Viharos, Zs. J.; Monostori, L.; Automatic input-output configuration of ANN-based process models and its application in machining, *Lecture Notes of Artificial Intelligence,* LNAI 1611, *Multiple Approaches to Intelligent Systems*, Cairo, Egypt, May 31-June 3, 1999, *Springer Computer Science Book, Springer-Verlag Heidelberg*, pp. 659-668.

Automatic input-output configuration and generation of ANN-based process models and their application in machining

Zs. J. VIHAROS; L. MONOSTORI

Computer and Automation Research Institute, Hungarian Academy of Sciences
Kende u. 13-17,H-1111 Budapest, Hungary, Tel.: (+36 1) 4665644, Fax: (+36 1) 4667503
viharos@sztaki.hu, monostor@sztaki.hu

Abstract

Reliable process models are extremely important in different fields of computer integrated manufacturing. They are required e.g. for selecting optimal parameters during process planning, for designing and implementing adaptive control systems or model based monitoring algorithms. Because of their model free estimation, uncertainty handling and learning abilities, artificial neural networks (ANNs) are frequently used for modelling of machining processes. Outlying the multidimensional and non-linear nature of the problem and the fact that closely related assignments require different model settings, the paper addresses the problem of automatic input-output configuration and generation of ANN-based process models with special emphasis on modelling of production chains. Combined use of sequential forward search, ANN learning and simulated annealing is proposed for determination and application of general process models which are expected to comply with the accuracy requirements of different assignments. The applicability of the elaborated techniques is illustrated through results of experiments.

Introduction

Modelling methods can be used in several fields of production e.g. in planning, optimisation or control. The production in our days incorporates several stages, the workpiece goes through a number of operations (Fig. 1.).

The output of one operation is the input of an another one or it is a feature of the end product. To build a model for a production chain, models have to be ordered to every stage of production. A chain of operations connected by their input-output parameters can model the sequence of production operations.

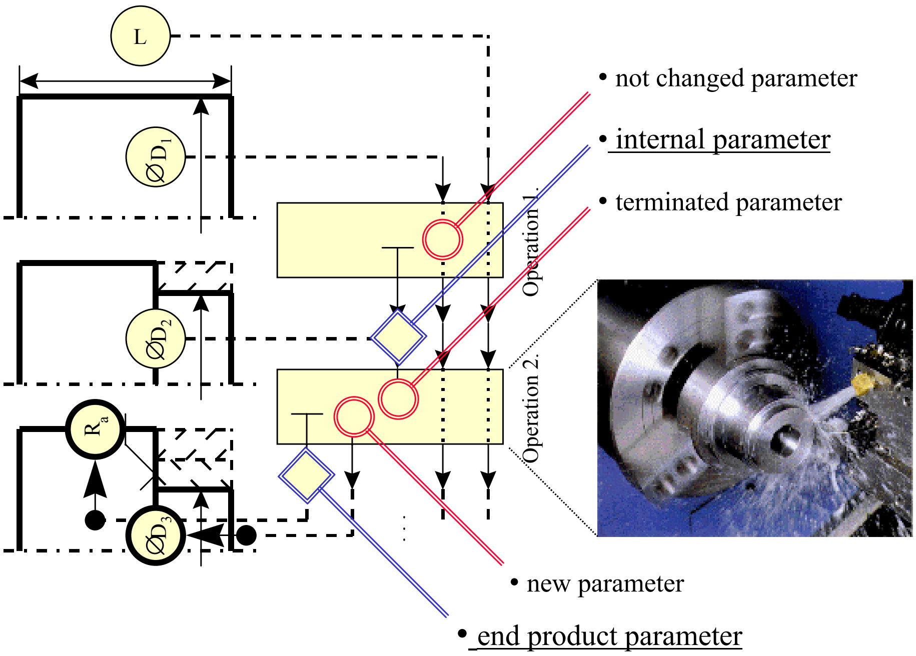
Operations have several input- and output parameters and dependencies among them are usually non-linear, consequently, the related model has to handle multidimensionality and non-linearity.

Artificial neural networks (ANNs) can be used as operation models because they can handle strong non-linearites, large number of parameters, missing information. Based on their inherent learning capabilities, ANNs can adapt themselves to changes in the production environment and can be used also in case there is no exact knowledge about the relationships among the various parameters of manufacturing.

Some error is usually incorporated into modelling of real processes, the model estimates its output variables only with a limited accuracy. The error by the output side of an operation model in the production chain depends on its own error and the error incorporated into the input variables of the model. These input variables are usually output parameters from previous operations. Consequently, model errors can be summed up and, therefore, the accuracy of the individual models is a crucial factor in the modelling of production chains.

A lot of effort has been made to apply ANNs for modelling manufacturing operations 00. The assignments to be performed determined the input-output configurations of the models, i.e. the parameters to be considered as inputs and the ones as outputs.

Considering the input and output variables of a given task together as a set of parameters, the ANN model estimates a part of this parameter set based on the remaining part. This partitioning strongly influences the accuracy of the developed model especially if dependencies between parameters are non-invertable. In different stages of production (e.g. in planning, optimisation or control) tasks are different, consequently, the estimation capabilities of the related applied models are different even if the same set of parameters is used.



Connections of the operations of the production chain through workpiece parameters. Stages of material removal from an axle, the related operations in the middle and the related parameter stream of the workpiece along the production chain are illustrated from left to right 0. **Fig. 1.**

One of the main goals of the research to be reported here was to find a general model for a set of assignments, which can satisfy the accuracy requirements. Research was also focused on how to apply the general model for various tasks.

Accordingly, the structure of the paper is as follows:

- Section 2 gives a short survey of approaches to modelling and monitoring of machining processes.
- In Section 3 the proposed method for automatic generation of ANN-based process models is described which are expected to be applicable for different assignments.
- The application phase of the general process model is detailed in Section 4. A novel technique based on simulated annealing search is introduced to find the unknown parameters of the model in given situations. The results of experimental runs justify the approach.
- Conclusion and further research issues are presented in paragraph 5.

ANN based approaches to modelling and monitoring of machining processes

Several approaches can be found in the literature to represent the knowledge of manufacturing operations 0000. The aim of this paragraph is to show the large variety of tasks and related input-output configurations of ANNs.

An interesting example is presented by Knapp & Wong 0 who used ANNs in planning.

ANN is also used for ordering of resources to workcenters 0.

Cutting tool selection is realised by Dini 0.

To generate an optimum set of process parameters at the design state of injection molding, Choi *et al.* use an ANN model 0.

The compensation of thermal distortion was the goal of Hatamura *et al* 0.

A fuzzy neural network is used for cutting tool monitoring by Li & Elbestawi 0. Optimisation and search for input variables are presented in the work by Rangwala & Dornfeld 0.

Monostori described models to estimate and classify tool wear 0. The paper presents different input-output configurations of ANN models according to various tasks.

A model building for creep feed grinding of aluminium with diamond wheels is presented by Liao & Chen 0. The paper also calls the attention to the problem that the measurement could not been satisfactory handled by the chosen ANN model realizing one to one mapping.

Automatic generation of ANN-based process models

The automatic generation of appropriate process models, i.e. models, which are expected to work with the required accuracy in different assignments, consists of the following steps:

- Determination of the (maximum) number of output parameters (No) from the available N parameters which can be estimated using the remaining Ni = N - No input parameters within the prescribed accuracy.
- Ordering of the available parameters into input and output parameter sets having Ni and No elements, respectively.
- Training the network whose input-output configuration has been determined in the preceding steps.

These steps can be formulated as follows. A search algorithm is needed to select all the possible outputs from the given set of parameters with regard to the accuracy demands. This algorithm results in a general ANN model, which realises mapping between the parameters of the given parameter set. The largest number of outputs can be found, the accuracy demands are satisfied and the ANN model is built up 0.

A general ANN model for drilling is shown in figure 2.

In the developed method the estimation error is used to evaluate an ANN configuration. This error assures the user that all of the outputs can be estimated within an average error given in advance.

Experimental results

To test the behaviour of the developed algorithm the case of non-invertable dependencies were investigated first ($x_2=x_1^2$, $x_3= x_1^2+ x_2^2$, $x_4= x_1^2+ x_2^2+ x_3^2$, sin(x)). Favourable results of these investigations promised real world applicability, too.

In the following space, results are presented with four engineering assignments where the required models work on the same parameter set but the feasible input-output configurations of these models are different.

1. The first task is planning. A surface has to be machined by turning to achieve roughness (parameter: R_a[mm]) demands of the customer. The engineer has to determine the tool (parameters: cutting edge angle: χ[rad], corner radius: r_ε[mm]), the cutting parameters (parameters: feed: f[mm/rev], depth of cut: a[mm], speed: v[m/min]) and predict phenomenon during cutting (parameters: force: F_c[N], power: P[kW] and tool life: T[min]) consequently a model is needed where R_a serves as input and other parameters as outputs. Usually, the customer gives only an upper limit for the roughness, in contrast to other parameters.
2. The second task is to satisfy the roughness demands of the customer but with a given tool. In this case the R_a, χ, r_ε are inputs and f, a, v, F_c, P, T are outputs.
3. The third task is to control the running cutting process with measured monitoring parameters such as force and power. Measured values of these parameters can be used as information about the current state of the cutting process. In this case R_a, χ, r_ε, F_c, P serve as input and f, a, v, T as outputs. The CNC controller has to select the appropriate cutting parameters to produce the requested surface.

4. The fourth task is the same as the third one but the CNC controller can change only the ‘f ‘and ‘a’ parameters because v is prescribed. This case needs a model with inputs R_a, χ, r_ε, F_c, P, v and with outputs f, a, v, T.

These assignments show several input-output configurations for modelling dependencies between the different elements of a parameter set. The question arises: which model describes the cutting process in the best way, i.e. with the highest accuracy? The heuristic search algorithm can answer this question.

In practical implementation sensors, machine controllers and computers would provide a part of parameters of an ANN operation model. For simulating the machining process in the investigations to be reported here all information were generated via theoretical models, which are functions of several input variables. It should be stressed that in a practical implementation theoretical models are not necessary. The validity of the equations is determined by the minimum and maximum boundaries of the parameters. Four equations are used in this paper for the above engineering tasks (force, power, tool life and roughness) 0.

$$F_c = 1560 \cdot f^{0.76} \cdot a^{0.98} \cdot (\sin(\kappa))^{-0.22}, P = 0.039 \cdot f^{0.79} \cdot a \cdot v \qquad (1)$$
$$T = 1.85 \cdot 10^{10} \cdot f^{-0.7} \cdot a^{-0.7} \cdot v^{-3.85}, R_a = 8.5 \cdot f^{1.8} \cdot a^{0.08} \cdot v^{-0.9} \cdot r_\varepsilon^{-0.5},$$

where the boundaries of the equations are as follows:

$$f: 0.1 \cdots 0.4[mm/rev], a: 1 \cdots 4[mm], \kappa: 1.3 \cdots 1.66[rad], v: 75 \cdots 200[m/\min], \qquad (2)$$
$$r_\varepsilon: 0.4 \cdots 1.2[mm], T: 5 \cdots 60[\min], \text{consequently}, Fc \approx: 800 \cdots 3000[N],$$
$$P \approx: 3.8 \cdots 13.5[kW], R_a \approx: 0.0015 \cdots 0.023[mm]$$

To create learning and testing parameter sets random values were determined in the allowed range of f, a, χ, v, r_ε considering also the boundaries of T and R_a, Fc, P, T while calculating their values using the above equations. The dependencies between parameters f, a, χ, v, r_ε, Fc, P, T, R_a were experienced as invertable in the given parameter range only the variable χ is the exception, consequently, to get an accurate ANN model the variable χ has to be always input. A hundred data vectors were created as stated above. To test this type of problems the described input-output configuration and model building approach were repeated a hundred times. Several variations of input-output configurations were generated. The allowed average estimation error was given as ±2.5%. Fifteen different ANN configurations were generated as results 0. The variable χ is always on the input size of the ANN model as expected.

The test all of the configurations shows that there are no significant differences among their estimation capabilities.

The results indicate that the developed technique is able to generate process models with the required accuracy, moreover, under given circumstances a result is a set of applicable models each guaranteeing the required accuracy performance.

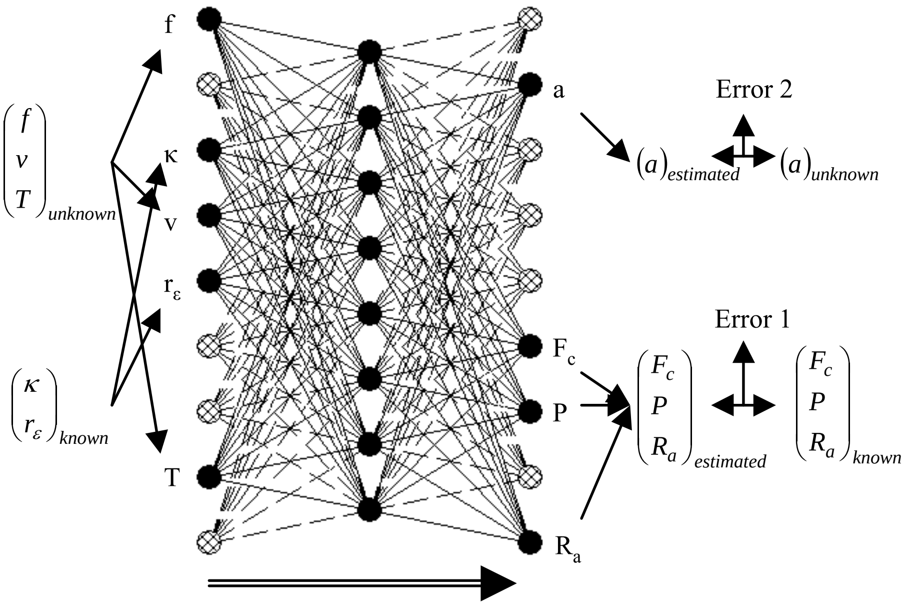
Satisfying various assignments with the general model

Some parameters of a process are usually known by the user and modelling is expected to determine the other parameters while satisfying some constraints. In the previous paragraph a search method was introduced to select a general ANN model which is accurate enough and can be used for different assignments. Consequently, in almost every case a part of input and a part of output variables of the general model are known by the user and the task of the modelling is to search for the remaining, unknown input and output parameters like in the engineering tasks presented before (Fig. 2.). A search method can solve this task. The search space consists of unknown input parameters. The task for the search method can be formulated as follows: It has to find the unknown input parameters but at the same time it satisfy three conditions (Fig. 2.):

1. One point of the search space can be represented by one possible value set of the unknown input parameters. After placing these parameters together with the known input parameters to the input side of the given ANN an output vector can be calculated by the ANN estimation (forward calculation). The first condition assures that only that points of the search space can be accepted as result, which can adequately estimate the known output parameters by using forward calculation. To measure the deviation between estimated and known output parameters an error can be calculated. For the search algorithm the user can prescribe upper limit for this error.
2. The second condition for the unknown input parameters is determined by the validity of the ANN model. This validity is usually specified by the data set used for the training 0. Boundaries of the model can be handled by minimum and maximum values of the related parameters like in the engineering tasks presented above. This means that the search algorithm can take values for the unknown input parameters only from the related allowed intervals.
3. The third condition relates also to the validity of the ANN. These boundaries come forward by that part of the estimated output vector, which is unknown by the user. Because of the limited validity of the ANN model there are also boundaries for parameters of this part of the estimated output vector. Values of the unknown input parameters are only acceptable if the estimated values of the unknown output parameters are within their allowed range. To measure this condition an error can be calculated for that unknown output parameters which estimated values are out of their boundaries. For the search algorithm the user can prescribe an upper limit also for this type of error.

The search algorithm is terminated if all of the three conditions above are met. Simulated annealing has been selected as search method 0. In the simulated annealing search an error value is ordered to all points of the search space. In the developed algorithm this value is the maximum of error1 and error2 presented above. The algorithm searches for the minimum error point.

The simulated annealing technique has a special parameter, the temperature, which decreases during the search algorithm. The algorithm discovers the search space by repeated change from the current point into a neighbour point. A probability value is used to evaluate a neighbour incorporating information about the error difference between the neighbour and the current point and about the current temperature. The algorithm stops if no neighbour can be selected and the current error value is below the prescribed error limit. This simulated annealing algorithm works on the discrete points of the search space. To realise this, the parameters of unknown part of the input vector consist of the discrete points of the related intervals. The distance between two points of an interval is chosen to satisfy the accuracy requirements of the estimation prescribed by the user.



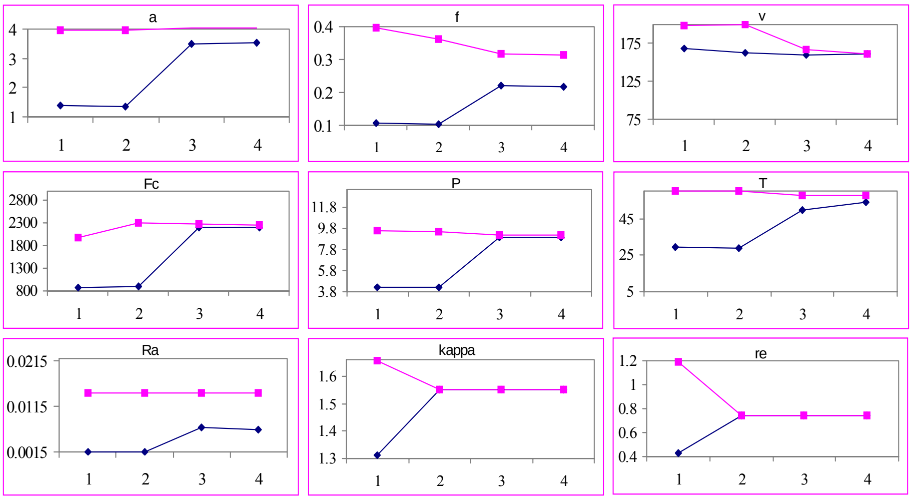
The simulated annealing search is used to satisfy various tasks of the user without regard to the given ANN configuration. Error 2 is used to hold the search between the boundaries of the ANN model, while error 1 measures the distance between estimated and known outputs. The search space consists of unknown input parameters, the evaluation of one point based on the maximum of error 1 and error 2. The developed algorithm searches for the minimum error value. This picture shows the third engineering task presented above. **Fig. 2.**

As a result, this algorithm gives one solution for a given assignment of the user. To look for a larger number of solutions the search has to be repeated.

Results of the simulated annealing search

Tests of the non-invertable dependencies enumerated above show the applicability of this search algorithm.

The results of the four engineering assignments presented in the paper are also worth mentioning. There are a large number of solutions for each of the enumerated assignments. To represent the whole interval of solutions for each parameter the search algorithm was repeated a hundred times at each assignment. To get a simple view about the possible solution field the maximum and minimum values of the results were selected for all parameters, for each task. These parameter fields are listed in Figure 3. Results in this table show the descending interval of acceptable parameters from the planning phase to the CNC control. The requested value of parameter R_a is special because the user gives only upper limit for this parameter. In the assignments the allowed highest value for the roughness of the produced surface is 0.014 mm. The tool used for cutting is determined in the second task, values of related parameters are χ=1.549 rad, r_ε=0.7394 mm. In monitoring, measured values of force and power were Fc=2247N and P=8.69kW, respectively. In the fourth engineering task the prescribed speed value was v=161 m/min. In every case the task of the modelling was to satisfy the roughness demand of the user through choosing appropriate values of related parameters.



Descending intervals of allowed parameter fields in cutting in the four engineering tasks presented above. The horizontal axis represents the number of the given tasks.
Fig. 3.

By every case from planning to CNC control one or more new parameter(s) becomes to be restricted to one value.

Results show that by the first planning task a large field of parameters can be chosen to satisfy the user demands. Using the given tool in the second task possible fields of intervals are only a bit smaller. The intervals in the third task, in monitoring the cutting process with measured parameters, are much smaller. In the fourth task when the speed is prescribed allowed intervals become even more smaller. It should be stressed that these results were received with only one ANN model with the same input-output configuration and using the developed simulated annealing search method, indicating the acceptability of the techniques presented here. The developed sequential forward selection algorithm determined the appropriate input-output configuration automatically, showing that the realisation of the new concept works adequately.

Conclusions and further research issues

Outlying the importance of accurate process models in the control of production chains, generation and application of ANN-based process models were addressed in the paper with special emphasis on the automatic input-output configuration of general process models which are expected to satisfy the accuracy requirements of a set of related modelling assignments. Combined use of sequential forward search, ANN learning and simulated annealing is proposed. The applicability of the elaborated techniques was illustrated through results of experiments.

Several steps of the new model are to improve further. Some of them are:

- By searching the appropriate input-output configuration a method could be useful which prunes the variables which are not important for output estimations.
- By searching the unknown variables an optimisation is to be included in the method like in the paper of Rangwala & Dornfeld 0., e.g. cost minimisation, manufacturing time minimization, etc. This is important only if there are more solutions for the given task.

The above improvements will be subject of future publications.

Acknowledgement

This work was partially supported by *National Research Foundation,* Hungary, Grant No. F026326 and T026486. A part of the work was covered by the Nat. Comm. for Techn. Dev., Hungary Grants (EU-96-B4-025 and EU-97-A3-099) promoting Hungarian research activity related to the ESPRIT LTR Working Groups (IiMB 21108 and IMS 21995).

Literature

[1] Choi, G.H.; Lee, K.D.; Chang, N.; Kim, S.G., 1994, Optimization of the process parameters of injection molding with neural network application in a process simulation environment, CIRP Annals, Vol. 43/1, pp. 449-452.

[2] Chryssolouris, G.; Lee, M.; Pierce, J.; Domroese, M., 1990, Use of neural networks for the design of manufacturing systems, Manufacturing Review, Vol. 3, No. 3, pp. 57-63.

[3] Devijver, P. A.; Kittler, J.; Pattern recognition, a statistical approach. Book. Prentice-Hall International Inc., England, London, 1982,

[4] Dini, G., 1995, A neural approach to the automated selection of tools in turning, Proc. of 2nd AITEM Conf., Padova, Sept. 18-20, pp. 1-10.

[5] Hatamura, Y.; Nagao, T.; Mitsuishi, M.; Kato, K.I.; Taguchi, S.; Okumura, T.; Nakagawa, G.; Sugishita, H., 1993, Development of an intelligent machining center incorporating active compensation for thermal distortion, CIRP Annals, Vol. 42/1, pp. 549-552.

[6] Kis, T.; Introduction into artificial intelligence (in Hungarian). Book. AULA Press, Budapest, Edited by I. Futó, 1999.

[7] Knapp, G.M.; Wang, Hsu-Pin, 1992, Acquiring, storing and utilizing process planning knowledge using neural networks, J. of Intelligent Manufacturing, Vol. 3, pp. 333-344.

[8] Krupp, F. Gmbh; Widia-Richtwerte für das drehen von Eisenwerkstoffen. Book. Fried. Krupp Gmbh., Germany, Essen, 1985.
[9] Li, S.; Elbestawi, M.A., 1996, Fuzzy clustering for automated tool condition monitoring in machining, J. of Mechanical Systems and Signal Processing, pp. 321-335.
[10] Liao, T.W.; Chen, L.J., 1994, A neural network approach for grinding processes: modeling and optimization, Int. J. Mach. Tools Manufact., Vol. 34, No. 7, pp. 919-937.
[11] Markos, S.; Viharos, Zs. J.; Monostori, L.; Quality-oriented, comprehensive modelling of machining processes. Proc. of 6th ISMQC IMEKO Symposium on Metrology for Quality Control in Production, September 8-10, 1998, Vienna, Austria, pp. 67-74.
[12] Monostori, L., 1993, A step towards intelligent manufacturing: Modeling and monitoring of manufacturing processes through artificial neural networks, CIRP Annals, 42, No. 1, pp. 485-488.
[13] Monostori, L.; Barschdorff, D., 1992, Artificial neural networks in intelligent manufacturing, *Robotics and Computer-Integrated Manufacturing*, Vol. 9, No. 6, Pergamon Press, pp. 421-437.
[14] Monostori, L.; Egresits Cs.; Kádár B., 1996, Hybrid AI solutions and their application in manufacturing, Proc. of IEA/AIE-96, The Ninth Int. Conf. on Industrial & Engineering Applications of Artificial Intelligence & Expert Systems, June 4-7, 1996, Fukuoka, Japan, Gordon and Breach Publishers, pp. 469-478.
[15] Monostori, L.; Márkus, A.; Van Brussel, H.; Westkämper, E., 1996, Machine learning approaches to manufacturing, CIRP Annals, Vol. 45, No. 2, pp. 675-712.
[16] Monostori, L; Egresits, Cs; Hornyák, J; Viharos, Zs. J.; Soft computing and hybrid AI approaches to intelligent manufacturing. Proc. of 11th International Conference on Industrial & Engineering Applications of Artificial Intelligence & Expert Systems, Castellon, 1998, pp. 763-774
[17] Rangwala, S.S.; Dornfeld, D.A., 1989, Learning and optimization of machining operations using computing abilities of neural networks, IEEE Trans. on SMC, Vol. 19, No. 2, March/April, pp. 299-314.
[18] Salomon, R; Hemmen, L; Accelerating backpropagation through dynamic self-adaptation. Journal of Neural Networks, Great Britain, 1996. pp. 589-601.
[19] Tang, Z.; Koehler, G. J.; Deterministic global optimal FFN training algorithms. Journal of Neural Networks, Great Britain, 1994. pp. 301-311.
[20] Tarng, Y.S.; Ma, S.C.; Chung, L.K., 1995, Determination of optimal cutting parameters in wire electrical discharge machining, Int. J. Mach. Tools Manufact., Vol. 35, No.12, pp. 1693-1701.
[21] Tollerane, B.; SuperSAB: fast adaptive back propagation with good scaling properties, *Neural Networks*, Vol. 3, pp. 561-573.
[22] Viharos, Zs. J.; Monostori, L.; Markos, S; Selection of input and output variables of ANN based modeling of cutting processes. Proceedings of the X. Workshop on Supervising and Diagnostics of Machining Systems of CIRP, Poland, 1999 (under appear)
[23] Viharos, Zs. J.; Monostori, L.; Optimization of process chains by artificial neural networks and genetic algorithms using quality control charts. Proc. of Danube - Adria Association for Automation and Metrology, Dubrovnik,1997. pp. 353-354
[24] Volper, D. J.; Hampson, S. E.; Quadratic function nodes: use, structure and training. Journal of Neural Networks, Great Britain, 1990. pp. 93-107.