An ANN Based Multi-Sensor Integration Approach for in-Process Monitoring of Product Quality in Turning Operations

Abderrazak El Ouafi and Noureddine Barka
Engineering Department, University of Quebec at Rimouski, Canada
Email: {abderrazak_elouafi, noureddine_barka}@uqar.ca

***Abstract*—The objective of this study is to develop an effective approach for prediction of part dimensional accuracy and surface roughness in turning operations using neural network based multi-sensor integration strategy. The prediction system is built progressively by examining cutting parameters known to have influence on product quality from various aspects and making integration decisions step by step. The integration procedure begins by establishing the relationships between the cutting parameters and machined part quality and their sensitivity to the process conditions. Based on these results and using various statistical tools, variables selection, modeling and multi-sensor fusion procedures are executed. The results concerning finish turning of an Al alloy on a CNC turning machine demonstrate that the proposed approach can accurately predict on-line the part dimensional deviations and surface roughness under various machining conditions. The ANN based multi-sensor integration approach can be effectively and gainfully applied to in-process monitoring of product quality in turning operations because it includes the advantages of simple application, reduced modeling time, sufficient model accuracy and robustness.**

***Index Terms*—cutting processes, part quality monitoring, quality prediction, sensor fusion, ANN.**

I. Introduction

Turning is one of the most fundamental metal removal operations commonly used in the machining industry because of its ability to remove material faster giving reasonably good quality. It is used in a variety of manufacturing industries including aerospace and automotive sectors, where quality is an important factor. The quality of finished products plays a crucial role in the functional capacity of the part and, therefore, a great deal of attention should be paid to keep consistent tolerances and surface finish. Producing a part with desired specifications present technological and economic issues. The production of the appropriate dimensional accuracy and surface finish affects not only the functional attributes of products but affects also their manufacturing costs. Working under ideal conditions, engineers can control the produced tolerances and surface finish by manipulating the cutting parameters. Usually, engineers set the cutting parameters based on experience or a handbook but these methods do not always yield the desired results.

Many different factors influence the part dimensional accuracy and surface finish, such as tool variables, (geometry, nose radius, stiffness, tool holder, etc.), workpiece variables (material, hardness, part fixtures, etc.), machining process parameters (spindle speed, feed rate, depth of cut, etc.) and machining operations conditions such as cutting forces, machine vibration, progressive tool wear, cutting tool deflections, cutting fluid, variation of process conditions during the cutting operation, and others dynamic variables. The complex correlations between these factors make it difficult to develop part dimensional accuracy and surface finish improvement approach based only on human experience. For this purpose, all factors must be considered simultaneously to build up an appropriate and successful approach. Under these conditions, an intelligent integration strategy of various information sources becomes the key for developing an efficient in-process quality prediction system.

Many research efforts in machining have been devoted to on-line prediction and control of dimensional deviation and surface roughness. In these efforts, adaptive control has been considered as a promising strategy to adapt on-line the process parameters to the widely varying machining conditions [1]. Such adaptive systems are difficult to implement in the industry. The most important reasons are the absence of sensing devices that reliably and effectively provide part quality measurements in a hostile machining environment, and the lack of deeply understanding of the cutting process leading to inadequate modeling strategies [2], [3]. Although during the past decade, some sensors have been designed for quality characteristics measurements such as on-line dimensional deviation and surface roughness. The accuracy and reliability of these sensors remain uncertain. Indeed, sensor development for quality measurements has followed two major trends: direct and indirect sensing methods. Direct sensing methods, which that measure the quality directly from the part, are not successful in producing reliable on-line measurements [2]. Contacting sensors are often ineffective mainly due to wear, fracture, vibration and chip evacuation problems, while non-contact sensors are impractical mainly due to the interference of chips and cutting fluid. On the other hand, indirect sensing

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methods measure physical quantities such as cutting forces, cutting power, vibrations and acoustic emissions. The measured variables are used in a model that estimates the quality characteristics. Indirect methods provide a more economic and flexible capability, particularly when combined with an efficient modeling technique.

Recently, further attention has been directed at using and improving sensor fusion and integration techniques [4]-[7]. The fusion of sensors is basically an indirect method using a combination of sensor as input into a mathematical model to extract corroborative and relevant information on the state of the machining operation. In machining, sensor fusion is suggested where only a few sensors can be applied and each sensor measures a different variable. On the other hand, two difficulties are encountered in this issue: selecting the robust modeling technique and selecting the appropriate sensors. No systematic method for sensor fusion can be found in the machining literature. However, it is reasonable to assume that sensor fusion is carried out through a series of steps in which decisions are made based on specific statistical tests. Typically, sensors are chosen based on available knowledge of the relationship between the sensor measurements and the characteristics to be identified. For modeling, two categories of models can be used: theoretical and empirical. Theoretical models are often very difficult to develop because of the reduced understanding of fundamental behavior of machining processes. The most current theoretical models are limited to very few measurable variables. Empirical modeling methods 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 information on machining operations can be used to establish models using a multivariate modeling technique such as multiple regressions and Artificial Neural Networks (ANN).

As compared to other techniques, ANNs provide a more effective modeling capability, particularly when the relationship between the sensors based information and the characteristic to be identified is non-linear. ANNs can handle strong non-linearity, large number of variables, and missing information. Based on their intrinsic learning capabilities, ANNs can be used in a case where there is no exact knowledge concerning the nature of relationships between various variables. This is very useful to reduce the experiment efforts.

On the other hand, model building analysis is often conducted with a large set of potential predictor variables. From these variables, only a specific subset is useful. Thus, the identification of important variables is crucial to the modeling success. The selection of variables can be carried out efficiently only if statistical techniques are applied systematically. Three existing methods have been widely used for variables selection. These methods are: engineering judgment (EJ), correlation analysis (CA) and step-wise regression (SWR). However, none of them can find the optimal models consistently. EJ is based on individual's experience about machining to determine simplified models. It is useful to choose preliminary variables for further investigation. It is risky to use a small number of variables without exact knowledge of process behaviors and impossible to find the best model only by the EJ method. CA uses the correlation coefficients to select highly correlated variables as a model. Because of the variables are also correlated to one another, this method is only suitable to find the model with a single variable. The standard SWR is able to find a better model with multiple variables, because the partial correlation between the variables is investigated. This regression method first includes the most strongly correlated variables and then adds or subtracts one variable at a time based on an F-distribution value that evaluates the contribution of the added or removed variable. The effect of combining two or more variables at a time is never considered. Since the variables are inter-correlated, the combinations of variables are important during the modeling. In addition to the above methods, there are two other variable selection procedures: forward selection and backward Elimination. These methods present a similar drawback as those of the SWR. Although the traditional selection procedures 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 since the interactions between variables cannot be considered. Thus, the basic condition to successfully implement an optimal variable selection requires a simultaneous application of the selection criteria.

The aim of this study is to develop an effective approach for in-process monitoring of product quality in turning operations using an ANN based multi-sensor integration strategy. The proposed approach is built progressively by examining cutting parameters known to have influence on part dimensional accuracy and surface roughness from various aspects and making sensor integration decisions step by step. In order to carry out the integration strategy, extensive experiments are required to provide an efficient and optimal modeling database.

II. Experimental Study

Numerous factors influence the dimensional accuracy and surface finish during turning operations. This study will be restricted to only five of them to illustrate the proposed approach. The first three factors are the cutting parameters, which include cutting feed (f), cutting speed (s) depth of cut (d). The two other factors include the process conditions that are believed to have a significant influence on dimensional deviation (D_d) and surface roughness (R_a). These represent cutting fluid flow and tool wear. The effects of the five factors on seven other measured variables will also be analyzed. These variables include the three components of the cutting forces (F_x, F_y, and F_z), the three components of the machine tool system vibrations (V_x, V_y and Vz) and acoustic emissions (AE).

A. Experimental Design

In any experiment, the results depend to a large degree on the way by which the data was collected. In a lot of cases, full factorial experiments are conducted. This design cannot be implemented when there are too many factors are under consideration because the number of repetitions required would be prohibitive in time and cost. Typical fractional factorial designs cannot produce credible results in a case where interactions among the factors exist. By contrast, the use of a testing strategy such as the orthogonal arrays (OAs) developed by Taguchi led to an efficient and robust fractional factorial design of experiments that can collect all the statistically significant data with the minimum possible number of repetitions. Accordingly, the OAs will be used in this paper for the design of experiment and the fusion procedure.

TABLE I. FACTORS LEVELS CHOSEN FOR THE EXPERIMENTS

	Training sets	Validation sets
Depth of cut (mm)	0.25 to 1.5	0.5 to 1.125
Feed (mm/rev)	0.05 to 0.2	0.075 to 0.15
Speed (mm/min)	150 to 350	200 to 300
Cutting tool wear	Small - Average	Small - Average
Cutting fluid	Yes - No	Yes - No

TABLE II. THE 24 REPETITIONS OF THE EXPERIMENTS "#1 TO #16 FOR TRAINING AND #17 TO 24 FOR VALIDATION"

Test #	Dimensional deviation: D_d (μm) 1st	2nd	3rd	Average	Surface roughness: R_a (μm) 1st	2nd	3rd	Average
1	5.0	6.0	4.0	5.0	1.67	1.64	1.70	1.67
2	7.0	9.0	5.0	7.0	2.81	2.43	2.52	2.51
3	18.0	18.0	15.0	17.0	3.97	3.57	3.54	3.60
4	15.0	16.0	14.0	15.0	2.54	2.83	2.87	2.81
5	7.0	7.0	4.0	6.0	2.25	2.21	2.27	2.24
6	12.0	13.0	12.0	12.0	3.30	3.14	3.02	3.10
7	8.0	9.0	7.0	8.0	3.51	3.11	3.17	3.18
8	6.0	7.0	5.0	6.0	3.01	2.84	2.85	2.86
9	18.0	18.0	15.0	17.0	3.40	3.11	3.04	3.11
10	13.0	15.0	14.0	14.0	2.71	2.93	3.02	2.95
11	19.0	19.0	16.0	18.0	3.57	3.35	3.45	3.42
12	14.0	15.0	13.0	14.0	3.22	2.93	2.99	2.99
13	8.0	10.0	9.0	9.0	2.66	2.20	2.29	2.29
14	14.0	15.0	12.0	14.0	4.01	3.25	3.30	3.35
15	21.0	22.0	21.0	21.0	4.22	4.36	4.30	4.32
16	13.0	14.0	14.0	14.0	3.08	3.08	3.17	3.12
17	5.0	6.0	3.0	5.0	2.75	2.92	2.53	2.73
18	7.0	8.0	6.0	7.0	3.51	3.54	2.89	3.25
19	16.0	18.0	17.0	17.0	3.76	3.60	3.50	3.57
20	14.0	16.0	14.0	15.0	4.21	4.20	3.83	4.04
21	5.0	6.0	7.0	6.0	3.03	2.80	2.88	2.86
22	13.0	14.0	10.0	12.0	2.87	3.03	2.89	2.95
23	9.0	9.0	6.0	8.0	2.54	2.76	2.61	2.67
24	5.0	7.0	6.0	6.0	3.16	3.05	2.55	2.84

The experiments were carried out on a vertical CNC machine using a high-speed steel cutter. The workpiece material used was an aluminum 6061-T6 type. The dimensional deviation D_d is simply the difference between the reference and finished part dimensions. These dimensions are measured using an accurate micrometer. On the other hand, the surface roughness R_a was measured using a portable Mitutoyo Surftest profilometer. In order to measure cutting forces, the workpiece was mounted on a Kistler three component piezoelectric dynamometer, bolted rigidly onto the machine table. A three components accelerometer and an acoustic emission transducer mounted close to the cutting zone measured, respectively, the accelerations due to the machine-workpiece-tool system vibrations and the acoustic emissions generated by the machining operation.

Single pass, linear cuts were executed according to the factor levels of each repetition. The factor levels chosen are given in Table I. The fact that finishing and semi-finishing conditions are examined limits the depth of cut to below 1.5 mm. Feed and cutting speed levels were chosen in the range recommended by the manufacturer. The choice for small or average cutting tool wear was made based on the fact that in the finishing processes the cutter would be changed before there was a chance for increased wear to arise. Average wear was defined as corresponding to 10 min of cutting time. Use of cutting fluid was considered as a binary variable. Consequently, there are a total of five factors in the experiment, three of which have three levels and two have two levels each. The OA that best fits this experiment is the Ll6. In order to evaluate the capacity of the fusion model, another set of 8 tests was designed as illustrated in Table II. The total of 24 tests is repeated five times. To determine D_d and R_a three measurements were taken on a specific area of the workpiece and the average values were calculated. All sensor signals were acquired then conditioned so that only the steady-state portions were retained. For each repetition, the minimum, maximum and mean values of the cutting forces, the vibrations, and the acoustic emissions in the steady state portions were calculated. The maximum values were considered as most representatives. The results of the experimental tests are reported in Table II.

B. *Experimental Data Analysis*

The experimental data was analyzed using three statistical tools: the % contribution from ANOVA, the average effect of each factor level, and the correlation between sensor measurements and the characteristics D_d and R_a. The % contribution of a factor reflects the portion of the variation observed in the experiment attributed to this factor. Ideally, the total % contribution of all considered factors must add up to 100. The difference from 100 represents the contribution of some other uncontrolled factors and experimental errors. Another interesting way to analyze the effect of a given factor on sensor responses is the graph of average effects. As the experiments were designed using an OA, the estimates of the average effects will not be biased.

Graph of average effects in Fig. 1 shows that D_d and R_a are affected at different degrees by all process conditions and cutting parameters. In this graph, the horizontal axe indicates the factor levels. The plotted points correspond to the averages of the observations realized under each factor level. The factors predominantly affecting D_d and R_a are feed rate, depth of cut and wear. The effects of cutting speed and fluid are negligible. These results are expected since the cutting forces, which are recognized as having a large effect on part quality, are more sensitive to changes in feed and depth of cut than to variations of the cutting speed. Wear appeared as the most important uncontrolled factor.

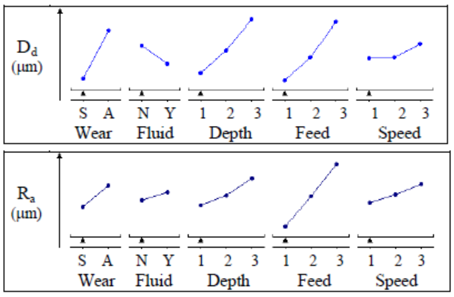

Figure 1. Effect of cutting parameters and process conditions on D_d and R_a

Similar conclusions can be clearly established from the percentage contributions reported in Table III. As expected, the cutting forces are affected by feed and depth of cut. Apparently, tool wear has a relative effect on AE, while vibrations are much affected by the cutting speed. However, these results show that the error contribution associated with these sensors is very high, indicating that other factors could perturb the generated AE and vibrations. Accordingly, these variables cannot be used reliably to monitor D_d and R_a. Cutting forces present similar responses. However, as can be seen, F_x is more affected by tool wear than F_y and F_z. On the other hand, D_d and R_a show strong correlations with depth of cut, cutting feed and cutting forces. Accordingly, one can presume that D_d and R_a can be controlled only by these factors. Finally, Table III shows that the error contributions are acceptable (less than 10%). This implies that the most important cutting conditions that influence D_d and R_a were included in the experiments. Based on these results, it still remains difficult to select the appropriate modeling variables. A systematic and rigorous approach for best variable combination selection is required.

TABLE III. % CONTRIBUTIONS OF EXPERIMENTAL VARIABLES

	Wear	Fluid	Depth	Feed	Speed	Error
F_x	9.28	-	42.64	46.5	0.99	*0.59*
F_y	5.35	-	45.72	46.63	0.78	*1.52*
F_z	4.19	-	39.93	50.34	0.04	*5.5*
V_x	-	-	4.55	24.83	45.6	25.02
V_y	-	-	-	11.74	67.44	20.82
V_z	-	-	0.22	13.57	58.77	27.44
AE	6.49	-	5.13	14.44	65	8.94
D_d	35.44	3.61	*26.91*	*23.66*	2.82	*7.56*
R_a	13.8	2.26	*17.2*	*59.58*	5.59	*1.57*

III. BUILDING OF THE PREDICTION MODEL

A. *Proposed Modeling Strategy*

Machining is a complicated dynamic process with various nonlinearities and stochastic disturbances. The difficulty to build an effective prediction model lies in the selection of the modeling conditions and the number and the type of the variables to include in the model. These choices represent the basic ingredients of any sensor fusion strategy. Selecting the model form and modeling technique is not sufficient to produce the best model. Under these conditions, because the deterministic models are typically valid only for a limited range of cutting conditions, ANNs present the best modeling alternative. While various neural techniques can be used in this approach, multilayer feedforward network seems to be one of the most appropriate because of its simplicity and flexibility. On the other hand, in order to extract a cost effective and rapid best combination of variables to be included in the quality model, Taguchi's OAs is used again. The variables selection is based on the analysis of the effect of each variable combination on the model's performance as well as the variable contribution to decrease modeling and validation errors.

Many criteria can be used to assess whether a reduced model adequately represents the relationship between the machined part quality and the cutting parameters under various process conditions. Measuring the performance of fitted models is based on the principle of reducing several statistical criteria. These include the residual sum of squared error (SSE), the residual mean square error (MSE), the total squared error (Mallow's C_p), and the coefficient of determination (R^2). For the majority of modeling techniques, the model is determined by minimizing the residual sum of squares (SSE). All the criteria, MSE, C_p, and R^2 are a linear function of SSE. The combination of variables minimizing the SSE creates 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 shows a gradual increasing trend when the number of variables in the model is increased. Thus, the use of R^2 as a criterion for the selection can allow some subjectivity. If p variables among q variables are selected, the residual mean square is $MSE_p=SSE_p/n-p-1$. Where n is the total number of observations. The terms SSEp and n-p both reduce with an increase in the number of independent variables p. Therefore, MSE_p has the ability of showing an extreme value. In this study, the used judgment function consists in minimizing the training residual mean square error (MSE_t), and the validation residual mean square error (MSE_v).

B. *Application of the Proposed Strategy*

To illustrate the proposed fusion strategy, ten variables were considered. Before selecting the variables and modeling, it was important to establish the ANN parameters in order to optimize the training performances. The idea is to approximate the relationship between the size of the hidden layer, the number of input variables and the complexity of the parameters to be estimated. For all trained models, an average error of less than 1% was used, irrespective of the hidden layer size. Consequently, to avoid long training and overfitting that could disturb its accuracy, the [NP*2NP+1*2] network structure was selected (NP: number of inputs). For variable selection, the procedure begins by selecting the OA for models design. The OA that best fits this modeling procedure is the L12. The performances of the designed models are presented in Table IV. The (+) and (-) signs respectively indicate, whether the variables are used as input to the model or not. The models accuracy is presented as a function of the seven selection criteria.

Table IV shows that all models fitted the data relatively well as indicated by the MSE values. Using these results, the average effect of each variable on the model's performance was calculated. The average effect of each input variable on the criteria represented by its percentage contribution in improving the model's accuracy is presented in Table V. The average effect graphs demonstrate that the variables that have positive effects on the designed models are cutting parameters and cutting forces. The presence of the speed, the vibrations an acoustic emission in the model increase the MSE values. These results reveal that the variables that can significantly reduce the MSE values are d, f and F_z. Accordingly the model including the selected variables was built. As shown in Table IV, the results demonstrate that this quasi-optimal model (QO) performs better than all former ones.

TABLE IV. MODELS EVALUATION USING MSET AND MSEV

Predictor variables											Criteria						
#	d	f	s	F_x	F_y	F_z	V_x	V_y	V_z	AE	D_d-MSE_t	D_d-MSE_v	D_d-MSE_{tot}	R_a-MSE_t	R_a-MSE_v	R_a-MSE_{tot}	MSE_{tot}
1	+	+	+	+	+	+	+	+	+	+	3.24	1.42	4.66	1.16	0.85	2.01	6.67
2	+	+	+	+	+	-	-	-	-	-	3.35	1.61	4.96	1.27	0.89	2.16	7.12
3	+	+	-	-	-	+	+	+	-	-	3.45	1.56	5.01	1.25	0.90	2.15	7.16
4	+	-	+	-	-	+	-	-	+	+	3.72	1.64	5.36	1.35	0.97	2.32	7.68
5	+	-	-	+	-	-	+	-	+	-	3.85	1.64	5.49	1.43	0.99	2.42	7.91
6	+	-	-	-	+	-	-	+	-	+	3.86	1.80	5.66	1.44	1.08	2.52	8.18
7	-	+	-	-	+	+	-	-	+	-	3.67	1.73	5.40	1.29	0.89	2.18	7.58
8	-	+	-	+	-	-	-	+	+	+	3.98	1.68	5.66	1.39	1.01	2.40	8.06
9	-	+	+	-	-	-	+	-	-	+	3.90	1.74	5.64	1.40	0.99	2.39	8.03
10	-	-	-	+	+	+	+	-	-	+	3.94	1.66	5.60	1.40	0.96	2.36	7.96
11	-	-	+	-	+	-	+	+	+	-	4.27	1.82	6.09	1.47	1.11	2.58	8.67
12	-	-	+	+	-	+	-	+	-	-	4.04	1.66	5.70	1.40	1.00	2.40	8.10
QO	+	+	-	-	-	+	-	-	-	-	3.17	1.43	4.60	1.13	0.83	1.96	6.56

TABLE V. % CONTRIBUTIONS OF MODELING VARIABLES

	d	f	s	F_x	F_y	F_z	V_x	V_y	V_z	AE	Error
D_d_MSE_t	*45.65*	*36.1*	1.41	1.73	2.69	*11.23*	-	0.34	0.21	-	0.64
D_d_MSE_v	*31.41*	*26.73*	2.25	8.98	5.70	*18.8*	2.61	1.28	0.56	0.46	1.22
R_a_MSE_t	*14.00*	*55.48*	0.80	2.84	2.59	*23.23*	-	-	-	-	1.06
R_a_MSE_v	*30.18*	*39.97*	-	0.16	4.59	*19.00*	-	-	2.05	1.51	2.54
MSE_{tot}	*31.67*	*39.36*	0.79	4.29	1.96	*19.59*	0.11	0.76	-	-	1.47

IV. CONCLUSION

The current study presents an effective approach for in-process part dimensional accuracy and surface roughness prediction in turning operations using a neural network based sensor fusion strategy. Several sensors were analyzed, and their correlation with dimensional deviation and surface roughness during a turning operation was investigated under different practical process conditions. The proposed fusion strategy successfully selected the variables providing the best information about the machining operation. Using this information, the quasi-optimal model was established. The results demonstrate that the proposed approach can accurately predict on-line dimensional deviation and surface roughness with an average error less than 10 % under various machining conditions.

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Abderrazak El Ouafi is a professor in the Department of Mathematics, Computer Science and Engineering at the University of Quebec at Rimouski. His research interests are mainly oriented in precision engineering, manufacturing system design and control, performance enhancement of manufacturing processes and intelligent control related to sensor fusion, neural networks and fuzzy control.

Noureddine Barka is an assistant professor in the Department of Mathematics, Computer Science and Engineering at the University of Quebec at Rimouski. His research field includes manufacturing materials, CAD/CAM, manufacturing processes improvement, experimental design and quality control for industrial applications.