J Intell Manuf (2012) 23:797–809
DOI 10.1007/s10845-010-0436-x

Tool wear estimation using an analytic fuzzy classifier and support vector machines

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Received: 10 October 2008 / Accepted: 10 July 2010 / Published online: 23 July 2010

Abstract A new type of continuous hybrid tool wear estimator is proposed in this paper. It is structured in the form of two modules for classification and estimation. The classification module is designed by using an analytic fuzzy logic concept without a rule base. Thereby, it is possible to utilize fuzzy logic decision-making without any constraints in the number of tool wear features in order to enhance the module robustness and accuracy. The final estimated tool wear parameter value is obtained from the estimation module. It is structured by using a support vector machine nonlinear regression algorithm. The proposed estimator implies the usage of a larger number and various types of features, which is in line with the concept of a closer integration between machine tools and different types of sensors for tool condition monitoring.

Keywords Tool wear estimation · Fuzzy logic · Support vector machines · Dynamic feature selection

Introduction

The development of production systems toward higher levels of automation and flexibility is an on-going process stimulated by a requirement for a continuous improvement in the quality of new products while simultaneously maintaining a high productivity level. The trend is especially marked in the field of machine tools which constantly undergo different design and control system modifications. In that sense, the development of monitoring systems capable of identifying the machining process dynamics and the condition of all machine modules in the real time has became one of the most important imperatives. The primary segment of the overall monitoring process is tool condition monitoring (TCM) since tool wear is the main generator of random process disturbances with a direct influence on the safety, quality and productivity of the machining process. Additionally, a continuous estimation of chosen wear parameters is also essential for the realization of tool wear regulation which would improve tool efficiency, i.e. extend tool life or increase productivity in the scheduled tool change period in the mass production environment (Landers et al. 2002; Liang et al. 2004). In that sense, TCM systems for a continuous estimation of wear parameters is expected to be utilized mainly in situations where the variability of process parameters is relatively low and the influence of tool efficiency maximization on the overall productivity is big.

Research efforts in the field of TCM systems have intensified in past years. They have resulted in a number of various solutions usually based on different types of computational intelligence algorithms. The ones most commonly used are artificial neural networks (ANN) due to their features, such as abilities of identification of complex systems and processes, parallel data processing, noise suppression characteristics, and adaptability to varying machining conditions and tool wear dynamics (Wang et al. 2001). Among a number of neural network types, the most frequently used are Multilayer Perceptron Neural Network—MLP NN (Sick 2002), commonly trained by the Error-Back Propagation algorithm (Huang & Chen 2000; Tandon & El-Mounayri 2001; Chen & Chen 2004; Ghosh et al. 2007; Alonso & Salgado 2008). Besides them, TCM systems built on Radial Basis Function NN (Srinivasa et al. 2002), Adaptive

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Resonance Theory—ART2 (Hong et al. 2001), Kohonen Self-organizing Maps (Silva et al. 1998), Time-Delay NN (Sick 1998), and Recurrent Neural Networks (Venkatesh et al. 1997; Ghasempoor et al. 1999; Kamarthi et al. 2000) are also occasionally proposed. Recently, Wang et al. (2008) proposed a TCM model developed using Fully Forward Connected NN which is a generalized version of MLP NN trained with the Extended Kalman filter algorithm, and Silva (2009) utilized a self-organized Spiking Neural Network.

In order to achieve a more transparent internal TCM algorithm structure, whereby it could be possible to establish the correlation between its parameters and achieved outputs more clearly, fuzzy logic solutions (Li et al. 2000; Susanto and Chen 2003; Liang et al. 2004) and hybrid TCM systems, in the form of neuro-fuzzy models and fuzzy neural networks, have also been studied over past years (Li et al. 2000; Balazinski et al. 2002; Chungchoo & Saini 2002; Lo 2002; Sharma et al. 2008; Zuperl et al. 2009). Their structures are generally formed using a fuzzy rule base which represents a translated human-level description of the problem/solution, and are more perspicuous than the artificial neural networks which use a set of input-output learning data. However, most of the proposed fuzzy logic-based TCM algorithms are limited in the number of utilized tool wear features because of exponential growth of fuzzy rules or model complexity. This characteristic represents their major drawback, especially in the case of continuous tool wear estimation.

As an alternative to ANN, support vector machines (SVMs) are increasingly used as new data-driven modeling algorithms for solving classification and regression types of problems. Compared with other learning algorithms, SVMs have a firm background from the statistical learning theory (Vapnik 1998). They are less vulnerable to overfitting problem and have greater generalization ability since they are designed to minimize structural risk, whereas ANNs are usually based on the minimization of empirical risk, especially those used in TCM. At first, SVM algorithms were developed for pattern recognition problems, and afterwards they were extended to regression estimation problems (Burges 1998; Smola and Schölkopf 1998). In the field of tool condition monitoring, several tool wear classification (Sun et al. 2004, 2006) and estimation (Shi & Gindy 2007; Salgado & Alonso 2007) solutions have been proposed so far.

In spite of intensive research efforts taken in the field of TCM models, only a few, mainly classification solutions, have been commercialized (Jemielniak 1999). The most important reasons why they are so rarely used in practice is the unsatisfactory implementation and the installation of measurement equipment, together with the insufficient quality of proposed feature-extraction and decision-making algorithms. Therefore, a higher degree of integration between machine tools and easily mounted, precise and robust sensors is proposed (Danai 2002). Furthermore, it is necessary to implement the multi-sensor approach with signal processing and feature extraction in real time within the machine control unit (Mehrabi et al. 2002). Additional efforts will have to be taken in the development of TCM algorithms development. Taking into account the need for cost-effective solutions that are adaptable and easily implemented to existing machine tool structures, a substantial number of proposed TCM models are intended for tool breakage or wear classification, based on one or two types of process signals and a relatively small number of tool wear features. However, continuous quantification of tool wear parameters, especially in the case of more complex machining operations such as milling, is not possible without a multiple sensors/features approach and a permanent adaptation of TCM model structure. This is particularly significant in the context of different process disturbances and other varying process parameters (O'Donnell et al. 2001) due to which the correlation between the wear feature and the tool wear level can significantly oscillate. A certain feature may well correlate with the tool wear parameter for some wear level classes, while poorly for others. Also, for some combinations of cutting conditions there is generally a strong connection between the analyzed feature and the wear parameter, while for others this feature may be completely useless.

In this paper, a new hybrid model for continuous flank wear parameter estimation is presented as an adaptive and a multi-feature selection TCM system. It is based on the tool state fuzzy classification in one of wear levels followed by the estimation of flank wear parameter using support vector machine algorithm for nonlinear regression. The main characteristics of the proposed estimator are:

- *Analytic fuzzy logic classification (AFC).* Unlike the majority of proposed fuzzy logic based solutions, fuzzy logic is realized in the analytic form, i.e. without a rule base. That way, the fuzzy decision approach can be applied regardless of the number of tool wear features.
- *Dynamic continuous selection of features.* At first, an independent analysis of every feature with respect to the tool wear intensity is conducted and the final classification of the actual wear level is subsequently obtained on the basis of their mutual influence and contribution in the inference and defuzzification phase. This individual approach provides a possibility for dynamic selection of features, i.e. multiple filtrations regarding to the capacities of a certain feature to fulfill the criteria defined by the parameters of the classifier. For every combination of machining process parameters a representative set of features are extracted together with the intervals of their values which are then used in the estimation process. Thereby, it is possible to greatly reduce negative influences associated with locally or globally overlapped wear level classes of a certain feature.

- *Utilization of multiple features.* The proposed estimator implies the usage of a large number and various types of features extracted from different types of sensors, thus supporting the concept and trends of closer integration of TCM sensors and machine tools. The increase in the number of features does not result in a substantial and problematic increase in the structure complexity, but can significantly improve the model robustness and accuracy.
- *Adaptive and flexible structure.* Once defined, the AFC-SVM structure can be additionally changed and/or extended, and this partial reconfiguration does not affect the rest of the structure which has been previously set according to the identified tool wear dynamics.

Mathematical model of the proposed TCM system, details about signal processing and feature extraction methods, and experimental results are presented in the following chapters.

AFC-SVM Tool wear estimation model

Model structure

The tool wear parameter estimation is performed by processing tool wear features, such as mean values of the signal, standard deviation, dominant amplitudes of the frequency spectra, effective values of the signal, and others, through two modules (Fig. 1).

In the first module, features are classified into one of previously defined wear level classes. After that, features that classified the wear parameter into the winning class in i-th classification/estimation step are used in the estimation module. Only the feature values from the chosen class can participate in the final step of estimation.

The AFC-SVM structure is configured in two phases. In the first phase, also called initialization phase, structure parameters are defined for every combination of cutting conditions (speed, feed rate, depth of cut, tool and workpiece characteristics, etc.) and for every feature. In this phase, all features are used. If this initial structure shows unsatisfactory results, it needs to be further adapted in the second, stabilization phase. The stabilization can be carried out in two ways.

Firstly, the selection of features is implemented for every combination of cutting conditions separately. The selection of a representative set of features that would have to ensure an acceptable estimation error has to be made on the basis of the test results of initially structured estimator. All features showing generally a low correlation with the wear intensity for the considered n-th combination of cutting conditions are excluded from that set. The correlation is quantified by the feature utilization factor—FU_n^j, defined as a ratio of correctly classified samples and the total number of samples of the j-th feature for the n-th combination of cutting conditions. The final FU value is then calculated as the average value of the factors related to all tests—$\overline{FU}_n^j$. In order to be used in the i-th classification/estimation step for the n-th combination, j-th tool wear feature needs to fulfill the condition $\overline{FU}_n^j \geq FU_{\min}$, where the minimal value of FU factor is experimentally determined on the basis of the best estimation characteristics of the model.

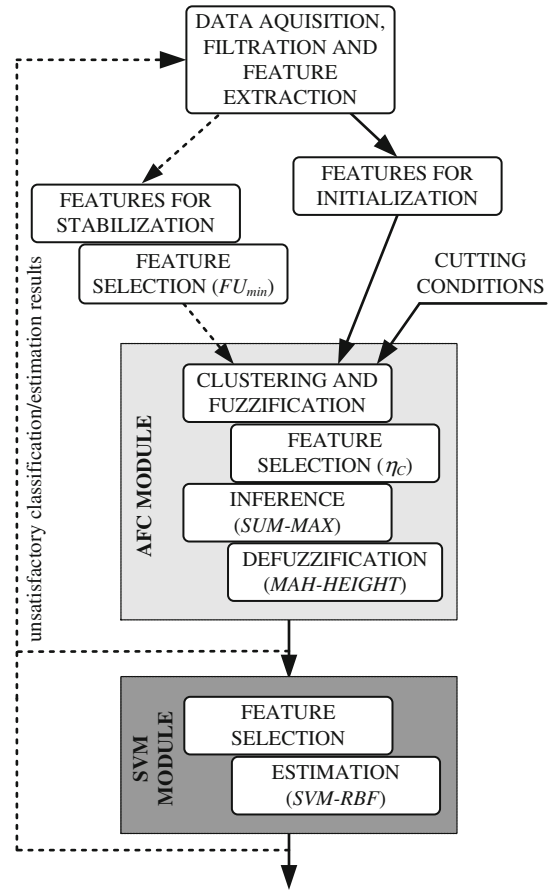

Fig. 1 Schematic diagram of an AFC-SVM model

However, if it turns out that the results remain poor for some combinations of cutting conditions, then, for these combinations, additional structure stabilization has to be conducted using the features extracted from new process signals. This partial adaptation has no influence on the rest of the model structure. The identical approach can be used in the case of possible subsequent model extensions related to the new combination of cutting conditions.

AFC Classification Module

The estimation process starts in the wear level classification module which is built in the form of an analytic fuzzy classifier, i.e. a fuzzy classifier without a rule base. In the beginning, all samples belonging to a certain wear feature are

arranged into that feature belonging clusters. After that, the centre and the shape of every cluster are determined. Clusters are defined for every classification group, i.e. wear level, and neighboring fuzzy sets are partially overlapped. Every fuzzy set is characterized by the type of feature, wear level, and combination of cutting conditions. The membership functions are calculated individually for every wear level class. Additional filtration of features is then carried out and the selected features, the SUM-MAX operator in the inference, and the Max-Height method in the defuzzification phase are then used in order to obtain the final crisp wear level class in the i-th classification step.

Generally speaking, the number and type of cutting parameters influencing the tool wear process dynamics can be miscellaneous. The mathematical model proposed in this paper takes into account three most significant and common parameters—cutting speed, feed and depth of cut. However, the model can be very easily extended to an arbitrary number of other parameters.

Clustering and membership function determination

Learning data are depicted with four types of elements divided into four input sets associated with cutting speeds - V_c, feed rates - F_z, depths of cut - A_p and tool wear features - X.

$$\begin{aligned} V_c &= \{v_{cr} \,|\, r = 1, ..., R\} \\ F_z &= \{f_{zs} \,|\, s = 1, ..., S\} \\ A_p &= \left\{a_{pu} \,\middle|\, u = 1, ..., U\right\} \\ X &= \left\{x_i^j \,\middle|\, i = 1, ..., N,\ j = 1, ..., K\right\} \end{aligned} \tag{1}$$

The clustering process begins with the selection of learning samples belonging to the j-th feature and the n-th combination of cutting conditions

$$t_n^j = \left\{x_i^j \,\middle|\, \forall x_i^j = f\left(v_{cr}, f_{zs}, a_{pu}\right), n = 1, ..., R \cdot S \cdot U\right\}. \tag{2}$$

This set of samples (t_n^j) is then divided into CN_n^j number of τ_{ng}^j subsets which describe the characteristics of all CN_n^j fuzzy sets

$$\tau_{ng}^j \subset t_n^j, \quad g = 1, ..., CN_n^j. \tag{3}$$

The algorithm for the groups, for fuzzy sets centers and for determination of widths is divided into several steps:

- At the beginning, borders of all wear level classes need to be determined. In this paper, three wear level classes were defined using the most important tool wear parameter—flank wear width (VB) in the ranges from $0 \le VB \le 0.1$ mm; $0.1 < VB \le 0.3$ mm; $VB > 0.3$ mm.
- Samples from the t_n^j set are then sorted from the minimal to the maximal value.
- All adjacent elements belonging to the same class form a group (τ_{ng}^j).
- When a sample that does not belong to the wear level class of the analyzed g-th group τ_{ng}^j occurs, the mentioned group is formed and clustering starts for the (g+*1*)-th group associated with other wear level class.
- The g-th group centre is calculated as an average value of the group elements $c_{ng}^j = \bar{\tau}_{ng}^j$.
- All elements clustered in the groups are excluded from a further procedure and the algorithm carries on until the maximal sample value of the analyzed t_n^j set is grouped.

Using this algorithm, it is possible to form homogenous groups of elements belonging to a single wear level class whose fuzzy sets overlap on their radius. Every group has two radius — r_1 and r_2. The first radius is determined by the following expression:

$$r_1\left(c_{ng}^j\right) = \left\| \max_h \left[\tau_{ng}^j(h)\right] - c_{ng}^j \right\| + \underline{r_1}, \quad h = 1, ..., CE_{ng}^j, \tag{4}$$

where c_{ng}^j is the g-th centre associated with the n-th combination of cutting conditions and j-th feature, h is an element of the g-th group with CE_{ng}^j samples and $\underline{r_1}$ is a radius increment defined as

$$\underline{r_1} = \left\{ \begin{array}{ll} \frac{1}{2} \left\| \begin{array}{l} \max_h \left[\tau_{ng}^j(h)\right] \\ -\min_h \left[\tau_{ng+1}^j(h)\right] \end{array} \right\|, & 1 \le g < CN_n^j \\ 0, & g = CN_n^j \end{array} \right\}. \tag{5}$$

The second radius (r_2) is defined in a similar way:

$$r_2\left(c_{ng}^j\right) = \left\| \min_h \left[\tau_{ng}^j(h)\right] - c_{ng}^j \right\| + \underline{r_2}, \quad h = 1, ..., CE_{ng}^j, \tag{6}$$

$$\underline{r_2} = \left\{ \begin{array}{ll} \frac{1}{2} \left\| \begin{array}{l} \max_h \left[\tau_{ng-1}^j(h)\right] \\ -\min_h \left[\tau_{ng}^j(h)\right] \end{array} \right\|, & 1 < g \le CN_n^j \\ 0, & g = 1 \end{array} \right\}. \tag{7}$$

In order to fully define fuzzy set widths, two additional boundary conditions are set

$$\begin{aligned} &if \max_h \left[\tau_{n1}^j(h)\right] = \min_h \left[\tau_{n1}^j(h)\right] = c_{n1}^j \quad \text{then } r_2 = r_1 = \underline{r_1}, \\ &if\ g = CN_n^j \quad \text{and} \quad \max_h \left[\tau_{ng}^j(h)\right] = \min_h \left[\tau_{ng}^j(h)\right] \\ &\qquad = c_{ng}^j \quad \text{then} \quad r_1 = r_2 = \underline{r_2}. \end{aligned} \tag{8}$$

Normalized value $\left(\mu_{ik}^j\right)$ of the membership function $\left(\tilde{\mu}_{ik}^j\right)$ of the j-th feature belonging to the k-th wear level class in

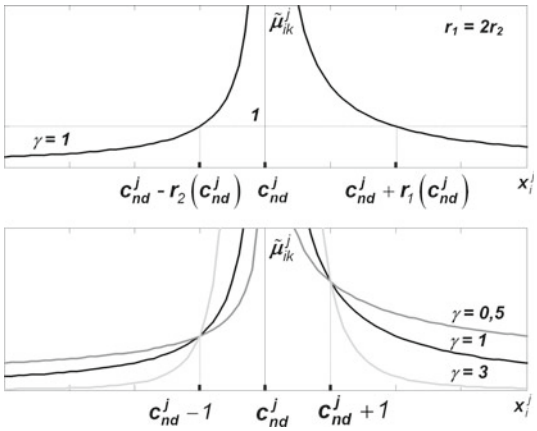

Fig. 2 Example of the form of membership functions

the i-th step is then obtained from the following expressions:

$$\mu^j_{ik} = \frac{\tilde{\mu}^j_{ik}}{\sum_{k=1}^{C}\sum_{d=1}^{NC^j_{nk}} r\left(c^j_{nd}\right)\left|x^j_i - c^j_{nd}\right|^{-\gamma}}, \quad \mu^j_{ik} \in [0, 1], \tag{9}$$

$$\tilde{\mu}^j_{ik} = \sum_{d=1}^{NC^j_{nk}} r\left(c^j_{nd}\right)\left|x^j_i - c^j_{nd}\right|^{-\gamma}, NC^j_{nk} < CN^j_n, \quad k = 1, \ldots, C, \tag{10}$$

$$r\left(c^j_{nd}\right) = \left\{\begin{matrix} r_1\left(c^j_{nd}\right), & x^j_i \geq c^j_{nd} \\ r_2\left(c^j_{nd}\right), & x^j_i < c^j_{nd} \end{matrix}\right\}, \tag{11}$$

where d is the number of neighboring groups to the analyzed feature value x^j_i that belongs to the same wear level class ($d \leq 2$), and exponent γ is an experimentally defined factor by which it is possible to change the influence of the distance from that element to the neighboring centers on the membership function ($\gamma > 0$). The neighboring groups are defined as the closest groups to the analyzed feature value from both sides. From the practical point of view it is necessary to limit the maximal value of the membership function in the vicinity of its center. An example of different forms of membership functions for different γ values is given in Fig. 2.

Normalized membership functions of all K features for all C wear level classes in the i-th step can finally be written in the matrix form

$$\boldsymbol{M}_i = \begin{bmatrix} \mu^1_{i1} & \mu^1_{i2} & \ldots & \mu^1_{iC} \\ \vdots & \vdots & \ddots & \vdots \\ \mu^j_{i1} & \mu^j_{i2} & \ldots & \mu^j_{iC} \\ \vdots & \vdots & \ddots & \vdots \\ \mu^K_{i1} & \mu^K_{i2} & \ldots & \mu^K_{iC} \end{bmatrix}. \tag{12}$$

Inference and defuzzification

After establishing the matrix $\boldsymbol{M}_i$, additional filtration of features is conducted individually for every feature on the basis of the analysis of normalized membership functions. This process is based on η^j_i factor which represents the minimal difference between maximal and all other normalized membership function values

$$\eta^j_i = \min_l \left[\max_k \left(\mu^j_{ik}\right) - \mu^j_{il}\right], \quad l \neq k,\ l = 1, \ldots, C, \quad k = 1, \ldots, C. \tag{13}$$

If this factor is higher than some previously defined critical value (η_c), normalized membership functions of the j-th feature will be accepted. Otherwise, they will be reduced to zero and the feature will have no influence on the final result in the i-th estimation step. The row vectors of $\boldsymbol{M}_i$ matrix can finally be written as

$$\left\{\begin{matrix} \underline{\boldsymbol{\mu}}^j_i = \boldsymbol{\mu}^j_i, & \eta^j_i > \eta_c \\ \underline{\boldsymbol{\mu}}^j_i = [\boldsymbol{0}], & \eta^j_i \leq \eta_c \end{matrix}\right\}, \quad \forall j. \tag{14}$$

All features satisfying the condition $\eta^j_i > \eta_c$, i.e. all non–zero row vectors of $\boldsymbol{M}_i$, are taken in the inference phase that is based on the SUM–MAX operator. At the beginning, the maximal normalized membership function is isolated for every feature separately and other values are set to zero

$$\left\{\begin{matrix} \underline{\underline{\boldsymbol{\mu}}}^j_{ik} = \underline{\boldsymbol{\mu}}^j_{ik}, & \underline{\mu}^j_{ik} = \max_k \left(\underline{\boldsymbol{\mu}}^j_i\right) \\ \underline{\underline{\boldsymbol{\mu}}}^j_{ik} = \boldsymbol{0}, & \underline{\mu}^j_{ik} \neq \max_k \left(\underline{\boldsymbol{\mu}}^j_i\right) \end{matrix}\right\}, \quad \forall j, k. \tag{15}$$

All normalized membership functions belonging to a certain wear level class are then added together forming a vector of membership functions of all classes

$$\underline{\underline{\boldsymbol{\mu}}}_i = \left[\underset{j}{sum}\left(\underline{\underline{\mu}}^j_{i1}\right), \ldots, \underset{j}{sum}\left(\underline{\underline{\mu}}^j_{ik}\right), \ldots, \underset{j}{sum}\left(\underline{\underline{\mu}}^j_{iC}\right)\right]. \tag{16}$$

Finally, the classification of wear level in i-th step is determined in the defuzzification phase using *Max-Height Method*

$$\tilde{O}_{ik} = \left\{\begin{matrix} 1, & \underline{\underline{\mu}}^j_{ik} = \max\left(\underline{\underline{\boldsymbol{\mu}}}_i\right) \\ 0, & else \end{matrix}\right\}, \quad \forall k. \tag{17}$$

In the case of more than one maximal membership values, the one associated with a higher wear level is chosen as the "winner", that is, tool wear state will be classified into a higher wear level class.

The proposed algorithm is firstly used for the initial structure determination of the AFC classification module. After that, the structure needs to be tested and additionally stabilized if necessary. Testing has to be carried out using some arbitrarily or empirically chosen γ factor and together with all wear features involved. In the case of smaller test errors, additional tests have to be done by changing γ, η_c and $FU_{\min}$

factors, i.e. by changing the shape of membership functions and the types of tool wear features used in every i–th classification/estimation step. However, in the case of greater errors, the structure needs to be primarily stabilized by redefining the previously formed fuzzy sets and/or by adding fuzzy sets for new combinations of cutting conditions.

SVM estimation module

The estimation module is built upon the SVM nonlinear regression algorithm with radial basis kernel functions (Kecman 2001). The process is based on the mutual influences of all chosen features, i.e. features that classified tool wear state in the "wining" wear level.

On the basis of the selected wear features ($j = 1, \ldots, \tilde{K} \leq K$) and wear level in the i-th step, the structure of the SVM module first needs to be established in the learning phase. Model input elements (wear features) can be written in the vector form as

$$\boldsymbol{x}_{i,\,e} = \left[x_{ik}^{1} \ldots x_{ik}^{j} \ldots x_{ik}^{\tilde{K}}\right]^{T}\Big|_{e}, \quad e = 1, \ldots, \tilde{N}, \tag{18}$$

or in the matrix notation

$$\boldsymbol{X}_i = \left[\boldsymbol{x}_{i,1} \ldots \boldsymbol{x}_{i,e} \ldots \boldsymbol{x}_{i,\tilde{N}}\right]^{T}. \tag{19}$$

The number of these vectors ($\tilde{N}$) is equal to the number of sampled wear feature values belonging to the k-th wear level. Elements of output vector (measured values of wear parameter, $\boldsymbol{VB}_i$) are respectively associated with every row vector of matrix $\boldsymbol{X}_i$

$$\boldsymbol{VB}_i = \left[VB_{i,1} \ldots VB_{i,e} \ldots VB_{i,\tilde{N}}\right]. \tag{20}$$

Based on these input–output relations it is possible to define the vector of Lagrange multipliers

$$\boldsymbol{\alpha} = \left[\alpha_1 \ldots \alpha_e \ldots \alpha_{\tilde{N}}\ \alpha_1^* \ldots \alpha_e^* \ldots \alpha_{\tilde{N}}^*\right], 0 < \left(\alpha_e, \alpha_e^*\right) < C, \tag{21}$$

by minimization of dual Lagrangian

$$L_D(\boldsymbol{\alpha}) = \frac{1}{2}\boldsymbol{\alpha}^T \boldsymbol{H}\boldsymbol{\alpha} + \boldsymbol{f}^T\boldsymbol{\alpha}. \tag{22}$$

Matrix $\boldsymbol{H}$ is the Hessian matrix composed of the Grammian matrix $\boldsymbol{G}$

$$\boldsymbol{H} = [\boldsymbol{G}\ \ -\boldsymbol{G};\ \ -\boldsymbol{G}\ \boldsymbol{G}]. \tag{23}$$

Since the Gauss function has been chosen as a radial basis kernel function, elements of the Grammian matrix are defined as

$$G_{e\underline{e}} = K\left(\boldsymbol{x}_{i,e}, \boldsymbol{x}_{i,\underline{e}}\right) = e^{-\frac{1}{2}\left(\frac{\left\|\boldsymbol{x}_{i,e} - \boldsymbol{x}_{i,\underline{e}}\right\|}{\sigma_{i,\underline{e}}}\right)^2}, \quad e \neq \underline{e}, \quad \underline{e} = 1, \ldots, \tilde{N}, \tag{24}$$

where the Gaussian widths vector is obtained from

$$\sigma_{i,\underline{e}} = k_\sigma \min\left(\left\|\boldsymbol{x}_{i,e} - \boldsymbol{x}_{i,\underline{e}}\right\|\right). \tag{25}$$

In the case of $\underline{e} = e$, the width has to be increased to an arbitrary small non-zero value. Vector $\boldsymbol{f}$ from (22) is written in the form

$$\boldsymbol{f} = \left[\varepsilon - VB_{i,1} \ldots \varepsilon - VB_{i,\tilde{N}}\quad \varepsilon + VB_{i,1} \ldots \varepsilon + VB_{i,\tilde{N}}\right], \tag{26}$$

and the bias parameter is calculated from the following expressions:

$$b_U = \sum_{e=1}^{\tilde{N}}\left[VB_{i,e} - \left(\sum_{\underline{e}=1}^{\tilde{N}}\left(\alpha_{\underline{e}} - \alpha_{\underline{e}}^*\right) K\left(\boldsymbol{x}_{i,e}, \boldsymbol{x}_{i,\underline{e}}\right)\right) - \varepsilon\right], \quad \text{for } 0 < \alpha_e < C, \tag{27}$$

$$b_L = \sum_{e=1}^{\tilde{N}}\left[VB_{i,e} - \left(\sum_{\underline{e}=1}^{\tilde{N}}\left(\alpha_{\underline{e}} - \alpha_{\underline{e}}^*\right) K\left(\boldsymbol{x}_{i,e}, \boldsymbol{x}_{i,\underline{e}}\right)\right) + \varepsilon\right], \quad \text{for } 0 < \alpha_e^* < C, \tag{28}$$

$$b = \frac{b_U + b_L}{Nsv_U + Nsv_L}, \tag{29}$$

where Nsv_U and Nsv_L are free or unbounded support vectors on an upper and lower bound of Vapnik's ε-insensitivity zone, respectively.

This learning procedure has to be conducted individually for every i-th step. Constant parameters ε, C and k_σ have to be defined by the user, by means of, for example, the random sub-sampling method, k-fold cross-validation method, or comparing the average estimation errors of all tests obtained for every chosen combination of parameter values. The latter approach was applied in this work.

When all learning parameters are determined, the estimated flank wear width can finally be determined as

$$\widehat{VB}_i = \sum_{e=1}^{\tilde{N}}\left(\alpha_e - \alpha_e^*\right) K\left(\boldsymbol{x}_{i,e}, \boldsymbol{x}_i\right) + b. \tag{30}$$

The kernel function $K(\bullet)$ is defined as

$$K\left(\boldsymbol{x}_{i,e}, \hat{\boldsymbol{x}}_i\right) = e^{-\frac{1}{2}\left(\frac{\left\|\boldsymbol{x}_{i,e} - \boldsymbol{x}_i\right\|}{\sigma_{i,e}}\right)^2}, \tag{31}$$

where $\boldsymbol{x}_i$ is an input vector whose elements represent the tool wear features that classified the wear rate as the k-th wear level class in i-th classification step. If it turns out that the estimation error is not acceptable, it is necessary to additionally adapt the AFC structure using new values and/or types of features.

Data acquisition and feature extraction

Experimental set-up

In order to obtain tool wear features, the feed force, acoustic emission and feed drives nominal current signals were measured during a horizontal flat end-milling process using the MIKRON VCP 600 3-axis vertical machining centre, tool steel 1.2343 (DIN), and Iscar's endmill E90XC-D12-06-C12-06 with SOMT 060204-HQ IC 328 insert. Feed force components were measured in two horizontal axes (F_x, F_y) using a Kistler dynamometer 9257B and a 5017B charge amplifier at 30 kHz sampling rate. Acoustic emission signals (*AE*) were taken with Kistler a 8152B sensor, filtered through a 50–400 kHz frequency bandwidth by a 5125B coupler device and sampled using 2 MHz sample rate within 0.1 s. Feed drive nominal currents (I_x, I_y) were obtained directly from a Heidenhain TNC 426 CA control unit and sampled with a maximum frequency of 1.66 kHz.

Three different cutting speeds (70; 95; 120 m/ min), depths of cut (0.5; 1; 2 mm) and feed rates (0.07; 0.095; 0.12 mm/rev) were combined with 9 different flank wear widths—*VB* (0; 0.05; 0.1; 0.15; …; 0.4 mm) classified into three wear level classes ($0 \leq VB \leq 0.1$ mm; $0.1 < VB \leq 0.3$ mm; $VB >$ 0.3 mm). Five samples have been recorded for every combination of these cutting conditions and every type of signals. A total of 6075 samples, each in the duration of 0.1s have been extracted from the signals and analyzed. Features obtained from the first group of samples (1215 samples) were used in the initial AFC-SVM model structuring. The other two groups of samples (Test 1, Test 2) have been utilized for the fine tuning of the model structure and the remaining two groups (Test 3, Test 4) in the final test phase.

Signal Processing and Extraction of Features

After measuring, and before the extraction of features, frequency spectra of force and current signals have been analyzed using a Fast Fourier Transformation (FFT) algorithm. Both, the tool and the tooth frequency were isolated from the spectrum as the dominant frequencies and then used for the filter bandwidth determination. Filtering was carried out using a low-pass FIR filter with 120 Hz cut-off frequency since the highest spindle rotation frequency was around 53 Hz, i.e. the highest tooth frequency was then approximately 106 Hz. After the first phase of signal processing, separate analyses of signals were performed in the time and the frequency domain. Several frequently used statistic variables from the time domain such as:

$$\text{mean} - \bar{x} = \frac{1}{N}\sum_{k=1}^{N} x_k, \tag{32}$$

$$\text{standard deviation} - \sigma = \sqrt{\frac{1}{N-1}\sum\nolimits_{k=1}^{N}(x_k - \bar{x})^2}, \text{ and} \tag{33}$$

$$\text{power} - pow = \frac{1}{N}\sum_{k=1}^{N} x_k^2 \tag{34}$$

were extracted from the signals together with an average RMS signal value defined as

$$\overline{rms} = \frac{1}{N_k}\sum_{j=1}^{N_k}\sqrt{\frac{1}{\Delta K}\sum_{k=(j-1)*\Delta K+1}^{j*\Delta K} x_k^2},$$
$$\Delta K = \frac{N}{\tau}\tau_{RMS}, \quad N_k = \frac{N}{\Delta K}, \quad j = 1, \ldots, N_k, \tag{35}$$

where N is the number of samples of the feature vector x recorded in the period τ.

Additional features have been extracted from the frequency domain. Since the FFT analysis showed that tool and tooth frequencies turn out to be two dominant spectral components (Prickett & Johns 1999), their amplitudes (*tlAmp* and *thAmp*, respectively) are then utilized as tool wear features.

Although AE signals have been filtered during the acquisition process, additional filtrations were carried out using discrete wavelet transformation (DWT), i.e. Matlab's *Wavelet 1-D* function (Misiti et al. 2005). Signals were first decomposed into five levels of wavelet packets (D levels). Every level was separately filtered and then analyzed using the autocorrelation function of residual signal. Finally, all five segments were composed into a filtered signal ready for the feature extraction. Statistical features were the same as for forces/currents. However, for the features from the frequency domain, the energy in frequency ranges has been used (Scheffer et al. 2003)

$$\psi^2 = \int_{fl}^{fh} S_y df, \tag{36}$$

where S_y is the one-sided PSD function of the AE signal, while f_l and f_h are lower and upper frequency values chosen to reflect the energy in the range of interest. Analyses of different bandwidths were conducted and finally a combination of four groups of equally distributed frequencies between 50 and 250 kHz was selected. A complete list of all 32 features used for the tool wear estimation conducted in this paper is given in Table 1.

Table 1 Tool wear features

	F		I		AE
	F_x	F_y	I_x	I_y	
$\bar{x}$	(1)	(2)	(13)	(14)	(25)
σ	(3)	(4)	(15)	(16)	(26)
pow	(5)	(6)	(17)	(18)	(27)
$\overline{\text{rms}}$	(7)	(8)	(19)	(20)	(28)
tlAmp	(9)	(10)	(21)	(22)	–
thAmp	(11)	(12)	(23)	(24)	–
ψ^2(50–100 kHz)	–	–	–	–	(29)
ψ^2(100–150 kHz)	–	–	–	–	(30)
ψ^2(150–200 kHz)	–	–	–	–	(31)
ψ^2(200–250 kHz)	–	–	–	–	(32)

Experimental results

Performance of the AFC-SVM model

On the basis of all types of tool wear features, initial structuring, i.e. clustering and membership function determination, has been conducted. After that, the initially defined structure was stabilized by defining $FU_{\min}$, η_c and γ parameters. At the beginning, using $FU_{\min} = 0$, a set of γ and η_c values ($\gamma = [0, 0.1, 0.2, \ldots, 9]$, $\eta_c = [0, 0.1, 0.2, \ldots, 0.9]$) were combined in order to determine boundaries out of which the gradient of classification error increases.

From the results of classification errors presented in Fig. 3, it can be concluded that low classification error can be achieved for $\gamma > 1.5$ and practically all chosen η_c values. Surfaces of classification errors of both tests for $3 < \gamma \leq 9$ are not presented since the errors remained within the same interval as for $1.5 < \gamma \leq 3$. On the basis of these results, five best $\gamma - \eta_C$ combinations presented in Table 2 were then taken and combined with a set of $FU_{\min}$ values ($FU_{\min} = [0, 0.1, \ldots, 0.7]$).

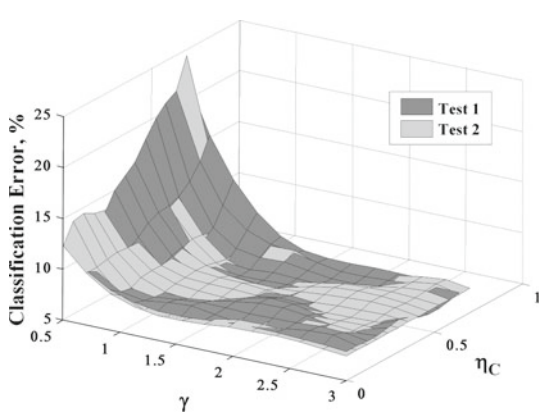

Fig. 3 Classification error for $\gamma - \eta_C$ parameters combination

Table 2 Results for top five $\gamma - \eta_c$ combinations with $FU_{\min} = 0$

Comb.	γ	η_C	Classification errors, %		
			Test 1	Test 2	Average
1	2	0.6	8.2	8.6	8.4
2	3	0.5	7.8	9.1	8.5
3	2	0.5	7.8	9.9	8.9
4	1.5	0.5	9.1	9.1	9.1
5	2.5	0.3	8.6	9.5	9.1

Table 3 Results for top five $\gamma - \eta_c$ combinations with $FU_{\min} = 0.7$

Test	**ΔVB**[mm]	Combinations				
		1	2	3	4	5
		Classification errors, %				
1	–	3.7	3.3	3.3	3.7	3.3
2	–	5.3	6.2	4.9	5.3	4.9
3	–	5.3	3.3	2.9	5.3	3.7
4	–	6.6	5.3	6.2	6.2	5.3
		Proportion of samples with estimation error within ΔVB interval, %				
3	≤ 0.03	74.9	75.3	76.1	72.8	75.7
	> 0.05	12.4	12.4	10.3	11.9	12.8
4	≤ 0.03	71.6	72.8	72.8	71.6	71.6
	> 0.05	14	12.8	13.2	14	12.8

In another words, tool wear features that satisfied these five $\gamma - \eta_C$ combinations and $FU_{\min} = 0$ condition were additionally filtered by increasing $FU_{\min}$ parameter. In the case of $FU_{\min} > 0.7$, the number of features has rapidly decreased, thus resulted in poor classification/estimation capabilities of the AFC-SVM model. Moreover, for 20% of all tested samples none of the features could satisfy this condition. All combinations were tested in the SVM estimation module using experimentally defined parameters $\varepsilon = 10^{-1}$, $C = 1$ and $k_\sigma = 0, 6$. The results are compared on the basis of percentage of all samples that accomplished the tool wear estimation error of less than 0.03 mm and the percentage of those samples with the estimation error of more than 0.05 mm. Although the differences between the model outputs achieved by $FU_{\min} = 0.6$ and by $FU_{\min} = 0.7$ are not significant, for the best combination of AFC-SVM model parameters is chosen to be following: $\gamma = 2$, $\eta_c = 0.5$ and $FU_{\min} = 0.7$. Classification and estimation errors of tests for all five $\gamma - \eta_c$ combinations and $FU_{min} = 0.7$ are given in Table 3.

The average number of features used in the estimation module for the chosen combination of parameters was 8, and, unfortunately, in some cases only one feature satisfied the given η_c and $FU_{\min}$ condition (Fig. 4). In practice, such

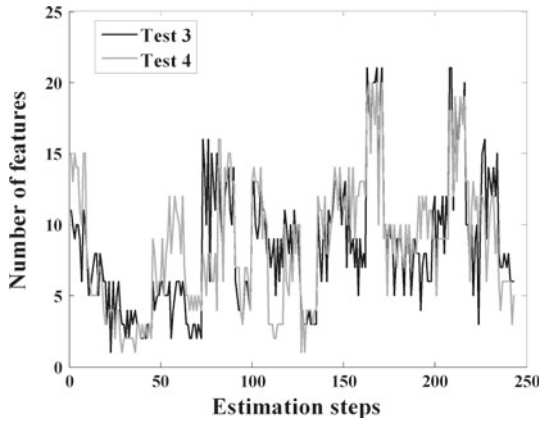

Fig. 4 Number of features used in every estimation step

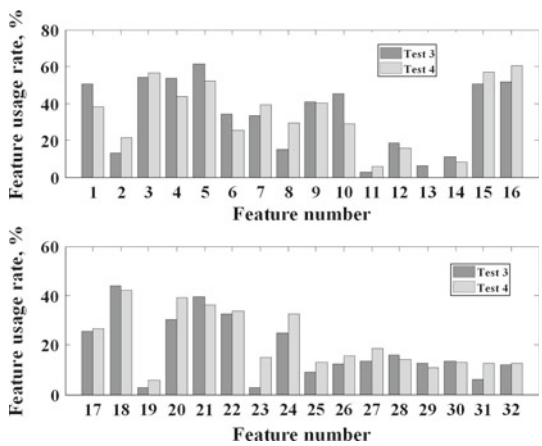

Fig. 5 Feature usage rates

situations should be avoided by using additional tool wear features extracted from new types of signals.

The feature usage rate, defined as the ratio between the number of classification steps in which a certain feature participated in the wear level classification and the total number of classification steps, is shown for every utilized tool wear feature in Fig. 5.

These results show that wear features obtained from cutting forces and feed axis servomotor currents were more often used than the AE features. However, some of the features, such as the tooth frequency amplitude of F_x force (11), the mean value and the average RMS value of I_x current (13,19) did not satisfy η_c and/or a relatively high value of $FU_{\min}$ parameter. They were used in up to 5% of all tested samples.

The final estimation results of the AFC-SVM model, presented in the form of the proportion of samples with estimation errors within defined ΔVB intervals, are given in Table 4.

Approximately 50% of the tested samples achieved the estimation error of up to 0.01 mm, for more than 70% of samples the error was below 0.03 mm and approximately 12% of samples could not estimate the *VB* parameter with an error less than or equal to 0.05 mm. This results indicate that a set of features which have correctly classified tool wear state were also able to successfully estimate flank wear width for the most of analyzed samples.

Table 4 Proportion of samples (in [%]) with estimation error within ΔVB interval for $FU_{\min} = 0.6(\gamma = 1.5; \eta_c = 0.5)$ and $FU_{\min} = 0.7(\gamma = 2; \eta_c = 0.5)$

ΔVB, mm	$FU_{\min} = 0.6$		$FU_{\min} = 0.7$		
	Test 3	Test 4	Test 3	Test 4	Average
[0 – 0.01]	54.32	45.68	52.67	47.33	50.00
(0.01 – 0.02]	12.76	14.81	13.99	12.35	13.17
(0.02 – 0.03]	6.58	11.11	9.47	13.17	11.32
(0.03 – 0.04]	9.47	7.41	9.47	6.17	7.82
(0.04 – 0.05]	2.88	8.23	4.12	7.82	5.97
(0.05 – 0.08]	8.23	6.58	6.58	7.41	7.00
> 0.08	5.76	6.18	3.7	5.76	4.73
≤ 0.03	73.66	71.6	76.13	72.84	74.49
> 0.05	13.99	12.76	10.28	13.17	11.73

A representative set of estimation results for twelve different combinations of cutting parameters is graphically presented (Figs. 6, 7, 8) in order to analyze the distribution of estimated flank wear widths with absolute estimation error greater than 0.05 mm. AFC-SVM system outputs ("Estimated VB" curves) are compared with the belonging predefined flank wear widths ("Measured VB" curves) related to the unworn cutting tool insert ($VB = 0$ mm) and inserts initially worn to the chosen *VB* values (0.05; 0.1; 0.15; …; 0.4 mm). From these figures, it can be noticed that high estimation errors are not concentrated within one group of estimated wear widths related to a certain combination of cutting parameters. This could have been expected considering low rates of AFC module misclassifications, which are the main causes of high estimation errors. Higher errors can also be generated by the features that are unable to more precisely estimate flank wear width within the correctly classified wear level, as was the case in this study.

Performance comparison between AFC-SVM and SVM tool wear estimation algorithm

The main part of the AFC-SVM tool wear estimator is the AFC module. Its influence on the quality of estimation process can be noticed from the results obtained using only SVM estimation algorithm presented in the subsection 7. In view of the fact that from 32 features, used in this research, 2^{32}-1different groups of features can be formed, their number first has to be reduced. In the case of AFC-SVM model, features are selected on the basis of their individual performance in

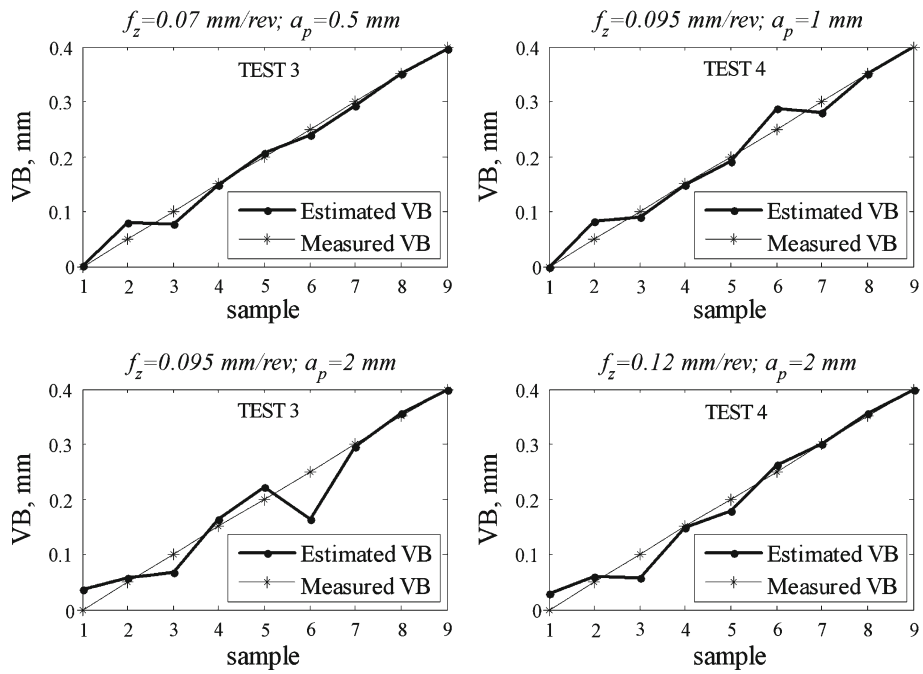

Fig. 6 Examples of AFC-SVM system outputs for $v_c = 70\,\mathrm{m/min}$

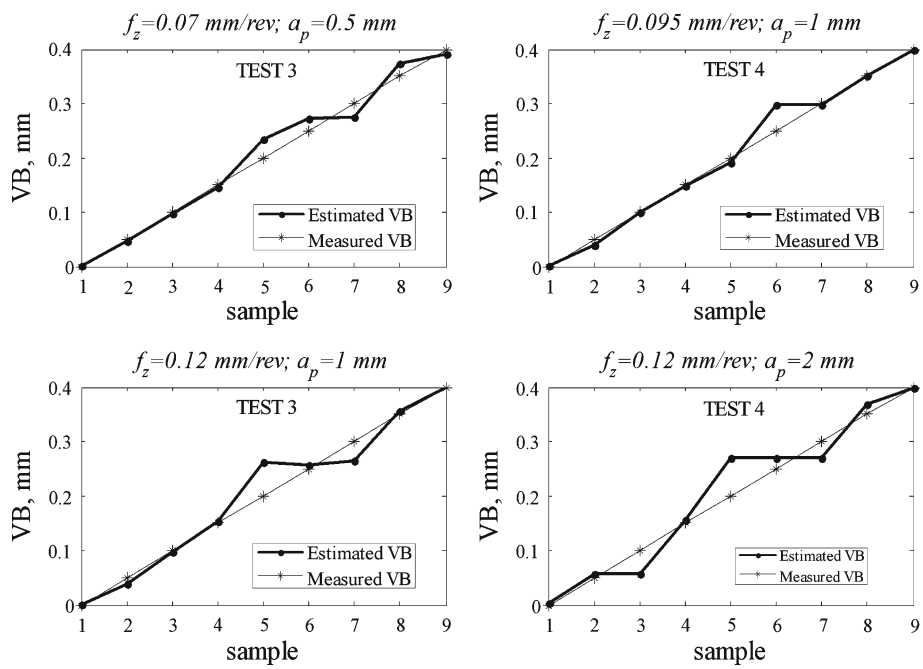

Fig. 7 Examples of AFC-SVM system outputs for $v_c = 95\,\mathrm{m/min}$

the tool wear classification process. The same approach is applied in the analysis of the SVM estimator, except features are selected on the basis of their tool wear estimation performance because they were not previously classified into one of tool wear levels.

In the first case, features were grouped into six groups. First five groups (A1, …, E1) were formed using 10, 20, 40, 60 and 80% of the best ranked features according to the quality of their results obtained with SVM estimator. The last group (F1) is constituted using all 32 features. The results are presented in the form of the proportion of samples which accomplished estimation error within two ΔVB intervals: $\Delta\mathrm{VB} \leq 0.03$ mm and $\Delta\mathrm{VB} > 0.05$ mm (Table 5).

The best results are obtained for the group F1, that is, when all features participated in the estimation. However, the estimation accuracy was lower than the one achieved with the AFC-SVM estimator (Table 4).

In order to compare AFC-SVM and SVM estimation algorithms under more similar conditions, another analysis has been done with features grouped into new five groups (A2, …, E2). In this case, groups were formed using 10, 20, 40, 60 and 80% of the features, which were most frequently used

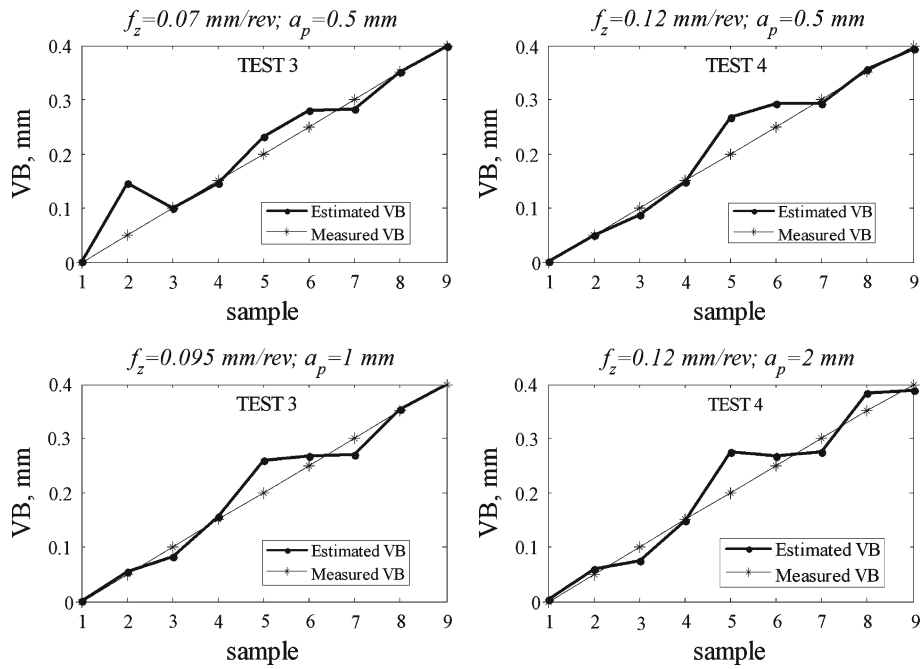

Fig. 8 Examples of AFC-SVM system outputs for $v_c = 120\,\mathrm{m/min}$

Table 5 Proportion of samples (in [%]) with estimation error within ΔVB interval—results achieved using the features selected by the SVM estimator

Group of features	Test 3 ΔVB, mm		Test 4 ΔVB, mm		Average ΔVB, mm	
	≤ 0.03	> 0.05	≤ 0.03	> 0.05	≤ 0.03	> 0.05
A1 (10%)	49.79	34.98	47.33	35.8	48.56	35.39
B1 (20%)	51.44	28.81	48.97	36.63	50.21	32.72
C1 (40%)	48.97	29.63	48.15	37.45	48.56	33.54
D1 (60%)	54.32	29.63	53.09	30.86	53.71	30.25
E1 (80%)	58.44	22.22	59.67	24.69	59.06	23.46
F1 (100%)	59.67	18.93	62.14	22.22	60.91	20.58

Table 6 Proportion of samples (in [%]) with estimation error within ΔVB interval—results achieved using the features selected by the AFC-SVM estimator

Group of features	Test 3 ΔVB, mm		Test 4 ΔVB, mm		Average ΔVB, mm	
	≤ 0.03	> 0.05	≤ 0.03	> 0.05	≤ 0.03	> 0.05
A2 (10%)	49.38	30.04	48.97	33.38	49.18	31.71
B2 (20%)	65.84	19.34	56.79	27.98	61.32	23.66
C2 (40%)	64.61	20.16	60.08	25.1	62.35	22.63
D2 (60%)	60.49	21.8	59.67	22.22	60.08	22.01
E2 (80%)	60.91	17.28	59.67	22.22	60.29	19.75

by the AFC-SVM estimator among all 32 features (Table 6). The results achieved with all features (group F1) are already presented in the Table 5.

Although higher than in the previous case, maximal estimation accuracy still remained lower than in the case of AFC-SVM outputs (Table 4). Some groups with smaller number of features achieved higher estimation accuracy than groups with larger number of features. This can be explained by a negative influence of a subset of features for some combinations of cutting conditions because features were not previously filtered according to their classification performance. In addition, all feature values defined for the n-th combination of cutting conditions participated in the estimation process, while in the case of AFC-SVM estimator only those values belonging to the classified tool wear level were used.

Better results accomplished with the AFC-SVM estimator can generally be explained by the influence of the AFC module in the sense of dynamic feature selection based on the $FU_{\min}$ and η_c parameters, as well as tool wear level classification. This module excludes from further estimation process all those features whose capability to estimate tool wear parameter ($FU_{\min}$) is too small for the analyzed combination of cutting conditions, or features for which minimal difference between maximal and other membership functions defined for all wear levels are below the defined limit (η_c). Additionally, all those features which did not classify selected tool wear level in the i-th classification/estimation step are also omitted from the rest of the process.

Conclusions and future work

In order to be widely accepted in the industrial environment, TCM systems will have to ensure fast and reliable quantification of tool wear parameters with a permanently adaptive

structure according to the wear process dynamics, without any constraints on the number of wear features and with dynamic feature selection in every step of estimation process. These characteristics were the main guidelines in the design of a new hybrid TCM system for the continuous flank wear parameter estimation proposed in this paper. The system is built in the form of a classification and an estimation module, structured using analytic fuzzy logic and support vector machines, respectively. Using the analytic fuzzy logic approach, without a fuzzy rule base, the proposed AFC-SVM tool wear estimator has became independent of the number of utilized tool wear features (32 features were used in this research). Also, the type and the number of wear features used in the classification and the estimation phase are chosen separately for every estimated value of flank wear parameter based on the predefined efficiency criteria. Thereby, the structure of proposed estimator is not fixed, but it adapts continuously at the entrance and within the classification module, and also at the entrance of the estimation module. The number, position and width of fuzzy sets are defined on the basis of learning data by using the proposed clustering algorithm. The estimation module is realized with a nonlinear SVM regression algorithm which provides an optimal solution regarding the initial adjustment of parameters. The AFC-SVM algorithm is based on six parameters ($FU_{\min}$, η_c, γ, C, ε, k_σ) which have been determined experimentally in the learning phase.

As a precondition for quality tool wear parameter estimation, it is necessary to configure a highly accurate classification module since only those features which classified the tool state into the "winning" wear level class are involved in the final estimation of tool wear parameter. An error that occurs in the classification module is afterwards non-recoverable. Hence, the error has to be reduced by using multi-sensor approach which can provide a sufficient set of features capable of classifying the tool wear condition correctly. However, data acquisition and feature extraction processes in such cases are often time-consuming. On the other hand, a fast response of TCM system for continuous estimation of wear parameter is required for the implementation of tool wear regulation process and for the cases of efficient tool breakage detection. The most common solution to that problem implies the usage of parallel processing with several PCs or microprocessors. Unlike that approach, in the next step of this research, an attempt will be made to design a fast field programmable gate array (FPGA) based module with integrated filtration, feature extraction and AFC-SVM algorithms. It will be connected to a Linux based open architecture controller system (Enhanced Machine Controller) of the 3-axis retrofitted milling machine, and analyzed as a part of the neural network based adaptive tool wear control system.

Acknowledgments The authors wish to thank the Ministry of Science, Education and Sport of the Republic of Croatia for funding this research through national scientific projects.

References

Alonso, F. J., & Salgado, R. J. (2008). Analysis of the structure of vibration signals for tool wear detection. *Mechanical Systems and Signal Processing, 22*, 735–748.

Balazinski, M., Czogala, E., Jemielniak, K., & Leski, J. (2002). Tool condition monitoring using artificial intelligence methods. *Engineering Applications of Artificial Intelligence, 15*, 73–80.

Burges, C. J. C. (1998). A tutorial on support vector machines for pattern recognition. *Data Mining and Knowledge Discovery, 2*, 121–167.

Chen, J. C., & Chen, J. C. (2004). An artificial-neural-networks-based in-process tool wear prediction system in milling operations. *The International Journal of Advanced Manufacturing Technology, 21*, 339–347.

Chungchoo, C., & Saini, D. (2002). On-line tool wear estimation in CNC turning operations using fuzzy neural network model. *International Journal of Machine Tools & Manufacture, 42*, 29–40.

Danai, K. (2002). Machine tool monitoring and control. In D. Osita, I. Nwokah, & Y. Hurmuzlu (Eds.), *Mechanical systems design handbook (Section I)*. Boca Raton: CRC Press.

Ghasempoor, A., Jeswiet, J., & Moore, T. N. (1999). Real time implementation of on-line tool condition monitoring in turning. *International Journal of Machine Tools and Manufacture, 39*, 1883–1902.

Ghosh, N., Ravi, Y. B., Patra, A., Mukhopadhyay, S., Paul, S., Mohanty, A. R., & Chattopadhyay, A. B. (2007). Estimation of tool wear during CNC milling using neural network-based sensor fusion. *Mechanical Systems and Signal Processing, 21*, 466–479.

Hong, G. S., Rahman, M., & Wong, Y. S. (2001). Tool condition monitoring in manufacturing systems using neural networks. In C. Leondes (Ed.), *Computer aided design, engineering and manufacturing (Vol. VII): Artificial intelligence and robotics in manufacturing* (pp. 4–1–4-39). Boca Raton: CRC Press.

Huang, P.-T., & Chen, J. C. (2000). Neural network-based tool breakage monitoring system for end milling operations. *Journal of Industrial Technology, 16*(2), 1–8.

Jemielniak, K. (1999). Commercial tool condition monitoring systems. *The International Journal of Advanced Manufacturing Technology, 15*, 711–721.

Kamarthi, S. V., Kumara, S. R. T., & Cohen, P. H. (2000). Flank wear estimation in turning through wavelet representation of acoustic emission Signals. *Journal of Manufacturing Science and Engineering, 122*, 12–19.

Kecman, V. (2001). *Learning and soft computing: Support vector machines, neural networks, and fuzzy logic models*. Cambridge, MA: The MIT Press.

Landers, R. G., Ulsoy, A. G., & Furness, R. J. (2002). Process monitoring and control of machining operations. In D. Osita, I. Nwokah, & Y. Hurmuzlu (Eds.), *Mechanical systems design handbook (Section I)*. Boca Raton: CRC Press.

Li, X., Dong, S., & Venuvinod, P. K. (2000). Hybrid learning for tool wear monitoring. *The International Journal of Advanced Manufacturing Technology, 16*, 303–307.

Li, X., Li, H.-X., Guan, X.-P., & Du, R. (2004). Fuzzy estimation of feed-cutting force from current measurement—A case study on intelligent tool wear condition monitoring. *IEEE Transactions on Systems, Man and Cybernetics – Part C: Applications and Reviews, 34*(4), 506–512.

Li, X., Tso, S. K., & Wang, J. (2000). Real-time tool condition monitoring using wavelet transforms and fuzzy techniques. *IEEE Transactions on Systems, Man and Cybernetics – Part C: Applications and Reviews, 30*(3), 352–357.

Liang, Y. S., Hecker, L. R., & Landers, G. R. (2004). Machining process monitoring and control: The state of the art. *Journal of Manufacturing Science and Engineering, 126*, 297–310.

Lo, S.-P. (2002). The application of an ANFIS and grey system method in turning tool-failure detection. *The International Journal of Advanced Manufacturing Technology, 19*, 564–572.

Mehrabi, M. G., Ulsoy, A. G., & Koren, Y. (2002). Manufacturing systems and their design principles. In D. Osita, I. Nwokah, & Y. Hurmuzlu (Eds.), *Mechanical systems design handbook (Section I).*. Boca Raton: CRC Press.

Misiti, M., Misiti, Y., Oppenheim, G., & Poggi J.-M. (2005). Wavelet toolbox user's guide, The MathWorks Inc., http://www.mathworks.com/access/helpdesk/help/pdf_doc/wavelet/wavelet_ug.pdf,Accessed 19 September 2008.

O'Donnell, G., Young, P., Kelly, K., & Byrne, G. (2001). Towards the improvement of tool condition monitoring systems in the manufacturing environment. *Journal of Materials Processing Technology, 119*, 133–139.

Prickett, P. W., & Johns, C. (1999). An overview of approaches to end milling tool monitoring. *International Journal of Machine Tools and Manufacture, 1*, 105–122.

Salgado, D. R., & Alonso, F. J. (2007). An approach based on current and sound signals for in-process tool wear monitoring. *International Journal of Machine Tools and Manufacture, 47*, 2140–2152.

Scheffer, C., Heyns, P. S., & Klocke, F. (2003). Development of a tool wear-monitoring system for hard turning. *International Journal of Machine Tools and Manufacture, 43*, 973–985.

Sharma, V. S., Sharma, S. K., & Sharma, A. K. (2008). Cutting tool wear estimation for turning. *Journal of Intelligent Manufacturing, 19*, 99–108.

Shi, D., & Gindy, N. N. (2007). Tool wear predictive model based on least squares support vector machines. *Mechanical Systems and Signal Processing, 21*, 1799–1814.

Sick, B. (1998). On-line tool wear classification in turning with time-delay neural networks and process-specific pre-processing. International Joint Conference on Neural Networks – IJCNN 1998 (pp. 84–89). Anchorage, Alaska.

Sick, B. (2002). On-line and indirect tool wear monitoring in turning with artificial neural networks: A review of more than a decade of research. *Mechanical Systems and Signal Processing, 16*(4), 487–546.

Silva, R.G. (2009). Condition monitoring of the cutting process using a self-organizing spiking neural network map. Journal of Intelligent Manufacturing, http://www.springerlink.com/content/gw8887538888715v/fulltext.pdf. Accessed 24 September 2009.

Silva, R. G., Reuben, R. L., Baker, K. J., & Wilcox, S. J. (1998). Tool wear monitoring of turning operations by neural network and expert system classification of a feature set generated from multiple sensors. *Mechanical Systems and Signal Processing, 12*(2), 208–221.

Smola, A. J., & Schölkopf, B. (1998). A tutorial on support vector regression. Royal Holloway College-University of London. http://www.kernel-machines.org/publications/SmoSch98c, Accessed 24 October 2009.

Srinivasa, P. P., Nagabhushana, T. N., & Ramakrishna Rao, P. K. (2002). Flank wear estimation in face Milling based on radial basis function neural networks. *The International Journal of Advanced Manufacturing Technology, 20*, 241–247.

Sun, J., Hong, G. S., Wong, Y. S., Rahman, M., & Wang, Z. G. (2006). Effective training data selection in tool condition monitoring system. *International Journal of Machine Tools and Manufacture, 46*, 218–224.

Sun, J., Rahman, M., Wong, Y. S., & Hong, G. S. (2004). Multiclassification of tool wear with support vector machine by manufacturing loss consideration. *International Journal of Machine Tools and Manufacture, 44*, 1179–1187.

Susanto, V., & Chen, J. C. (2003). Fuzzy logic based in-process tool-wear monitoring system in face milling operations. *The International Journal of Advanced Manufacturing Technology, 21*, 186–192.

Tandon, H., & El-Mounayri, A. (2001). Novel artificial neural networks force model for end milling. *The International Journal of Advanced Manufacturing Technology, 10*, 693–700.

Vapnik, V. (1998). *Statistical learning theory*. New York: J. Wiley & Sons Inc.

Venkatesh, K., Zhou, M., & Caudill, R. J. (1997). Design of artificial neural networks for tool wear monitoring. *Journal of Intelligent Manufacturing, 8*, 215–226.

Wang, J., Tang, W. S., & Roze, C. (2001). Neural network applications in intelligent Manufacturing: An updated survey. In J. Wang & A. Kusiak (Eds.), *Computational intelligence in manufacturing handbook (Part I).* Boca Raton: CRC Press.

Wang, X., Wang, W., Huang, Y., Nguyen, N., & Krishnakumar, K. (2008). Design of neural network-based estimator for tool wear modeling in hard turning. *Journal of Intelligent Manufacturing, 19*, 383–396.

Zuperl, U., Cus, F., & Kiker, E. (2009). Adaptive network based inference system for estimation of flank wear in end-milling. *Journal of Materials Processing Technology, 209*, 1504–1511.