A Comprehensive Approach for On-line Tool Condition Identification in Metal Cutting Processes

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***Abstract*—On-line cutting tool condition monitoring becomes one of the most critical requirements in machining processes for improving the efficiency and the autonomy of CNC machine tools. The processes can be significantly improved by using an intelligent integration of sensor information to detect and identify accurately the tool condition under various cutting parameters. This paper presents a structured and comprehensive approach for on-line tool condition identification in metal cutting processes using ANN based multi-sensor fusion strategy. Various sensing techniques are combined with different preprocessing techniques to select suitable monitoring indices and then numerous models for on-line tool condition identification. The proposed approach is built progressively by examining monitoring indices from various aspects and making modeling decision step by step. The results indicate a significant improvement and a good reliability in identifying various tool conditions regardless of the variation in cutting parameters.**

***Index Terms*—metal cutting processes, tool condition identification, tool condition monitoring, ANN, multi-sensor fusion, monitoring indices.**

I. Introduction

On-line cutting tool condition identification (CTCI) is one of the most important components in modern and flexible manufacturing systems. The majority of the processes, when operating near their operational limits, are affected by failures that seriously compromise their reliability and increase the frequency of human interventions. Tool failure can lead to undesirable and excessive machine vibrations and a possible devastating tool breakage causing damage to the machine tool as well as the workpiece. The cost of such damages can be drastically reduced by using techniques allowing avoidance, prediction or detection of such a failure. As a result, many approaches have been proposed in the past decades [1]-[2]. However, much more research is required to develop a reliable and cost-effective CTCI system for applications on the shop floor, especially when dealing with variable conditions.

In general, there are three major monitoring tasks, which have been identified in the literature. These are monitoring tool breakage, tool wear and tool vibrations. The majority of the research work conducted so far follows the same framework shown in Fig. 1. It usually consists of three major steps: acquisition of signals, processing signals and decision-making. The issues dealing with the understanding of CTCI systems can be classified according to the development of accurate and reliable on-line measurement of machining conditions, the selection of appropriate preprocessing techniques and analysis strategy and the development of improved signals classification procedures.

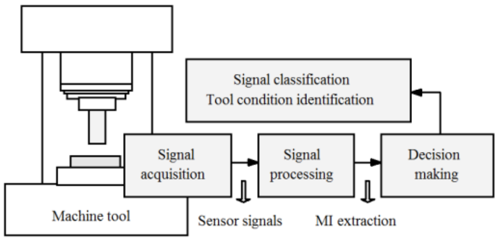


Figure. 1. Diagram of the set-up for CTCI

The main measurements that have been identified as important indicators for monitoring machining processes [3]-[4] include cutting forces, cutting torque, vibrations, acoustic emissions, temperature and motor current. Others direct measuring methods such as touch trigger probes, proximity sensors, optical, radioactive and electrical resistance measurement techniques have also been reported but their reliability under real conditions is limited. The analysis of data from these measurements has demonstrated the difficulties involved in extracting representative characteristics of all process conditions from only one source of information. Data from several sensors simultaneously for machining process monitoring and control is needed. This analysis also shows that two main requirements need to be satisfied when implementing an on-line tool condition identification system: (i) the measurements must reflect the process behavior under its varied operating conditions and (ii) the generated data must allow some discrimination between specific states of the process. Alternatively, integrating several sensors has greatly improved the quality of the process representation [5]. The approach remains however dependent on the used preprocessing, modeling and classification methods.

The preprocessing strategy is related to extraction of monitoring indices (MI). Typical MI include principally:

Manuscript received September 1, 2013; revised November 25, 2013.

doi: 10.12720/jiii.2.2.91-97

time-domain, time-frequency domain, higher order spectrum and wavelet indices. For CTCI, one of the best-known approaches consists in monitoring amplitude increases or variations in the signals. However, such techniques are problematic since variations are strongly contaminated by noise and quickly become difficult to interpret. The introduction of some new preprocessing techniques such as spectral analysis method, has improved the efficiency of the detection, particularly for tool wear and tool breakage [6]-[7]. These techniques have a good resolution in the frequency domain but a very limited resolution in the time domain. Moreover, some signal detail may be lost in the spectral analysis process. The requirement of CTCI for metal cutting applications in terms of accuracy, resolution and timeliness requires more powerful and efficient approaches.

The classification process consists of using MI to recognize the current tool condition (TC) based on pre-defined conditions. The classification can be implemented using weighting methods such as pattern recognition and ANN or decomposition methods, such as decision trees and knowledge-based systems. For specific failure mode detection, the majority of research efforts are concentrated on acoustic emission and cutting forces. These techniques are sensitive to tool failures but require extensive calibration. Recently, attempts have been made to use sensor fusion to generate the required signature features using information from multiple sensors [8]. Sensor fusion techniques enhance the richness of the underlying information contained in each sensor signal [9]-[10] and increase the accuracy and the reliability of the CTCI process when deficient sensitivity in one signal could be compensated by others signals. The sensitivity of TC potentially increases with the number of fused sensors. The major advantage of sensor fusion are its enriched information for MI extraction and decision-making strategy, and its aptitude to take into account the information changes due to calibration, drift, or failure. Other efforts have been made in the development of signal classification procedures for automatic identification of several defect classes [11] and in the use of artificial intelligence techniques, which are rather attractive since they offer the ability to deal with the substantial degree of uncertainty, which is characteristic of machining [12]. Results obtained indicate an interesting reliability for detecting tool failure under fixed conditions. For automatic CTCI applications, however, these classification methods must be more consistent for variable cutting parameters and conditions.

This paper proposes an improved approach for on-line TC identification in metal cutting processes. The considered TC include normal cutting air cutting, transient cutting, change in cutting parameters, tool breakage, vibrations, moderate and severe wear. The approach is structured around an ANN based sensor fusion strategy. A variety of sensing techniques are combined with five preprocessing procedures to select appropriate MI. Forces, vibrations, acoustic emissions and motor current sensors are used in this study to generate a set of signatures, which characterize various TC. A total of nine MI are selected to describe the signature characteristics of three different classes of TC. Several models are developed using a systematic optimization procedure in order to achieve the relationship between TC and MI. A classification scheme is then developed and tested under various cutting conditions.

II. The Proposed Tool Condition Identification Approach

The suggested approach follows basically the steps described previously. Signals are acquired from various sensors, preprocessed and then processed in the time domain by several models to detect and identify various process and tool conditions. As illustrated in Fig.2, during each control step, signals obtained from «p» sensors are preprocessed and used to extract «q» signatures representing «r» MI formed by the most recent successive «s» samples. Then, the «r» MI are forwarded into a model that generate the classification code identifying the «t» cutting TC.

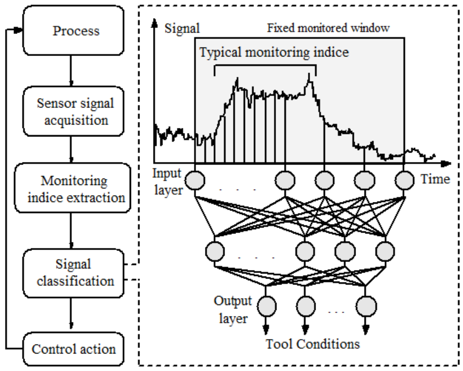


Figure. 2. The identification approach - Stationary time-domain pattern classification

The sensor fusion strategy proposed in this paper is basically an indirect method using a combination of sensors as input into a mathematical model to extract corroborating and relevant information on the machining process conditions. The difficulty to implement such strategy lies in the selection of appropriate sensors, preprocessing schemes and modeling procedures. These choices represent the basic ingredients of any sensor fusion technique. No established systematic method for sensor fusion can be found in the machining literature. However, it is reasonable to assume that the fusion procedure is carried out through a series of steps in which decisions are made based on specific statistical tests. Typically, sensors are chosen based on existing knowledge of the process parameters and conditions. For the preprocessing, five different signal preprocessing procedures (PP) have been attempted. These procedures can be classified as follows:

- PP_1-Unprocessed signals: the model inputs correspond to the pattern made of the most recent successive no preprocessed «s» signal samples.
- PP_2 - Normalized signals: the model inputs patterns consist of the most recent preprocessed «s» signal samples.

- PP_3 - First derivative signals: the model inputs correspond to the pattern made of the most recent successive first derivative «s» signal samples.
- PP_4 - Wavelet transform signals: the model inputs patterns consist of the discrete wavelet transform of the most recent «s» signal samples [6].
- PP_5 - Ratio of the average variances of the dynamic signals: the model inputs correspond to the resulting pattern made of the most recent «s» signal samples [7].

For modeling, two categories of models can be used: theoretical and empirical. Theoretical models are often difficult to develop because of the limited understanding of fundamental behavior of machining processes. The most current theoretical models are limited to very few measurable variables. Empirical modeling use experimental data to adapt the parameters of the model in order to compensate for the inability to adequately describe the process mechanisms.

As suggested in various works, easily available data on machining can be used to establish models using multivariate modeling techniques. However, the material variations and the random nature of the cutting process require an information system capable of handling this profusion of signals satisfactorily. Conventional techniques have shown limited success. This is partially attributed to the wide range of signal noise and misunderstood variations in the process conditions. Consequently, modeling techniques with adaptive capability could reduce the apparent error in the sensor signal. In these conditions, ANN presents one of the best modeling options. As compared to other modeling techniques, ANN provides an effective modeling capability, particularly when the relationships between sensors based information and the characteristic to be identified are non-linear. ANN can handle strong non-linearities, large number of parameters, missing information and successfully deal with the abundant data generated in machining process. Based on their inherent learning capabilities, ANN can be used in a case where there is no exact knowledge about the relations between various inputs/outputs variables. This is very useful to reduce the experiment efforts. Many ANN paradigms have been developed to achieve different learning and processing speed capabilities. While various ANN techniques can be used in this approach, multiplayer feedforward network seems to be one of the most appropriate because of its simplicity and flexibility.

Selecting the modeling technique and the model form is not sufficient to produce the best CTCI model. Several parameters that greatly influence the models quality remain to be defined. The selection of the number and the type of variables to include in the model and the modeling conditions are crucial. Model building analysis is often conducted with a large set of potential variables. From these variables, only a specific subset is useful. Thus, the identification of important variables is decisive to the modeling success. The selection of variables can be carried out efficiently only if statistical tools are applied systematically. Five existing methods have been widely used as variables selection procedures: engineering judgment, correlation analysis, forward selection, backward elimination and step-wise regression [13]. However, none of them can find the optimal models consistently. Although these methods offer the possibility of isolating one reduced model, they are unable to identify alternative candidate subsets of the same size or a model considered to be optimal according to various criteria. Hence, these procedures could lead to poor results.

In order to extract at low cost the best combination of variables, an efficient experimental design method is used. Using Taguchi's orthogonal arrays (OA), the CTCI system can be designed by considering the most sensitive group of MI, which shows high dependency on the monitored TC. Taguchi's OA are highly fractional orthogonal designs, which can significantly reduce the number of combinations to be tested where many parameters and potential combinations are involved [13]. The selection of the best CTCI model is based on the analysis of the effect of each MI combination on the model performances as well as the MI contribution to decrease modeling and identification errors. The following steps can summarize the proposed sensor fusion strategy: (i) Collect data to train and verify the models; (ii) Select the modeling technique and models performance criteria; (iii) Select the appropriate OA to design the required models (rows of the matrix are the models and columns represent which variables are to be included in each model); (iv) For each of the five preprocessing procedures, train the generated models and evaluate their performances according to the established criteria; (v) Determine the effects of each variable and evaluate its contribution in each performance index, and finally, (vi) Determine the appropriate model configuration.

III. Implementation of the Tool Condition Identification Approach

A. Experimental Planning

Implementing a CTCI approach implies preliminary ANN training. Typical MI for training and validation are extracted from signals recorded during turning operation under various cutting conditions. A successful CTCI must be sensitive to changes in TC and insensitive to cutting parameters variations. Hence, a total of 108 machining tests are conducted under various cutting conditions. Thereafter, the acquired signals are used to extract the MI and to build the signature patterns representing normal operating conditions as well as failure conditions. In this study, emphasis has been placed on the coherent choice of MI rather than using other methods such as curve fitting and correlation analysis. A systematic examination of sensor signals monitored under various cutting parameters as well as a review of pertinent literature provided the basis of the choice of the MI. The selected indices are: cutting forces (F_x, F_y, F_z); average resultant cutting force

(F_r); electric spindle motor current (sM_c); vibrations (V_x, V_y, V_z); acoustic emission (AE). These indices represent the most important features of cutting tool conditions in time domain.

B. Experimental Conditions

Experimentation and data collection was carried out using the following apparatus: Single point turning was achieved on a Mori Seiki 34 KVA turning center using a CNM P32 Kennametal carbide insert to machine cylindrical parts made of 6Al-4V titanium alloy. The carbide inserts are installed on a holder on which vibration and AE sensors are mounted. This tool holder is firmly fixed to a Kistler dynamometric table located on the turret. Because carbide insert wear and breakage takes a large time under normal conditions, tests are carried out in three phases as indicated in Table I.

TABLE I. EXPERIMENTAL CONDITIONS

Cutting tests	Feed (mm/rev)	Speed (m/min)	Edge weakening
Normal cutting conditions	0.1 ↓ 0.5	100 ↓ 300	Non-weakened edge
Cutting with moderate and severe wear conditions	0.1 ↓ 0.5	100 ↓ 300	Non-weakened edge
Cutting with tool breakage conditions	0.1 ↓ 0.5	100 ↓ 300	Position Depth 3.00 2.00 3.00 2.25 3.00 2.50 4.00 2.00 4.00 2.25 4.00 2.50

The first phase covers normal operations using variable cutting conditions. This phase has produced normal cutting, air cutting and transient cutting patterns. The second phase covers moderate and severe wear conditions. The choice of tool wear levels was based on finishing criteria where the cutter would be replaced before the beginning of accelerated wear. Moderate and severe wear was defined as corresponding to 15 - 20 and 30 - 35 minutes of cutting time respectively. The third phase covers operations during which tool breakages are caused deliberately. In order to accelerate tool deterioration, the depth of cut was progressively increased and the cutting inserts were weakened with a small notch. The notch on each insert was produced on the tool rake surface by a diamond coated thin cut-off wheel. These machining tests have been carried out with depths of cut ranging between 0 and 5 mm. During the experiments the signals are simultaneously monitored, conditioned and preprocessed before extracting the MI from the acquired dynamic signals.

C. Modeling Investigation

The methodology used to design the CTCI model can be summarized by the four following tasks: (i) design and train a sufficient number of models, each one is developed in order to preserve the OA orthogonality, (ii) estimate the performance for each model; (iii) evaluate the effects of each MI on the models performances and finally, (iv) establish the optimal model. For this purpose, nine MI are combined to design the OA. The dimension of the problem suggests that 12 models are required to investigate efficiently the MI contributions to the CTCI performance.

Many statistical criteria can be used to assess whether a model adequately represents the relationship between TC and MI. The performance of fitted models evaluation is based on the principle of reducing several statistical criteria such as the residual sum of squared error (SSE), the residual mean square error (MSE), the total squared error (TSE), Mallows C_p statistics, and the coefficient of determination (R^2). In the majority of modeling techniques, a model is determined by minimizing SSE. MSE, C_p and R^2 are linear functions of SSE. Under a fixed number of variables, a set of variables minimizing the SSE led to MSE and C_p as the minimum, and R^2 as the maximum under a fixed number of variables. Among these criteria, R^2 does not have an extreme value and presents a regular increasing trend with the number of variables in the model. Consequently, the use of R^2 as a criterion in the variables selection procedure can permit subjective interpretations. If p among q independent variables are selected to form a model, the residual mean square is $MSE_p = SSE_p / n\text{-}p\text{-}1$, where n is the total number of observations. The terms SSE_p and n-p both reduce with an increase in the independent variables number p. Therefore, MSE_p has the ability of showing an extreme value. In this study, the used judgment function consists to minimize the training (MSE_t), the validation (MSE_v) and the total (MSE_{tot})

Before training the designed ANN models, it was important to establish the size of the hidden layer and optimize the training performances. The idea is to approximate the relationship between the size of the hidden layer and the complexity of the MI related to various TC. For this evaluation, 4 network topologies were studied. For all trained models, an adequate knowledge representation with an average error of less than 1% was used. Consequently, to avoid long training and overfitting, the [(i)x$(2i+1)$x(o)] structure was selected where i and o are the number of inputs and outputs respectively. In order to test the validity of the proposed sensor fusion approach, the three validation procedures summarized in Table II are adopted.

TABLE II. VALIDATION PROCEDURE

Procedures	Training	Validation
VP_1	100% of data	100% of data
VP_2	50% of data picked randomly	Remaining data (50%)
VP_3	Data acquired under specific conditions	Remaining data

D. Modeling Analysis

Two statistical indices, derived from ANOVA, are used to analyze the models performances. The % contributions and the average effects of variables included in each model. The % contribution of a variable reflects the portion of the total variation observed in the models attributed to this variable. The graph of average effects is an interesting way to analyze the effects the variables on the models performances. As the modeling procedure is designed using an OA, the estimates of the average effects will not be influenced. Both statistical indices are applied to all modeling performance criteria according to the three validation procedures.

The modeling procedure for the selection of variables begins by choosing an OA that allows the design of models where all potential variables are included. As illustrated in table 3, the OA that best fits this problem is a L12 with a total of 12 models to be designed where + and - indicate respectively whether the MI is used as input to the model or not. Model deviation estimates are evaluated as a function of three main criteria (MSE_t, MSE_v and MSE_{tot}) for each preprocessing procedure. These criteria represent the average MSE values estimated from the three validation procedures.

TABLE III. MODELS EVALUATION USING VARIOUS MSE VALUES

Models	F_x	F_y	F_z	F_r	sM_c	V_x	V_y	V_z	AE
M_1	1	1	1	1	1	1	1	1	1
M_2	1	1	1	1	1	0	0	0	0
M_3	1	1	0	0	0	1	1	1	0
M_4	1	0	1	0	0	1	0	0	1
M_5	1	0	0	1	0	0	1	0	1
M_6	1	0	0	0	1	0	0	1	0
M_7	0	1	0	0	1	1	0	0	1
M_8	0	1	0	1	0	0	0	1	1
M_9	0	1	1	0	0	0	1	0	0
M_{10}	0	0	0	1	1	1	1	0	0
M_{11}	0	0	1	0	1	0	1	1	1
M_{12}	0	0	1	1	0	1	0	1	0

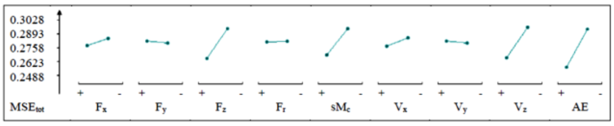


Figure. 3. Average effects of the MI in increasing / decreasing the average of the MSE_{tot} values for the five preprocessing procedure (Variable levels: (+) → MI included in the models and (-) → not included)

The modeling design reveals that all models fitted the data relatively well for the five preprocessing procedures. For the sake of comparison, all the MSE values were calculated using normalized data. The results demonstrate that the proposed approach works well in identifying normal cutting, air cutting, transient cutting, tool breakage and changes of cutting parameters but performs rather poorly for moderate and severe wear. A careful examination indicates that this is because a number of moderate tool wear samples were misclassified to normal cutting and severe tool wear samples were misclassified to tool breakage. Using these results, the average effect of each MI on the models performance was calculated. Average effects graph in Fig. 3 shows that the average total residual mean square errors MSE_{tot} related to the five preprocessing procedures are affected at different degrees by the considered MI. In this graph, the horizontal axis indicates the variable levels. The plotted points correspond to the averages of observations realized under each variable level. This graph reveals that the MI predominantly affecting the models performances are F_z, sM_c, V_z and AE. Similar conclusion can be clearly established from the % contributions reported in Table IV. On the other hand, if we consider MSE_{tot} as the main criteria, the first derivative preprocessing procedure presents the best modeling performance.

TABLE IV. AVERAGE % CONTRIBUTION OF THE MI IN REDUCING THE AVERAGE MSE VALUES

Criteria		Monitoring indices									
		F_x	F_y	F_z	F_r	sM_c	V_x	V_y	V_z	AE	Error
PP_1	MSE_t	4.2	6.2	20.2	-	26.1	-	-	20.1	10.5	12,7
	MSE_v	10.6	2.3	14.7	1.5	25.6	3.1	4.1	23.3	-	14,7
	MSE_{tot}	5.3	7.0	18.1	-	25.7	2.1	2.4	22.1	3.6	13,7
PP_2	MSE_t	7.1	1.4	22.8	-	27.0	-	-	21.5	12.7	7,5
	MSE_v	3.1	-	19.9	7.8	11.2	4.9	2.3	18.9	17.9	14,0
	MSE_{tot}	4.5	1.1	20.2	4.1	21.1	2.9	-	19.3	15.2	11,6
PP_3	MSE_t	5.4	-	25.6	1.9	25.9	-	-	23.8	11.2	6,2
	MSE_v	1.7	2.7	22.1	-	19.9	3.5	2.8	18.6	17.9	10,8
	MSE_{tot}	3.9	-	23.8	0.9	23.5	5.0	-	19.3	14.9	8,8
PP_4	MSE_t	-	8.2	11.5	-	6.1	7.9	5.6	11.4	32.9	16,4
	MSE_v	3.1	11.2	12.1	1.4	8.9	12.2	9.5	4.5	22.9	14,3
	MSE_{tot}	1.4	9.1	11.9	1.1	7.7	8.5	8.9	8.8	26.8	15,8
PP_5	MSE_t	-	4.1	28.5	4.7	26.0	-	-	7.2	14.7	14,8
	MSE_v	11.5	5.5	12.9	10.3	16.3	3.2	1.1	14.4	7.8	16,9
	MSE_{tot}	9.1	4.5	19.6	6.1	22.3	-	-	9.6	12.9	15,8
$\overline{MSE_{tot}}$		4,84	4.34	18.7	2.45	20.0	3.70	2.27	15.8	14.7	13.12

Assuming a limit of 5% and by considering MSE_{tot} as the main criteria, F_z, sM_c, V_z and AE are the variables that affect directly the models performances. The others MI have marginal contributions and sometimes they increase the MSE values as reported in Fig. 3 and Table 5. On the other hand, the results show that the error contribution remains relatively low (less than 20%). This implies that no important variable was omitted in the modeling procedure. These results make possible the identification of five quasi-optimal models (QOM) configurations (QOM_{PP1}, QOM_{PP2}, QOM_{PP3}, QOM_{PP4}, and QOM_{PP5}) related to the five preprocessing procedures. These QOM are achieved by setting each selected MI at a level which minimizes the MSE values. Accordingly, the five QOM were built and tested.

TABLE V. AVERAGE % CONTRIBUTION OF THE MI IN REDUCING THE AVERAGE MSE_{TOT} VALUES USING A LIMIT OF 5%

Criteria	Monitoring indices								
	F_x	F_y	F_z	F_r	sM_c	V_x	V_y	V_z	AE
PP_1	5.32	6.98	18.1	-	25.72	-	-	22.11	-
PP_2	-	-	20.2	-	21.1	-	-	19.3	15.2
PP_3	-	-	23.8	-	23.5	-	-	19.32	14.85
PP_4	-	9.09	11.89	-	7.65	8.5	8.94	8.81	26.8
PP_5	9.13	-	19.6	6.11	22.3	-	-	9.64	12.9
$\overline{MSE_{tot}}$	2.89	4.02	18.72	1.22	20.05	2.13	2.24	15.84	13.95

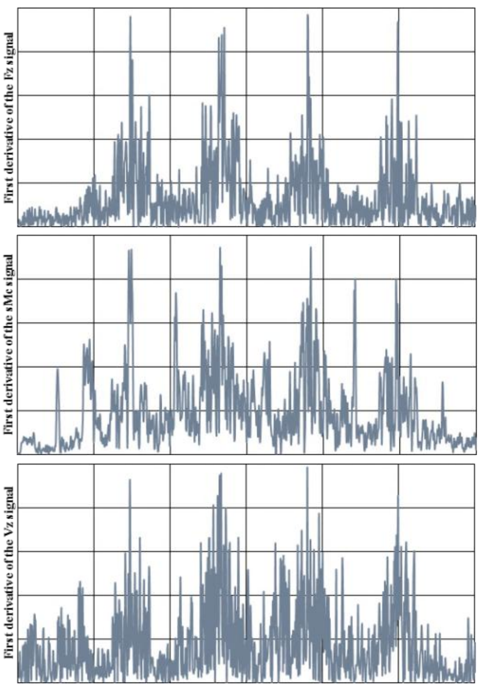
As shown in Table VI where + and - indicate respectively whether the MI is used as input to the model or not, the results demonstrate that the four QOM perform better than the 60 tested models. However, when comparing the five models with each other, there is a clear superiority of COM_{PP3} with MSE_t, MSE_v and MSE_{tot} as minimum. The performances of others models are similar with a small advantage for COM_{PP1} and COM_{PP2}. COM_{PP4} and COM_{PP5} with more variables are slightly less efficient. Hence, one can presume that F_z, sM_c, V_z and AE are ultimately sufficient to achieve a significantly reduced

MSE values and produce the best model.

TABLE VI. QUASI-OPTIMAL MODELS EVALUATION USING VARIOUS MSE VALUES

Model		COM_{PP1}	COM_{PP2}	COM_{PP3}	COM_{PP4}	COM_{PP4}
Monitoring indices	F_x	+	-	-	-	+
	F_y	+	-	-	+	-
	F_z	+	+	+	+	+
	F_r	-	-	-	-	+
	sM_c	+	+	+	+	+
	V_x	-	-	-	+	-
	V_y	-	-	-	+	-
	V_z	+	+	+	+	+
	AE	-	+	+	+	+
MSE values	MSE_t	0.0521	0.0683	0.0443	0.1120	0.0724
	MSE_v	0.0858	0.1075	0.0733	0.1563	0.1126
	MSE_{tot}	0.1393	0.1758	0.1076	0.2683	0.1850

Fig. 4 and 5 present F_z, sM_c, V_z and AE first derivative signals and COM_{PP3} outputs respectively for training and validation phases. The simulation results show that the model is able to identify without difficulty the considered TC. It can be observed that the model outputs stay below a virtual threshold of 20% for normal cutting conditions. The figures show some variations in signals and models responses due to the resemblance between signals relative to moderate wear conditions (between 20 and 50%) and variations in cutting parameters and several similarities between signals relative to severe wear (between 50 and 75%) and tool breakage conditions (more than 75%). These results demonstrate that the model is excellent and presents a good reliability in identifying various tool conditions with accuracy better than ±5% for varying operating conditions. The results suggest that the first derivative preprocessing procedure have decisive effects on the model efficiency.



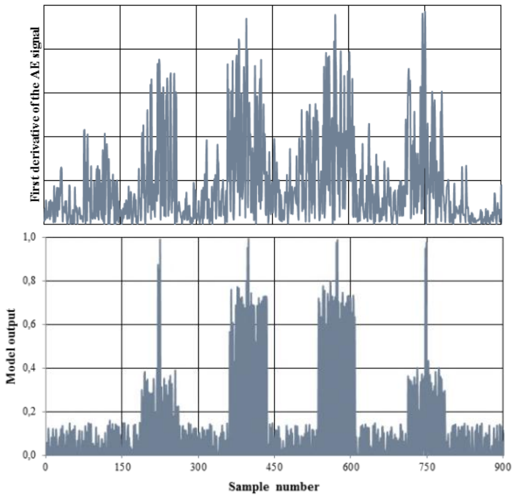


Figure. 4. Tool condition identification model response using training data

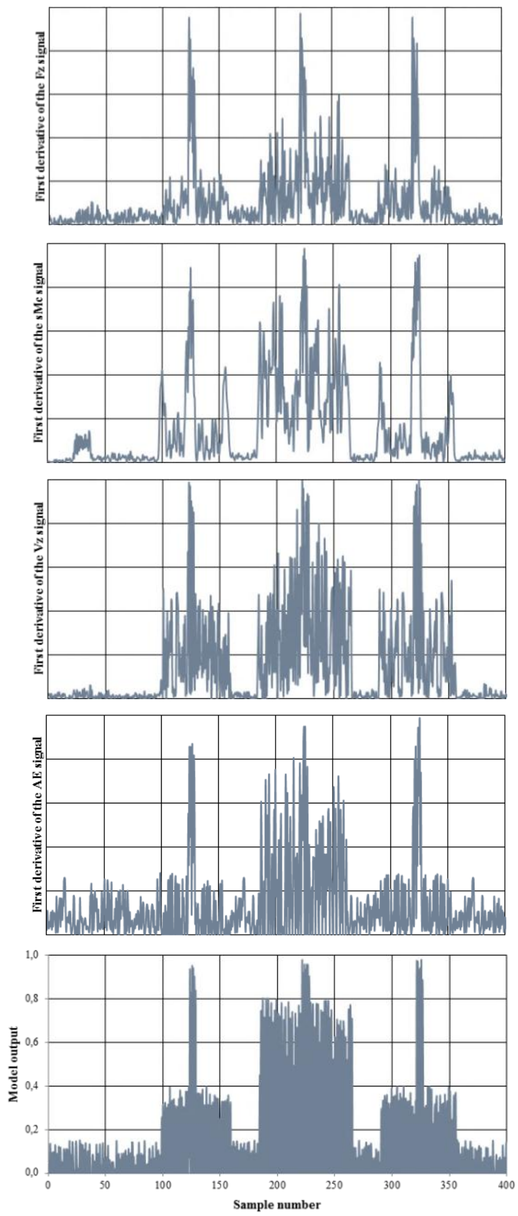


Figure. 5. Tool condition identification model response using validation data

IV. Conclusion

This paper has presented a structured and comprehensive approach for on-line tool condition identification in metal cutting processes using an ANN based multi-sensor fusion strategy. Several models are developed in order to describe the relationships between tool conditions and various monitoring indices. An improved modeling procedure is then developed and tested under various conditions. Built progressively by examining multiple monitoring indices from various aspects and making modeling decisions step by step, the proposed approach offers the ability to evaluate the effects of each modeling parameter on the performance and the efficiency of the identification models. Using an example applied to turning, the paper demonstrates the possibility of establishing a general model able to identify not only one specific failure mode but also detect and identify several tool conditions and failure modes under various process conditions.

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