A Multisensor Approach for Error Compensation in CNC Machine Tools

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***Abstract*—This paper presents a comprehensive ANN based multisensor fusion approach designed to support the implementation of an adaptive error compensation of geometric, thermal and dynamic errors for enhancing the accuracy of CNC machine tools. Accurate and efficient model to perform on-line error prediction is an essential part of the compensation process. The proposed approach consists of the following major steps: (i) design of an integrated spatial-variant model describing the machine topology, (ii) measurement of path-dependent rigid-body errors according to the model, (iii) design of time-variant models for error components through sensors fusion, (iv) continuous monitoring of the machine conditions using position, force, speed and temperature sensors for one-line error components prediction and integration to produce a correction vector, (v) total positioning error synthesis and software compensation. Implemented on a turning center, the proposed approach led to a consistent model able to accurately and reliably provide an appropriate error identification and compensation under variable machine tool conditions.**

***Index Terms*—machining, machine tools, machine tool accuracy, error compensation, sensor fusion, neural network**

I. Introduction

The quest for higher precision has stimulated the development of highly accurate CNC machine tools (MT). Unfortunately, the machining task is usually performed in the presence of disturbances, which can induce systematic and random errors that tend to adversely affect the MT accuracy. Indeed, the MT accuracy is affected by various errors related to geometric imperfections, thermal deformations, load effects and dynamic disturbances. These errors are generally classified according to their source and behaviour in the time domain [1]. In typical MT, quasistatic errors are responsible for a very large proportion of the observed machine inaccuracy. Considered as slowly varying in time, quasi-static errors associated to the MT structure are due to imperfect geometry, defective kinematics of moving components, static deflections and thermal distortions [1], [2]. On the other hand, dynamic errors are related to tool wear, tool chatter, spindle run-out, machine self-induced and forced vibrations, and other disturbances associated to the machining process. Considering all these error sources, helps to easily outline the diversity and variability of their effects and assess the difficulties involved in improving the MT accuracy.

The traditional procedure for providing relatively error-free MT involves improving the design and manufacturing of the machine structural components. However, additional design refinements lead, in general, to excessive costs. An alternative approach using software technologies to compensate for dimensional errors has proven to be economical and more effective in upgrading the machine accuracy [3], [4]. Various efforts related to MT metrology focusing on error measurement, analysis, modeling, prediction and compensation have been proposed over the last three decades [1]-[5]. Early research has concentrated on applying methods based on analytic, trigonometric, vectorial, matrix representation and empirical models to describe the final observed volumetric error in MT workspace [6-9]. More recent attempts propose artificial intelligence based approaches for errors compensation [10], [11].

To perform active error compensation, individual error components have to be evaluated on-line. Since there is no reliable method for direct error measurements, only on-line error prediction using indirect methods offers potential for the compensation of both quasistatic and dynamic effects. The approach proposed in this paper is designed to support the implementation of an adaptive error compensation for MT accuracy improvement by compensating for geometric, thermal, load-induced, and inertial errors. The proposed compensation scheme is based on continuous monitoring of the MT conditions using position, forces, speed and temperature sensors for error components prediction and integration. Built on a Mori Seiki SL25SE turning center, the essential feature of compensation scheme consists of one-line individual error components prediction through an improved ANN based multi-sensor fusion strategy and errors integration through time and spatial variant error models for total positioning error synthesis and compensation.

II. The Proposed Identification and Compensation Approch

The accuracy of machine tools is adversely affected by various error sources such as geometric imperfections, thermal deformations, load effects, and dynamic disturbances. Implementing active error compensation as

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a way to achieve MT accuracy improvements needs to ensure on-line evaluation of various error components. The ideal solution consists of measuring on-line the deviations of the cutting tool tip from its ideal trajectory resulting from various error components. This solution is however compromised by the lack of reliable sensors for direct measurements. The alternative approach presented here consist to measure off-line a set of error components, combine these errors to the MT parameters and operating conditions through an improved sensors fusion strategy to build error components prediction models, and synthesize the total positioning error through a global model.

A. Error Integration Models

In a typical MT, error is the difference between the actual and the anticipated response of the machine to a command issued according to accepted protocol. This error results in a deviation of the cutting tool tip from the desired trajectory. Assuming that the structural components of the MT are rigid bodies, the resultant error at the tool tip can be described by a combination of individual displacement and rotational path-dependant errors. The first step of a compensation scheme consists, as stated above, to establish a model in order to estimate the total positioning error and hence derive the correction vector. For this purpose, a general model has been developed from four sub-models: the basic geometric model, the coordinate system thermal drift model, the spindle error model, and the dynamic model.

Basic geometric model: The total positioning error is defined with respect to a key reference point representing the origin of the MT coordinate system. Displacement of the cutting edge from the MT origin position [X_0, Z_0] to any position [X, Z] introduces an error vector [Δx, Δz]. These position-dependent errors resulting from the displacement of the MT components are obtained through a combination geometric errors induced along a MT axis that are described with six degrees of freedom consisting of three translational and three rotational errors.

Coordinate system thermal drift model: The second part of the general model intends to take into account the problem of the coordinate system drift due to the thermal disturbances. Assuming linear effects, the error vector is defined as the thermal drift. Obtained at various machine thermal conditions, the thermal drift vector is added to the error vector derived from the geometric model.

Spindle error model: The third model is used to evaluate the spindle thermal drift errors. In a turning center, three components associated to the spindle thermal drift are critical to the machine accuracy. The axial thermal drift responsible for a displacement along the *Z*-axis, the radial thermal drift acting in a direction perpendicular to the *Z*-axis, and the tilt thermal drift representing the angular deviation of the spindle axis in the *xz*-plane.

Dynamic error model: The fourth model is used to evaluate the dynamic effects on the MT accuracy. The dynamic effects include here two categories of error sources: the cutting force effects and the inertial effects.

As already mentioned, the components required sub-models building and consequently the general global model are determined at various MT thermal states. The error components are obtained in terms of the MT measured parameters and operating conditions. As can be noticed, the absence of time as a variable is created by the need to simplify the modeling procedure. The use of time as a variable is susceptible of unnecessarily complicating the modeling procedure. The algorithm relative to the implementation of this model is schematically illustrated in Fig. 1. Process sensing devices monitoring the nominal positions of the machine slides, temperature at various positions on the machine structure, cutting forces, spindle speed, and feed-rate generate signals that are scanned at a constant sampling rate. At every sample, each individual error is predicted using the appropriate model.

B. Sensor Fusion Strategy

The on-line error compensation needs the prediction of various error components using multiple variable models at any location within the MT working space. These models are developed to include all factors contributing to the deviation of the cutting tool from the desired trajectory. Since error sources exhibit highly non-linear interactions with the MT operating conditions, a precise quantitative prediction of errors is difficult to achieve using theoretical analysis. Indeed, on-line errors estimation through multiple-input/output empirical models can allow faster processing and enhanced prediction accuracy. However, implementing this idea comes up with two major difficulties: The choice of the modeling technique and the selection of the most consistent variables to include in the model.

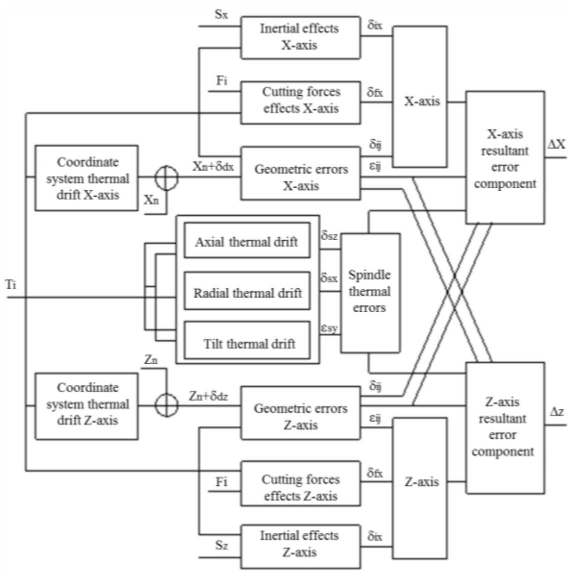

Figure 1. Schematic illustration of the models integration

Model building analysis is often conducted using a large set of variables. From these candidate predictor variables, only a subset is indeed useful for predicting the optimal response. The identification of important input variables is crucial to the success of any empirical model. In this study, a comprehensive and systematic procedure designed for model building is presented.

Modeling analysis: As suggested in many reports, ANN techniques have demonstrated real potential to express the geometric path-dependent errors as a function of the cutting tool nominal position, temperature, cutting forces, speed and feed-rate. As compared to other modeling techniques, ANN provides a more effective modeling capability, particularly when the relationships between geometric, thermal and dynamic error components and total positioning errors are non-linear. ANN can automatically handle strong non-linearities, large number of variables and missing information. Because of their intrinsic learning capabilities, ANN can be used when there is no exact and explicit knowledge about the relationships between various variables. These very useful capabilities are helpful to reduce the measurement and the off-line calibration efforts. The important advantage of the ANN model over the other empirical models is that multiple error components can be easily established at the same time using only one model. The multi-input/output capability of the ANN not only appreciably simplifies the tedious task of modeling but also improves model accuracy by including the most significant interaction effects between the variables.

Variable selection analysis: The selection of an appropriate modeling paradigm is not sufficient alone to ensure the best model. Model building analysis is often conducted with a large set of potential variables. From these variables, only a specific subset is useful. The identification of adequate combination of variables to include in the model remains an essential step and a prerequisite for the success of the modeling task.

Three existing methods can be used to select the appropriate combinations of variables. These methods are: engineering judgment, correlation analysis and step-wise regression. However, none of these methods can identify the optimal models systematically. Based on individual knowledge and experience about MT and machining, the engineering judgment method is useful to suggest preliminary variables for further investigation. But, the use of a limited number of variables without exact knowledge of actual machine behaviors is generally risky and cannot lead systematically to the best combination of variables. The correlation analysis method selects the highly correlated predictor variables to include in the model, using the correlation coefficients as criteria. In this method, the partial correlations between the selected variables have to be explored otherwise the method is only suitable to find the model with a single variable. Since the partial correlations between response and variables are investigated, the step-wise regression method [12] is able to identify models with multiple variables. This method first includes the most strongly correlated variables and then adds or subtracts one variable at a time according to the values of an F-distribution that estimates the contributions of the added or removed variables. However, the effect of combining two or more variables at a time is never considered. As the predictor variables are characteristically interrelated, this method could result in models with inconsistent variables selection. In addition to the above three methods, there are two other variable selection methods, forward selection and backward elimination [12]. These methods have similar disadvantages as the step-wise regression. Although traditional selection methods always offer the possibility to isolate 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 selection criteria. Hence, these methods can lead to poor results and often to different subsets since interactions between variables cannot be considered. Thus, the basic condition to successfully implement an optimal selection of variables requires a simultaneous application of multiple selection criteria.

Modeling and variable selection procedure: The selection of the optimal combination of variables is based on comparing a complete model containing all variables and a model with a reduced number of variables. This process can be achieved by: (i) building a sufficient number of models, where each model is designed with a subset of specifically selected variables, (ii) evaluating the modeling and prediction performance of these models according to multiple criteria, and finally, (iii) estimating the effect of each variable on the models performance using appropriate statistical tools.

Many statistical criteria can be used to assess whether a reduced model adequately represents the relationship between the thermal errors and the temperature variables. The evaluation of the performance of fitted models is based on the principle of minimizing 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 most 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 *SSE* leads to *MSE* and C_p as the minimum, and R^2 as the maximum. Among these criteria, R^2 does not have an extreme value and tends to increase with the number of variables in the model. Consequently, this criterion can lead to subjective interpretations. If p among q independent variables are selected to form a model, the residual mean square error is $MSE_p = SSE_p$ / n-p-1, where n is the total number of observations. The terms SSE_p and n-p decrease with an increase in the number p of variables. Therefore, MSE_p has the ability to show an extreme value. In this study, the judgment function consists in minimizing the training (MSE_t), the validation (MSE_v) and the total (MSE_{tot}).

In order to extract rapidly a cost-effective and optimized combination of variables to be included in the prediction models, an efficient experimental design method is used. Using Taguchi's orthogonal arrays, a quasi-optimal model can be designed by selecting the most sensitive group of variables that show high correlation with geometric deviations. Orthogonal arrays (OA) can significantly reduce the number of combinations to be tested where many parameters and potential combinations are involved [12]. The selection of the best model is based on the analysis of the effects of each combination of variables on the model accuracy as well as on the estimation of the contribution of each variable to the reduction of modeling and prediction errors. The predictor variables that show high sensitivity on geometric deviations are potential candidates for use in the model. The OA-based model building procedure can be summarized in the following steps:

- Collect data for models training and validation. All variable that may influence the machine accuracy must be identified and considered in the measurement tests;
- Select a modeling method and performance criteria;
- Select an appropriate OA to design the models
- Train and test the generated models and evaluate their performances according to the selected criteria;
- Determine the effect of each variable on every performance index. These effects can be considered as rates of reduction in the MSE values when a variable is input to the fitted model or not. Using these results, variables that contribute significantly to the models improvement are selected otherwise they are rejected;
- Determine the fusion models configuration. Once the variables providing the best information on the error sources are identified, the best model can be built.

III. Models Building and Simulation

To build the ANN compensation models, the error components were classified into five groups having similar characteristics and requiring the same measurement procedures and instrumentation. These groups are the coordinate system thermal drift errors, the geometric errors, the cutting force induced errors, the inertial errors and the spindle thermal drift errors.

A. *Error Components Measurement*

Typical, regular three-axis MT have only three prismatic joints and a total of 21 independent systematic geometric error components, i.e., 18 errors (six each axis) in addition to three squareness errors. The geometric error components along a moving axis are described with six degrees of freedom error components consisting of three translational (δ_{ij} - linear error and straightness errors) and three rotational or angular (ε_{ij} - pitch, yaw and roll) errors. To compensate for these errors, they need to be evaluated. The traditional method uses commercially available machine tools calibration systems. Among these systems, laser interferometer is widely used. Geometric errors measurement was conducted using a 5528*A*-laser interferometer system. The displacement intervals for recording the error values are 10 mm along the *X*-axis and 20 mm along the *Z*-axis. The measurements results revealed the following remarks: (i) the coordinate system thermal drift error observed over a 12 hrs machine warm-up introduced an error of about 20 μm resulting from the machine frame thermal expansion, (ii) at an average temperature of 20.83 ℃, linear displacement error reaches 15 μm and 70 μm along *x*-axis and z-axis respectively, exceeding the specified MT accuracy (± 20 μm), (iii) evaluated at 21.17 ℃, the maximum straightness error reaches 10 μm along the *X*-axis and 12 μm along the *Z*-axis, (iv) the yaw errors measured along the *X* and *Z* axis reaches 5 and 3 arcsec respectively.

B. *Error Components Modeling*

To provide on-line compensation, the error components are predicted using time-variant models through an improved sensors fusion strategy. These models are based on data derived from an array of sensors that monitor continuously the MT parameters related to the cutting tool nominal position, temperature at various locations, forces, vibrations, speed, and feed-rate. To illustrate the procedure designed to build the ANN based sensors fusion error models, the three spindle thermal drift errors were considered. Spindle thermal errors (STE) can be observed as a displacement through space of the nominal axis of the spindle caused by thermally induced deformations of the spindle components. For CNC turning center, spindle drift errors include three errors: radial thermal drift (δ_{sx}), axial thermal drift (δ_{sz}), and tilt thermal drift (ε_{sy}). As shown in Fig. 2, these error components are often measured by using capacitance probes mounted on the turret of the turning center. As a result, radial drift is provided by the average of probe #1 and probe #2 signals, axial drift is measured by probe #3, and tilt drift is calculated by the difference in the signals of probes #1 and #2.

In any thermal error compensation scheme, sensor location is crucial. Whenever possible, the sensors have to be located directly on the structural elements undergoing thermal distortion. A total of sixteen thermistors were carefully installed throughout out the machine structure in order to monitor the temperature field in the main thermal part on the machine. Results from initial investigations indicated that some machine elements have only very minor temperature variations and some other elements are not correlated to the spindle thermal drift errors. These investigations suggested also that there was a strong relationship between thermal errors and the average temperature increase along the spindle, as well as the spindle speed. Hence, only 8 of the 16 temperature sensors were selected as the practical temperature variables for this study. The actual locations of the 8 temperature sensors are listed in Table I.

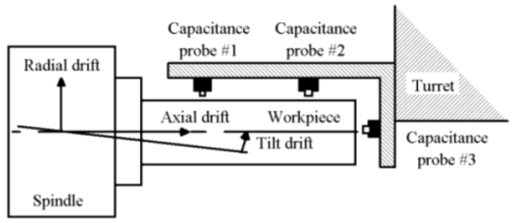

Figure 2. Schematic representation of the used system for STE measurement using capacitance probes

In order to provide a modeling database and execute the modeling procedure, measurements of MT temperature variations and STE are required. STE are assumed to be strongly correlated to the temperature rises from a reference temperature. Since the environment temperature is the most stable variable on the machine, T_1 used in the modeling are the differences from this reference. In addition, the variables with small variations are removed, because they generally have no significant effect and could possibly induce noise-based predictions.

TABLE I. TEMPERATURE SENSOR LOCATIONS

Sensor #	Sensor location	Sensor #	Sensor location
S_1	Environments	S_5	Z-slide drive mechanism
S_2	Side of the spindle nose	S_6	Side of the spindle end
S_3	Bottom of the spindle nose	S_7	Bottom of the spindle end
S_4	X-slide drive mechanism	S_8	Tool holder

Thermal behaviour of any MT can be very complex, because different machine operations can warm up different portions of machine structure. Non-symmetric temperature distributions happen frequently. Thus, a variety of operating conditions are needed to create a wide range of machine thermal conditions. The proposed thermal error measurement system has been applied to the following operating condition cycles: (i) constant operating conditions where the MT runs for 4 hours at 1000 rpm maximum spindle rotation and stops for another 4 hours, (ii) progressive operating conditions where the MT runs for 8 hours at a progressively increased / decreased spindle rotation (0, 1500, 3000, and 4500 rpm at 10-minute intervals) and (iii) random conditions cycle where the MT runs for 8 hours at a randomly assigned spindle speed. The STE and the temperature history were continuously monitored under these selected running conditions. The STE and temperature variations histories measured under constant and progressive running conditions are shown in Fig. 3 and 4. Measures acquired under random operating conditions present similar characteristics. As presented in Fig. 3, the temperature variations increase around the spindle with an average of 11.5 ℃. The temperature gradients in the other locations were relatively less important (4 to 7 ℃). In all cases, the temperature rise reached a peak after nearly four hours and became relatively constant. Fig. 4 shows the resultant STE variations. The maximum axial thermal drift reached about 19 μm. The radial thermal drift and the tilt thermal drift were less large reaching 7 μm and 3.25 arcsec. These Fig. s reveal that the STE and the temperature variation during the three operation cycles are correlated to the spindle speeds. From these results, a robust relationship can be observed between temperature variations and STE indicating that an accurate model can be reached by the proposed sensor fusion strategy.

While various ANN techniques can be used in this approach, generalized feed forward network seems to be one of the most appropriate because of its simplicity and flexibility. Before selecting the variables and training the models, it was important to establish the network topology and optimize the training performances. The idea is to approximate the relationship between the network parameters and the complexity of the variables to be estimated. For this evaluation, 4 ANN architectures were studied. The best results were achieved using the [n|2n+1|3] network, where n is the number of inputs. Consequently, this network structure was selected.

In order to test the validity of the modeling approach, three validation procedures (*VP*) are designed. In the first procedure (VP_1), all the samples are used as training and also as validation samples. In second procedure (VP_2), half of the samples are randomly picked as training samples, while the remaining samples are used for validation. In third procedure (VP_3), the samples obtained under specific conditions are used as training samples while the remaining samples are used for validation. In the majority of previous studies, modeling performances are evaluated using only procedures similar to VP_1.

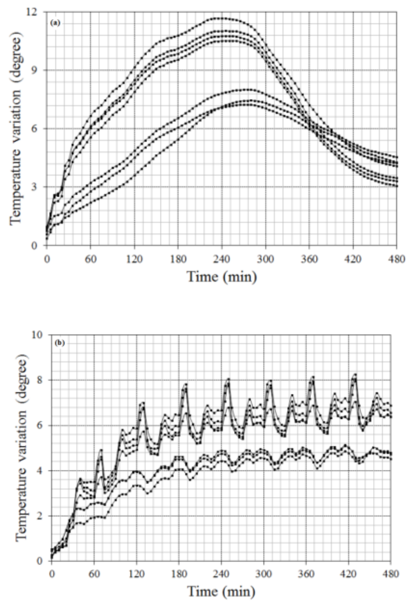

Figure 3. Typical temperature variations during the operating cycles: (a) Constant conditions cycle and (b) Progressive conditions cycle

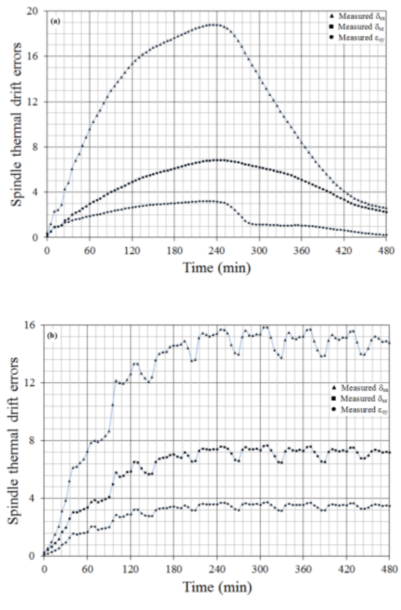

Figure 4. Typical STE variations during the operating cycles: (a) Constant conditions cycle and (b) Progressive conditions cycle

Two statistical indices, derived from ANOVA, are used to analyze the performance of the models: the percent (%) contributions and the average effects of variables included in each model. The % contribution of a variable reflects the portion of the observed total variation attributed to this variable. Ideally, the total % contribution of all considered variables must add up to 100. The difference from 100 represents the contribution of some other uncontrolled modeling variables and experimental errors. The graph of average effects is an interesting way to visualize and estimate approximately the effects of each variable on the modeling 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. Our method for the selection of variables begins by choosing an OA that allows the design of models where all potential temperature variables are included. As illustrated in Table II, the OA that best fits this modeling procedure is a L8 with a total of 8 models to be built. The signs 1 and 0 indicate whether the variable is included in the model or not. Table II presents also the performances of each designed model for training and validation phases. Model deviation estimates are presented as a function of twenty-eight selection criteria. The design reveals that accurate relationships for error prediction can be achieved and shows that all models fitted the training and validation data relatively well as indicated by the MSE values.

Using these results, the average effects of each variable on the performance of the models was evaluated. Graphs of average effects in Fig. 5 show that the MSE values related to the three VP are affected at different degrees by the temperature variables. In these graphs, the horizontal axis indicates the variable levels. The plotted points correspond to the averages of observations realized for each variable level. These graphs reveal that *ΔT2*, *ΔT3*, *ΔT6* and *ΔT7* are the variables that predominantly affect the models performance by contributing to significant reduction of the MSE values. The variables *ΔT5* and *ΔT8* have much less pronounced effects. The variable *ΔT4* has a marginal effect and sometimes contributes in increasing MSE values. Similar conclusion can be clearly established from the % contributions. The average effects of each input variable on the twenty-eight MSE values, represented by its % contribution in improving models accuracy, are illustrated in Table III. The results show that the error contributions remain relatively low. This implies that no important variable was omitted in the procedure.

TABLE II. MODELS EVALUATION USING MSE VALUES

Models identification			M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8
Temperature variables		ΔT_2	1	1	1	1	0	0	0	0
		ΔT_3	1	1	0	0	1	1	0	0
		ΔT_4	1	1	0	0	0	0	1	1
		ΔT_5	1	0	1	0	1	0	1	0
		ΔT_6	1	0	1	0	0	1	0	1
		ΔT_7	1	0	0	1	1	0	0	1
		ΔT_8	1	0	0	1	0	1	1	0
VP_1	Training MSE values	δ_{sx}	0.1119	0.2274	0.2149	0.2399	0.2464	0.2417	0.2949	0.2519
		δ_{sz}	0.3141	0.7489	0.6994	0.6854	0.6263	0.6716	0.8363	0.7246
		ε_{sy}	0.0241	0.0499	0.0532	0.0582	0.0544	0.0566	0.0684	0.0619
		$VP_1\_MSE_t$	0.4501	1.0262	0.9675	0.9835	0.9270	0.9698	1.1996	1.0384
	Validation MSE values	δ_{sx}	0.1119	0.2274	0.2149	0.2399	0.2464	0.2417	0.2949	0.2519
		δ_{sz}	0.3141	0.7489	0.6994	0.6854	0.6263	0.6716	0.8363	0.7246
		ε_{sy}	0.0241	0.0499	0.0532	0.0582	0.0544	0.0566	0.0684	0.0619
		$VP_1\_MSE_v$	0.4501	1.0262	0.9675	0.9835	0.9270	0.9698	1.1996	1.0384
	$VP_1\_MSE_{tot}$		0.9002	2.0524	1.9350	1.9670	1.8541	1.9397	2.3992	2.0768
VP_2	Training MSE values	δ_{sx}	0.1947	0.3204	0.2654	0.2638	0.2556	0.2784	0.3357	0.2662
		δ_{sz}	0.5968	0.8192	0.8563	0.8176	0.7819	0.7694	0.9320	0.7775
		ε_{sy}	0.0447	0.0553	0.0601	0.0596	0.0540	0.0578	0.0731	0.0641
		$VP_2\_MSE_t$	0.8362	1.1949	1.1818	1.1410	1.0915	1.1056	1.3408	1.1078
	Validation MSE values	δ_{sx}	0.2575	0.3293	0.2200	0.2400	0.2324	0.2720	0.2500	0.2100
		δ_{sz}	0.6662	0.8779	0.9271	0.8779	0.8605	0.8481	0.9688	0.8548
		ε_{sy}	0.0538	0.0717	0.0727	0.0790	0.0662	0.0757	0.0945	0.0810
		$VP_2\_MSE_v$	0.9775	1.2789	1.2198	1.1969	1.1591	1.1958	1.3133	1.1458
	$VP_2\_MSE_{tot}$		1.8137	2.4738	2.4016	2.3379	2.2506	2.3014	2.6541	2.2536
VP_3	Training MSE values	δ_{sx}	0.008	0.0181	0.0175	0.0176	0.0169	0.0174	0.0213	0.019
		δ_{sz}	0.0545	0.1215	0.1037	0.1077	0.103	0.1119	0.1379	0.116
		ε_{sy}	0.0052	0.0116	0.0115	0.0116	0.011	0.0109	0.014	0.0119
		$VP_3\_MSE_t$	0.0677	0.1512	0.1327	0.1369	0.1309	0.1402	0.1732	0.1469
	Validation MSE values	δ_{sx}	2.0253	4.0975	3.7863	3.787	3.6762	3.8725	4.8	4.3223
		δ_{sz}	17.5589	24.97	23.6666	24.0767	23.8669	24.7961	27.7976	26.4111
		ε_{sy}	1.0526	1.323	1.5232	1.425	1.5982	1.5315	2.0669	1.8318
		$VP_3\_MSE_v$	20.6368	30.3905	28.9761	29.2887	29.1413	30.2001	34.6645	32.5652
	$VP_3\_MSE_{tot}$		20.7045	30.5417	29.1088	29.4256	29.2722	30.3403	34.8377	32.7121
$VP_{1\text{-}3}\_MSE_{tot}$			23.4184	35.0679	33.4454	33.7305	33.3769	34.5814	39.8910	37.0425

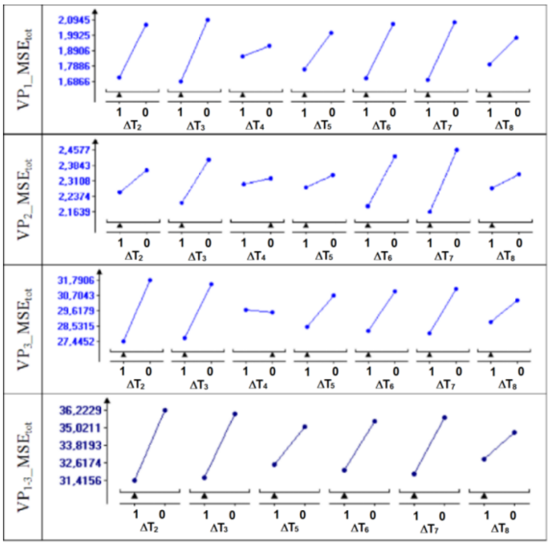

Figure 5. Average effects of each temperature variable in increasing / decreasing the MSE values

Assuming a limit of 10%, the % contribution coefficients from the three *VP* suggest that the variables ΔT_4, ΔT_5, and ΔT_8 have negligible effects and confirm that only the temperature variables ΔT_2, ΔT_3, ΔT_6, and ΔT_7 have significant effects on the designed models. These results make possible the identification of four quasi-optimal model (QOM) configurations QOM_VP_1, QOM_VP_2, QOM_VP_3 and QOM_$VP_{1\text{-}3}$ related to VP_1, VP_2, VP_3 and the total MSE ($VP_{1\text{-}3}$) respectively. Table IV presents the QOM achieved by setting each selected variable at a level that minimizes the MSE values. In this case, because VP_1, VP_3, $VP_{1\text{-}3}$ suggest ΔT_2, ΔT_3, ΔT_6, and ΔT_7 as optimal combination and VP_2 suggests ΔT_3, ΔT_6, and ΔT_7 as optimal combination, only two QOM models (QOM_1 and QOM_2) were built and tested.

The assessment of the quasi-optimal models using the three VP and the performance criteria demonstrates that the two QOM perform better than the 8 former ones. However, when comparing the models with each other, there is a clear superiority of QOM_1. Using VP_1, the two models provide a good agreement between real and estimated thermal errors with a correlation coefficient greater than 0.95. QOM_1 presents the best results with VP_1. This is due to the fact that QOM_VP_1 is based on 100% of the available information and the validation test was performed using training samples. In VP_2 and VP_3, the performances of the two models are similar with a small advantage for the model QOM_2 in the validation phase. Moreover, if we consider $VP_{1\text{-}3}\_MSE_{tot}$ as main criteria, the results show that the error contribution remains relatively low (under 5%). This implies that no important variable was omitted in the procedure. Hence, the global quasi-optimal model (GQOM) including ΔT_2, ΔT_3, ΔT_6, and ΔT_7 as inputs was built and tested.

In order to verify the prediction accuracy in conditions not included in the training and the validation sets, a new constant and random speed tests were conducted. The performances of the model demonstrate that the resultant model can predict thermal errors efficiently with accuracy better than ±5% for varying or new operating conditions. The results suggest that only the temperature variations around the spindle have decisive effects on the STE. This implies that the major heat source comes from the spindle rotation. Globally, the modeling procedure reveals that each error component depends strongly on the temperature distributed along its generative axis. The models for the other error components prediction are found in a similar manner. The results confirm that the thermal errors are more conditioned by the temperatures at local and specific positions than by the temperatures at randomly distributed locations in the MT workspace.

TABLE III. (%) CONTRIBUTION OF VARIABLES IN REDUCING MSE VALUES

% Contribution			ΔT_2	ΔT_3	ΔT_4	ΔT_5	ΔT_6	ΔT_7	ΔT_8
VP_1	Training	δ_{sx}	35.67	17.83	0.32	3.81	21.11	8.95	-
		δ_{sz}	12.45	25.46	-	9.19	17.59	27.34	6.14
		ε_{sy}	30.96	31.9	1.88	5.78	11.29	7.26	-
		$VP_1\_MSE_t$	18.40	24.69	-	7.87	18.56	21.57	4.15
	Validation	δ_{sx}	35.67	17.83	0.32	3.81	21.11	8.95	-
		δ_{sz}	12.45	25.46	-	9.19	17.59	27.34	6.14
		ε_{sy}	30.96	31.9	1.88	5.78	11.29	7.26	-
		$VP_1\_MSE_v$	18.40	24.69	-	7.87	18.56	21.57	4.15
	$VP_1\_MSE_{tot}$		18.39	24.69	-	7.87	18.56	21.57	4.15
VP_2	Training	δ_{sx}	6.98	5.36	1.63	4.40	27.23	45.80	-
		δ_{sz}	5.65	33.75	1.89	-	23.96	31.67	2.71
		ε_{sy}	22.77	54.06	0.79	0.56	6.15	15.13	-
		$VP_2\_MSE_t$	7.45	26.18	0	0.73	25.56	37.15	1.93
	Validation	δ_{sx}	7.74	36.69	7.74	9.75	9.93	21.21	-
		δ_{sz}	7.36	31.99	4.57	-	18.77	29.73	5.50
		ε_{sy}	20.07	45.28	-	4.54	9.52	14.69	0.97
		$VP_2\_MSE_v$	2.90	11.60	-	3.24	28.54	47.94	1.96
	$VP_2\_MSE_{tot}$		5.46	19.73	-	1.58	27.17	42.07	1.99
VP_3	Training	δ_{sx}	20.21	25.6	-	7.30	16.00	18.35	5.08
		δ_{sz}	20.39	17.03	-	10.33	21.72	27.09	3.16
		ε_{sy}	16.07	28.37	-	3.71	19.81	17.9	3.71
		$VP_3\_MSE_t$	20.49	19.24	-	9.66	21.22	25.65	3.72
	Validation	δ_{sx}	24.37	25.18	-	8.81	15.25	20.75	3.35
		δ_{sz}	31.34	22.85	-	10.69	13.52	17.13	4.32
		ε_{sy}	54.36	33.55	0.41	-	3.91	5.11	0.44
		$VP_3\_MSE_v$	32.03	24.53	-	8.71	13.21	17	4.2
	$VP_3\_MSE_{tot}$		31.94	24.5	-	8.72	13.26	17.07	4.2
$VP_{1\text{-}3}\_MSE_{tot}$			29.26	24.69	-	8.38	14.59	18.81	4.22

(Header "Predictor variables" spans ΔT_2–ΔT_8.)

TABLE IV. QUASI-OPTIMAL MODELS EVALUATION AND COMPARISON USING VARIOUS MSE VALUES

Quasi-optimal models identification		QOM_1			QOM_2	GQOM
		VP_1	VP_3	$VP_{1\text{-}3}$	VP_2	
Temperature variables	ΔT_2	1	1	1	0	1
	ΔT_3	1	1	1	1	1
	ΔT_4	0	0	0	0	0
	ΔT_5	0	0	0	0	0
	ΔT_6	1	1	1	1	1
	ΔT_7	1	1	1	1	1
	ΔT_8	0	0	0	0	0
VP_1	MSE_t	0.40090			0.41261	0.40090
	MSE_v	0.40158			0.53114	0.40158
	MSE_{tot}	0.80316			0.94375	0.80316
VP_2	MSE_t	0.35750			0.38326	0.35750
	MSE_v	0.54341			0.43526	0.54341
	MSE_{tot}	0.90092			0.81851	0.90092
VP_3	MSE_t	0.16666			0.21075	0.16666
	MSE_v	19.30706			19.29824	19.30706
	MSE_{tot}	19.47372			19.50899	19.47372
$VP_{1\text{-}3}\_MSE_{tot}$		21.17779			21.27126	21.17779

C. Models Integration

Once the various individual error models were established, the compensation values *Δx* and *Δz* are synthesized using the algorithm illustrated in Fig. 1. Simulation tests conducted using various MT conditions display the effectiveness of the proposed one-line identification and compensation approach. Fig. 6 and 7 present measured and predicted total positioning errors *Δx* and *Δz* in the *xz*-plane at an average temperature of 22.93 ℃. Before compensation, maximum errors are about 35 µm and 65 µm in *X* and *Z* directions respectively. As illustrated in Fig. 8, residual errors estimated after compensation are within a 4 µm range.

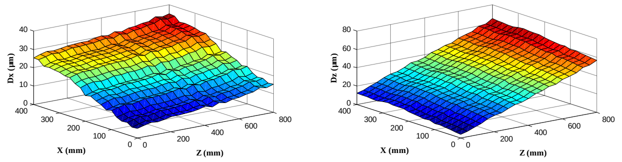

Figure 6. Measured *ΔX* and *ΔZ* error surfaces in the *xz*-plan

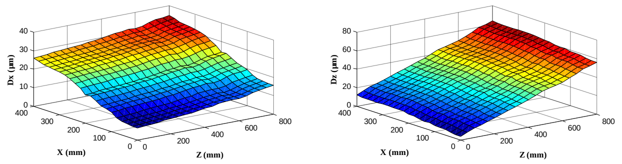

Figure 7. Predicted *ΔX* and *ΔZ* error surfaces in the *xz*-plan

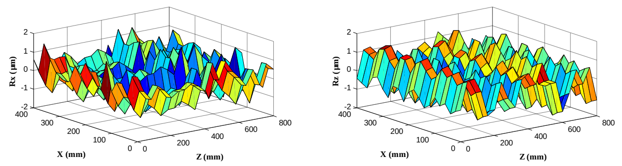

Figure 8. Residual error surfaces in the *xz*-plan after compensation

IV. Conclusion

Machine tools accuracy is affected by various errors related to geometric imperfections, thermal deformations, and dynamic disturbances. These errors can be compensated efficiently when using accurate and efficient error prediction models. This paper presents a comprehensive and systematic ANN based sensor fusion approach designed to support the implementation of adaptive software error compensation for enhancing the accuracy of CNC machine tools. The proposed approach is based on continuous monitoring of various sensors to relate geometric, thermal and dynamic errors to the machine tool operating conditions and build efficient one-line error prediction and integration models. The combination of ANN modelling capability to an improved variables selection procedure provides a powerful fusion strategy. A performance evaluation demonstrates that the proposed approach can lead to a consistent model able to provide accurately and reliably an appropriate error identification and compensation under variable machine tool conditions.

References

[1] R. Ramesh, M. A. Mannan, and A. N. Poo, "Error compensation in machine tools - A review," *International Journal of Machine Tools and Manufacture*, vol. 40, no. 9, pp. 1235-1284, 2000.

[2] H. Schwenke, W. Knapp, H. Haitjema, A. Weckenmann, R. Schmitt, and F. Delbressine, "Geometric error measurement and compensation of machines - An update," *CIRP Annals - Manufacturing Technology*, vol. 57, no. 2, pp. 660-675, 2008.

[3] X. Li, "Real-time prediction of workpiece errors for a cnc turning centre," *International Journal of Advanced Manufacturing Technology*, vol. 17, pp. 649-669, 2001.

[4] S. Mekid and T. Ogedengbe, "A review of machine tool accuracy enhancement through error compensation in serial and parallel kinematic machines," *International Journal of Precision Technology*, vol. 1, no. 3-4, pp. 251-286, 2010.

[5] A. C. Okafor and Y. M. Ertekin, "Vertical machining center accuracy characterization using laser interferometer," *Journal of Materials Processing Technology*, vol. 105/3, pp. 394-420, 2000.

[6] M. A. Donmez, D. S. Blomquist, R. J. Hoccken, C. R. Liu, and M. M. Barash, "A general methodology for machine tool accuracy enhancement by error compensation," *Precision Engineering*, vol. 8, no. 4, pp. 187-196, 1986.

[7] P. M. Ferreira and R. C. Liu, "A method for estimating and compensating quasi-static errors of machine tools," *Journal of Engineering for Industry*, vol. 115, no. 1, pp. 149-159, 1993.

[8] N. A. Barakat, A. D. Spence, and M. A. Elbestawi, "Adaptive compensation of quasi-static errors for an intrinsic machine," *International Journal of Machine Tools and Manufacture*, vol. 40, no. 15, pp. 2267-2291, 2000.

[9] J. W. Fan, J. L. Guan, W. C. Wang, Q. Luo, X. L. Zhang, and L.Y. Wang, "A universal modeling method for enhancement the volumetric accuracy of CNC machine tools," *Journal of Materials Processing Technology*, vol. 129, no. 1-3, pp. 624-628, 2002.

[10] C. D. Mizea and J. C. Ziegertb, "Neural network thermal error compensation of a machining center," *Precision Engineering*, vol. 24, pp. 338-346, 2000.

[11] J. M. Finesa and A. Agahb "Machine tool positioning error compensation using artificial neural networks," *Engineering Applications of Artificial Intelligence*, vol. 21, no. 7, pp. 1013-1026, 2008.

[12] G. E. P. Box, W. G. Hunter, and J. S. Hunter, *Statistics for Experimenters - An Introduction to Design, Data Analysis, and Model Building*, John Wiley & Sons, 1978.

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