was not satisfactory, indicating the smart way to improve the prediction accuracy the flow stress is a very effective combination of two methods . As the training sample does not contain the test samples, the prediction results are universal ,that is, HLS-SVM has good generalization performance. By the above analysis we can see that HLS-SVM is a feasible and promising technology in the area of flow stress prediction.

5. Conclusion

In this paper, A new prediction method to predict flow stress based on HLS-SVM and mathematical models was proposed. The experiments's results show that the model prediction accuracy and generalization performance are achieved remarkable improved. This method is the introduction of POS algorithm, so that the network is automatically selected parameters, to avoid human interference, enhance network performance prediction.

References

[1] SUYKENSJ A K,VANDEWALLEJ.Least squares support vector machine classifiers[J].Neural Processing Letters,199,9(3) :293-300.

[2] TAKUDA H, FUJIMOTO H,HATTAN. Modeling on flow stress of Mg-A1-Zn alloys at elevated temperatures[J]. Journal of Material Processing Technology,1998,(80/81):513-516

[3] RAO K P,PRASADM T KDV.Neural network approach to flow stree evaluation in hot deformation[J].Journal of Materials Processing Technology,1995,53(3/4):552-566.

[4] PHANIRAJ M P, LAHIRI A K. The applicability of neural network model to predict flow stress for carbon steels[J].Journal of Materials Processing Technology ,2003,[4](2):219-227

[5] LI P,XUE M ,LU Y,et al.Neural network prediction of flow stress of Ti-15-3 alloy under hot compression[J].Journal of Materials Processing Technology ,2004,148(2):235-2

978-1-935068-01-3 © 2009 SciRes.