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DEVELOPMENT OF OPTIMAL SVM MODEL FOR WEAR RATE PREDICTION

Radomir Slavkovic, Snezana Dragicevic, Zvonimir Jugovic
Faculty Of Technical Sciences, University Of Kragujevac
Svetog Save 65, Cacak, Serbia

Vladimir Slavkovic
School Of Electrical Engineering, University Of Belgrade
King Alexander Avenue 73, Belgrade, Serbia

ABSTRACT
This paper shows the analysis of using different kernel function for development of optimal Support Vector Machine (SVM) model which could be applied for prediction of wear rate of casting parts. Development of SVM model is designed with the three kernel functions: Radial Basis Kernel Function (RBF), Exponential Radial Basis Kernel Function (ERBF) and Polynomial Kernel Function (POLY). For the development of Improved Support Vector Machine (ISVM) model mixture of kernels RBF+POLY from the real operating conditions. In order to select the optimal model the statistical indicators for all models are presented. Results show that the ISVM using ERBF+POLY mixed kernel function show the best results for the practical purposes. The proposed ISVM model with a mixture of kernels is able to accurately predict the wear rate of casting parts.
Keywords: Support Vector Machine, Kernel functions, wear rate

1. INTRODUCTION
SVM is based on statistical learning theory and is a new achievement in the field of data-driven modelling and has been successfully implemented in classification, regression and function estimation [1]. The concept underlying this algorithm is that of observing the relationships that are valid for a finite set of data. By identifying and learning these relationships, SVM acquires the characteristic of generalization, which means that the algorithm will be able to perform predictions for a new data set generated by the same source. Recently, SVM has been widely used to solve various problems in almost all scientific disciplines [2-7].
SVM requires a database that consists of a finite number of data pairs. In this study, the input database consists of the technological properties of flotation balls and measured wear rate data in the milling process. A database obtained by experimental measurement of the wear rate, served in algorithm training. There is no simple and general deterministic functional relationship between the input characteristics of the balls and wear. For determination of these relationships a statistical learning theory is used. Thus, a great number of functions that are based on the SVM algorithm are developed. A trained algorithm is used for estimating the wear rate of floatation balls with new chemical compositions and mechanical characteristics. For the prediction of the flotation balls' wear rate in the process of copper ore milling, the input data are the balls hardness (HRC) and chemical composition and the output data are the balls wear rate during the milling process. In this paper, a developed SVM and ISVM models are used for defining the optimum chromium content, for a known composition of other chemical elements, which will reduce flotation balls’ wear rates to a minimum.

2. DEVELOPMENT OF SVM AND ISVM MODELS
Relationships between the observed data in real situations are often nonlinear. The main strategy of kernel techniques is mapping from the original space, into space where models can be identified as linear relationships. After data mapping in an appropriately selected characteristic space, standard

algorithms for the analysis of models that are based on linear algebra, geometry and statistics were applied. In the process of data preparation, appropriate kernel functions were used, and combined with various other algorithms, to solve a wide range of set problems.
In this study, the SVM regression function and appropriate learning SVR algorithm are used for analysis. The SVR algorithm consists of two phases: the training (off- line) phase, and the test (online**)** phase. Experimental results are used for development of the SVM and ISVM models. ISVM is an improved SVM method which processes data from the database by two functions connected by the appropriate relations. In order to determine the advantages of applying SVM or ISVM methods in the development of machine learning models, 50 sets of data, each with 57 experimental results (40 for training and 17 for test), were randomly generated from the given database using MATLAB software system. Results for assessing the advantages of the application of SVM or ISVM developed model were obtained during each iteration (50 iterations in total).
In the training phase of all iterations, the algorithm has input data, as well as appropriate output data, that represent the measured values of the wear rate. Based on these data, the SVR algorithm sets the parameters of the regression function, in order to model an appropriate set of data in the best possible way. After optimization of the parameters in the training phase through all iteration of the test phase, the trained SVR function regression was used to predict the level of wear floating balls for the results obtained by measuring and provided by the database for the test phase. The process of development and verification of the SVM and ISVM models performance is simulated in the MATLAB software package using functions svdatanorm, svr and svroutput.
Development of SVM model is designed concurrently with the three kernel functions: Radial Basis Kernel Function (RBF), Exponential Radial Basis Kernel Function (ERBF) and Polynomial Kernel Function (POLY). For all used kernel function at each iteration the average error Δ, absolute mean error $|\Delta|$, standard deviation σ and root mean square error ***rms*** are determined. The statistical indicators for all 50 iterations of SVM model are given in Table 1.

Table 1. The statistical indicators of SVM model.

Function	Δ			| Δ |			σ			rms	
	rms		AVG	rms		AVG	rms		AVG	Min	Max
	Min	Max		Min	Max		Min	Max			
POLY	0.0202	-0.0865	0.0103	0.0225	0.0865	0.0425	0.0308	0.0675	0.0548	0.0368	0.1097
RBF	0.0181	-0.0038	0.0133	0.0210	0.0660	0.0365	0.0258	0.0836	0.0493	0.0315	0.0836
ERBF*	**0.0013**	**-0.00015**	**0.0083**	**0.0161**	**0.0647**	**0.0340**	**0.0204**	**0.0832**	**0.0470**	**0.0204**	**0.0832**

* The best results are highlighted in bold

For the development of ISVM model RBF and ERBF as local functions are used, and POLY function as a global function [8]. The statistical indicators of ISVM model are given in Table 2.

Table 2. The statistical indicators of ISVM model.

Function	ρ	Δ			| Δ |			σ			rms	
		rms		AVG	rms		AVG	rms		AVG	Min	Max
		Min	Max		Min	Max		Min	Max			
RBF + POLY*	0	0.0181	-0.0038	0.0133	0.0210	0.0660	0.0365	0.0258	0.0836	0.0493	0.0315	0.0836
	0.05	0.0181	-0.0108	0.0124	0.0212	0.0679	0.0371	0.0258	0.0826	0.0495	0.0315	0.0833
	0.1	0.0178	-0.0024	0.0119	0.0213	0.0660	0.0381	0.0260	0.0842	0.0501	0.0315	0.0842
	0.2	0.0183	-0.0117	0.0104	0.0212	0.0698	0.0393	0.0270	0.0851	0.0504	0.0326	0.0859
	0.3	0.0190	-0.0669	0.0100	0.0214	0.0683	0.0398	0.0274	0.0573	0.0506	0.0333	0.0881
	0.4	0.0198	-0.0729	0.0095	0.0220	0.0732	0.0402	0.0277	0.0596	0.0508	0.0341	0.0942
	0.5	0.0189	-0.0798	0.0093	0.0226	0.0798	0.0406	0.0295	0.0624	0.0511	0.0350	0.1013
	0.6	0.0190	-0.0789	0.0091	0.0222	0.0838	0.0409	0.0298	0.0662	0.0518	0.0353	0.1031
	0.7	0.0189	-0.0787	0.0088	0.0221	0.0837	0.0411	0.0299	0.0668	0.0525	0.0354	0.1032
	0.8	0.0190	-0.0520	0.0094	0.0219	0.0751	0.0409	0.0302	0.0868	0.0531	0.0356	0.1012
	0.9	0.0192	-0.0552	0.0093	0.0219	0.0723	0.0410	0.0305	0.0817	0.0536	0.0360	0.0986
	0.95	0.0195	-0.0544	0.0082	0.0262	0.0719	0.0417	0.0267	0.0822	0.0541	0.0331	0.0986
	1	0.0202	-0.0865	0.0103	0.0225	0.0865	0.0425	0.0308	0.0675	0.0548	0.0368	0.1097
ERBF + POLY	0	0.0013	-0.00015	0.0083	0.0161	0.0647	0.0340	0.0204	0.0832	0.0470	0.0204	0.0832
	0.05	0.0016	-0.0108	0.0078	0.0164	0.0679	0.0347	0.0206	0.0826	0.0477	0.0207	0.0833
	0.1	0.0018	-0.0024	0.0073	0.0167	0.0660	0.0355	0.0209	0.0842	0.0481	0.0209	0.0842
	0.2	0.0022	-0.0117	0.0058	0.0171	0.0698	0.0368	0.0212	0.0851	0.0489	0.0213	0.0859
	0.3	0.0024	-0.0669	0.0054	0.0174	0.0683	0.0374	0.0215	0.0573	0.0493	0.0216	0.0881
	0.4	0.0026	-0.0729	0.0046	0.0176	0.0732	0.0379	0.0217	0.0596	0.0494	0.0219	0.0942
	0.5	0.0027	-0.0799	0.0047	0.0178	0.0799	0.0382	0.0219	0.0624	0.0497	0.0221	0.1014
	0.6	**0.0047**	**-0.0841**	**0.0047**	**0.0173**	**0.0841**	**0.0382**	**0.0217**	**0.0628**	**0.0497**	**0.0222**	**0.1049**
	0.7	0.0046	-0.0717	0.0050	0.0173	0.0777	0.0381	0.0218	0.0779	0.0501	0.0222	0.1059
	0.8	0.0047	-0.0717	0.0051	0.0173	0.0777	0.0382	0.0217	0.0780	0.0502	0.0222	0.1059
	0.9	0.0047	-0.0717	0.0053	0.0173	0.0777	0.0385	0.0217	0.0779	0.0506	0.0222	0.1059
	0.95	0.0033	-0.0717	0.0054	0.0182	0.0777	0.0386	0.0224	0.0780	0.0509	0.0227	0.1059
	1	0.0202	-0.0865	0.0103	0.0225	0.0865	0.0425	0.0308	0.0675	0.0548	0.0368	0.1097

* The best results are highlighted in bold;
$\rho = 0 \div 1$ - scalar value: $\rho = 0$ for ERBF or RBF function, $\rho = 1$ for POLY function;

3. RESULTS AND DISCUSSION

Given the above, it can be concluded that the best results were obtained for SVM with an ERBF kernel function. Results of ISVM model show satisfactory statistical indicators for mixture of kernels ERBF+POLY. Figure 1 shows the rms values for each iteration for all used ISVM kernel functions. The best results are achieved by using ERBF function for most iteration.
Analyzing the results of each iteration, 32nd and 42nd iterations were separated and marked in Figure 1, as points ***a*** and ***b***. Point ***a*** is obtained with ERBF+POLY kernel function (ρ=0.6) with better results than the ones obtained with ERBF function. However, the point of which is obtained with the ERBF+POLY kernel function presents the results which are distinctly worse than the ones obtained with ERBF function.
The analysis of training and test data showed that during data processing the extrapolation was performed in some cases (some data in the test phase are beyond the limits of the training data). Satisfactory results were obtained in eight cases with ERBF+POLY (ρ=0.6) function of ISVM model.

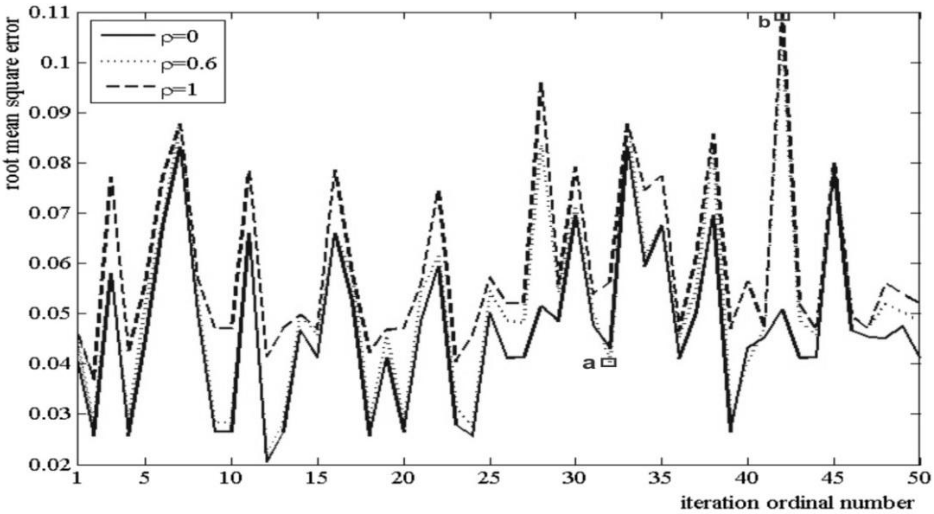

Figure 1. The root mean square error values of the different ISVM kernel function.

4. CONCLUSIONS

In this study, the predictive performance of SVM using three standard kernel functions (RBF, ERBF and POLY) was compared with ISVM using two mixed kernel function (RBF+POLY, ERBF+POLY). The statistical indicators of the SVM model show the best results are achieved using ERBF kernel function, and in ISVM using the ERBF+POLY mixed kernel function. Generally, it has been found that ISVM using ERBF+POLY (ρ=0.6) mixed kernel function show better results for the practical purposes, because the extrapolation is often used for processing of industrial process data.

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