Online adaptive learning system for reconfigurable machine tool

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Abstract: -Batch manufacturing is a widely used technique in today economy. The conceptual change of the way in which the manufacturing machines are controlled is the most important aspect in which is possible to conform with the market demands so their reconfigurability would not affect competitiveness. The problem to be solved in this paper consists in a control method development for predictive control based on prediction of the controlled variables deviation values in respect with their programmed values and also to predict the process parameters for which chatter will appear. . The basic idea is to use the data set obtained by monitoring the process during the manufacturing of the previous workpieces and during the current workpiece in order to predict the controlled variable value and to train a clasiffier algorithm. The method proposed consists in determining of the causal relation between one controlled variable and the monitored variables and then predicting its value in order to compensate the deviation from the program.

Key-Words: - online learning system, reconfigurable machining system, adaptive control, predictive control, error compensation, chatter, turning

1 Introduction

The characteristic aspects of the actual mechanical parts market are: *i)* the volume of orders has a lowering tendency; *ii)* the tendency of product customization implies accentuated diversity of shapes, dimensions and mechanical characteristics for the products solicited by the market; *iii)* the manufacturing machines flexibility and the reconfigurability tends to be the main characteristics which determine the manufacturers profitability; *iv)* the main direction in which is possible to progress in order to adjust the manufacturing machines to the market requirements is to change at conceptual level the manner in which they are controlled so the reconfigurability of the control system, according to the orders imposed by the market, to be done in technical and economical circumstances that do not affect the competitiveness.

This is why small batch manufacturing is widely used in today's economy. An appropriate solution for small batch manufacturing is to use of reconfigurable machines. But after reconfiguration stage, behavior of the reconfigurable machining system is generally unknown. The models for the manufacturing processes are also unknown. In order to compensate the machined workpiece errors for each machine configuration an error model must be constructed. Also in order to maximize the productivity the material removal rate must be maximized while maintaing the proces stability. In order to increase the productivity the cutting speed must be increased. But by increasing process intensity, forced vibration and increased cutting force mai appear. This phenomenon is called chatter. The result of chatter causes several adverse effects, including the lowering life span for tools, inexact dimensions, unsatisfactory surface quality, unacceptable noise and even tool damage. A model for the stability limit must be determined. In order to proper control the cutting process the machining parameters must be properly selected near the stability limit but in the stable domain. A lot of time must be spend in order to identify these unknown models because during system and process identification several experiments must be conducted. Moreover, the manufacturing system behavior is changing in time. This change implies modification of both the model parameters and the causal relations between the model variables.

The solution reported in the literature in order to diminish the machining errors consists in using an adaptive predictive control system. Generally, for an adaptive control system the model structure remains unchanged but the parameters of the model are changed in order for a better modeling of the reality.

The identification is a repetitive and frequent process which requires stopping the machine, launching of specific experimental programs and numerical data processing. This requires time thus affects efficiency.

Solutions reported in the literature for model parameter evaluation are based on several algorithms. In most cases these algorithms consists in two stages:

- obtaining of experimental dataset from the sensor system and
- fitting the system model over the dataset.

For obtaining the dataset several solutions are proposed:

1-manufacturing process is stopped and then measurements are made upon the system [1], [2],
2-machining and measuring of test workpieces [3],
3-current workpiece is measured during its machining [4] ,
4-measurement is made during the entire batch manufacturing [5].

Model fitting over the dataset is usually done using analytical techniques [6], techniques based on artificial neural network or on genetic algorithms [7].

The main drawbacks which emerge from applying the techniques reported in the literature are:
1-some of them are time consuming techniques requiring the machine stop and launching specific procedures,
2-model parameters evaluation require many experiences (neural network case) thus the first workpieces have no benefit from using the adaptive system,
3-some of the approaches are used only to control a single variable thus other important components will remain uncontrolled and will affect in a negative way the output control,
4-in all the cases it is assumed that the model causal relations remain unchanged even though this assumption is not always confirmed in practice.

The vibration caused by using improper process parameters is a dynamically unstable phenomenon. This phenomenon has been studied for long time, but no approach of modeling this phenomenon for the reconfigurable machine tools is new. Dhupia [9] studied the stability dynamics of the arch-type reconfigurable machine tool. A comparison of frequency response functions and stability lobes of the arch-type reconfigurable machine tool was made for different reconfiguration position. Thed study revealed that similar dynamic characteristics exist for different reconfiguration structures. This similarity is possible the dominant mode where chatter occurs is caused by the spindle-tool and tool –tool holder assembly. Moreover, the conclusion was that in order to guarantee constant dynamic behavior in any case, the machine's structural frequencies must be less dominant than the structural frequencies of the spindle, tool and tool holder. So the general approach of the chatter phenomenon may be used for reconfigurable machine tools. The general approach [10, 11] consists in modeling of the dynamics of the system and determining the frequency response functions, by modeling the workpiece, the tool holder and the tool and then the model parameters must by identified. In some papers a predictive control aproach is made. In [12] the stability is assessed by using the ratio of the predicted maximum dynamic cutting force to the predicted maximum static cutting force. The cutting force is predicted by using as input parameters workpiece material properties, the tool geometry and the cutting conditions.

Chatter monitoring is done usually by using accelerometers [13], microphones [14], force dynamometers [13,15] or even by measuring the spindle drive current [16]. By using these sensors the stability of the process is assessed. However the in these papers the control of the chatter phenomenon is preventive. The models used for preventive control are often analytical and their structure is obtained by using simplifying hypotheses.

In order to control reconfigurable machine tools we propose a novel control structure. This control structure includes an online learning system which supplies input data to a general operation scheduling algorithm which controls the reconfigurable machine tool hardware structure The online learning system is used for generating corrections for the machine axes and also for specifying the limit conditions before the chatter phenomenon appearance. The process is monitored and the instability tendencies situations are used for determining the stability limit.

The dataset used for process modeling is filled only using the monitoring system, without stopping the process or using a test workpiece.

The algorithm used for dimensional control includes in a unitary manner both the model update and model use for corrections estimation. Each algorithm running consists in determination of the causal relations between state variables and in generation of the best linear model describing manufacturing system and process. The model is then used for preventive control of the current workpiece so that its deviations are compensated. Thus the control error is actually the prediction error. Algorithm is permanently run during the batch machining so it can detect the systems evolution.

The algorithm design allows its use with few previous workpiece, because it includes a procedure for working with small datasets.

The remainder of this paper is organized in four sections. Formulation of the problem is presented in section 2. The proposed control structure, the ontline learning sistem along with the results of simulations using artificial data and data resulted from laboratory experiments are presented in section 3. Section 4 contains the main research conclusions.

2 Problem Formulation

The problem solved in this paper arises from the following remarks:

1- the classical CNC is not suitable for reconfigurable machine tools because the models of these machine is changing dramatically during the reconfiguration stage and their models is not known in order to properly control the machine

2.- the CNC structures are not suitable for chatter predictive control

4, The CNCs are not using data obtained from the process in order to improve their performance

3- In manufacturing process the measurement of the process controlled variables can be sometime done with big delay in respect with to the control action; thus a classical control approach based on error driven controllers does not always avoid the appearance of rejection parts.

3- The model parameters values and the causal relations on which the model is based change during the batch manufacturing.

The problem to be solved in this paper consists in development of novel control system suitable for reconfigurable machine tools which will use a method for predictive control, based on prediction of deviation of the controlled variables values with respect to their programmed values and a method for predictive control of the process stabilty. Also the control must be adaptive for discerning manufacturing system and process dynamics.

The basic idea is to use the dataset obtained by monitoring the process during the manufacturing of the previous workpieces and during the current workpiece in order to predict the controlled variable value and to avoid the apearence of chatter phenomenon. The predicted deviation value will be used for minimizing its difference with respect to the programmed value.

Moreover, the proposed method involves integration of the system behavior identification stage with the resulted model using stage for obtaining the predicted values.

Finally, instead of using global models, the simple, local and ephemeral models will be preferred and the stability limit will be determined online.

3 Problem Solution

3.1 The RMT programming

As depicted in fig. 1 modern CNC machine programming architecture is considering the following data flow. A CAD program is used for workpiece design. Based on the workpiece specification process planning is then performed using a CAPP (Computer Aided Process Planing) software package. Then using a manufacturing process plan as input the part program is generated by a CAM software. The CNC process this program and the result is the finished workpiece. No correction is performed during the machine running. Also the stability of the process is not taken in account. Only the stability of each axis is assured during the machine setup by setting choosing a set of servoparameters. The proposed control system has a similar structure for CAD-CAPP software.

The classical CAM software is replaced by an adaptive CAM which have the advantage of providing the values for technological description of the process and by CAE (Computer Aided Engineering) which performs the simulation of current RMT kinematical configuration. The algorithm computed in the A-CAM is also computed in Algorithm running unit (ARU). The CAM running in process design phase is virtual machining considering nominal values. Consequently, the ARU running on the machine is running with measured values, which are continuously updated. The ARU uses as input parameters the values obtained from the online learning system. This system corrects the dimensional errors and assures the process stability

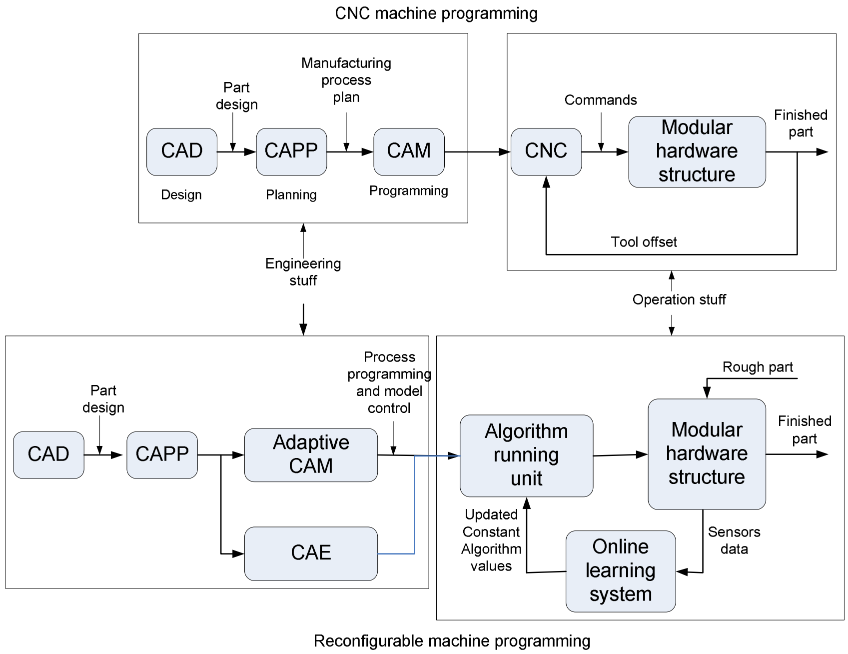

Fig.1 Proposed RMT programming

3.2 The reconfigurable lathe

We will describe a reconfigurable lathe structure for exemplification. Our proposed architecture for the reconfigurable lathe is composed of virtual processing planning system, machining database, and "plug-and-play" hardware modules.

The reconfigurable lathe considered is build out of four independent modules, numerical controlled, with independent sensor and motors. These modules are main spindle, X and Z axis asembly, and the rotary tool assembly. The reconfigurable lathe, configured for cutting of longitudinal profiles, as shown in the picture, is made of the following parts: bed 1, main spindle 2, workpiece 3, cutting tool 4, tool holder 5, carriage 6, rotary tool assembly 7, cross-slide 8, slideway 9. Having a supplementary degree of freedom represented by rotation of cutting tool it is an advantage for tool to positioning, and using interpolation for x and z axis and the rotation of the tool it can be achieved peculiar surface processing. Using a configuration with rotary assembly tool parallel with the axel of the spindle, it can be processed surfaces such as poliexcentric revolution surfaces, complex surfaces or cams.

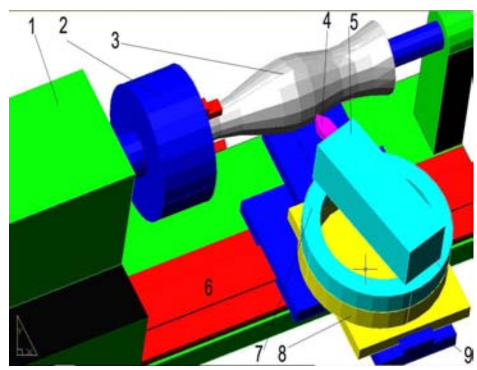

Fig.2 The reconfigurable lathe

The hardware modules (main spindle, tool holder, etc) are design as "plug and play" and are controlled directly using optimal control variable, by-passing the post processing phase of G-code generation. The control of the modules it is performed by sending simultaneously successive position of controlled variables X(k), Z(k), $\theta(k)$ and $\varphi(k)$ computed from (i,j) pair.

In order to control the machine, each blanck of the current batch is measured using by on-machine measurement. The workpiece profile is inputted form CAM CAD model. So the machining allowance is known for the entire workpiece surface. The algorithm running unit is used

Part surface generation it is performed by moving tool profile along helicoidally generating path, obtained by combining revolution of the part and the translation of the tool. The trajectory of the helicoidally path is divided, by coordinates computing of a many successive *(i,j)* pair points to control motors that performs movement actions of the machine. For each point, the online learning system will generate dimensional correction parameters and also the parameters that will be used as input data for the algorithm running unit. These input parameters will be La (the length of cutting active), allowable chip thickness - aa (chip thickness). The learning system controls the stability by correcting the length of the active cutting edge and the cutting speed limits and in order to maintain the process stability. Also an equation for the stability limit will be supplied by the learning system. This equation will be used for validation purposes.

3.3 The chatter predictive control

The chatter phenomenon appearance is often a regenerative phenomenon. In the case repetitive machining of the same surface the chatter may appear as a consequence of the previous workcycle. The length of the chatter waves λ fig. 3 will be determined by the variable force F which is generated by the variability of the machining allowance.

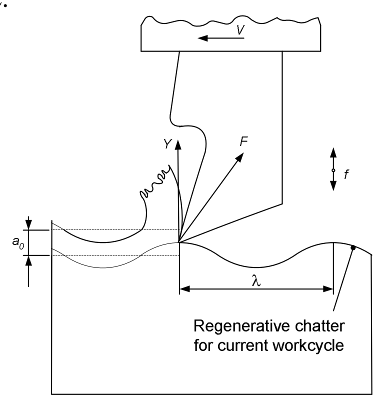

Fig.3. The regenerative chatter phenomenon

The chatter phnomemon apearence may be avoided by properly controlling three paramenters: the active lenght of the cutting tool, the feed rate and the cutting speed. Our purpose is to determine the stability limit in order to supply the parameter La for the algorithm runing unit. This algorithm will control the machinig process near the stability limit in order to maximize the productivity. We will present briefly the influence of each parameter.

As depicted in figure 4, the active lenght of the cutting tool has a great influence over the the stability of the maching process. The chatter amplitude exponentialy increases with the active lenght of the cutting tool if over a limit value t_{lim}..

The value tlim which must be identify isn't constant for the entire workpiece. It depends of the machine rigidity which is not constant over the entrire work space, the workpiece rigidity and the machining parameters affect this value.

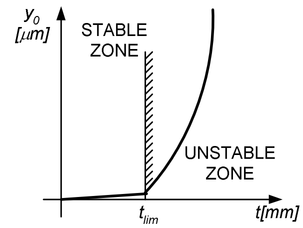

Fig.4. Variation of chatter amplitude with the value of the length of the active cutting edge

In figure 5 the variation of t_{lim} with the feed rate is showed. Often the feed rate do not have a significative influence.

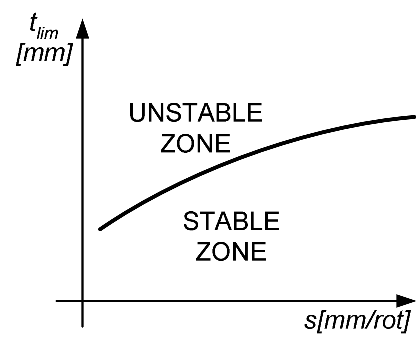

Fig.5. Variation of chatter amplitude with the value of the length of the active cutting edge

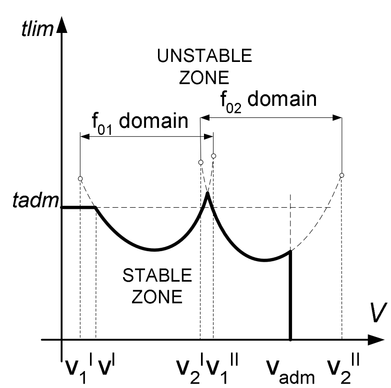

Fig.6. Variation of chatter amplitude with the value of the length of the active cutting

The dependency between the cutting speed and t_{lim} is complicated. Each dominant characteristic frequency determines the existence of associate lobe in the diagram. These characteristic frequency must be avoided because the t_{lim} parameter value is very low in these circumstances.

In order to avoid the chatter appearance a model must be build in order to predict for a certain process parameter (cutting speed, feed rate and cutting lenght) if the process will be stable or not. In order to model this dependency the machine will be monitored during the entire batch processing. First the input parameters for the algorithm running unit that controls the trajectory will be set by default to low values.

Then these parameters will be gradualy increased and if chatter appears: firstly the tlim parameter is deacresed by actuating the rotary tool assembly, the feed rate and upon the cutting speed. A database will record each situation encountered during maching,.. This dataset will be use for training a SVM classifier that will be used for prediction of the stability state. Although other modeling techniques are availibale [19]

SVM is a supervised learning technique used for regression or classification. Several fields such as medicine, economy and engineering, are using classification techniques [17-18]. In many cases it is necessary to discriminate the results or phenomenon in two classes.

Usually, classification model is trained using observation set $S = \{(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), ...(\mathbf{x}_n, y_n)\}$, where $\mathbf{x}_i \in R^m$ - are vectors containing data used for discrimination and $y_i \in \{-1,+1\}$ are the labels for each class. In our paper the $\mathbf{x}$ vectors will be represented by the machning parameters. The labels y_i for each workpiece denote the fact that the process is stable or not. After the model is trained, it can be used for prediction by inputing a vector $\mathbf{x}$ into a decision function D($\mathbf{x}$) where $D : R^m \to \{-1,+1\}$. A linear classifier uses a hiperplane $\mathbf{w} \cdot \mathbf{x} + b = 0$ for separating the dataset in two classes where '$\cdot$' is the dot product operator, $\boldsymbol{w}$ is the normal vector of the hiperplane and b is a bias (Fig. 7). In this paper we will input data in this decision function and we will get an answer referring to the workpiece assessment. SVM classifier determines the vectors from each class with shortest distances from the separation hiperplane. SVM classifier algorithm determines the hiperplane parameters for which these distances are maximized by defining two margin hiperplanes:

$\mathbf{w} \cdot \mathbf{x} + b$=1 and $\mathbf{w} \cdot \mathbf{x} + b$=-1.

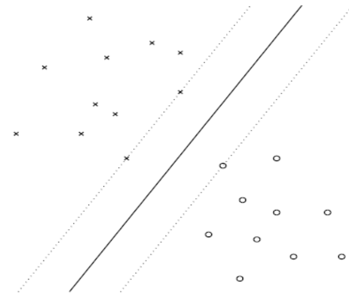

Fig. 7. Linear classification using SVM

If $\mathbf{w} \cdot \mathbf{x} + b \le -1$ then y=-1, if $\mathbf{w} \cdot \mathbf{x} + b \ge 1$ then y=+1. The decision function is :

$$D(\mathbf{x}) = sign(\mathbf{w} \cdot \mathbf{x} + b)$$

The algorithm solves the following optimization problem:

- maximize the margin= $2/\|\mathbf{w}\|$,

Subject to $y_i(\mathbf{w} \cdot \mathbf{x} + b) \ge 1$ where i=1..n

The problem can be solved in its dual form:

-max $\sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j} \alpha_i \alpha_j y_i y_j \mathbf{x}_i \cdot \mathbf{x}_j$,

subject to $\alpha_i \ge 0$ and $\sum_{i=1}^{n} y_i \alpha_i = 0$. Where α terms are the dual representation of the weight vector $\mathbf{w} = \sum_{i=1}^{n} \alpha_i y_i \mathbf{x}_i$, which is zero for all the vectors that are not located on the margins hiperplanes. The vectors for which $\alpha_i \ne 0$, are called support vectors.

The soft margin method allows training data to be mislabeled in order to have a hyperplane that separates data which is linearly inseparable .This method introduces using positive ξ_i slack variables. $y_i(\mathbf{w} \cdot \mathbf{x}_i + b) \ge 1 - \xi_i$. The optimization problem will be:

$$\min \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{n} \xi_i,$$

subject to $y_i(\mathbf{w} \cdot \mathbf{x}_i + b) \ge 1 - \xi_i$.

The problem can be solved using the Lagrange multipliers:

$$\max \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j} \alpha_i \alpha_j y_i y_j \mathbf{x}_i \cdot \mathbf{x}_j$$

where $C \ge \alpha_i \ge 0$, and $\sum_{i=1}^{n} y_i \alpha_i = 0$.

SVM classifier can also be used for non-linear classification by using kernel functions. The algorithm is similar with the linear version except that the dot product used as a measure of similarity is replaced with a nonlinear kernel function, $K(\mathbf{x}_i,\mathbf{x}_j) = \phi(\mathbf{x}_i)\cdot\phi(\mathbf{x}_j)$, which computes the scalar product in a feature space defined by the transformation $\phi(\mathbf{x})$. The dimension of the future space can be very high or virtually infinite. However, using the kernel trick the computation is not done in the feature space. Typical kernel functions are:

-polynomial: $K(\mathbf{x}_i,\mathbf{x}_j) = (\mathbf{x}_i \cdot \mathbf{x}_j)^d$ or

$K(\mathbf{x}_i,\mathbf{x}_j) = (\mathbf{x}_i \cdot \mathbf{x}_j + 1)^d$

-radial basis function:

$$K(\mathbf{x}_i,\mathbf{x}_j) = e^{-\gamma\left\|\mathbf{x}_i - \mathbf{x}_j\right\|^2}, \gamma > 0 \text{, or}$$

$$K(\mathbf{x}_i,\mathbf{x}_j) = e^{\frac{-\left\|\mathbf{x}_i - \mathbf{x}_j\right\|}{2\sigma^2}}$$

-sigmoid- $K(\mathbf{x}_i,\mathbf{x}_j) = \tanh(\kappa\mathbf{x}_i \cdot \mathbf{x}_j + c)$.

Using a specific kernel function depends on the dataset structure because the kernel function can be considered as a measure of similarity between the training set data. Each kernel function has a set of parameters which must be properly chosen in order to avoid over fitting. Also the parameter C must be properly selected in order to minimize the prediction error on a test dataset. For selecting the proper parameters a grid search algorithm is used. For each parameter a set of coarse values is supplied, and then using k-fold cross validation method or leave one out method each combination is evaluated. These validation methods are used for dividing the training data in two parts. One part will be used for training the classifier and the other one for testing its performance. In k-fold cross validation the testing data is divided in k parts randomly. Each part will be used for testing the algorithm trained with k-1 folds. In leave one out method is a particular case of k-fold cross validation, k is equal with n the number of training instances. After that a fine search is performed. In both cases the data is divided in training data and test data.

In order to model the stability limit the stability was determined using this relation:
$\lambda = v / f$. where f is the frequency with the highest amplitude determined using Fourrier analysis, and v is the cutting speed. By experiments we determined that the system is unstable if λ. in the midddle off its variation interval $\lambda. = 0.5...18mm$. Based on λ. value the assesment of the stability is made. We modeled the clasification problem using a RBF kernel.. The kernel parameter and C parameter ware determined using cross-validation. The SVM accuracy was good over 90%.

For dimensional control we shall consider several machining cycles which will produce several workpieces. The machining surface will be divided in several zones (I, II, III, IV in Fig. 8). Each zone length is adopted so that the correction required is constant over the entire zone.

Each work cycle will be divided in a number of stages (figure 8) which are: measuring stages or prediction and compensation stages for each zone in which the part was divided.

During a measuring stage the variable values are measured using sensors embedded on machine. During a prediction stage only one variable, the variable of interest, will be predicted and compensated in order to null the deviation from the programmed value, before its appearance in the process. Finally for each variable of interest, a measuring stage will be performed in order to record the real value of the variable. A specific online learning algorithm will be used for identifying the model of the variable of interest. The dataset used by the algorithm is composed by the variables values recorded from the current workpiece until the current stage and also for all previous workpieces.

Let us consider a simple workpiece which is turned and tool path AB is divided in four zones (fig 8). In current moment the cutting tool machines the zone II. During the process six variables $V_1..V_6$ are monitored. All the variables are measured and some of them (V_1, V_2 and V_4) are predicted and then compensated based on their predicted values. The workcycle was divided in seven stages which three are prediction and compensating stages and four are measuring stages. For instance, stage 1 is a measuring stage which consists in measuring V_5 and V_6 variables. If for the current workpiece, the current stage is a prediction and compensation one, the variable of interest value would be predicted using a specific online learning algorithm which use the measured values during the current work cycle until the current stage and all the records from the dataset which contain the measured values for all the past workcycles. For the case shown in Fig. 8, the current stage is 4, the variable of interest is V_2, the variables for which the values were already measured are V_3, V_5 and V_6. A model will be build using these variables values and also using all the variables values recorded for the previous workpieces.

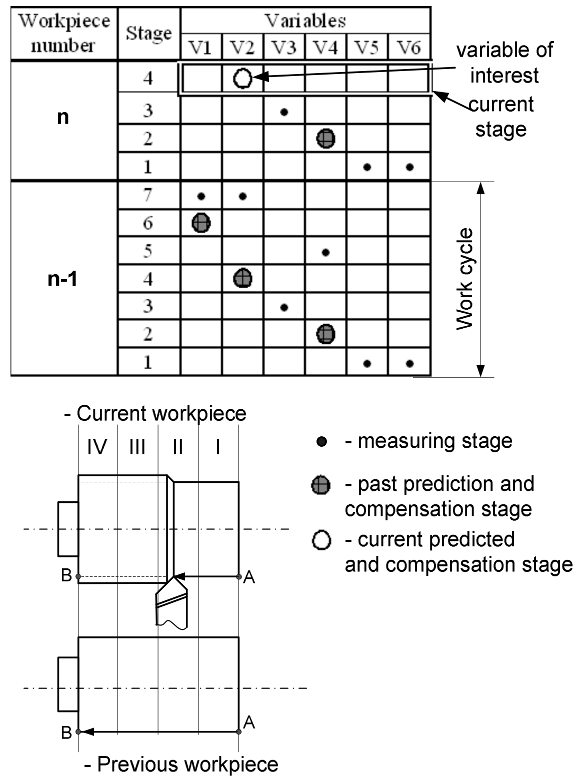

Fig 8. Dataset filling and exploiting

3.3 The proposed online learning algorithm

The proposed algorithm consists in the following steps:

• In the first step the normalization of the dataset is performed. Also the time evolution of the system is compensated. In practice the evolution of the variables values is quite monotonous and slowly varying with respect to the time period required for the entire batch manufacturing. Thus a linear model would fit properly the time evolution for the entire dataset. In this linear model, the time variable will be measured by the workpiece index number. The model structure will be:

$$\hat{V}_i(t) = a_i \cdot t + b_i \qquad (1)$$

where i denotes the order number of the variable, $\hat{V}_i(t)$ is the evaluated value of the variable $Vi(t)$, t is the index number of the workpiece and a_i and b_i are constants, specific for variable Vi. All the variables will be compensated using the following formula:

$$V_{ic}(t) = V_i(t) - \hat{V}_i(t) \quad (2)$$

where $V_{ic}(t)$ is the compensated value of the variable $V_i(t)$.

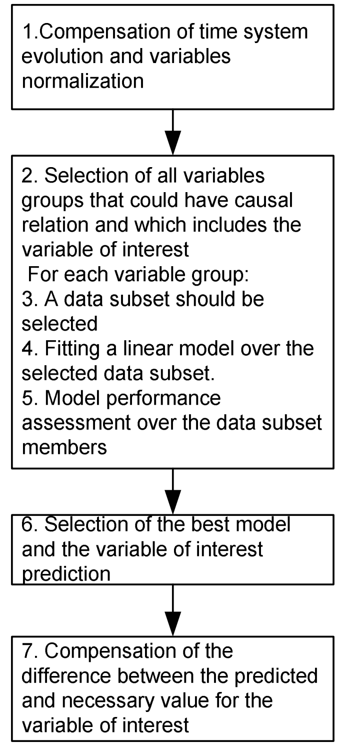

Fig. 9. The proposed online learning algorithm for dimensional control.

A new dataset which will contain the time compensated values for all the variables will be filled.

• In the second step all the monitored variables will be structured in all the possible combinations. Each combination contains a group of variables which always includes the variable of interest. These variable groups represent all the possible causal relations. For instance, in the example presented in Fig. 8, the variable of interest V_2 could be modeled only using the measured in current workcycle variables $V_3(n)$, $V_5(n)$ and $V_6(n)$. This is why the causal relation can appear on one of the following groups:

$(V_2\text{-}V_3)$, $(V_2\text{-}V_5)$, $(V_2\text{-}V_6)$, $(V_2\text{-}V_3,V_5)$, $(V_2\text{-}V_3,V_6)$, $(V_2\text{-}V_5,V_6)$, $(V_2\text{-}V_3,V_5,V_6)$

• In the third step for each variables group a data subset will be filled by selecting from the entire dataset only the data corresponding to a number of k workpieces. These k workpieces will be selected so their Euclidian distance to current workpiece, corresponding to the selected variables group, taking in account only the selected group's variables, would have the smaller values.

• In the fourth step for each data subset a linear model is fitted. This model should have as variables only those contained in this variables group. The coefficients of the linear model are computed using least square criterion.

• The next step implies the evaluation of each model. This evaluation is based on the deviation for each value of interest from the selected subset.

• In the sixth step the best linear model for fitting the causal relation between the variable of interest and the rest of monitored variables is selected. The model is the one for which the standard deviation of the variable of interest values is the lowest.

• The final step consists in the compensation action. The difference between the predicted value and the programmed value of the variables of interest is compensated.

3.3 Numerical and physical simulation results

The proposed control method for dimensional aspect was applied on artificial data and on data obtained from batch manufacturing in laboratory conditions. The obtained results were compared with the results obtained by using ANN models and best NN model facility.

Results obtained by simulation with artificial data

For a small number of previous manufactured workpieces best NNmodel did not identified the correct causal relation,

For a larger number of previous manufactured workpieces best NNmodel did identify the correct causal relation but the prognosis performance was low.

The proposed algorithm identified the correct causal relation in all the cases and the variable of interest was predicted with a average of 10% error.

Results obtained by data obtained from batch manufacturing in laboratory conditions

The physical simulations consisted in straight turning of a batch of 81 workpieces having the shape shown in Fig. 11.

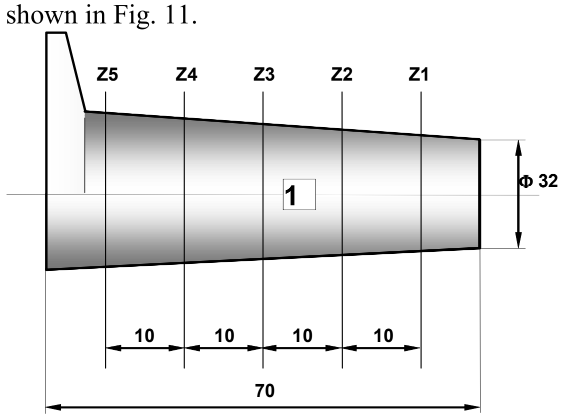

Fig 10. The blank used for simulation

During the machining several variables were monitored: cutting force, temperature of the cutting tool, power consumption in cutting process.

By applying the proposed algorithm, the average value of the workpiece errors decreased with more then a size range and the standard deviation decreased with 38%.

4 Conclusions

The research shown in this article pointed out the following conclusions:

• the proposed CNC structure permits integrates the error compensation algorithm and process stability will improve the RMT control

•the proposed procedure for chatter preventive control which is using SVM for stability evaluation is suitable for process control. The results of using this control structure with the stability preventive control were that the productivity increased.

• taking in account the time evolution of the system behavior, both with respect to the causal relations between the state variables and to the parameter values of the model, is important because it significantly increase the overall (dimensional) control performance,

• the proposed algorithm for dimensional control works well for all the batch workpieces even for the first machined workpieces,

• the reduced running time required by the algorithm allows its use for online correction,

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