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Adaptive Control System Based Cnc Controller Parameter Selection using Adaptive Neuro Fuzzy Inference System with Sliding Window Method (Anfis-Swm)

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ABSTRACT

In order to obtain the require shape and surface of the material the operation of machine is significant with the consideration of certain conventional geometric approaches. For the purpose of optimizing machine parameters, some of the researchers are undergoing with the usage of costliest tools. These optimization parameters include lower production time and extendable profit. For the purpose of achieving those parameters this work concentrates on improving the profit in computer Numerical Control (CNC) milling process. This improvisation is done by picking the cutting speed and feed options. A novel method named as Adaptive Neuro Fuzzy Inference System with Sliding Window Method (ANFIS-SWM)s proposed here to improve the overall profit in machining system with the greatest effect in milling process.

Keywords- *Controller, Fuzzy system, Machining process, M-codes and sliding window*

INTRODUCTION

Properly carried out machining of machine parts should provide the required dimensional accuracy and surface quality. The economic criteria of modern industry are also very important, which also pose high demands in terms of machining efficiency. Cutting tools manufacturers offer products that can carry out machining at high ranges of machining parameters [1]. The technological capabilities of modern machine tools allow for cutting with such parameters, however, in practice due to the occurrence of vibrations, it often turns out to be impossible. Self-excited chatter vibrations are caused by instability in the dynamic cutting process [2] and it is resulting in poor quality of machined surface, reduction of tool-life and faster wear of machine tool subassemblies. However, chatter may be avoided by proper selection of cutting parameters such as feed rate, cutting depth and rotational speed (of the workpiece for turning or the tool for milling). The selection of these parameters can be carried out using the stability lobes presented as a border cutting depth at which chatter vibration develops as a function of rotational speed [3]. The stability lobes are calculated basing on the cutting process model including cutting force coefficients and the dynamic properties of the machine tool-holder-workpiece system. These dynamic properties are determined for compliant part of the system: flexible workpiece (shaft with high length-to-diameter ratio) or slender tool with long overhang (ex. boring tools). The properties, presented as frequency response function (FRF) can be determined experimentally basing on impact test, performed for the compliant part [4]. However, in industrial practice the selection of the cutting parameters commonly is based on ranges proposed by the manufacturer of the tool inserts and the experience of the technologist. The dynamic properties of the machine tool - workpiece system and the risk of chatter vibrations are neglected. Along with this growth in development of next generation CNC systems, however, there is increasing concern over existing CNC systems that still continue utilize outdated and low-level codes as a programming language. This language is limited to small information and remains inflexible

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of the closed nature architecture of machine tools [5]. These limitations become major issues that need to be resolved for powerful and intelligent CNC system in future. Due to complex and dynamic shop floor environments nowadays, the flexibility of the existing CNC systems to react adaptively and dynamically are believed to be limited because the way they are being programmed remains unchanged. Reflect to that situation, predefined NC commands generated in early stages regularly found unusable or unsuitable for the dedicated resources, causing useless efforts used up in advanced process planning tasks and NC program generation activity. Additionally, with lack of intelligence and usage of low-level information in process planning, make detailed machining process mostly are depends on CAM programmers rather than CNC machine tool data feedback. This reliance on planners is due to the incapability of controller systems to interpret feedback forms of data [6]. Consequently, productivity is dropped since machines remain idle to wait re-adjust process planning activities and re-generate the command code being acting.

It can be observed that optimization methods such as the Cuckoo search, the Hybrid Differential Evolution Algorithm, the Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Shuffled Frog-Leaping (SFL) have mostly been used for the optimization of machining parameters. However, these methods are restricted to find a solution rapidly and cheaply, and if these methods are applied to a more complex optimization problem, it will take more time and effort. To overcome, these limitations, the concept of fuzzy is included in this work which efficiently improves the overall quality.

LITERATURE SURVEY

Hung-Wei Chiu et al., (2020) introduces an intelligent machining system (IMS) using an Adaptive-Network-based Fuzzy Inference System (ANFIS) predictor and the Particle Swarm Optimization (PSO) algorithm with a hybrid objective function. The proposed IMS provides suitable machining parameters for the users, to satisfy different machining requirements such as accuracy, surface smoothness, and speed. Subsequently, to establish the IMS, we combine the trained ANFIS model and establish a hybrid objective function optimization problem solved by PSO algorithm according the specific requirement of the user [7]. Wei-Feng Kuo et al., (2019) predict and optimize the processing parameters combination, we use the data-driven approach to establish the Back-Propagation Neural Network Particle Swarm Optimization (BPNN-PSO) algorithm to search the processing parameters based on the constraints of accuracy and surface roughness. That is, users can set the specified conditions of accuracy and surface roughness, then the CNC assistant has the ability to obtain the corresponding machining parameters, not only leading to the shortest machining time but also meeting the design conditions. Chen et al.(2019) were able to optimize machining parameters with a reduction in energy consumption and production time for the face milling process. They presented an integrated approach for minimizing the energy footprint and production time by optimizing cutting tools and cutting parameters. Three energy footprint-aware optimization models were used to demonstrate the necessity of the integrated approach. In model 1, the cutting tool-related parameters were preset according to the machining handbook. In model 2, the cutting tool-related parameters were optimized through the Cuckoo algorithm with feasible cutting parameters. In model 3, the integrated optimization of the cutting tool and parameters was used. When the energy footprint of each model was compared, the integrated approach achieved the most energy-efficient footprint. Therefore, they found that it is necessary to optimize the cutting tool and cutting parameters in an integrated manner [9]. Ay et al., (2019) proposed data –driven model-based control strategies can be applied using the collective knowledge and adapted online according to data. For the exchange data it is imperative to establish a generalizing learning technique for the controller design. A machine learning technique with inherent generalization ability is the Support

Vector Machines (SVM) algorithm where the choice of kernel is crucial for the resulting model quality [10]. Faisal et al., (2018) researched the optimization of machining process parameters in Electric Discharge Machining (EDM) by using the Particle Swarm Optimization (PSO) and Biogeography-Based Optimization (BBO) techniques. The PSO technique took initialization with a population of random solutions and then updating the generations to achieve an optimal solution. The BBO technique optimizes a function stochastically and iteratively. They found that the BBO method improved the material removal rate and reduced surface roughness [11]. Chiu et al.,(2017)propose a data driven method to predict machining quality of product by ANFIS model, which the inputs are CNC machining parameters and the outputs are two performance indexes (milling accuracy and surface quality). The corresponding fuzzy rules can be extracted from the ANFIS for user to understand the relationship between CNC parameters and performance indexes. Finally, simulation and experimental results illustrate that the two indexes can be predicted effectively for different machining parameters. Therefore, this predicted system can help user to achieve the required product quality and machining productivity [12]. Moreira et al., (2016) presents a novel approach of designing an intelligent supervision controller for real-time adjustments on feed rate and spindle speed to achieve desired surface quality of machined workpieces. The controller is an innovative model-based closed-loop system, consisting of a surface roughness prediction model and a multi-variable controller, to ensure real-time improvements on surface quality during machining processes [13].

RESEARCH METHODOLOGIES

This section aims to achieve more profit and hence it can be achieve by proposed architecture as shown in the figure 1. Initially, the Cartesian coordinates of the machine such as displacement, federate and speed are considered for coincide with M-code miscellaneous function. The outcome of this step is considered as CNC input parameter and feed to Adaptive Neuro Fuzzy Inference System with Sliding Window Method (ANFIS-SWM) block whereas; the fuzzification process is done for preparing set of rules. These rules are slided using windowing process base on requirement. Finally, they are validated in particular machine.

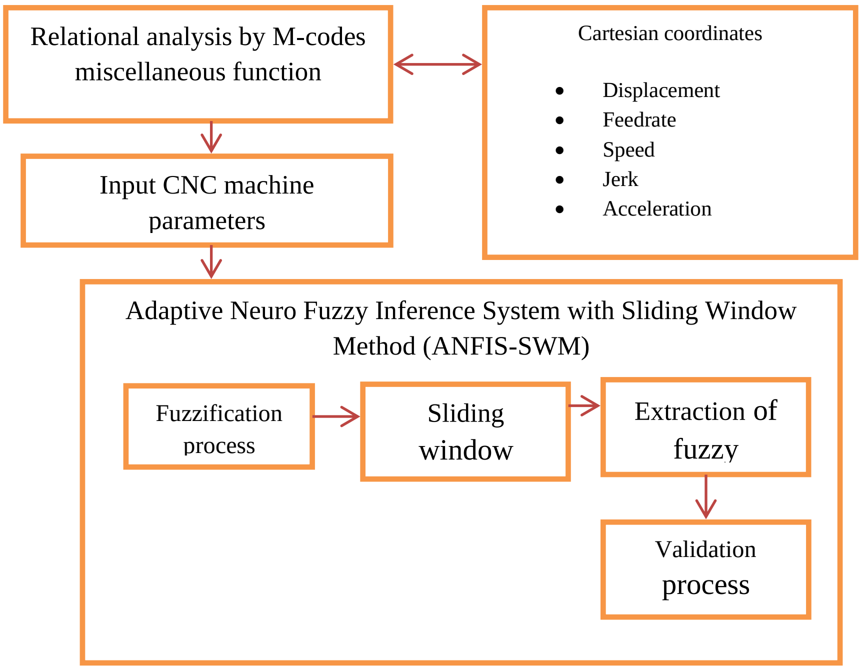

Figure-1 Proposed system architecture

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M-codes miscellaneous function with Cartesian coordinates

This method follows three axial fully coordinated CNC milling machines with the combination of M-Codes and its resembled self-organized programs. For loading this programs there is requirement of programmable Logic Controller (PLC) inside the CNC model. Actually, this PLC is indictedwith CNC in software structure. The reason of using M-codes is, it is easily accessible by the users and program developers whereas each comment are given with its ‘I’ interpretation for designing machine. M102, M101, M105, M106, M201, M150 are some of the M-codes that are chosen for temperature control process. Amongthem the M-CODES M105, M106 and M201 are added with addition process such as speed, jerk and acceleration control. Every M-codes are specified with its appropriate sub-program.

Code	Meaning
M104	Displacement
M140	Feed rate
M141	Speed
M109	Jerk
M190	Acceleration
M191	heating bed temperature
M105	work space temperature

After the application of M-codes, it is significant to notice the properties of machine. One of the important properties is temperature control at the hot end nozzle. During the optimization, the layer based manufacturing is assisted with cooling accessories. These coolers are distributed along with microcontroller oriented closed loop controller with the basic parameter such as hot-cups, temperature in workspace and speed of cooler. Among them, the hot bed is not considered in initial layers due to its effect in other layer. These are all included in reference model and hence they are indicated in figure-2 Adaptive mechanism based temperature control

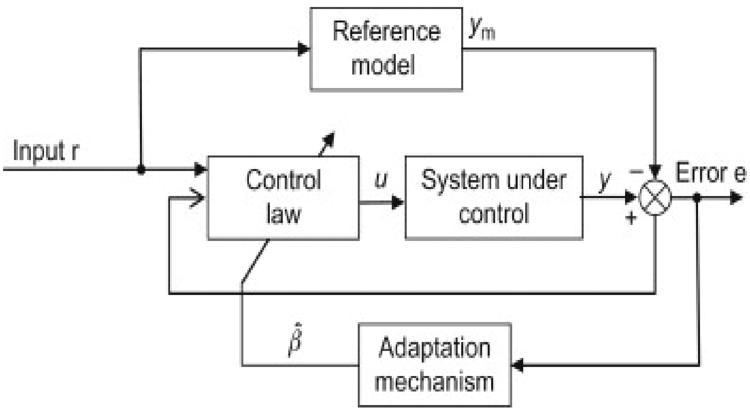

Fig. 2 - Adaptive mechanism based temperature control

CNC machine parameters

The outcome of the denoted coordinatesare feed as input machine parameters with the process of metal cutting. While doing so, the entire workpiece is concerned with multi-oriented degree format. There are some of the parameters such as efficiency, power, spindle

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torque, revolution axis; positional rate has to be considered. These parameters are mentioned as given below.

Ip= {A,T, aMax, hMax, Pr}
Whereas,
A= power
T= spindle torque
aMax= maximum speed of revolution axis
hMax=maximum feed rate
Pr=precision position of machine

After setting these parameters the surface of the machine are finalized with the proper profile. For the purposed of constructing the tool in critical knowledge. Our work concentrates on seven parameters such as {x,Ra,Rb,Rc,,y,z} with appropriate profile settings such as {x=0, Ra=A, Rb=B, Rc=C, y=0 and x=1} with the coincidence of angle such as rake angle, flank angle and helix angle.

ADAPTIVE NEURO FUZZY INFERENCE SYSTEM WITH SLIDING WINDOW METHOD (ANFIS-SWM)

The proposed Adaptive Neuro Fuzzy Inference System with Sliding Window Method (ANFIS-SWM) follows Neuro fuzzy based classification method with the consideration of features such as input pattern, fuzzy related patterns, membership factors and performance level characters. Assume that there are ‘M’ numbers of input patterns with ‘N’ number of classes and ‘A’ attribute functions. All these parameters are comprised of as symbolic sigmoidal function. The flow of this technique is arranged as below.

Sliding window

All the input CNC parameters are processed with acquisition; data streams with the assistance of sliding window method. Initially, the dimensions are calculated. Secondly, specify the parameters details for all the three dimensions. Thirdly, precise the constant window size for the entire process. Here, the streaming process is noted as, M102=A, M101=8, M105=C, M106=B:3,M201-C:10, M150=C:2

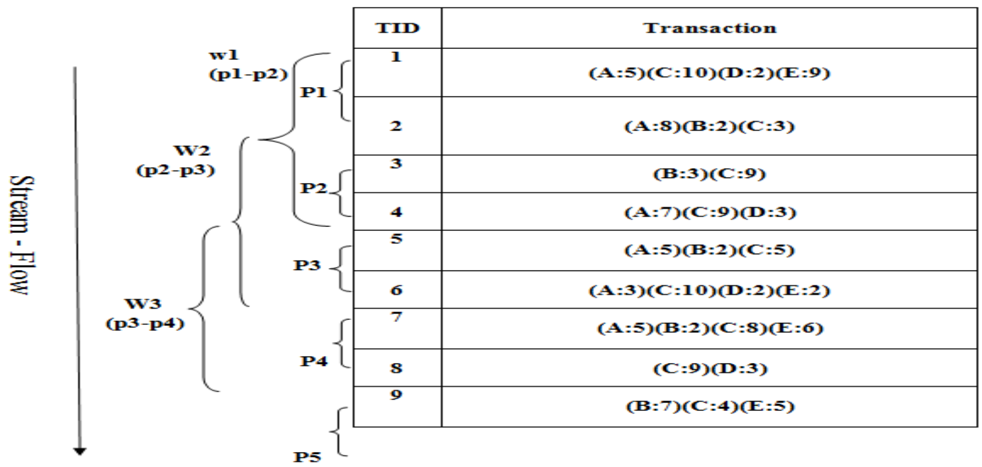

Fig. 3: Data Stream based on sliding window

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Fuzzification process

The output of sliding window is used for fuzzification process whereas two steps such as derivation of biological terms and arrangement of membership functions are involved. These membership function arrangement depends upon some of the design such as triangle, sigmoid, s-bend and circular shape. The constructed machine designs are participated with the function f(xi) where xi is the input pattern of the 'I'th constructed variable.

M(fxi)= Xi1,Xi2,Xi3…..Xik(1)

Where,

I is the degree

J is the class

The vector product is denoted as

$V(u) = v[xi(1),xi(2),xi(3)\ldots\ldots xi(n)]^T$

The transpose function is coincide with the temperature coefficients xi1=a, xi2=b, xi3=c, for the circular shaped material surface. Likewise the transpose function varies with respect to material layer. Consequently, the transpose function for the circular type machine is debated as

$$\textbf{Tf circular (a, b, c)} = mf(y;a,b,c) = sign\frac{1}{1+\left|\frac{y-c}{a}\right|^{2b}} \qquad (3)$$

The above mentioned parameter is specifically important to parametric analysis with the denotation of membership function. Likewise, the classification process id done for all the material and hence the overall membership matrix is represent as MF(y)

$$MF(y) = \begin{bmatrix} mf_{1,1}(y_1) & mf_{1,2}(y_1) & mf_{1,3}(y_1)\ldots & mf_{1,M}(y_1) \\ mf_{2,1}(y_2) & mf_{2,2}(y_2) & mf_{2,3}(y_2)\ldots & mf_{2,M}(y_2) \\ mf_{3,1}(y_3) & mf_{3,2}(y_3) & mf_{3,3}(y_3) & mf_{3,M}(y_3) \\ \ldots & \ldots & \ldots & \ldots \\ mf_{N,1}(y_N) & mf_{N,2}(y_N) & mf_{N,3}(y_N)\ldots & mf_{N,M}(y_N) \end{bmatrix}_i \qquad (4)$$

Where $mf_{i,j}(y_i)$ is the input vector membership of i-th pattern and y with i = 1, 2, ..., N and j = 1, 2, ..., M.

Classifier

After the construction of membership matrix, the classification is done using Recurrent Neural Network (RNN) with the assistance of accusable input ratio. Here the machine CNC parameters with the membership matrix are feed to the first layer. The nodes in the input layer are prepared with associative weights. Hence, the back propagation process is follow in hidden layer with the involvement of learning construction agents. Moreover, the error also calculated in the hidden layer by using Root-Mean Square (RMS) calculation method and hence the finalized goals are achieved

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Hidden or output layer with net input unit j of RNN is derived from the inputs which are linearly combined. The predicted result of unit j followed by

$$Output_j = \frac{1}{1+e^{-Net_j}} \quad (5)$$

where Net j = RNN model's the net input of unit j. The net input is calculated as a weighted sum of the connection strengths (or weights) and the previous layer output:

$$Net_j = \sum_i weight_{ij} * Output_i + bias_j \quad (6)$$

Where $weight_{ij}$ = unit i with link connection strength (or weight) in the former layer to unit j, $Output_i$ = preceding layer unit i output, and $bias_j$ = the bias of the unit. The aggregate of squared errors calculated from the predicted output, $Target_j$:

$$Error = \frac{1}{2}\sum_j (T\arg et_j - Output_j)^2 \quad (7)$$

The back propagation network's weights are decreases on the whole error.

$$\Delta Weight \infty - \frac{\partial Error}{\partial Weight} \quad (8)$$

Due to error is indirectly a weight function, elaborating it as follows:

$$\Delta Weight_{ij} = -\eta * \frac{\partial Error}{\partial Output_j} * \frac{\partial Output_j}{\partial Net_j} * \frac{\partial Net_j}{\partial Weight_{ij}} \quad (9)$$

where g is a positive constant is rate of learning. Weight updating formula is established as

$$weight_{ij} = weight_{ij} + \Delta weight_{ij} \quad (10)$$

Likewise, we can get the formula for bias updating formula is obtained as:

$$bias_j = bias_j + \Delta bias_j \quad (11)$$

After a thorough examination, a method of sigmoidal function with a RNN solitary hidden layer is chosen. The technique of RNN used slope drop with energy as an managed learning principle, and moves task in the hidden and output layer as tan sigmoid. The node quantity present RNN input layer is equivalent to the quantity of input properties in the set of data. Essentially, output layer nodes quantity is equivalent to the quantity of classes present in the data set. The quantity of processing elements (PEs) decision present in the hidden layer is additionally a critical parameter. After an appropriate examination the quantity of PEs in the hidden layer [29, 30], L is selected by the given equation.

$$L = (number\ of\ input\ attributes\ þ\ number\ of\ classes) * 2/3 \quad (12)$$

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Extracting fuzzy association rules

The current window obtains the fuzzy frequent patterns. With respect to certain confidence fuzzy association rules are reduced. The NFS classifier is designed for tough classification by deploying a maximum (max) operation for defuzzification of the RNN output activated in the final step. Designing an input pattern is y to a specific class j with the largest membership class value if and only if

Performance analysis

Extensive experiments were carried with the proposed Adaptive Neuro Fuzzy Inference System with Sliding Window Method (ANFIS-SWM) and the results obtained were compared with the existing algorithm namely Adaptive-Network-based Fuzzy Inference System Particle Swarm Optimization (ANFIS-PSO) and Back-Propagation Neural Network Particle Swarm Optimization (BPNN-PSO) algorithm for parametric analysis such as machining time, contouring error, cutting force and surface roughness.

Table-1 Analysis of various parameters between existing and proposed method

PARAMETER	ANFIS-PSO	BPNN-PSO	ANFIS-SWM
machining time (sec)	45sec	67sec	31sec
contouring error	56%	54%	32%
surface roughness (µm)	67%	54%	45%
Cutting Force (kN)	56%	43%	87%

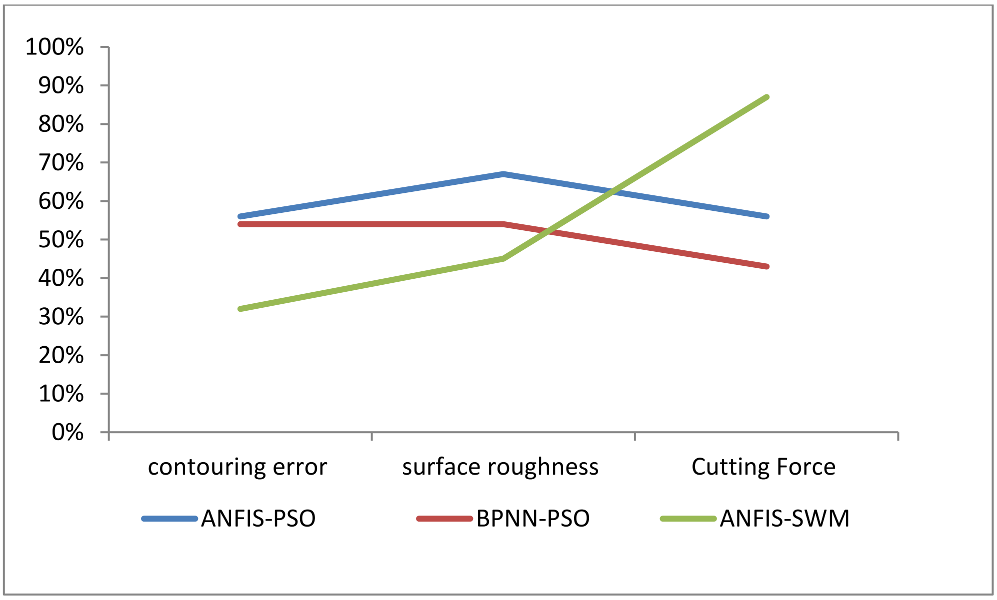

Figure-1 comparison of parameters between existing and proposed method

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CONCLUSIONS

Since the variations in the CNC machining parameters significantly affect the product quality during the operation of a machine tool, these parameters can be selected to varythe machining capabilities of the machining procedures. This paper introduced an intelligent machining system (IMS) using the ANFIS predictor and PSO algorithm with a hybrid objective function for users. The presented IMS provided suitable machining parameters for users to satisfy differentmachining requirement, e.g., accuracy, surface smoothness, and speed. As a result, the proposed method achieves 87% cutting force, 45% of surface roughness, 32% of contouring error within 31sec of machining time.

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