Journal of Achievements in Materials and Manufacturing Engineering
VOLUME 18
ISSUE 1-2
September–October
2006

Prediction of in-flight particle behaviors in plasma spraying

J.C. Fang [a], H.P. Zeng [b,*], W.J. Xu [b], Z.Y. Zhao [a], L. Wang [a]
[a] College of Mechanical Engineering and Automation, HQU, Quanzhou 362021 P.R. China
[b] Key Laboratory for Precision and Non-traditional Machining Technology of Ministry of Education, Dalian University of Technology, 116024, P.R. China
* Corresponding author: E-mail address: zenghaoping@sohu.com

Received 15.03.2006; accepted in revised form 30.04.2006

Analysis and modelling

ABSTRACT

Purpose: In plasma spraying, the coating properties such as porosity, hardness, strength, etc. are directly determined by particle behaviors, i.e. the temperature and velocity. Therefore, it is necessary and meaningful to predict the particle behaviors under a certain combination of process parameters before the spraying process is executed.
Design/methodology/approach: In this study, SVM (Support Vector Machines) is applied to the prediction of in-flight particle temperature and velocity in plasma spraying by argon flow rate, hydrogen flow rate and electric current. The influences of the three parameters on particle temperature and velocity are also investigated.
Findings: In the leave-one-out cross validation on an orthogonal experiment with 9 sets of parameters, the maximum relative errors of prediction for particle temperature and velocity are 0.68% and 1.42% respectively. The prediction results reveal that the most influential parameter for particle temperature is hydrogen flow rate, and argon flow rate exerts the greatest influences on particle velocity.
Research limitations/implications: Future work should focus on the modeling of the whole spraying process with all the spraying parameters.
Practical implications: It will be helpful to the prediction and controll of particle behaviors in plasma spraying.
Originality/value: First application of SVM to modeling the in-flight particle behaviors in plasma spraying.
Keywords: Statistic methods; Prediction; In-flight particle behaviors; Plasma spraying

1. Introduction

Plasma spraying has been showing prominent advantages in novel material forming with lower manufacturing cost, shorter production time, higher execution efficiency and more material versatility, and has been attached great importance by researchers in rapid manufacturing field [1-3]. In spraying, the particle behaviors i.e. the temperature and velocity, which influenced by the process parameters such as the gas flow rate, electric current and powder feed rate etc, are the important factors on the coating properties [4-5]. Therefore, there is an increasingly urgent requirement to study what the particle behaviors will be with a certain set of parameters.

Zhao [6] and Liu [7] investigated the correlation between spraying parameters and in-flight particle properties by experiments and numerical simulation respectively. Guessasma [8-9] modeled plasma spraying process with artificial neural networks. The experimentation method to the study always involves plenty of time and resources, while artificial neural networks require fine design of the network structure and vast program tuning work. In recent years, SVM has found successful application in pattern recognition, function regression and probability density estimation [10-12]. But SVM has not been employed to model the plasma spraying process. In this paper, a methodology based on SVM is introduced to predict the particle properties by process parameters.

2. SVM theory

As a machine learning method based on statistical learning theory, SVM is first proposed by Vapnik [13-14]. Unlike traditional ERM(Empirical Risk Minimization)-based machine learning method (e.g. neural networks), SVM is designed to minimize the expected risk based on SRM (Structural Risk Minimization). In many cases, minimizing the errors on the training data, which is the aim of ERM, cannot guarantee the minimum errors on test data, that is, the generalization ability is not warranted. The strategy of SVM tries to trade off between training errors and generalization errors, which enables minimizing the training errors with controllable generalization ability.

Suppose we are given a set of training data $\{(x_1, y_1), (x_2, y_2), \ldots, (x_m, y_m)\}$, where $x_i \in R^n$ is a set of n-dimension process parameters(e.g. argon flow rate, hydrogen flow rate, electric current, etc.) employed in plasma spraying and y_i R is the corresponding particle behaviors (e.g. particle temperature, particle velocity, etc.). Our goal is to fabricate a function y=f(x) by training the input data x_i and y_i, so that the function f(x) can predict the output particle properties y_r with a given set of parameters x_r outside the training data.

As usually a nonlinear function is expected, the input x_i is first mapped to a high dimensional feature space (Hilbert Space) by a nonlinear transformation $\Phi{:}\rightarrow\varphi(x)$, which transforms the nonlinear function regression problem in the original feature space to a linear function regression problem in the higher dimensional feature space. Suppose the function f(x) takes the following form:

$$f(x) = \langle w, \varphi(x) \rangle + b \tag{1}$$

where $\langle \bullet,\bullet \rangle$ denotes dot product.

The problem now is to minimize the Euclidean norm $\|w\|^2$ on the training data to enlarge the flatness of the function f(x). To allow for some regression errors, the slack variables ξ_i and ξ_i^* are introduced. Hence the problem can be written as a convex optimization problem by requiring:

$$\min \ \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{m}(\xi_i + \xi_i^*) \tag{2}$$

with constraints:

$$\begin{cases} y_i - \langle w, \varphi(x_i) \rangle - b \le \varepsilon + \xi_i \\ \langle w, \varphi(x_i) \rangle + b - y_i \le \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* > 0 \end{cases} \quad i = 1,2,\ldots,m$$

where $\varepsilon>0$ denotes the precision of regression, and the constant $C>0$ is a pre-specified penalty factor which trades off between the flatness of f(x) and regression error tolerance.

After introducing the kernel functions $k(x, x_i)$, f(x) can then be written as:

$$f(x) = \sum_{i=1}^{m}(\alpha_i - \alpha_i^*)k(x_i, x) + b \tag{5}$$

where x_i corresponding to α_i-$\alpha_i^* \neq 0$ is so-called support vectors.

In this work, the RBF (radial basis function) kernel function $k(x_i, x_j) = \exp\left|\|x_i - x_j\|^2 / 2\sigma^2\right|$ is used:

3. Prediction and results

In plasma spraying, the primary plasma gas flow rate, the second plasma gas flow rate and electric current are the main factors influencing the in-flight particle behaviors. The orthogonal experimental parameters and the results utilized by this paper are from Fang et.el [15], in which the commercially available ZrO2 spray powders with a size distribution of 50~80µm were used.

The regression and prediction are implemented with the RBF kernel SVM. To evaluate the precision of regression, the leave-one-out cross validation was employed. In this study, a set of C=90 and σ^2=15 were used for the prediction of particle temperature, and a set of C=320 and σ^2=180 for the prediction of particle velocity. The relative errors of prediction are illustrated in Fig. 1, and the contrast between the prediction and experimental results are diagrammatized in Fig. 2 and Fig. 3. The maximum relative errors of prediction for particle temperature and velocity in the leave-one-out cross validation are 0.6814% and 1.4201% respectively, which are usually acceptable for practical application.

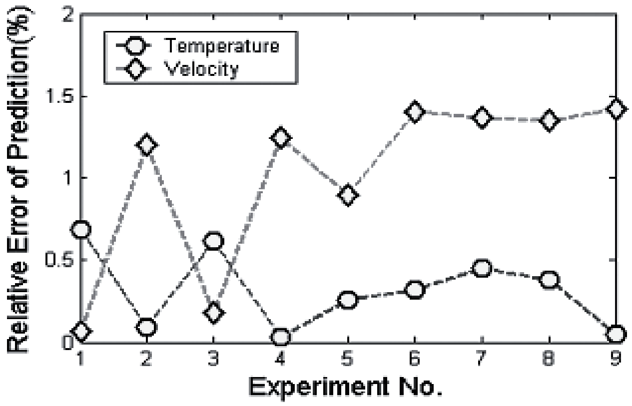

Fig. 1. Leave-one-out cross validation

It can also be seen from Fig. 2 and Fig. 3 that the predicted temperatures and velocities exactly follow the trends of experimental data.

To find out the influence of Argon flow rate, Hydrogen flow rate and electric current on particle temperature and velocity, therelationship between the particle temperature/velocity and the process parameters is investigated by fixing two of the three factors. It is shown in Fig. 4 and Fig. 5 that the increase of Argon flow rate results in a gentle decrease of particle temperature but a rapid increase of velocity. The reason is that the increase of Argon flow rate leads to the decrease of particle dwelling time in the plasma jet, hence reduces the energy obtained by heat transfer and results in the decrease of temperature. It is also revealed in Fig. 6 and Fig. 7 that the increase of Hydrogen flow rate accompanies the increase of both temperature and velocity, and the temperature is more sensitive to the change of Hydrogen flow rate.

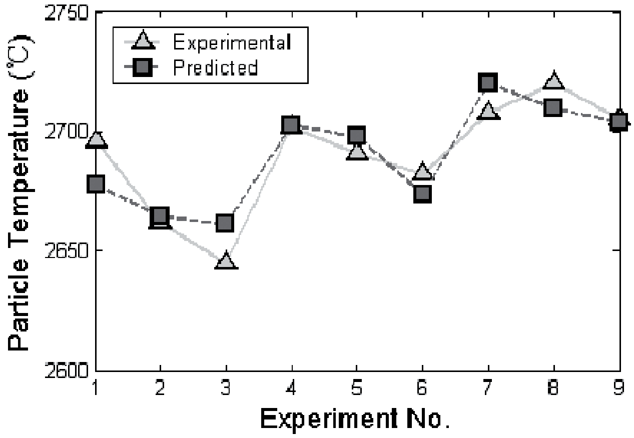

Fig. 2. Leave-one-out cross prediction of temperature

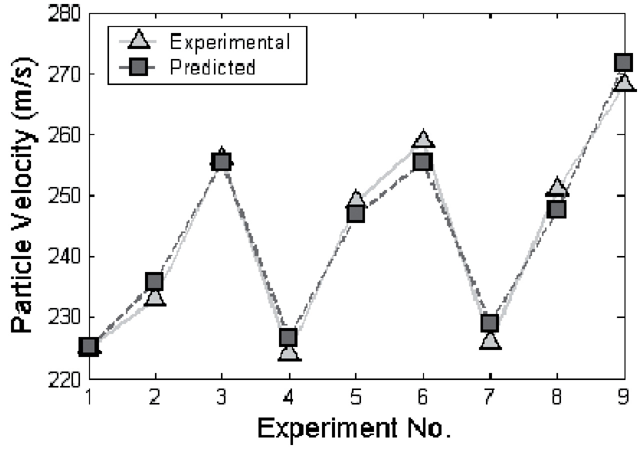

Fig. 3. Leave-one-out cross prediction of velocity

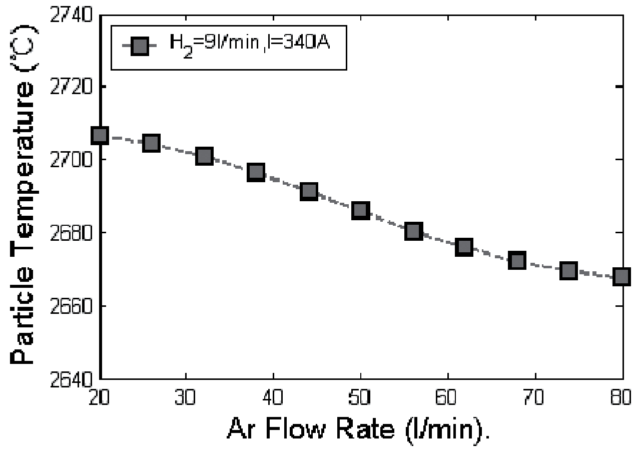

Fig. 4. Influence prediction of argon flow rate on temperature

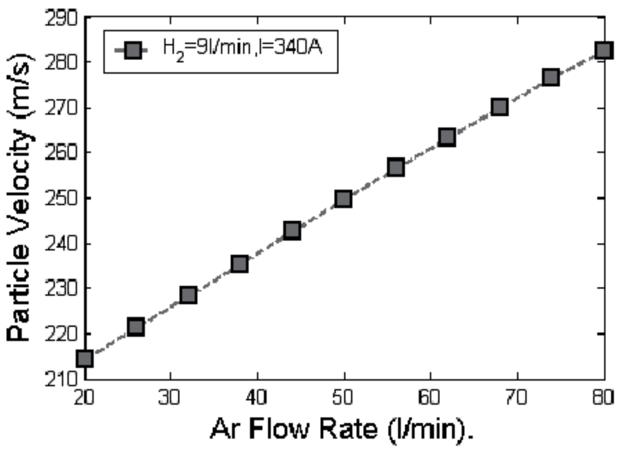

Fig. 5. Influence prediction of argon flow rate on particle velocity

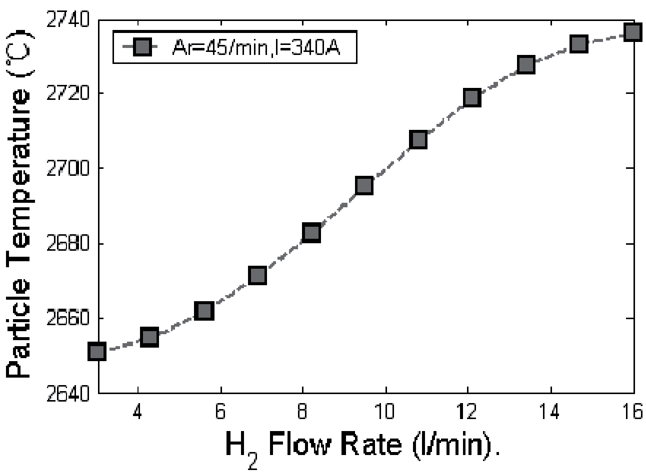

Fig. 6. Influence prediction of H_2 flow rate on particle temperature

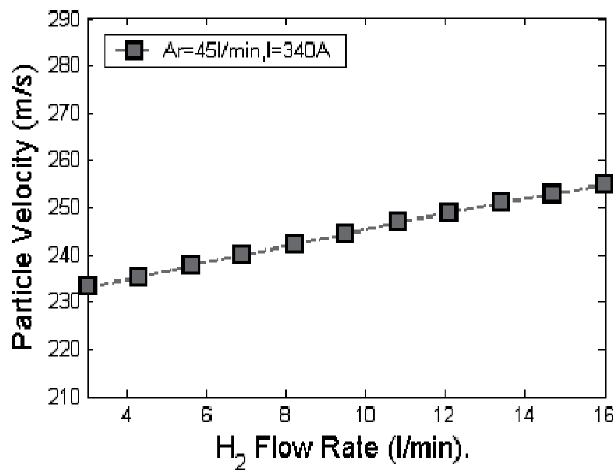

Fig. 7. Influence prediction of H_2 flow rate on particle velocity

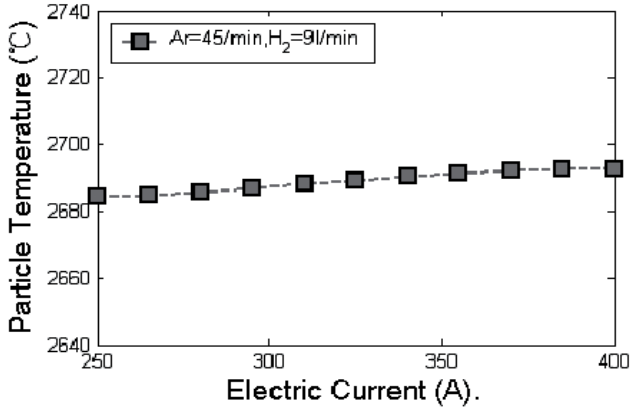

Fig. 8. Influence prediction of electric current on particle temperature

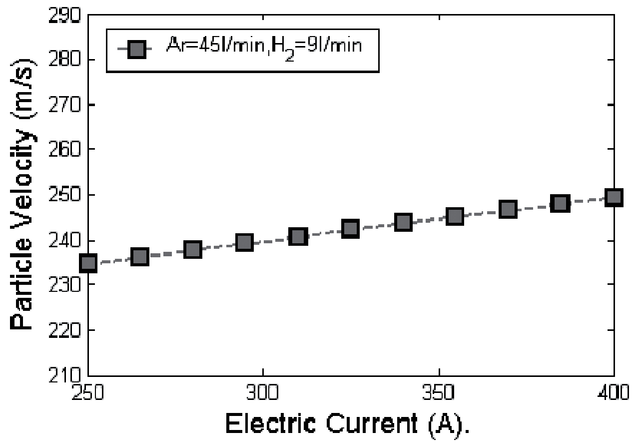

Fig. 9. Influence prediction of electric current on particle velocity

The reasonable explanation for that is the augmentation of Hydrogen flow rate leads to the increase of both plasma jet temperature and velocity, and that leads to the increase of particle temperature and velocity eventually. As Fig. 8 and Fig. 9 show, the increase of particle temperature and velocity caused by the change of electric current is similar to that of hydrogen flow rate, but the trend is much less remarkable.

From the analysis conducted above, it can be easily inferred that the Hydrogen flow rate is the most influential factor of all the three spraying parameters. As to the particle velocity, the flow rate of Argon exhibits the most influence.

4. Conclusions

The results of this work show that SVM has been successfully applied to the prediction of in-flight particle properties in plasma spraying. By choosing a set of input process parameters, the corresponding particle properties will be obtained with the trained SVM model. The prediction of particle behaviors implemented by this novel method may provide basis for the feedback control of coating properties in the future.

References

[1] J.C. Fang, W.J. Xu, Plasma spray forming, Journal of Materials Processing Technology 129 (2002) 288-293.

[2] H. Herman, S. Sampath, Plasma spray forming, Industrial Ceramics (Italy) 18 (1998) 1 29-32.

[3] A Geibel, L Froyen, L Delaey, Plasma spray forming: an alternate route for manufacturing freestanding components, Journal of Thermal Spray Technology 5 (1996) 4 419-430.

[4] J.F. Li, H. L.Liao, C. X. Ding, C. Coddet, Optimizing the plasma spray process parameters of yttria stabilized zirconia coatings using a uniform design of experiments, Journal of Materials Processing Technology 160 (2005) 34–42.

[5] M. Friis, C. Persson, J. Wigren, Influence of particle in-flight characteristics on the microstructure of atmospheric plasma sprayed yttria stabilized ZrO2, Surface and Coatings Technology 141 (2001) 115-127.

[6] L. Zhao, K. Seemann, A. Fischer, E. Lugscheider, Study on atmospheric plasma spraying of Al2O3 using on-line particle monitoring, Surface and Coatings Technology 168 (2003) 186–190.

[7] B. Liu, T. Zhang, Y. Bao and D. T. Gawne, Numerical modelling of motion and heating of particles during plasma spraying, Surface Engineering 18 [5] (2002) 350-357.

[8] S. Guessasma, Z. Salhi, G. Montavon, P. Gougeon, C. Coddet, Modeling of the APS plasma spray process using artificial neural networks: basis, requirements and an example, Computational Materials Science 29 (2004) 315–333.

[9] S. Guessasma, C. Coddet, Neural computation applied to APS spray process: Porosity analysis, Surface and Coatings Technology 197 (2005) 85–92.

[10] W. M. Campbell, J. P. Campbell, D. A. Reynolds, E. Singer, P. A. Torres-Carrasquillo, Support vector machines for speaker and language recognition, Computer Speech and Language 20 (2006) 210–229.

[11] H. Drucker, C. J. C. Burges, L. Kaufman, A. Smola, V. Vapnik, Support vector regression machines, Advances in Neural Information Processing Systems 9 (1997) 155-161,Cambridge, MA, MIT Press.

[12] P. Mantero, G. Moser, S.B. Serpico, Partially supervised classification of remote sensing images using SVM-based probability density estimation, 2003 IEEE workshop on Advances in Techniques for Analysis of Remotely Sensed Data, 27-28 October 2003, NASA Goddard Visitor Center, Greenbelt MD, USA, 327-336.

[13] V. Vapnik, The Nature of Statistical Learning Theory. NY: Springer Verlag, 1995.

[14] V. Vapnik, Statistical learning theory, John Wiley, New-York, 1998.

[15] J.C. Fang, W.J. Xu and Z.Y. Zhao, In-flight Behaviors of ZrO2 Particle in Plasma Spraying, Surface and Coatings Technology (accepted).