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Optimization of Surface Roughness in End Milling Using Potential Support Vector Machine

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Abstract This paper is concerned with the optimization of the surface roughness when milling aluminium alloys (AA6061-T6) with carbide coated inserts. Optimization of milling is very useful to reduce cost and time for machining mould. Potential support vector machine (PSVM) is used to develop surface roughness predicted model. Design of experiments method and response surface methodology techniques are implemented. The validity test of the fit and adequacy of the proposed models has been carried out through analysis of variance. The experiments results are compared with predictive model developed by PSVM. The optimum machining conditions in favor of surface roughness are estimated and verified with proposed optimized results. It is observed that the developed model is within the limits of the agreeable error (about 2–9 %) when compared to experimental results.

Keywords Potential support vector machine · Surface roughness · Aluminium alloy · Optimization

الخلاصة

تعنى هذه الورقة العلمية بتحسين خشونة السطح عند طحن سبائك الألمنيوم (T6-AA6061) مع مدرجات مطلية بالكربيد. إن تعظيم الاستفادة من الطحن هو مفيد جدا للحد من التكلفة والوقت اللازم لتشكيل القالب. وقد استخدمت آلة دعم المتجهات المحتملة (PSVM) في تطوير أنموذج توقع خشونة السطح، كما تم تطبيق أسلوب تصميم التجارب (DOE) وتقنيات منهجية استجابة السطح (RSM). وقد تم تنفيذ اختبار الصلاحية من حيث اللياقة والكفاية للنماذج المقترحة من خلال تحليل التباين (ANOVA). وتمت مقارنة نتائج التجارب مع أنموذج تنبؤي مطور بآلة PSVM وتقدير الظروف التصنيعية الأمثل لصالح خشونة السطح والتحقق منها مع النتائج المقترحة المثلى. وقد لوحظ أن الأنموذج المطور هو في حدود الخطأ المقبول (حوالي 2-9٪) بالمقارنة مع النتائج التجريبية.

1 Introduction

Surface quality is very critical to high precision part. Roughness plays an important role to determine how a real object will interact with its environment. Roughness is often a good predictor of the performance of

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a mechanical component, since irregularities in the surface may form nucleation sites for cracks or corrosion. Rough surfaces usually wear more quickly and have higher friction coefficients than smooth surfaces. Although roughness is usually undesirable, it is difficult and expensive to control in manufacturing. Decreasing the roughness of a surface will usually exponentially increase its manufacturing costs. This often results in a trade-off between the manufacturing cost of a component and its performance in application. Optimization of the milling process often proves to be difficult task owing to the many regulating machining variables. A single parameter change will influence the process in a complex way. Thus the various factors affecting the process have to be understood in order to determine the trends of the process variation. The selection of best combination of the process parameters for an optimal surface roughness involves analytical and statistical methods. In addition, the modeling of the process is also an effective way of solving the tedious problem of relating the process parameters to the surface roughness. Improving the surface quality is still a challenging problem that constrains the expanding application of the technology. When new and advanced materials appear in the field, it is not possible to use existing models and hence experimental investigations are always required. Undertaking frequent tests or many experimental runs is also not economically justified. In the light of this, the present work describes the development and application of a Potential support vector machine (PSVM) methodology to model and optimize the milling process.

Learning from examples in order to predict is one of the standard tasks in machine learning. Many techniques have been developed to solve classification and regression problems, but by far most of them were specifically designed for vectorial data. However, for many datasets a vector-based description is inconvenient or may even be wrong and other representations like dyadic data [1,2] which are more appropriate. Support vector machine (SVM) by Scholkopf and Smola [3] and Vapnik [4] are a successful class of algorithms to solve the supervised learning tasks. Although SVMs have been originally developed for vectorial data, the actual predictor and learning procedure make use of a relational representation. Given a proper similarity measure between objects, SVMs learn to predict attributes based on a pairwise "similarity" matrix, which is usually called the Gram matrix. Standard SVMs, however, underlie some technical as well as conceptual restrictions (for a more detailed discussion see Hochreiter and Obermayer [5]). First, SVMs operate on pairwise data and cannot be extended in a straightforward way to general dyadic representations. The similarity measure (kernel) has to be positive definite1 and the general case of dyadic data, where the relationships between two different sets of objects are quantified, cannot be handled directly. Second, standard SVM solutions also face a couple of technical disadvantages. The solution of an SVM learning problem for example is scale sensitive, because the final predictor depends upon how the training data had been scaled [5]. This problem of scale sensitivity is avoided by the PSVM approach through a modified cost function, which softly enforces a whitening of the data in feature space. A second disadvantage of standard SVMs relates to the fact, which all margin errors translate into support vectors. The number of support vectors can, therefore, be larger than necessary, for example, if many training data points are from regions in data space where classes of a classification problem overlap. Finally, the PSVM method leads to an expansion of the predictor into a sparse set of the descriptive "row" objects rather than training data points as in standard SVM approaches. It can therefore be used as a wrapper method for feature selection applications and previous results on quite challenging datasets had been promising [5,6].

The PSVM predictor for dyadic data has the form [6]:

$$o_c(k) = sign(norm(k, np) * \alpha + b) \tag{1}$$

for classification and

$$o_r(k) = norm(k, np) * \alpha + b \tag{2}$$

for regression tasks, where

k is dyadic description of the column object which is to be classified, and p the component vector which quantifies the relations to P row object

o_c : PSVM class prediction of k (+1 or −1)

o_r : PSVM real valued prediction of k

α : support features (part of the PSVM model): P-component vector which quantifies the importance of row objects for serving as features

b : bias (part of the PSVM model)

np : normalization statistics (part of the PSVM model)—breaks into maximum, minimum, mean, and variance for all P row objects and is used by the norm function.

Learning proceeds by [6]:

1. Data matrix : loading the L X P dyadic data matrix K
2. Normalization : gets statistics for all P column of K and stores its maxima, minima, mean, and a scaling factor in p-dimensional vectors *np*. *np* is then used to normalize each column of K
3. Calculation of b: the bias b is set to the mean of the L labels represented by the label vector y
4. Sequence minimal optimization (SMO): the SMO reads the normalized kernel matrix K and the labels y and calculates a p-dimensional vector α for a normalized kernel matrix K and labels y. α_i corresponds to the i-th column of K and is normally sparse.

The main differences to between PSVM and SVM are just as follows: Sphering: in order to judge the relevance of feature components, the variance should be normalized, that is, the data should be sphered (whitened). Therefore, an objective is formulated according to which the classifier is selected by maximizing the margin after sphering. It turns out that sphering has two advantages for support vector machine techniques. First, the derived new support vector machine approach is invariant to linear transformation of the data, which are the margin bounds. Second, tighter margin bounds can be obtained [7]. New constraints: the constraints of the optimization problem are modified in order to ensure that the classifier is optimal with respect to the mean squared error between the classification function and the labels. In contrast to previous approaches where one constraint is associated with each of the m training examples, each constraint is now associated with one feature and the number of new constraints is equal to the number N of features. Support features: the combination of the new objective with the new constraints allows assigning support vector weights to features, and the normal vector of the classification boundary is expanded in terms of these weights rather than in terms of support vector data points. This allows feature selection according to whether a feature is a support vector or not. As a side effect the dual optimization problem can be efficiently solved using a technique similar to sequential minimal optimization. In summary, a classifier is selected from the set of all classifiers with minimal mean squared error which yields the largest margin after sphering the data. The new support vector machine removes irrelevant features, which lead to a minimal increase of the mean squared error when removed [7].

2 Response Surface Method and PSVM

The Box–Behnken design is normally used when performing non-sequential experiments, i.e., performing the experiment only once. These designs allow efficient estimation of the first and second-order coefficients. Because Box–Behnken design has fewer design points, they are less expensive to run than central composite designs with the same number of factors. Box–Behnken design do not have axial points, thus we can be sure that all design points fall within the safe operating. Box–Behnken design also ensures that all factors are never set at their high levels simultaneously [8–10]. The design of experiment table and level of variables are shown in Tables 1 and 2. Genetic algorithm (GA) was used to find the optimum weight, momentum, and step size to be used in PSVM. Later the optimum weight would be fed to the PSVM. Then training would be needed until the R.M.S.E. reaches a satisfactory value. The training data acquired from response surface method to PSVM mode, and the epoch number was 10,000 [11]. After 1,000 iterations, the PSVM was better enough to produce acceptable results.

The adequacy of the above three proposed models have been tested on behalf of both cases, linear and quadratic by means of analysis of variance (ANOVA) as shown in Table 3. The variance is the mean of the squared deviations about the mean or the sum of the squared deviations about the mean divided by the degrees of freedom. The fundamental technique is a partitioning of the total sum of squares and mean squares into components such as data regression and its error. The number of degrees of freedom can also be partitioned in a similar way as discussed in Table 1. The usual method for testing the adequacy of a model is carried out by computing the F-ratio of the lack of fit to the pure error and comparing it with the standard value. The values of P ($< \alpha$-level) in the analysis ascertain that the regression model is significant. The P value of the lack of fit of 0.351 for SR is not less than α-level (0.05).

3 Experimental Set Up

The 27 experiments were carried out on Haans machining centre with 6-axis as shown in Fig. 1. The water soluble coolant was used in these experiments. Each experiment was stopped after 90 mm cutting length. For the surface roughness measurement surface roughness tester was used. Each experiment was repeated three times using a new cutting edge every time to obtain accurate readings of the surface roughness. The physical

Table 1 Design of experiment

Cutting speed (m/min)	Feedrate (mm/tooth)	Axial depth (mm)	Radial depth (mm)	Surface roughness (μm)
140	0.15	0.10	5.0	0.814
140	0.15	0.15	3.5	0.734
100	0.15	0.15	5.0	0.704
140	0.15	0.15	3.5	1.159
180	0.15	0.20	3.5	0.903
180	0.15	0.15	2.0	0.495
100	0.20	0.15	3.5	0.465
140	0.15	0.15	3.5	0.415
180	0.15	0.15	5.0	0.363
100	0.15	0.20	3.5	0.974
140	0.20	0.10	3.5	1.522
180	0.10	0.15	3.5	1.926
140	0.15	0.20	2.0	2.089
180	0.15	0.10	3.5	1.864
140	0.10	0.15	2.0	0.952
140	0.15	0.20	5.0	0.693
100	0.15	0.10	3.5	0.613
140	0.20	0.15	2.0	0.583
100	0.15	0.15	2.0	1.038
140	0.20	0.15	5.0	0.782
140	0.10	0.10	3.5	0.374
140	0.20	0.20	3.5	0.344
140	0.15	0.10	2.0	0.294
100	0.10	0.15	3.5	0.242
180	0.20	0.15	3.5	0.853
140	0.10	0.20	3.5	1.401
140	0.10	0.15	5.0	1.805

Table 2 Level of variables

Levels	Low	Medium	High
Coding	−1	0	1
Speed (m/min)	100	140	180
Feed f (mm/tooth)	0.1	0.15	0.2
Radial depth, d_r (mm)	2	3.50	5.0
Axial depth, d_a (mm)	0.1	0.15	0.2

Table 3 Physical properties for workpiece

Component	Al	Cr	Cu	Fe	Mg	Mn	Si	Ti	Zn
Wt %	95.8–98.6	0.04–0.35	0.15–0.4	Max 0.7	0.8–1.2	Max 0.15	0.4–0.8	Max 0.15	Max 0.25

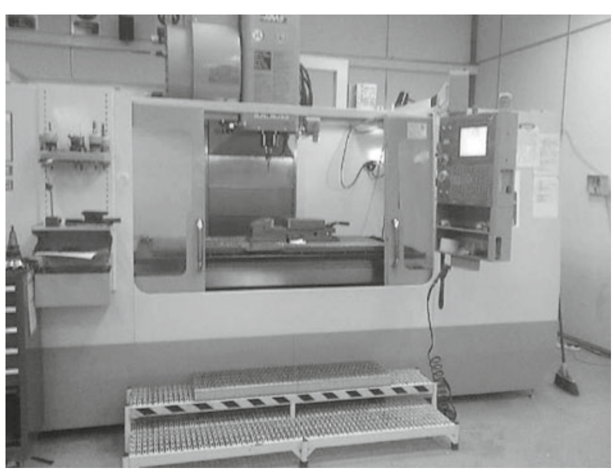

Fig. 1 Haans CNC milling with 6-axis

Table 4 Mechanical properties for workpiece

Hardness, Brinell	95
Hardness, Knoop	120
Hardness, Rockwell A	40
Hardness, Rockwell B	60
Hardness, Vickers	107
Ultimate tensile strength	310 MPa
Tensile yield strength	276 MPa
Elongation at break	12 %
Elongation at break	17 %
Modulus of elasticity	68.9 GPa
Density	2.7 g/cc

Table 5 Analysis of variance (ANOVA) and validity of fit

Source	DOF	Seq SS	Adj SS	Adj MS	*F*	*P*
Regression	4	0.9309	0.9309	0.2327	0.78	0.552
Linear	4	0.9309	0.9309	0.2327	0.78	0.552
Residual error	22	6.5937	6.5937	0.2997		
Lack-of-fit	20	6.3151	6.3151	0.3158	2.27	0.351
Pure error	2	0.2786	0.2786	0.1393		
Total	26	7.5246				

and mechanical properties of the workpiece are shown in Tables 3 and 4. After the preliminary investigation, the suitable levels of the factors are used in the statistical software to deduce the design parameters for aluminum alloys (AA6061-T6) as shown in Table 5. The lower and higher speed values selected are 100 and 180 m/s, respectively. For the feed, the lower value is 0.1 mm/rev and the higher value is 0.2 mm/rev. For the axial depth, the higher value is 0.2 mm and the lower value is 0.1 mm and for the radial depth the higher value is 5 mm and lower value is 2 mm.

The surface roughness of the work-piece can be expressed in different ways including arithmetic average (Ra), average peak to valley height (Rz), or peak roughness (RP), etc. Generally, the SR is measured in terms of arithmetic mean (Ra) which according to the ISO 4287:1999 is defined as the arithmetic average roughness of the deviations of the roughness profile from the central line along the measurement. Arithmetic mean or average surface roughness, Ra is considered in this study for assessment of roughness. Surface roughness values (Ra) were measured using a portable roughness tester model TR200. A total of six readings were taken to determine the average surface roughness of cuts, i.e., three readings in the center of the block and three readings at a distance of 25.40 mm from the right hand side of the block.

4 Results and Discussion

It has been reported that aluminium alloys strengthened by heat treatment are very sensitive to the change of microstructure due to their prominent strength at high temperature, high ductility, high tendency to work hardening, etc. Prolonged machining tends to increase the hardness of the surface layer and also deteriorates the quality of machined surface. This can be attributed to severe flank wear, which in turn causing the increase of component forces and cutting temperature due to the relative motion between the flank land of the tool nose region and the freshly machined surface of the workpiece. It has been also reported that significant tearing and considerable microstructural changes occur on the machined surface of the aluminium alloy. Machining conditions that introduce high tensile stress on the machined surfaces must be avoided and efforts shall be devoted to ensure a compressive state wherever possible. Undesirable effects on the machined surfaces can be minimised by the use of proper machining methods and conditions.

Generally, reduction in cutting speed, axial depth of cut will cause the surface roughness to become larger. On the other hand, the increase in feed rate and radial depth will slightly cause a reduction in surface roughness. The feed rate has the most dominant effect on the surface roughness, followed by the axial depth, cutting speed and radial depth. Hence, a better surface roughness is obtained with the combination of low cutting speed and axial depth, high feed rate and radial depth. Figure 2 shows the surface roughness values obtained by experimentation and the values predicted by PSVM. It is clear that the predicted values by PSVM are very close to the experimental readings as shown in Fig. 3. The error bar shows that the error is around 2–9 %.

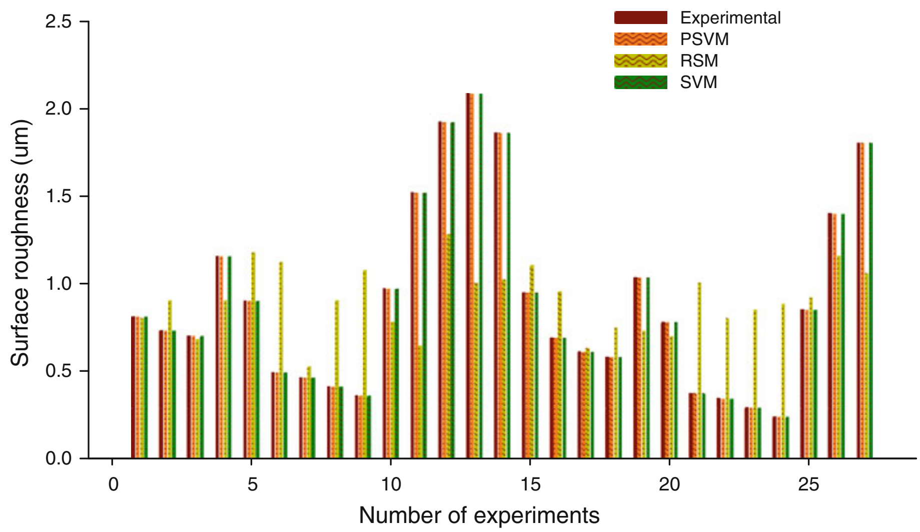

Fig. 2 Experimental and predicted comparison

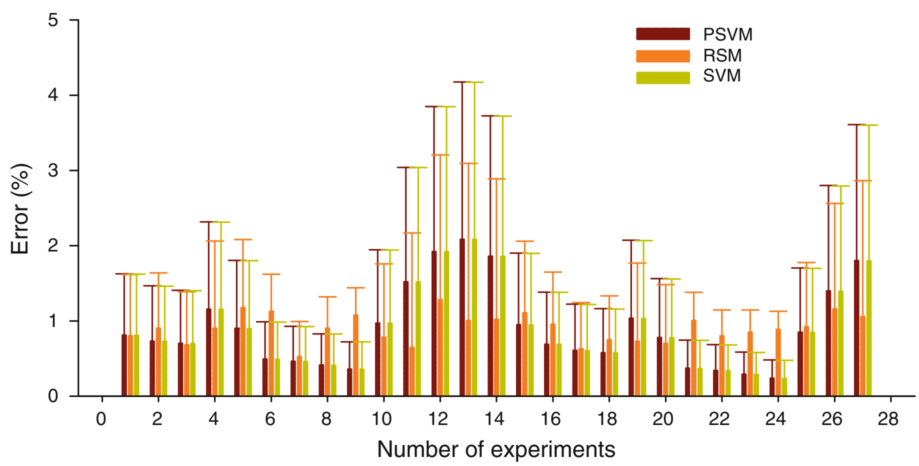

Fig. 3 Error bar for experimental and prediction

According to Hochreiter and Obermayer [6], the PSVM, however, is the only method so far, which can handle indefinite kernel functions and arbitrary dyadic data. This feature can lead to an enormous speed-up of the PSVM compared to standard SVM methods. While the generalization performance (measured through fivefold cross-validation) is 84 % for the PSVM converged to 79 % for the C-SVC, the computation time is a factor of 8554. CPU-time is roughly proportional to the number of training objects for both the PSVM and C-SVC, while the training time is much less for the PSVM. According to Kadirgama et al. [12], RBFN only can predict the accuracy of surface roughness around 12–14 %, meanwhile PSVM can predicted as close as 2–9 %. Even Tsai et al. [13] use a hybrid Taguchi-genetic algorithm (HTGA) to solve the problem of tuning both network structure and parameters of a feedforward neural network.

5 Conclusion

PSVM has been found to be the most successful technique to predict the surface roughness with respect to various combinations of four cutting parameters (cutting speed, federate, axial depth and radial depth). The models have been found to accurately representing surface roughness values with respect to experimental results. With the model equations obtained, a designer can subsequently select the best combination of design variables for achieving optimum surface roughness. This eventually will reduce the machining time and save the cutting tools.

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References

1. Hoff, P.D.: Bilinear, mixed-effects models for dyadic data. J. Am. Stat. Assoc. **100**, 286–295 (2005)
2. Hofmann, T.; Puzicha, J.: Unsupervised learning from dyadic data. Technical Report TRT-98-042. International Computer Science Insitute, Berkeley (1998)
3. Schölkopf, B.; Smola, A.J.: Learning with kernels—support vector machines, regularization, optimization, and beyond. MIT Press, Cambridge (2002)
4. Vapnik, V.N.: Statistical learning theory. Adaptive and learning systems for signal processing, communications, and control. Wiley, New York (1998)
5. Hochreiter, S.; Obermayer, K.: Support vector machines for dyadic data. Neural Comput. **18**, 1472–1510 (2006)
6. Hochreiter, S.; Obermayer, K.: Gene selection for microarray data. In: Schölkopf, B.; Tsuda, K.; Vert, J.-P. (eds.) Kernel methods in computational biology. MIT Press, USA (2004)
7. Guo, X.; Yuan, Z.; Tian, B.: Supplier selection based on hierarchical potential support vector machine. Expert Syst. Appl. **36**, 6978–6985 (2009)
8. Draper, N.R.; Smith, H.: Applied regression analysis. Wiley, New York (1981)
9. Box, G.E.P.; Draper, N.R.: Empirical model-building and response surfaces. Wiley, New York (1987)
10. Box, G.E.P.; Behnken, D.W.: Some new three level designs for the study of quantitative variables. Technometrics. **2**, 455–475 (1960)
11. Tsao, C.C.; Hocheng, H.: Evaluation of thrust force and surface roughness in drilling composite material using Taguchi analysis and neural network. **203**, 342–348 (2008)
12. Kadirgama, K.; Noor, M.M.; Zuki, N.M.; Rahman, M.M.; Rejab, M.R.M.; Daud, R.; Abou-El-Hossein, K.A.: Optimization of surface roughness in end milling on mould aluminium alloys (AA6061-T6) using response surface method and radian basis function network. Jordan J. Mech. Ind. Eng. **2**(4), 209–214 (2008)
13. Tsai, J.-T.; Chou, J.-H.; Liu, T.-K.: Tuning the structure and parameters of a neural network by using hybrid Taguchi-genetic algorithm. IEEE Trans. Neural Netw. **17**(1) (2006)