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MODELING OF SELF-INDUCED VIBRATIONS THAT OCCUR DURING THE MACHINING PROCESS OF CASTING PATTERNS WITH THE USE OF THE FUZZY-NEURAL NETWORKS METHOD

MODELOWANIE DRGAŃ SAMOWZBUDNYCH POWSTAJĄCYCH W PROCESIE MECHANICZNEJ OBRÓBKI FORMIERSKICH PŁYT ODLEWNICZYCH ZA POMOCĄ SIECI ROZMYTO-NEURONOWYCH

This article outlines a methodology of modeling self-induced vibrations that occur in the course of machining of metal objects, i.e. when shaping casting patterns on CNC machining centers. The modeling process presented here is based on an algorithm that makes use of local model fuzzy-neural networks. The algorithm falls back on the advantages of fuzzy systems with Takagi-Sugeno-Kanga (TSK) consequences and neural networks with auxiliary modules that help optimize and shorten the time needed to identify the best possible network structure.

The modeling of self-induced vibrations allows analyzing how the vibrations come into being. This in turn makes it possible to develop effective ways of eliminating these vibrations and, ultimately, designing a practical control system that would dispose of the vibrations altogether.

Keywords: self-induced vibrations, casting patterns, fuzzy-neural networks, local models

W procesie technologicznym wykonania odlewu, istotną pozycją jest omodelowanie odlewnicze, składające się z pojedynczych modeli lub zestawów modeli montowanych na płytach formierskich modelowych. Tak określone omodelowanie służy do odwzorowania w zagęszczonej masie formierskiej kształtu wnęki formy, odtwarzającej odlew zgodnie z technologicznością procesu. Szczególną rolę w jakości gotowego odlewu, przypisuje się jakości płyt modelowych wraz z zestawem modeli, stosowanych w automatach formierskich wykonujących formy odlewnicze.

Produkcja płyt modelowych odbywa się na zautomatyzowanych stanowiskach obróbczych CNC, w których podczas procesu obróbki ubytkowej występują niepożądane drgania, zwłaszcza samowzbudne. Drgania niekorzystnie wpływają na dokładność wymiarową i jakość powierzchni obrabianych płyt i modeli odlewniczych. Eliminacja drgań samowzbudnych w trakcie procesu skrawania jest jednym z warunków wykonania płyt modelowych o wysokiej jakości.

W artykule przedstawiona zostanie metodyka modelowania drgań samowzbudnych za pomocą sieci rozmyto-neuronowych. Jest to pierwszy etap w eliminacji niepożądanych drgań samowzbudnych występujących w procesie wytwarzania płyt modelowych.

Zamodelowanie drgań samowzbudnych umożliwia analizę procesu powstawania drgań i opracowanie skutecznych metod ich eliminacji, a docelowo zaprojektowanie układu regulacji niwelującego te drgania.

Ponadto scharakteryzowano problemy eksploatacyjne, jako następstwo występowania drgań samowzbudnych. Przeanalizowano możliwości zastosowania sieci rozmyto-neuronowych w celu modelowania drgań samowzbudnych wraz z omówieniem zalet i wad sieci. Przedstawiono również algorytm do tworzenia odpowiednich struktur sieci rozmyto-neuronowych dla modeli lokalnych i przykłady zastosowania algorytmu w procesie modelowania drgań samowzbudnych.

1. Introduction

A critical element in the engineering process of casting making are single-piece or multiple-piece patterns because their role is to replicate with utmost accuracy the shape of cavity or cavities in compacted-sand molds.

Patterns are machined on CNC centers. In the machining process unwanted self-induced vibrations occur that can significantly impact the pattern's dimensional accuracy and surface quality. Ridding the process of these vibrations is one of the prerequisites of producing high quality patterns. However, since machining is a largely non-linear process it is essential that modern programming tools be used to curb or eliminate the self-induced vibrations. This is where fuzzy systems and/or neural networks come into play as they lend themselves very well for the purpose. Fuzzy systems can be used primarily to control non-linear objects, with local Takagi-Sugeno models switched in a fuzzy manner [8] being one of the most popular and effective methods of that control.

This paper presents a method of creating and optimizing structures of fuzzy-neural networks which can be applied in

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order to model self-induced vibrations occurring during the machining process by means of local model networks.

Overall, it is made up of four parts: a description of self-induced vibrations occurring in the machining process, a brief outline of the fundamentals of computing and creating local model networks as structures used in modeling and controlling non-linear systems, a proposed algorithm that can create and optimize structures of fuzzy-neural networks of local models, and, in chapter five, selected results of simulated self-induced vibrations modeling tests.

2. Self-induced vibrations occurring during the machining process

Self-induced vibrations that occur in the process often result in casting pattern receiving uneven surfaces, which adversely impacts the pattern's quality. Figure 1 below exemplifies the influence of vibrations on the machined object. Although the occurrence of self-induced vibrations is a complex process, there are usually three primary causes responsible for it in mechanical systems: dynamic forcing, kinematic forcing, and the ability to store and transform potential and kinetic energies [5].

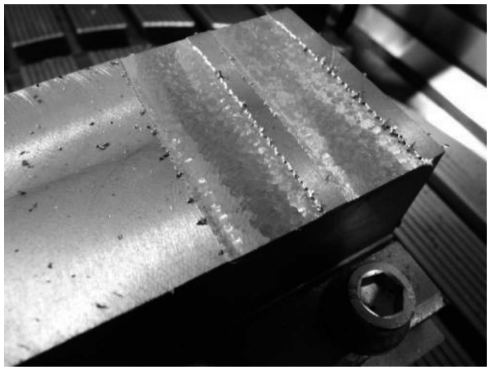

Fig. 1. Impact of self-induced vibrations of the machined object

The main feature of self-induced vibrations is that the variable force which feeds energy into the vibrating system is generated by the vibrations themselves.

Since self-induced vibrations occurring during the machining process adversely impact product quality, manufacturers make every effort possible to either reduce these vibrations or eliminate them altogether. Attempts to that effect are often undertaken as early as the designing stage of the machining equipment by research laboratories which place considerable focus on equipment's vibrostability. Work is also in progress on other methods of elimination of self-induced vibrations, such as: detection of self-induced vibrations, vibration eliminators: these are devices that make use of electromagnetic and/or piezoelectric actuators .

In both these instances (particularly in the latter one), constructing a control system that would steer in an appropriate manner the self-induced vibrations damping tools can be exceedingly complicated.

3. Local model fuzzy-neural networks

Fuzzy-neural networks are combinations of fuzzy systems with neural networks, common characteristics of which allow creating intelligent structures. In order to control dynamic non-linear processes it is critical that the proposed models well reflected the dynamics of the real system. Dynamic non-linear processes are characterized by vastly complex input-output interrelations, which is why computing a mathematical model to replicate the actual system seen from the global perspective can be extremely complicated. However it is perfectly possible to describe the dynamics of a non-linear process at a certain point of its work area. In order to do so the dynamics of the system must be decomposed (or divided) into local work areas (local models) for which it is possible to establish functions describing system dynamics with acceptable accuracy. A global model of a non-linear system can therefore be obtained by an appropriate combination of local models, mostly linear ones [2].

A rather effective method of creating a local models network is incorporating it in the structure of an artificial fuzzy-neural network, on the basis of which the best local model can then be identified and chosen by an implemented switching system [1, 8].

Assuming that a non-linear system dynamics which shall be examined below has the form of:

$$y(t) = f(\boldsymbol{\psi}(t-1)) \tag{1}$$

where: y is the network output, $\boldsymbol{\psi}$ is an information vector then a decomposition of system dynamics into local work areas will produce local models f_i, where $i = 1,\ldots,T$. Local models are usually applied as linear models and, once linearization around a given work point has been performed, assume the form of:

$$\begin{aligned} f_i(\boldsymbol{\psi}(t-1)) \approx & -a_{i,1}y(t-1)-,\ \ldots,\ -a_{i,n_y}y(t-n_y) \\ & +b_{i,1}u(t-1)+,\ \ldots,\ +b_{i,n_u}u(t-n_u) \end{aligned} \tag{2}$$

The network output can be expressed as:

$$y(t) = \sum_{i=1}^{T} f_i(\boldsymbol{\psi}(t-1))\rho_i(\boldsymbol{\varphi}(t)) \tag{3}$$

Expression (3) defines a global combination of local models f_i. Value $\rho_i(\boldsymbol{\varphi})$ means the degree of activation of the i-th rule, expression $\mu_i(\boldsymbol{\varphi})$ means membership functions. Gaussian membership functions were used for needs of this paper.

Similarly, based on the above description of the concept and of the mode of operation of local model networks, one can create a TSK-type local model network. A TSK network is an instance of a local model network which is unique in that its consequences are not fuzzy sets but determining functions, also referred to as linear consequences. A TSK network can be illustrated as a multi-model system made up of a number of rules, each rule containing a consequence corresponding to a single model [3]. Figure 2 shows a structure of a TSK-type local model network.

There are five layers that can be distinguished in the structure presented in Figure 2:

– layer 1, which fuzzes each input variable,
– layer 2, which computes levels of activation of individual rules,

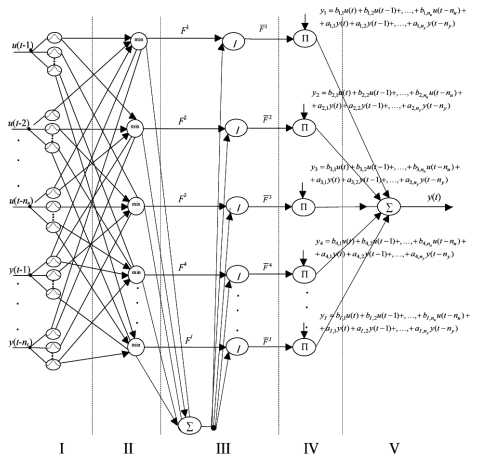

Fig. 2. Structure of a TSK-type local model network [2]

– layer 3, which is responsible for the standardization of activation levels,
– layer 4, which computes output signals for each rule based on:

$$y_i = \rho_i(\boldsymbol{\varphi}) f_i \tag{4}$$

– layer 5, which sums up output signals for all rules.

An unquestionable advantage of fuzzy TSK models is that they allow introducing formal knowledge on the structure of the object which is being modeled to the function of the consequences [6].

4. A method of determining and optimizing TSK-type local model fuzzy-neural networks

The proposed method of determining an optimal structure of local model networks can be divided into two major parts – one establishing the parameters of the consequences (the learning part), and the other computing outputs from the network (the modeling part). The structure of the networks under construction will correspond to the one presented in Figure 2, with consequences having the form of (2) and the input structure same as that in NARX models (Nonlinear Auto-Regressive models with eXogenous input). An 'each-to-each' connection between layer 1 and 2 shown in Figure 2 is used.

The algorithm proposes that the initial input space be uniformly divided relative to the number of initial areas defined for all network inputs by the operator. Also, the manner of determining parameters of the consequences has been altered by application of the Least Squares Method, where the way of establishing project matrixes X described in [2] has been modified.

The operation of the algorithm can be best presented by means of the following steps:

step 1: identification of the number of inputs into the network, the number of initial membership functions for these inputs, and the error e;

step 2: creating the structure of the network, as shown in Figure 2, determining activation degrees based on:

$$F^i(\mathbf{x}(t)) = \min\{\mu_{A_1^i}(x_1(t)),\ \mu_{A_2^i}(x_2(t)),\ \ldots,\ \mu_{A_m^i}(x_m(t))\} \tag{5}$$

where: $\mathbf{x}$ means an extended input vector estimation of the parameters of the consequences for the rules in accordance with [4].

step 3: identifying outputs from $y(t)$ network, (a mean squared error J_{LSM}) for the obtained structure; if $J_{LSM} > e$ go to **Step 4**, otherwise THE END.

step 4: looking for a rule with the largest index (6) value by arranging index values in an order from the largest to smallest one:

$$J(\boldsymbol{\theta}_i) = \sum_{t=1}^{L} \bar{F}^i(\mathbf{x}(t)) \left[y_r(t) - y_i(x(t))\right]^2 \tag{6}$$

where: $y_r(t)$ – the desired output, $\bar{F}^i(\mathrm{x(t)})$ – a standardized degree of activation of an i-th rule at the moment t can be expressed as:

$$\bar{F}^i(\mathbf{x}(t)) = \frac{F^i(\mathbf{x}(t))}{\sum_{j=1}^{I} F^j(\mathbf{x}(t))},\ \text{with } i = 1,\ \ldots,\ I \tag{7}$$

All membership functions found within each rule arranged based on the index value $J(\boldsymbol{\theta}_i)$ are then divided. The areas are divided axially into halves.

step 5: choosing a structure with the smallest mean squared error and checking if the stopping criterion $J_{LSM} > e$. If so, than this means THE END, if not, proceed to check whether $J_{LSM} < J_{LSP}$ (J_{LSP} is the criterion for the initial structure). If so, go to **Step 2**, if not, this means THE END.

See Figure 3 for a schematic presentation of the operation of the algorithm.

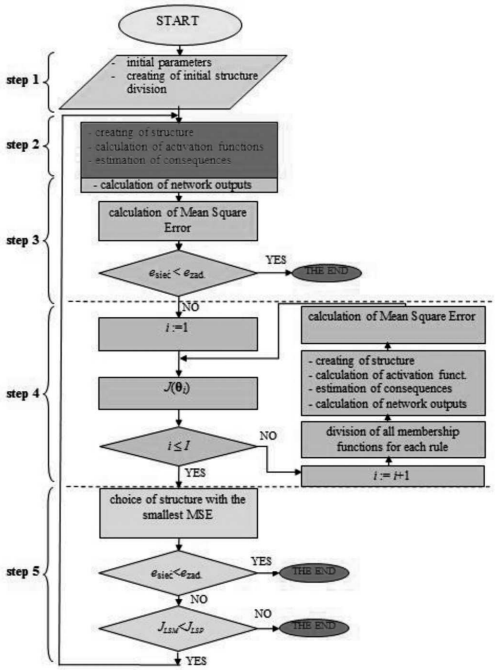

Fig. 3. A schematic diagram of the operation of the algorithm

This algorithm structure is to assure an optimal and faster than usual determination of local models defined by initial division for certain nonlinearities of the process under investigation. In the proposed algorithm, the division of input space begins with a uniform division (at least two membership functions for each input). By means of index $J(\boldsymbol{\theta}_i)$ indication, the

algorithm is capable of choosing 'the path' of further division and of optimizing the structure, which assures quicker convergence in finding the best possible structure.

An alternative though unverified way of improving the algorithm while searching for an optimal network could be the introduction of a memory with $J(\boldsymbol{\theta}_i)$ index values, a method which would allow returning to the structure with a smaller mean squared error and expanding the network in another direction whenever undesirable convergence occurred during subsequent network divisions.

5. Results of simulation tests

Figure 4 shows a progression of the machining force without and with self-induced vibrations acting on the machined object along the feed axis, y. The parameters of the machining operation for which the simulation was performed are: the feed of the machined object: 0.1 mm/s, machining depth: 0.1 mm, number of cutting blades: 4, rotational speed of the cutting tool: 112 rev./min.

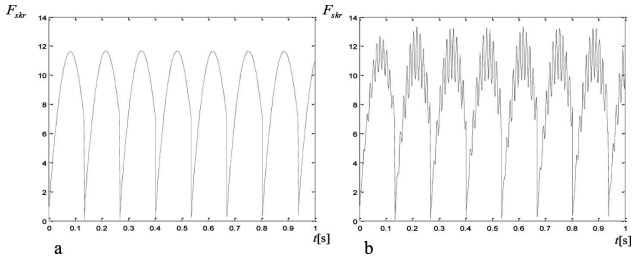

Fig. 4. The impact of the machining forces on the object: (a) without self-induced vibrations, (b) with self-induced vibrations

Two tests of network structure were run, both covering the initial 0 – 0.3 s of the force progression. The initial structure that was tested first contained four regressors: $u(t)$, $u(t\text{-}1)$, $y(t\text{-}1)$, $y(t\text{-}2)$, and eight membership functions, two for each of the regressors. An error that allowed concluding that a sufficient accuracy was obtained was MSE (Mean Squared Error) ≤ 0.5.

The other test yielded results for an initial structure with five regressors and initial parameters which were similar to those in the first test. In tables with subsequent tests it was assumed that a test number signifies each new beginning of determination of structure division with new initial parameters, while an iteration number presents the initial structure division and the best division obtained in the course of algorithm operation. The learning time is the time from the beginning of operation of the algorithm for the initial network to the moment when determination of a network with best structure division has been completed.

With test 1 completed, the algorithm computed the best structure in iteration 3. Initial progression paths along with the division of the structure are presented in Figure 5a. Based on test 1 results, iteration 1, (MSE), it would seem that further expansion of the network should improve the quality of the obtained output signal even more. Yet it was not the case. What caused that situation was the inability of the network to model the progression due to an insufficient number of input signals and, by the same token, an inadequate number of rules in the structure.

TABLE 1
Summary of results obtained for two modeling structures from 0 to 0,3[s]

Test No	Iteration No	Qty of inputs	Qty of membership functions for the signals						MSE	Learning time [s]
			$u(t)$	$u(t\text{-}1)$	$u(t\text{-}2)$	$u(t\text{-}3)$	$y(t\text{-}1)$	$y(t\text{-}2)$		
1	1	4	2	2	-	-	2	2	1.82	165
	3	4	2	3	-	-	3	2	1.20	
2	1	5	2	2	2	2	2	-	2.61	1718
	6	5	2	2	2	2	3	-	0.28	

It was decided therefore that the number of inputs into the network be increased and tests be re-run. Initially, test 2, iteration 1, yielded unsatisfactory results, but the algorithm continued to expand the structure and in iteration 6 it determined a network with the smallest MSE. Progressions received are shown in Figure 5b.

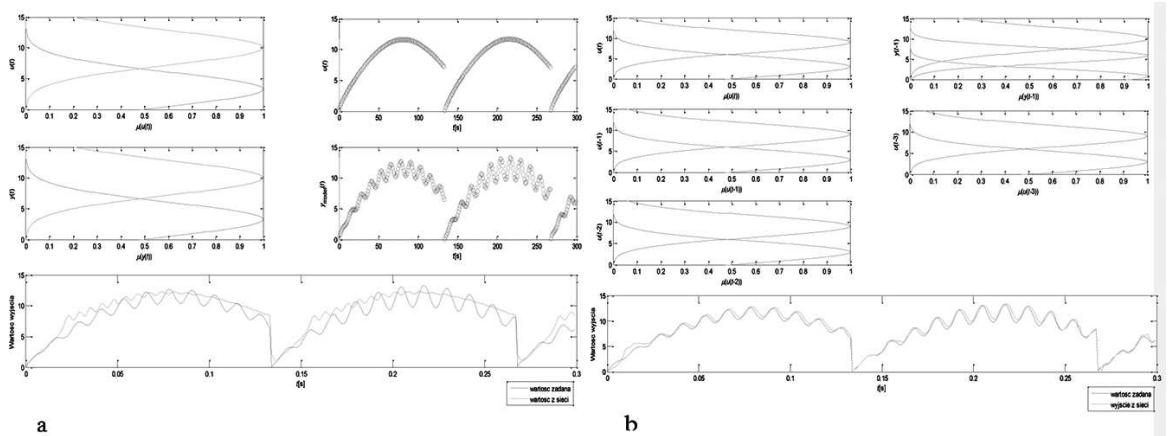

Fig. 5. (a) Initial division of the structure, including an expected progression and a progression actually received from the network, test 1, iteration 1; (b) Divisions of membership functions, including an expected progression and a progression actually received from the network, test 2, iteration 6

As can be seen in Figure 5b, the result obtained for this particular structure division matched the expectations. Of course, increasing the number of inputs contributed to the lengthening of time required to determine the best possible network, but taking into account the actual results the extended duration should be viewed as acceptable.

6. Conclusion

Based on the above results, it can be concluded that the proposed algorithm successfully determines appropriate structures of local model fuzzy-neural networks which model the progression of self-induced vibrations. Furthermore, it can also be maintained that models of self-induced vibration processes so generated will be able to be used in further research into the construction of a system eliminating self-induced vibrations that occur during the machining operation.

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