COMPUTATIONAL INTELLIGENCE APPROACH FOR PREDICTION OF HARDNESS PERFORMANCE IN COATING PROCESS

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This thesis is special dedicated to my lovely family for their endless love, support and encouragement.

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ABSTRACT

Nowadays, coated materials are widely used due to their excellent properties especially for the hardness performance. The hardness of coated tools is determined by the coating process parameters. Traditionally, optimization to obtain the best coating performance of the parameters in a coating process was done by trial and error approach. However the traditional approach has raised issues with regards to cost and customization. In this research, these two issues were addressed by using a computational intelligence approach to develop a model for predicting the output responses in order to identify the optimal parameters used in coating process. Previous studies have shown that this approach was successfully adopted for optimization purpose in many types of domains. However, it was not yet applied in the coating process domain. Thus, two methods from computational intelligence approach were applied, namely Support Vector Machine (SVM) and Artificial Neural Network (ANN). The comparisons of the performances of the developed models were conducted based on predictive performance measurements such as percentage error, mean squared error (MSE), co-efficient determination (R^2), and model accuracy and complexity. The results showed that, SVM obtained better predictive performances and less complicated in comparison to other prediction models. As a conclusion, SVM has demonstrated its capability in predicting the hardness performance of coating process and outperformed the other models. Besides that, the model is a promising alternative tool for coating process optimization as compared to the traditional approach.

ABSTRAK

Bahan bersalut kini digunakan secara meluas kerana mempunyai ciri-ciri yang amat baik terutamanya dari sudut prestasi kekerasan. Kekerasan bahan bersalut adalah dipengaruhi oleh parameter tertentu dalam proses salutan. Secara tradisional, pengoptimuman untuk mendapatkan prestasi salutan yang terbaik berdasarkan parameter proses salutan adalah melalui kaedah cuba jaya. Walau bagaimanapun, pendekatan ini mempunyai kekangan dari segi kos dan proses suai padan. Dalam kajian ini, kedua-dua isu ini ditangani dengan menggunakan pendekatan kepintaran perkomputeran untuk membangunkan satu model bagi meramalkan respon output dalam usaha mengenalpasti parameter yang paling optimum untuk digunakan dalam proses salutan. Kajian lepas menunjukkan bahawa pendekatan ini telah diterima pakai secara meluas untuk tujuan pengoptimuman dalam pelbagai jenis bidang. Walau bagaimanapun, pendekatan ini masih belum diaplikasikan dalam bidang proses salutan. Oleh itu, kajian ini mengaplikasikan dua kaedah daripada pendekatan kepintaran perkomputeran, iaitu *Support Vector Machine* (SVM) dan *Artificial Neural Network* (ANN). Perbandingan prestasi model yang telah dibangunkan dilakukan berdasarkan peratusan kesilapan, *mean squared error* (MSE), *co-efficient determination* (R^2), ketepatan dan kompleksiti model. Hasil daripada kajian ini menunjukkan bahawa, model SVM memberikan ramalan yang lebih baik dan modelnya lebih mudah berbanding model ramalan lain. Kesimpulannya, model SVM berupaya dalam meramalkan prestasi kekerasan proses salutan yang lebih baik berbanding model lain. Disamping itu, model ini boleh dijadikan sebagai pendekatan alternatif untuk pengoptimuman proses salutan berbanding dengan pendekatan tradisional.

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LIST OF ABBREVIATIONS

AADT	Annual Average Daily Traffic
AlTin	Aluminium Titanium Nitride
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Network
BP	Back Propagation
CI	Computational Intelligence
ERM	Empirical Risk Minimization
FFNN	Feed Forward Neural Network
FL	Fuzzy Logic
GPa	Gigapascal
ITS	Intelligent Transport Systems
LM	Levenberg-Marquardt
MAE	Mean Absolute Error
MLP	Multi-Layer Perceptron
MQL	Minimum Quantity Lubrication
MSE	Mean Square Error
NN	Neural Network
PVD	Physical Vapor Deposition
R^2	Co-Efficient Determination
RBF	Radial Basis Function
RMSE	Root Mean Squared Error
RSM	Response Surface Modelling
SRM	Structural Risk Minimization
SVC	Support Vector Classification
SVM	Support Vector Machine
SVR	Support Vector Regression

TiA1N	Titanium Aluminium Nitride
TiAl	Titanium Aluminium
TiN	Titanium Nitride
WEDM	Wire Electrical Discharge Machine

LIST OF SYMBOLS

b	-	bias
$\boldsymbol{r}$	-	Coef0
C	-	cost constant
$\boldsymbol{d}$	-	degree
γ	-	gamma
α_i - α_i^*	-	lagrange multipliers
ε	-	loss function
ϕ	-	mapping function
ρ	-	Margin separation
N	-	number of sample data
$\xi,\xi*$	-	slack variables
$\boldsymbol{w}$	-	Weight

CHAPTER 1

INTRODUCTION

1.1 Introduction

Nowadays, coated material is widely used due its excellent properties in producing high quality surface. One particular study undertaken by Tuffy *et al.* (2004) indicated that coated tool's wear performance is forty times better than uncoated tools. A coating is a covering that is applied to the surface of an object, usually referred to as the substrate. In many cases coatings are applied to improve surface properties of the substrate, such as appearance, adhesion, wettability, corrosion resistance, wear resistance, and scratch resistance. The performance of the coated tool has been proven in wear mechanism (Bhatt *et al.*, 2010), hardness and adhesion (Jianxin *et al.*, 2008) and tool life (Su *et al.*, 2004) tests. The findings promise prolonged tool life, and enable the implementation of minimum liquid lubrication to reduce cost of coolant which makes up 16% to 20% of manufacturing cost (Sreejith and Ngoi, 2000). Also it contributes to minimizing the environmental impact of discarded cutting fluid (Byrne and Scholta, 1993).

A large variety of techniques and methods are used in coating industry, such as chemical vapour deposition, physical vapour deposition, chemical and electrochemical technique, and spraying. In coating manufacturing, there are two main issues that need to be addressed in the coating process: cost, and customization. The challenge is to ensure both reasonable costs and high efficiency of treatment. These factors should be well-addressed as they directly affect the cutting tool market value (Bradbury and Huyanan, 2000). Besides the equipment maintenance, other factors that lead to high machining costs are material usage, labor, and the number of trial-and-error experiments.

With the help of recently developed computational-intelligence based approaches, we can make excellent predictions of the coating process in an effort to maximize efficiency, thus creating a more valuable product.

To predict and determine future values is a very difficult task. Catfolis (1996) has said that prediction of the future has always fascinated mankind due to the possible benefits of this knowledge. In prediction, modeling plays a very important role when trying to understand the various issues. According to Chai (2006), modeling can comprise into two categories: statistical modeling and intelligent modeling. Nowadays, intelligent models such as the Artificial Neural Network (ANN), Fuzzy Logic (FL), and Support Vector Machine (SVM) have become the main focusing points for researchers in prediction.

SVM is a relatively new machine learning technique that can provide a new model to improve prediction accuracy (Jae and Young, 2005). Developed by Vapnik (1998), SVM is gaining popularity due to its many attractive features and excellent general performance on a wide range of problems (Jae and Young, 2005). SVM, which is technique that embodies structural risk minimization (SRM) principles that theoretically minimizes the expected error of a learning machine, reduces the problem of over-fitting. Although SVM has been used in applications for a relatively short time, this learning machine has proven to be a robust and competent algorithm for both classification and regression in many disciplines. The success of SVM in prediction techniques is evident from several previous research papers in electricity load forecasting (Chen *et al.* 2004), stock price forecasting (Bao *et al.* 2004), traffic speed prediction (Vanajakshi and Rilett, 2004) and travel time series prediction (Wu *et al.* 2004). In bankruptcy prediction, Jae and Young (2005) have proven that SVM can outperform other techniques (Mutiple Discriminit Analysis (MDA), Logitic Regression Analysis (Logit) and Back- Propogation NN (BPNN)). Therefore there is evidence that SVM is the best technique in prediction in general, and that it can successfully compete with other techniques. The performance of this SVM needs to be explored in this research in order to prove the successes of this particular model in prediction.

ANN is an intelligent model comparable to SVM that is also widely used. ANN is a mathematical model or computational model that tries to simulate the structure of biological neural networks, consisting of an interconnected group of artificial neurons and processes information which uses a connectionist approach to computation. In addition, an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase. Neural networks are modeling tools that can be used to model complex relationships between inputs and outputs or to find patterns in data. Unlike the SVM, ANN uses Empirical Risk Minimization (ERM) to minimize the errors of the training data. Since 1980, ANN techniques have been successfully applied in many predictions, especially in flood forecasting (Bazarterseen *et al.* 2003; Chang and Chen, 2003; Lekkas *et al.* 2005 and etc).

The capability of these two method (i.e. SVM and ANN) in the coating process not yet been evaluated. As mentioned by Nisbet *et al.* (2009), the different methods work best for different database. Therefore, the aim of the research is to study the advantages of these two methods (i.e., SVM and ANN) in predicting the best parameter values that lead to the best (i.e. highest quality) hardness performance in TiA1N coating process. The significant of this study is that it will provide an alternative to the traditional approach which is more time consuming and expensive. Thus, we expect that the outcome of this study will contribute to overcoming that problem.

1.2 Problem Background

In the high-speed machining process, cutting tools are consistently dealing with high temperatures and localized stress at the tool tip. During this process, the cutting tool might slides off the chip along the face and rake the newly cut workpiece surface (Kalpakjian and Schmid, 2006). These conditions will cause a tool wear, reducing the cutting tool performances, affected the quality of parts and deteriorate the tool life. Therefore, cutting tool surface hardness is very important in order to reduce the tool wear. In addition, tool wear condition has a direct effect on the economics of cutting operations, final product quality and process reliability (Yen *et al.*, 2004).

The hardness performance can be improved by applying thin film coating on the cutting tool. The main purpose of this is to improve the tool surface properties while maintaining its bulks properties. One of the general coating processes in applying thin films is Physical Vapor Deposition (PVD) magnetron sputtering.

In PVD magnetron sputtering, coating process parameters like sputtering power, substrate bias voltage, substrate temperature, gas pressure and turntable speed all influence the coating performance. Jiang *et al.* (2010) investigated the effects of gas pressure on coating performance, which is argon pressure on the microstructure and magnetic properties of amorphous TbFe magnetostrictive films. Other papers investigating the influencing of coating process parameters on coating performance were done by Nizam (2010), Sun *et al.* (2010) and Zhou *et al.* (2009). Details on this research are discussed in Chapter 2. Consequently, these conditions have caused limitations- especially in the process of applying the coating technology in a new area. In addition, it requires trial and error experiments in order to determine the suitable parameter values of the process with the material used, so that the optimal coating performance could be obtained. Trial and error experiments have resulted in an increase of coating process costs and a more intricate process of customization in coating.

Therefore with the help of computational approaches currently under development, the coating process can be performed in different ways with the same objective. Using computational approaches in estimating coating process performance, there is no need to conduct traditional lab experiments, and hence the costs can be reduced. Jaya *et al.* (2011) proposed the hybridization RSM-Fuzzy method for prediction of hardness coating. This model has achieved 88.49% accuracy compared to the actual data (i.e., experiments-based data). Moreover, from literature survey, we found that another computational-based approach such as SVM and ANN could be applied for the same purpose and might produce higher accuracy.

To the best of our knowledge, no such work has been conducted to explore the ability of SVM and ANN in this particular matter. Thus, this research aims to explore other computational approaches, namely SVM and ANN, to predict the values of parameters of hardness in the coating process. Titanium Aluminum Nitride TiA1N coating process will be considered in this research as a case study. At the end of this study, the prediction results from SVM and ANN will be compared with the hybrid RSM-Fuzzy method. The comparison analysis will be based on predictive performances and complexity of the models. In terms of predictive performance evaluation, four performance metrics will be applied, which are: percentage error, mean square error (MSE), co-efficient determination (R^2) and model accuracy.

1.3 Research Question

There are two fundamental questions that need to be answered through this study:

i. What is an alternative approach applied in this study for estimating the coating process in order to find the best hardness performance in TiA1N coating process?
ii. Can the SVM and ANN approaches applied in this study improve the performance achieved by the hybrid RSM-Fuzzy method proposed by Jaya *et al.* (2011)?

1.4 Objective

The main objectives of the study are:

i. To develop an SVM model for predicting the hardness performance of tools following the coating process.
ii. To develop an ANN prediction model for predicting the hardness performance of tools following the coating process.
iii. To compare the performances of the models with the RSM-Fuzzy model, and recommend the best model that could be used to predict the hardness performance of coated tools.

1.5 Scopes

The scopes of the study are:

i. Hardness has been selected as a function of coating performance, which will be evaluated in this study.
ii. Coating process parameters considered in this study are sputtering power, substrate bias voltage and temperature.
iii. The Titanium Aluminum Nitrite (TiAlN) is the material used for coating process and considered as case study.
iv. Comparison of performance predictions are based on four evaluation matrix predictive values: percentage error, mean square error (MSE), co-efficient determination (R^2), and accuracy.
v. Measurement of hardness is in gigapascal (GPa).
vi. Experimental data of hardness TiA1N coating is based on Jaya *et al.* (2011)

1.6 Thesis Organization

This thesis is organized into seven chapters. Chapter 1 presents the introduction of the study, problem background, problem statement, scope, objectives and the importance of the study**.** Chapter 2 explains the previous work and the literature review of existing techniques for support vector regression (SVM), Neural Network (NN) techniques in coating prediction. The methodology of the project is discussed in Chapter 3. Chapters 4 and 5 explain the prediction model development using SVM and ANN. Chapter 6 discusses numerical analysis and results. Finally, the conclusions and suggestions for future work are discussed in Chapter 7.

1.7 Summary

The coating process plays an important role in determining the performance of coated tools. To produce a good coating, a selection of values of coating process parameters including sputtering power, substrate bias voltage, and substrate temperature are taken into consideration. However, there are no standard methods that can be used to determine the parameters values accurately. The traditional approach of investigating the process through lab experiments requires much more time and money, because multiple lab experiments must be undertaken to obtain the optimal values. In contrast, a researcher has demonstrated that a computational-based approach such as the hybridization RSM-Fuzzy method can be applied to predict the best parameter values of hardness of coating process. This model has achieved 88.49% accuracy compared to the actual data (i.e. experiments-based data). In addition, from literature survey, we found that other computational-based approaches such as SVM and ANN could be applied for the same purpose, possibly producing better accuracy. Thus, this research has been conducted to explore the possibility that the proposed SVM and ANN techniques may achieve better predictive performance compared to the hybrid RSM-Fuzzy method.

REFERENCES

Abhishek, K., Kumar, A., Ranjan, R. and Kumar, S. (2012). A Rainfall Prediction Model using Artificial Neural Network. *IEEE Control and System Graduate Research Colloquium*. 16-17 July. 82-87. IEEE

Abraham, A. (2005). Artificial Neural Networks. John Wiley and Sons Ltd *Handbook for Measurement Systems Design*, 901-908. London.

Abraham, A., Steinberg, D. and Philip, N. S. (2001). Rainfall Forecasting Using Soft Computing Models and Multivariate Adaptive Regression Splines. *IEEE SMC Transactions: Special Issue on Fusion of Soft Computing and Hard Computing in Industrial Applications*, 1, 1-6. IEEE

Arun, G. and Mahesh, P. (2008). Application of Support Vector Machine in Scour Prediction on Grade-Control Structures. *Journal of Engineering Applications of Artificial Intelligence.* 22, 216 - 223. Elsevier.

Bao, Y., Lu, Y., and Zhang, J. (2004). Forecasting Stock Price by SVMs Regression. In C. Bussler and D. Fensel (Eds): AIMSA 2004. *Lecture Notes Artificial Intelligence*, 295–303. Berlin: Springer-Verlag.

Barshillia, H.C. and Rajam, K.S. (2004). Nanoindentation and atomic force microscopy measurements on reactively sputtered TiN coatings. *Material Science*, 27(1), 35-41.

Basari, A.S.H., Jaya, A.S.M., Muhamad, M.R., Rahman, M.N.A., Hashim, S.Z.M., and Haron, H. (2011). Application of ANFIS in predicting TiAlN coatings flank wear. *Third International Conference on Computational Intelligence Modelling & Simulation*. September. 57-62. IEEE

Basheer, L.A., and Hajmeer, M., (2000). Artificial neural network: Fundamentals, computing, design, and application. *Journal of Microbiological Method.* 43, 3-31. Elsevier Science B.V

Bazartseren, B., Hildebrandt, G., and Holz,K.P. (2003). Short-Term Water Level Prediction Using Neural Networks And Neuro-Fuzzy Approach. *Neurocomputing*. 55, 439-450. Elsevier Science B.V.

Bhatt, A., Attia, H., Vargas, R. and Thomson V. (2010). Wear mechanism of WC coated and uncoated tools in finish of Inconel 718. *Tribology International*. 43, 1113-1121. Elsevier

Bishop, C., (1995). *Neural Networks For Pattern Recognition*. Clarendon Press, Oxford.

Bradbury, S. R. and Huyanan, T. (2000). Challenges facing surface engineering technologies in the cutting tool industry. *Vacuum*. 56, 173-177. Elsevier

Burges, C.B.J. (1998). A Tutorial on Support Vector Machines for Pattern Recognition. *Data Mining and Knowledge Discovery*, 2, 121–167. Kluwer Academic

Byrne, G. and Scholta, E. (1993). Environmentally Clean Machining Processes :A Strategic Approach. *Manufacturing Technology*. 42, 471-474. Elsevier

Catfolis, T. (1996). Neural Networks Models for the Prediction of Stock Return Volatility. *IEEE International Conference on Neural Networks*. 03-06 June. 4, 2118 - 2123.IEEE

Caydas, U. and Hascalik, A. (2007). A study on surface roughness in abrasive waterjet machining process using artificial neural networks and regression analysis method. *Journal of Materials Processing Technology*. 202, 574-582. Elsevier

Chai, C.L. (2006). *Finding Kernel Function for Stock Market Prediction with Support Vector Regression*. Master of Science (Computer Science), Universiti Teknologi Malaysia.

Chang, F.J. and Chen, Y.C. (2003). Estuary Water-Stage Forecasting By Using Radial Basis Function Neural Network. *Journal of Hydrology*. 270, 158–166. Elsevier Science B.V.

Chen, B.J., Chang, M.W. and Lin, C.J. (2004). Load Forecasting Using Support Vector Machines: A Study on EUNITE Competition 2001. *IEEE Transactions on Power Systems*. 19(4), 1821-1830.IEEE

Cristianini, N. and Taylor, J.S. (2000). *An introduction to Support Vector Machines and Other Kernel-based Learning Methods,* Cambridge University Press.

Daehyon, K., Yongtaek, L. and Seongkil, C. (2005). Performance Improvement in Traffic Vision Systems Using SVMs. *Journal of the Eastern Asia Society. for Transportation Studies*. 6, 2589-2599. EASTS

Dagli C.H. (ed.) (1994) *Artificial Neural Networks In Intelligent Manufacturing.* Chapman and Hall, London

Evans, R.D., Doll, G.L., Meng, W.J., Mei, F. and Glass, J.T. (2007). Effects of applied substrate bias during reactive sputter deposition of nanocomposite tantalum carbide/amorphous hydrocarbon thin films. *Thin Solid Films*. 515, 5403-5410. Elsevier

Gilles, S., Bourhila, N., Ikeda, S., Bernard, C. and Madar, R. (1997). Deposition of TiAIN thin films by organometallic chemical vapor deposition: thermodynarnic predictions and experimental results. *Surface and Coatings Technology*. 94-95, 285-290. Elsevier B.V.

Gonzalez, L.G., Romo, M.G.G., Torres, J.H. and F.J.E. Beltran, (2007).A study of TiAlN coatings prepared by RF co-sputtering. *Brazilian Journal of Chemical Engineering*.24(2), 249-257.

Haykin, S.S. (1999).*Neural Networks: A Comprehensive Foundation.* Prentice Hall, Upper Saddle River, NJ.

Hecht-Nielsen, R., (1990). *Neurocomputing*. Addison-Wesley, reading, MA.

Idowu, P. A., Osakwe, C., Kayode, A. A. and Adagunodo, E. R. (2012). Prediction of Stock Market in Nigeria Using Artificial Neural Network. *International Journal Intelligent Systems and Applications*. 11, 68-74. MECS.

Imrie, C.E., Durucan, S. and Korre A. (2000). River flow prediction using artificial neural networks: Generalisation beyond the calibration range. *Journal of Hydrology*. 233, 138-153. Elsevier.

Jae, H.M. and Young L.C. (2005). Bankruptcy Prediction Using Support Vecto Machine with Optimal Choice of Kernel Function Parameters. *Expert Systems with Applications.* 28, 603-614. Elsevier.

Jain, A.K., Mao, J., Mohiuddin, K.M., (1996). Artificial neural networks: a tutorial. Comput. *IEEE March*, 31–44.

Jaya, A.S.M, Muhamad M.R., Rahman M.N.A, Napiah Z.A.F.M, Hashim S.Z.M Haron H.(2011). Hybrid RSM-fuzzy modeling for hardness prediction of

Jaya, A.S.M., Hashim, S.Z.M., Rahman, M.N.A. (2010). Fuzzy logic-based for predicting roughness performance of TiAlN coating. *Proceedings of Intelligent Systems Design and Applications (ISDA)*. 91-96.

Jiang, H. C., Zhang, W. L., Zhang, W. X. and Peng, B. (2010). Effects of argon pressure on magnetic properties and low-field magneto striction of amorphousTbFe films. *Physica B*. 405, 834-838.

Jianxin, D., Wenlong, S., Hui, Z. and Jinlong, Z. (2008). Performance of PVD MoS2/Zr-coated carbide in cutting processes. *International Journal of Machine Tools & Manufacture*. 48, 1546-1552,

Kalpakjian, S. and Schmid, S. (2006). *Manufacturing Engineering and Technology.* 5th ed. Jurong, Singapore: Prentice Hall.

Kyoung, K.J. (2003). Financial Time Series Forecasting Using Support Vector Machines. *Neurocomputing*. 55, 307-319. Elsevier

Kyung, S.S., Taik S.L. and Hyun, J.K. (2004). An Application of Support Vecto Machines in Bankruptcy Prediction Model. *Expert System with Application*. 28, 127-135.

Lachtermacher, G., Fuller, J.D., (1995). Backpropagation in time- series forecasting. *Journal of Forecasting* . 14, 381–393.

Lapedes, A., Farber, R., (1988). How neural nets work. In: Anderson, D.Z., (Ed.), *Neural Information Processing Systems*, 442–456. American Institute of Physics, New York,

Lekkas, D.F, Onof, C., Lee, M.J. and Baltas, E.A (2005). Application of Artificial Neural Networks For Flood Forecasting. *Global Nest International Journal.* 6(3), 205-211.

Lippmann, R.P., (1987). An introduction to computing with neural nets. *IEEE ASSP Magazine*. 4, 4–22.

Liu, T.C., Li, R.K., and Chen, M.C. (2006). Development of an artificial neural network to predict lead frame dimensions in an etching process. *International Journal Advance Manufacturing Technology*. 27, 1211-1216.

Lu, W. Z., Wang, W. J., Leung, A. Y. T., Lo, S. M., Yuen, R. K. K., Xu, Z. and Fan, H.Y. (2002). Air Pollutant Parameter Forecasting Using Support Vector Machines. *Proceedings of the 2002 International Joint Conference on Neural* .

Lulseged, A. and Dietmar, P.F. (2006). Using Artificial Neural Networks (ANN) for Real Time Flood Forecasting, the Omo River Case in Southern Ethiopia. *Proceedings of the Summer Computer Simulation Conference.* Article No. 19. July 15-18. USA

Mabel M. C. and Fernandez E. (2008). Analysis of wind power generation and prediction using ANN: A case study. *Renewable Energy*. 33, 986-992. Elsevier.

Manoel, C.N., Jeong, Y., Jeong, M. K. and Han L. D. (2008). AADT Prediction Using Support Vector Regression with Data-Dependent Parameters. *Expert System with Application*. 36, 2979-2986

McCulloh, W.S., Pitts, W., (1943). A Logical Calculus Of The Ideas Immanent In Nervous Activity. *Bull. Math. Biophys*. 5, 115–133

Mitroff, I.I., Betz, F., Pondy, L.R. and Sagasti, F. (1974). On managing science in the systems age: two schemas for the study of science as a whole systems phenomenon. *Interfaces*. 4(3), 46-58. Informs.

Nisbet, R., Elder, J. and Miner, G. (2009). *Handbook of Statistical Analysis & Data Mining Applications*. San Diego, CA: Academic Press.

Nizam, A. R.M. (2010). *Modelling of Physical Vapur Deposition (PVD) Process on Cutting Tool using Response Surface Methodology (RSM*). vol. PhD: Coventry University,

Pao, S.Y., Shien, T.C. and Chang, I.F. (2006). Support Vector Regressionn For Real-Time Flood Stage Forecasting. *Journal of Hydrology*. 328, 704-716.

Radhika, Y. and Shashi, M. (2009). Atmospheric Temperature Prediction Support Vector Machine. *International Journal of Computer Theory and Engineering*. 1(1), 1793-8201. IACSIT

Rahayu, H. (2004).*Bioactivity Prediction and Compound Classification Using Neural Network and Support Vector Machine: A Comparison*. Master of Science (Computer Science). Universiti Teknologi Malaysia.

Razali, M.M., Esmar, B., Sivarao, P.S., Hadzley, A.B.M., Nizam A.R.M. and Ismawati, I. (2006). Properties of PVD TiAlN coatings: A survey. *International Conference on Manufacturing. Science and Technology*. August 28-30.

Rosenblatt, F. (1958).The perceptron: a probabilistic model for information storage and organization in the brain. *Psychological Review*, 65,386–408.

Rumelhart, D.E., Hinton, G.E., Williams, R.J., (1986). Learning representations by backpropagating errors. *Nature 323* (6188), 533-536.

Salam, S. (2007). *Daily Wind Speed Prediction In Kota Bharu Using Artificial Neural Network.* Master of Science (Computer Science). Universiti Teknologi Malaysia.

Samui, P. and Dixon, B. (2011). Application of support vector machine and relevance vector machine to determine evaporative losses in reservoirs. *Hydrological Processes*. 26 (9), 1361-1369.

Md Sap, M.N. and Awan, A.M. (2006). SVR-Financial Forecaster: A Tool for Stock Market Prediction Using Support Vector Regression. *Jurnal Teknologi Maklumat*. 1(18). Penerbit UTM Press

Shi Y. and Eberhart R. (1998). Review of Biomedical Applications of Computational Intelligence. Proceedings of the 20th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. 20(3), 1116-1120. IEEE

Scholkopf, R.J., 1997. *Artificial Neural Networks*. McGraw-Hill, New York

Smola, A. J. and Scholkopf, B (2003). A Tutorial on Support Vector Regression. Technical Report. NC2-TR-1998-030. NeuroCOLT2.

Sreejith, P. S. and Ngoi, B. K. A. (2000). Dry machining: Machining of the future. *Journal of Materials Processing Technology*. 101, 287-290.

Steve, R.G. (1998). Support Vector Machine for Classification and Regression. Technical Report. Faculty of Engineering, Science and Mathematics School of Electronics and Computer Science. University of Southampton.

Su, Y. L., Liu, T. H., Su, C. T., Yur, J. P., Kao, W. H. and Yao, S. H. (2004). Tribological characteristics and cutting performance of Crx%Ccoated carbide tools. *Journal of Materials Processing Technology*. 153-154, 699-706.

Sun, P. L., Hsu, C. H., Liu, S. H., Su, C. Y., and Lin, C. K. (2010). Analysis on microstructure and characteristics of TiAlN/CrN nano-multilayer films deposited by cathodic arc deposition. *Thin Solid Films*

Tang, Z., Fishwick, P.A., 1993. Feedforward neural nets as models for time series forecasting. *ORSA Journal on Computing* 5 (4), 374–385.

Tosun, N., and Ozler, L. (2002). A study of tool life in hot machining using artificial neural networks and regression. *Journal of Materials Processing Technology*. 124, 99-104.

Tuffy K., Byrne, G., and Dowling, D. (2004). Determination of the optimum TiN coating thickness on WC inserts for machining carbon steels. *Journal of Materials Processing Technology*, 155 (156), 1861-1866.

Vanajakshi, L. and Rilett, L.R. (2004). A Comparison of the Performance of Artificial Neural Network and Support Vector Machines for the Prediction of Traffic Speed. *IEEE Intelligent Vehicles Symposium*.14-17 June.

Vapnik V. (1998). *Statistical Learning Theory*. Wiley. New York, USA.

Vapnik, V.N (1995). *The Nature of Statistical Learning Theory*. New York. Springer-Verlag.

Vapnik, V.N. (1999). An overview of statistical learning theory. *IEEE Transactions on Neural Networks*. 10 (5), 988-999.

Wahlstrom, U., Hultman, L., Sundgren, J.E., Adibi, F., Petrov, I. and Greene, J.E. (1993). Crystal growth & microstruct of polycrystalline TiAIN alloy films deposited by ultra-high vacuum dual-target magnetron sputtering. *Thin Solid Films*, 235(1-2), 62-70.

Wei, C.H. and Ping, F.P. (2006). Potential Assesment of the Support Vector Regression Technique in Rainfall Forecasting. *Water Resource Manage*. 21, 495-513. Springer.

Wei, Z.L. and Wen, J.W. (2004). Potential assessment of the support vector machine method in forecasting ambient air pollutant trends. *Chemosphere.* 59, 693-701. Elsevier.

Widrow, B., Rumelhart, D.E., Lehr, M.A., (1994). Neural networks: Applications in industry, business and science. Communications of the ACM 37 (3), 93–105.

Wong, F.S., (1991). Time series forecasting using backpropagation neural networks. *Neurocomputing* 2, 147–159.

Wu, C.H., Ho, J.M., and Lee, D.T. (2004). Travel Time Prediction with Support Vector Regression. *IEEE Transaction on Intelligent Transportation Systems*, 5(4), 276-281.

Wuhrer, R. and Yeung, W.Y. (2004). Grain refinement with increasing magnetron discharge power in sputter deposition of nanostructured titanium aluminium nitride coatings. *Scripta Materialia*, 50, 813-818.

Xu, X.Q., Ye, H. and Zou, T. (2006).Characterization of DC magnetron sputtering deposited thin films of TiN for SBN/MgO/TiN/Si structural waveguide. *SCIENCE A*, 7(3): 472-476. Zhejiang Univ

Xue, X., Yang, Q. and Chen, S., (2009). SVM: Support Vector Machines. In Wu, X., and Kumar, V., *The Top Ten Algorithms in Data Mining* 1st Ed., 37-59. New York. CRC Press.

Yang, J.Y., Yang, M.Q., Niemierko, A., Luo, Z. and Li, J. (2007). Predicting Tumor Malignancies using Combined Computational Intelligence, Bioinformatics and Laboratory Molecular Biology Approaches. *Proceedings of the 2007 IEEE Symposium on Computational Intelligence in Bioinformatics and Computational Biology*. 46-53. IEEE

Yen, Y.C., Sohner, J., Lilly, B. and Altan, T. (2004). Estimation of tool wear in orthogonal cutting using the finite element analysis. *Journal of Materials Processing Technology.* 146, 82-91. Elsevier

Yukun, B., Lu, Y. and Zhang, J. (2004).Forecasting Stock Price by SVMs Regression. AIMSA, *Lecture Notes Artificial Intelligence*, 319 (pp. 295-303). Berlin: Springer-Verlag.

Zadeh L.A. (1965). Fuzzy Sets. *Information and Control*. 8, 338-353

Zain, A. M., Haron H., Qasem, S. N. and Sharif S. (2001). Regression and ANN models for estimating minimum value of machining performance. *Journal of Applied Mathematical Modelling*. 36, 1477-1492. Elsevier.

Zhang, G., Patuwo, B. E. and Hu, M.Y., (1998). Forecasting with artificial neural networks:The state of the art. *International Journal of Forecasting* 14, 35–62. Elsevier Science B.V.

Zhou, T., Nie, P., Cai, X. and Chu, P. K. (2009). Influence of N2 partial pressure on mechanical properties of TiAIN films deposited by reactive magnetron sputtering. *Vacuum*. 83, 1057-1059.

Zupan, J., and Gasteiger, J. (1993). *Neural Networks For Chemists: An Introduction*. VCH, New York