SELECTION OF OPTIMAL CUTTING CONDITIONS BY USING GONNS

*I.N. Tansel[1], B. Ozcelik[2], W.Y. Bao[1], P. Chen[1], D. Rincon[1], S.Y. Yang[1], A. Yenilmez[3]

[1] Mechanical Engineering Department
Florida International University
10555 West Flagler Street, (EAS-3473)
Miami, FL 33174

[2] Department of Design and Manufacturing Engineering
Gebze Institute of Technology,
41400 Gebze, Kocaeli, Turkey

[3] Faculty of Mechanical Engineering
Istanbul Technical University,
Gumussuyu, 34439 Istanbul, Turkey

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ABSTRACT. Machining conditions are optimized to minimize the production cost in conventional manufacturing. In specialized manufacturing applications, such as micro machining and mold making, achievement of specific goals may be the primary objective. The Genetically Optimized Neural Network System (GONNS) is proposed for the selection of optimal cutting conditions from the experimental data when analytical or empirical mathematical models are not available. GONNS use Backpropagation (BP) type neural networks (NN) to represent the input and output relations of the considered system. Genetic Algorithm (GA) obtains the optimal operational condition by using the NNs. In this study, multiple NNs represented the relationship between the cutting conditions and machining related variables. Performance of the GONNS was tested in two case studies. Optimal operating conditions were found in the first case study to keep the cutting forces in the desired range while a merit criterion (metal removal rate) was maximized in micro-end-milling. Optimal operating conditions were calculated in the second case study to obtain the best possible compromise between the roughness of machined mold surfaces and the duration of finishing cut. To train the NNs 81 mold parts were machined at different cutting conditions and inspected.

*Please use the following address for communications:

I.N. Tansel*, Mechanical Engineering Department, Florida International University
10555 West Flagler Street, (EAS-3473), Miami, FL 33174
E-Mail: tanseli@fiu.edu

I. INTRODUCTION

The objective is the minimization of the product cost in conventional manufacturing. However, during the manufacturing of precision parts the achievement of very high quality standards becomes the primary objective. Avoidance of premature tool breakage and creation of very smooth surfaces are the primary concerns in micro machining and mold making, respectively. Most of the time, it is very difficult to find the related analytical or empirical expressions and proper coefficients to calculate the optimal operating conditions for the considered material and tool. The Genetically Optimized Neural Network System (GONNS) is proposed to represent the relationship between the operating conditions and the cutting related variables by using neural networks (NN) and to determine the optimal machining parameters by using the Genetic Algorithm (GA) with minimal human interference.

GAs have been widely used for the selection of the operating conditions in machining operations [1-22]. To simplify the modeling, simulated annealing [23-24], fuzzy logic [25-26], and NNs [27-33] have been used with the GAs. The GA finds the optimal solutions quickly when the analytical or empirical models are available. However, the development of models and the creation of large databases for each material and tool combination is time consuming and costly. GONNS have its own modeling and optimization tool to model the system from experimental data and to obtain the optimal operating conditions.

GONNS [31-33] use multiple Backpropagation (BP) type NN [34-37] to represent the characteristics of a system. For each output such as cutting force, metal removal rate, surface roughness, and machining time, one NN is used to achieve the best possible accuracy. Multiple NNs and a GA [38-41] are located in a cluster. The GA finds the optimal machining parameters of this complex system by adjusting the values of the selected inputs of the NNs [34] by following an efficient procedure that mimics nature. If necessary, multiple clusters are used to represent different environments such as different types of machine tools. The number of GAs is equal to the number of clusters.

The handbooks [42] and conventional optimization programs have been prepared by considering the widely used materials, tools, and operating conditions. They cannot be used if micro tools, complex tool paths of mold making, and exotic materials are involved. In this paper, the performance of the GONNS was evaluated in two case studies, which involve micro tools and mold making.

In micro-end-milling operations, the tool life is very short and unpredictable compared to the conventional machining. Many manufacturers change these tiny tools according to a very conservative schedule to avoid tool breakage until the machining of each part is completed. The premature tool breakage can be avoided if the feed direction cutting force is kept below an experimentally determined limit. In this study, machining parameters were selected to limit the feed direction cutting force and to maximize the metal removal rate.

In mold making, the creation of complex shapes with very smooth surface finish is required. The molds are generally prepared in two stages. In the first stage, sculptured or free form surfaces are preferably machined by using multi-axis (3 to 5 axis) milling machines. In the second stage, surfaces are manually polished. For precision and minimization of the polishing cost, the best possible surface finish should be obtained at the first stage without sacrificing the productivity [43]. In this study, operating conditions were selected to minimize the machining time while the surface roughness was kept at the desired level.

The theoretical background of the components of GONNS will be introduced briefly in the next section. Implementation of the GONNS in machining, experimental setups, results and conclusion will follow.

II. THEORETICAL BACKGROUND

BP [34-37] is one of the basic and most frequently used NNs. The user determines the number of inputs, outputs, hidden layers, and nodes of the hidden layers. In most applications, each node is connected to all the nodes of the next layer. The hidden and output layer nodes multiply the incoming values by weights and use a transfer function to determine their output. Sigmoid is the most commonly used transfer function. Linear, Gaussian, and various hyperbolic functions have also been used depending on the need. The network starts to process the incoming training signals with arbitrary weights. The error is calculated by comparing the output of the network with the corresponding values in the training file. All the weights are adjusted by back-propagating the errors through the network at each interaction. This process is repeated many times until the network's output errors are reduced to an acceptable level. The user selects the learning rate and the momentum to control the speed and the stability of the network.

GA uses the biological evolution principles including natural selection, and survival of the fittest [38-41]. The user determines the number of the binary digits to be assigned for each parameter and their boundaries. Additional bits can be assigned for switches. All the parameters and the switches are represented with a chromosome. The algorithm tries to find the best 0 and 1 combination of this string either to minimize or to maximize the objective function. The penalty functions might be used to force some of the parameters to stay in the selected range. The user generally selects the population size, the number of children for each set of the parents, and the probability of mutation. The chromosomes are generated randomly for the first generation. Generally, GAs follow a five-step optimization procedure which includes: (1) selection of the mating parents; (2) selection of the hereditary chromosomes from the parents; (3) gene crossover; (4) gene mutation, and (5) creation of the next generation.

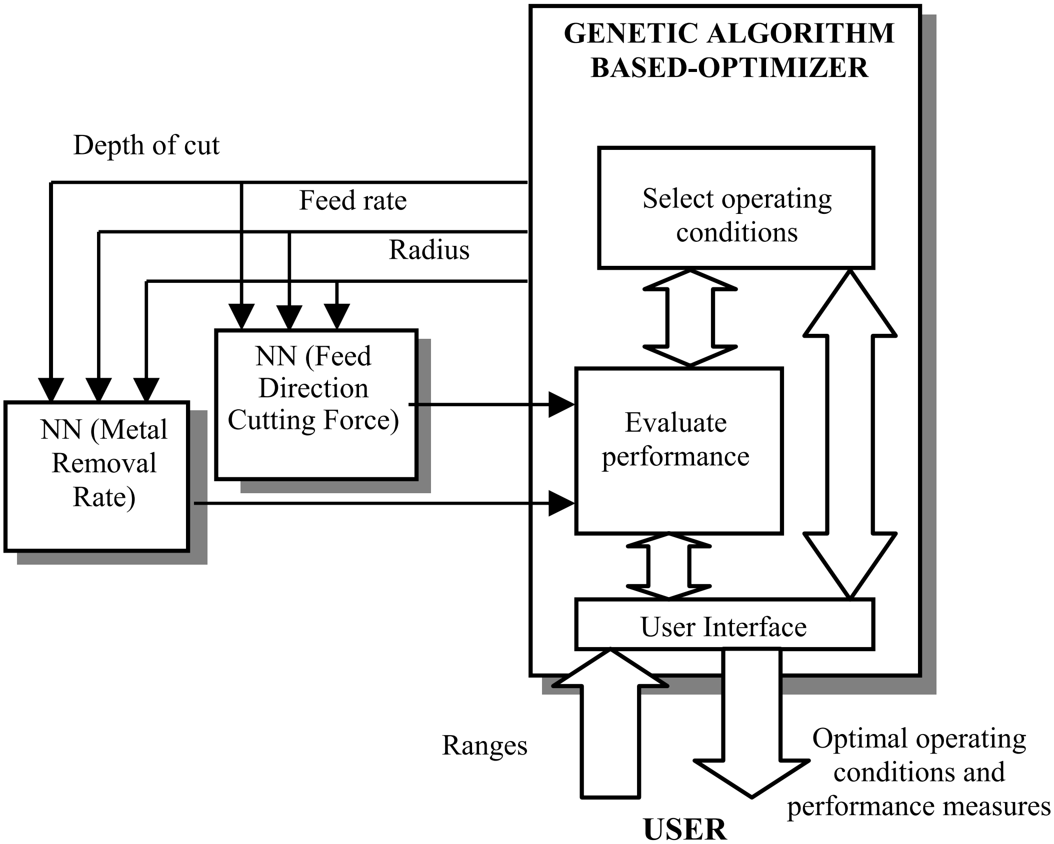
The cutting forces of the micro-end-milling operations can be estimated by using analytical expressions [44]. In this study, the NNs of the GONNS were used instead of the analytical expressions. The NNs are capable of representing the characteristics of many systems as long as proper training data is available.

III. PROPOSED OPTIMIZATION SYSTEM BASED ON THE GONNS

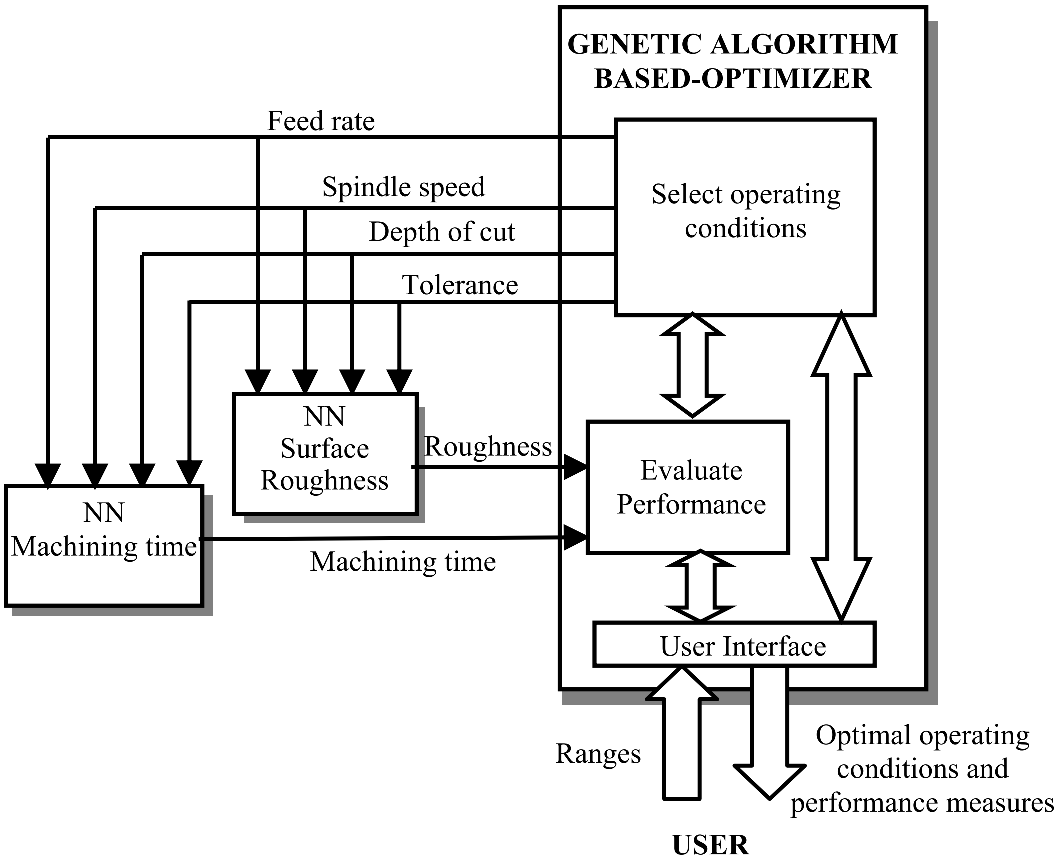
The same GONNS was used for both case studies in this paper after its architecture was slightly modified (Figure 1) by considering the problem. The GONNS used two BP type NNs and one GA in both case studies. Each NN had one output to have the best possible accuracy; however, the number of their inputs was different in the considered problems.

For micro-end-milling operations, the NNs were trained to estimate the maximum feed direction cutting force and the merit criteria (Figure 1a) by using the experimental data presented in Appendix 1 and calculated metal removal rate, respectively. The inputs of both NNs were the depth of the cut, feed rate and tool radius. The operator selected the tool radius according to the part geometry. The GA selected the optimal depth of the cut and feed rate to maximize the merit criteria which was the metal removal rate while the feed direction cutting force was selected below an experimentally obtained value to have the desired tool life.

In mold making, the surface finish at the critical locations is important. To obtain the desired surface characteristics and to keep the machining time within a reasonable range, two NNs and one GA was used (Figure 1b). The inputs of the NNs were the feed rate, spindle speed, radial depth of the cut and the tolerance. One NN was trained to estimate the surface roughness while the other one was trained to estimate the machining time by using the experimental results in Appendix 2. The GONNS estimated all the cutting parameters either to minimize the surface roughness or the machining time.



a) GONNS' architecture for the-end-milling operations.



b) GONNS' architecture for mold making.

Figure 1. The architecture of the proposed GONNS.

IV. EXPERIMENTAL SETUP AND DATA COLLECTION

Separate experimental set-ups were used for the case studies. A Fadal 3 CNC milling machine was used to obtain the micro-end-milling data in the first case study. A POCO 3 work piece was installed on a Kistler 9257B 3-component piezoelectric dynamometer to monitor the feed and thrust direction-cutting forces. Nicolet 310 and

Integra model 10 digital oscilloscopes were used to monitor and save the cutting force data.

In the second case study, the molds were machined by using the five axis Deckel Maho DMU 60 P high speed CNC milling machine with 12,000 rpm maximum spindle speed, and 10 m/min maximum feed rate. The machine had a 15 kW spindle motor and equipped with a 30 collet tool holder. CNC part programs were prepared by using ProENGINEER CAD/CAM software on a personal computer with Intel Pentium IV 2.0 GHZ processor. The workpiece was Aluminum 6061 (Figure 2). The surface roughness of the machined parts was measured by using Mitatoyu Surftest 301 portable surface roughness tester.

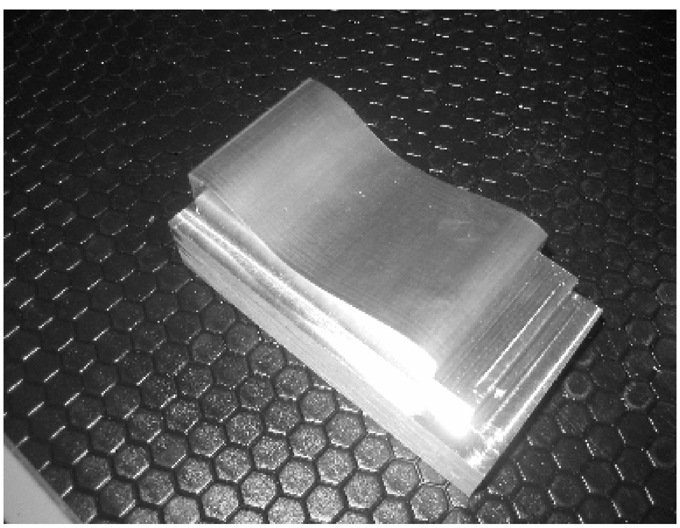


Figure 2. The completed part after the machining operation.

V. RESULTS AND DISCUSSION

The performance of the GONNS was evaluated previously by the same group [31] on a simulated system which was defined by two analytical expressions. Each one of these equations was represented by one BP type neural network. GONNS was asked to identify the function which gives the maximum and minimum values and the proper input values to obtain these results. GONNS identified the function accurately, and the estimation error was less than 2% of the range of the considered variable. When the maximization of the difference of these two functions was asked, the GONNS estimated the input parameters and the result with less than 2% and 3% accuracy respectively.

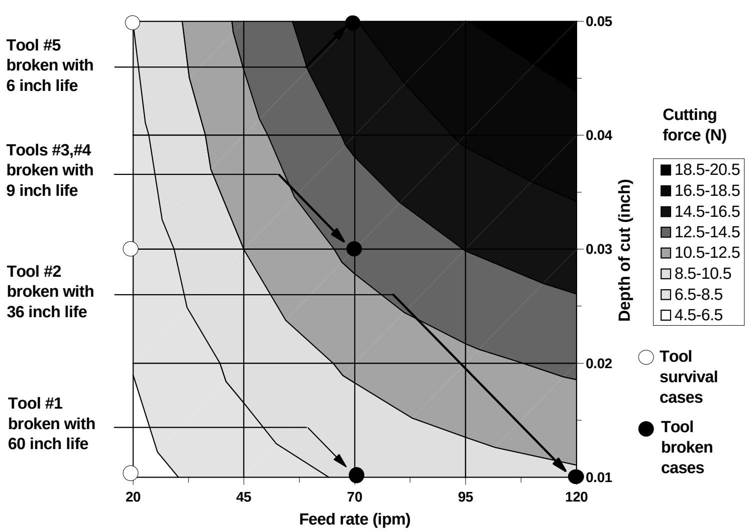
Performance of the GONNS was evaluated in two case studies by using the experimental data in this study. The optimal cutting conditions were obtained for micro-end-milling operations to maximize the metal removal rate while the feed direction cutting force was kept below a critical value to have the desired tool life. In the second case study, the cutting conditions were optimized to obtain the best possible compromise between the machining time and surface quality.

Case Study 1: Optimization of the machining parameters to avoid premature tool breakage:

Two-flute micro-end-mills with 0.020”, and 0.0625” diameter were used to machine the POCO-3 graphite workpiece. The spindle speed was 15,000 rpm and 50% overlapping climb milling operations were performed with both tools. The feed direction maximum cutting forces were found at 16 different cutting conditions and presented in Appendix 1.

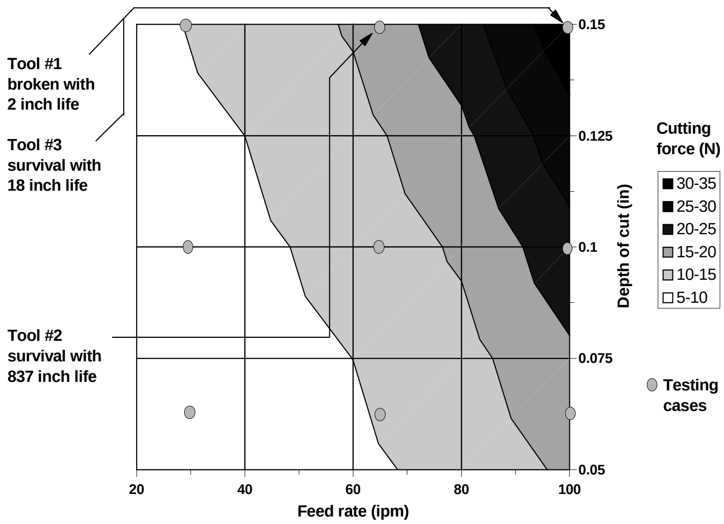
The contour plots of the feed direction cutting force variation (Figure 3) were generated by using the NNs to visualize their characteristics at different operating conditions. The feed rate and the depth of the cut were the two inputs of the NNs. Two separate BP type NNs with 10 hidden nodes were trained to estimate the feed direction of the cutting forces of the micro-end-mills with 0.020” and 0.0625” tool diameters. The performance of the NNs was evaluated for the training cases. Their estimation errors were averaged at 8.4 % and 4.8% (of the force and machining time range) for the micro-end-mills with 0.020” and 0.0625” diameters, respectively.

Micro-tool Cutting Force in Feed Direction
15,000 rpm spindle speed, 0.02” HSS tool, graphite workpiece



a) Tool diameter is 0.02 inch.

Micro-tool Cutting Force in Feed Direction
15,000 rpm spindle speed, 0.0625” HSS tool, graphite workpiece



b) Tool diameter is 0.0625 inch.

Figure 3. Some of the training cases, tool life and the typical feed direction cutting force estimations with a trained NN.

GONNS used two BP type NNs. First NN was trained by using the 16 values in Table A.1.1 and A.1.2 to estimate the feed direction cutting forces. The second NN was trained to estimate the merit. In this case, the merit was the metal removal rate. The training file was prepared by calculating the metal removal rate at all the possible 100 combinations of the tool diameters of 0.02”, 0.03”, 0.04”, 0.05” and 0.06”, and also the depth of the cuts of 0.01”, 0.05”, 0.10” and 0.15”, and the feed rates of 20 ipm, 40 ipm, 60 ipm, 80 ipm, and 100 ipm. Both NNs had 8 nodes in their single hidden layer.

During the optimizations, the tool diameter was fixed since the operator selects it according to the part of the geometry. Experimental studies indicated that the life of micro-end-mills was correlated to the feed direction cutting force. The selected values for the maximum allowable cutting forces are presented in Table 1. GONNS was asked to maximize the metal removal rate. The population size, child number, cross-probability, mutation-probability, creep-probability was selected as 6, 1, 0.2, 0.1, and 0.05, respectively during the optimization process. The Pentium VI processor at 2.8 GHz clock speed was used for the optimization. Optimum values were found in less than 500 iterations. GA was stopped after at least 3,000 iterations were completed. The program completed 4,000 iterations in less than one minute in all the studied cases. The optimization results are presented in the Table 2. The metal removal rate estimation error of the related NN at these new conditions (it was seen during the training) was less than 2% of the range of this parameter.

Table 1. The range of the parameters in the optimization study.

Given values to the optimization program		**Cutting conditions (acceptable range)**			
		Depth of cut (inch)		Feed rate (ipm)	
Fixed Radius (inch)	Feed force Range (N)	Minimum (inch)	Maximum (inch)	Minimum (inch)	Maximum (inch)
0.03	0-28	0.02	0.07	24	100
0.04	0-40	0.05	0.1	26	100
0.05	0-50	0.06	0.125	28	100

Table 2. The optimization results for micro-end-milling operations.

Given values to the optimization program		**Results of the optimization**			
		Optimized output values of the NNs		Estimated input values to work at the optimal conditions	
Fixed Radius (inch)	Feed direction force Range (N)	Optimal Feed direction force (N)	Metal removal rate (in^3/min)	Depth of cut (inch)	Feed rate (inch per minute)
0.03	0-28	28.00	0.087	0.070	84.07
0.04	0-40	40.00	0.179	0.1	90.82
0.05	0-50	50.00	0.297	0.125	92.53

Case Study 2: Optimization of the machining parameters to obtain the best compromise between the surface quality and machining time:

A critical part of a mold was selected. That part was manufactured 81 times out of Aluminum 6061 blocks with 30 mm × 30 mm × 90 mm dimensions. Machining was performed at three stages. The first two stages, rough and semi-finish cut were the same for all the parts. A flat end mill with a 12 mm diameter was used for rough cutting. The depth of the cut was 1.5 mm. 3-D spiral tool motions were performed with 3 mm stepovers at 2,500 mm/min feed rate and 5,000 rpm spindle speed. The rough cutting continued until 0.6 mm thick material was left on the desired final surface. A ball-end mill with a 12 mm diameter was used at the second stage to machine the material with a 0.3 mm depth of cut. The tool moved parallel to the longest axis of the experimental workpiece in the horizontal plane. The step over, feed rate, and spindle speed were 3 mm, 700mm/min, and 3,000 rpm, respectively. 0.3 mm thick material was left on the desired mold surface after the second stage.

The finishing cut (third stage) was performed with a ball-end mill with 10 mm diameter. The tool motions were in 5 axis and perpendicular to the tool motions in the second stage of cutting. Finishing cut continued until the desired surface was obtained. The range of the cutting parameters (cutting speed, feed, radial depth of cut and tolerance) was selected by considering the recommendations of the tool manufacturer [45], and the test values were determined according to the statistical experimental design technique; three-level full factorial design [46] for four parameters. A Sandvik (R216.42-10030-AK191 1010) ball end-mill (10 mm diameter, 45° helix angle, TiAlN coated solid carbide, 2-flutes) was used for the final cut. The compressed cooling oil was directed to the machined surface at a very high velocity. The machining times of only the final cuts were listed in Appendix 2.

The surface roughness of the machined surfaces was measured by using a Mitatoyu Surftest 301 portable surface roughness tester. The stylus traced the surface with a 0.25 mm cut of length in the perpendicular direction to the path of the cutting tool in the finishing cut. The surface roughness was measured three times at 10 different regions for each cutting condition and the average R_a value is presented in Appendix 2.

One NN was trained to estimate the surface roughness while the other one was trained to estimate the machining time by using the experimental values in Appendix 2. The population size, child number, cross-probability, mutation-probability, and creep-probability were selected the same as the first case study. Since the NNs had one more input, and the number of optimized parameters was doubled, the GA was allowed to iterate between 9,000 and 12,000 times. The ranges of the cutting parameters are presented in Table 3. The cutting conditions were optimized to obtain the best compromise between two critical cutting related values: surface roughness and machining time. Spindle speed, feed rate, radial depth of cut and tolerance were optimized while any one of the two key performance parameters were kept in the desired range while the other one was minimized. A series of alternatives were provided to the user. The optimization results are presented in Table 4.

Table 3. Range of cutting parameters for the second case study.

Cutting speed (m/min)	**Feed Rate** (mm/tooth)	**Radial depth of cut** (mm)	**Tolerance** (mm)
74-123	0.07-0.12	0.1-0.3	0.01-0.001

Table 4. Optimization results.

OPTIMIZATION OF OPERATING CONDITIONS FOR MOLD MAKING							
Optimize to minimize one parameter while keeping the other in the desired range		Optimized operating conditions - The minimized critical parameter is underlined					
Minimize the following parameter	Range is selected for	Critical parameters		Operating conditions			
	Machining time (min)	Roughness (µm)	Machining time (min)	Cutting Speed (m/min)	Feed Rate (mm/tooth)	Radial depth of cut (mm)	Tolerance (mm)
Roughness	Full (7.3-65)	0.142	54.985	89.508	0.07	0.1	0.01
	7.3-10	0.342	9.999	88.645	0.12	0.27	0.001
	7.3-20	0.207	15.968	86.262	0.082	0.3	0.001
	Roughness (µm)						
Machining time	Full (0.2-1.58)	1.013	7.174	122.996	0.12	0.3	0.001
	0.2-0.5	0.5	8.682	97.924	0.12	0.297	0.001
	0.2-0.8	0.683	7.398	123	0.12	.3	0.01

VI. CONCLUSION

GONNS was proposed for selection of the optimal cutting conditions in specialized machining operations from the experimental data without developing any analytical or empirical models. NNs were trained by using a series of experimental results to represent the relationship between the machining parameters and the cutting related values such as feed direction cutting force, metal removal rate, surface roughness, and machining time. GA determined the optimal cutting conditions to minimize or maximize one of the machining related values while the machining parameters and secondary values were kept in the desired range. The performance of the GONNS was evaluated in two case studies.

In the first case study, two NNs represented the relationship between the operating conditions and the feed direction cutting force and a merit. Metal removal rate was used as the merit. GA estimated the optimal machining parameters to obtain the maximum metal removal rate while the feed direction cutting force was kept below a critical value to avoid premature tool breakage. Since there are no analytical equations to represent the system, the accuracy of the result cannot be calculated quantitatively. However, the contour maps obtained by the NNs represented the data well and had very small error for the training cases. The selected optimal operating points coincided with the suggestion of the trend of the contour maps of the NNs.

In the second case study, the cutting conditions were optimized to obtain the best compromise between two critical machining related values: surface roughness and machining time. Spindle speed, feed rate, radial depth of cut and tolerance were optimized while any one of the two key performance values were kept in the desired range while the other one was minimized. GONNS generated a series of alternatives for the user. The results demonstrated the compromise between the machining time and estimated surface roughness. When the minimization of the surface roughness requested, GONNS selected high cutting speed and very small feed rate. To minimize the machining time, very high cutting speed and the feed rate were selected. The surface roughness deteriorated in these cases. The tendency of the estimations of the GONNS agreed with the theoretical expectations.

GONNS was originally developed for the selection of the optimal material and the operating conditions for composite materials. The mapping tool of the GONNS, BP type NNs are very flexible. They create reliable models even when the training data set is pretty small and the system has nonlinear characteristics. The only drawback is the long computational time of the training process. The GA generally finds the optimal operating conditions even if multiple NNs represent highly nonlinear systems. After the training, NNs make the estimations very quickly and GA obtains the optimal solutions efficiently. The simplicity of the modeling, the speed of the optimization, and the reliability of the process even with small data sets are the main advantages of the GONNS and make it an excellent optimization tool for metal cutting operations. These characteristics were observed in both of the cases studies in this paper.

The previous studies indicated that better than 3% accuracy could be expected from GONNS when the NNs represented the simulated systems. The characteristic equations of these systems could be represented with 3-D surface plots with smooth surface and single peak. The input and output relationships are very complex in the manufacturing operations and the estimation errors are expected to depend on the characteristics and quality of the training data. In the both cases studied, the estimations of the GONNS agreed with the observed trend of the data and theoretical expectations.

GONNS allows definition of a series of clusters. Each cluster may represent machining at a different type of machine tool. In our implementation, there was no limit for the number of allowable clusters. However, up to six NNs can be used in each cluster with one GA. All the clusters could be optimized at the same time and the best machine and optimal operating conditions could be obtained.

REFERENCES

1. L. Yan, K. Krishnamurthy, "Selection of Optimal Machining Parameters Using a Genetic Algorithm," American Society of Mechanical Engineers, Dynamic Systems and Control Division (Publication) DSC, v 70, 2002, p 105-111.
2. K. Krishnamurthy, L. Yan, "Selection of Optimal Machining Parameters Using a Genetic Algorithm," International Mechanical Engineering Congress and Exposition, Proceedings, v 2, 2001, p 1051-1057.
3. C.T. Su, M.C. Chen, "Optimizing Parameters for Machining General Continuous Forms Using Genetic Algorithm," International Journal of Industrial Engineering: Theory Applications and Practice, v 4, n 2, June 1997, p 103-114.
4. M.C. Chen, H.Y. Tseng, "Machining Parameters Selection for Stock Removal Turning in Process Plans Using a Float Encoding Genetic Algorithm," Journal of the Chinese Institute of Engineers, Transactions of the Chinese Institute of Engineers, Series A/Chung-kuo Kung Ch'eng Hsuch K'an, v 21, n 4, July 1998, p 493-506.
5. K. Zhang, Z. Han, G. Yu, "Using Genetic Algorithm to Realize Real Time Optimization of Cutting Parameter in Workplace," Qinghua Daxue Xuebao/Journal of Tsinghua University, v 39, n 2, February 1999, p 27-29, 38.
6. Y. Liu, C. Wang, "Modified Genetic Algorithm Based Optimization of Milling Parameters," International Journal of Advanced Manufacturing Technology, v 15, n 11, 1999, p 796-799.
7. R. Saravanan, P. Asokan, M. Sachidanandam, "A Multi-Objective Genetic Algorithm (GA) Approach for Optimization of Surface Grinding Operations," International

Journal of Machine Tools and Manufacture, v 42, n 12, September 2002, p 1327-1334.

8. Krimpenis, G.C. Vosniakos, “Optimization of Multiple Tool CNC Rough Machining of a Hemisphere as a Genetic Algorithm Paradigm Application,” International Journal of Advanced Manufacturing Technology, v 20, n 10, 2002, p 727-734.

9. M. Hao, Y. Mizugaki, M. Sakamoto, “Optimal Tool Selection Based on Genetic Algorithm in a Geometric Cutting Simulation,” Seimitsu Kogaku Kaishi/Journal of the Japan Society for Precision Engineering, v 60, n 9, September 1994, p 1237-1241.

10. G.C. Onwubolu, T. Kumalo, “Multi-Pass Turning Operations Optimization Based on Genetic Algorithms,” Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, v 215, n 1, 2001, p 117-124.

11. M.R. Alam, K.S. Lee, M. Rahman, Y.F. Zhang, “Process Planning Optimization for The Manufacture of Injection Moulds Using a Genetic Algorithm,” International Journal of Computer Integrated Manufacturing, v 16, n 3, April/May 2003, p 181-191.

12. G.C. Onwubolu, T. Kumalo, “Optimization of Multipass Turning Operations with Genetic Algorithms,” International Journal of Production Research, v 39, n 16, November 2001, p 3727-3745.

13. K. Choudhuri, D.K. Pratihar, D.K. Pal, “Multi-Objective Optimization in Turning - Using A Genetic Algorithm,” Journal of the Institution of Engineers (India), Part PR: Production Engineering Division, v 82, n MAR., March 2002, p 37-44.

14. R.S. Schrader, M.L. Philpott, G. Subbarao, D.E. Holmes, “A Genetic Algorithm for Cost Estimating Turned Parts in an Interactive DFM Environment,” Proceedings of the ASME Design Engineering Technical Conference, v 3, 2003, p 187-193.

15. R. Saravanan, M. Sachithanandam, “Genetic Algorithm (GA) for Multivariable Surface Grinding Process Optimization Using a Multi-Objective Function Model,” International Journal of Advanced Manufacturing Technology, v 17, n 5, 2001, p 330-338.

16. F. Cus, J. Balic, J. Kopac, “Optimization of Milling Parameters by GA Approach,” Proceedings of Asian Simulation Conference; System Simulation and Scientific Computing (Shanghai), v 2, 2002, p 974-979.

17. F. Cus, J. Balic, “Optimization of Cutting Process by GA Approach,” Robotics and Computer-Integrated Manufacturing, v 19, n 1-2, February/April 2003, p 113-121.

18. P.E. Amiolemhen, A.O.A. Ibhadode, “Application of Genetic Algorithms-Determination of the Optimal Machining Parameters in The Conversion of a Cylindrical Bar Stock into a Continuous Finished Profile,” International Journal of Machine Tools and Manufacture, v 44, n 12-13, October 2004, p 1403-1412.

19. L.Y. Kuo, J.Y. Yen, “A Genetic Algorithm-Based Parameter-Tuning Algorithm for Multi-Dimensional Motion Control of a Computer Numerical Control Machine Tool,” Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, v 216, n 3, 2002, p 429-438.

20. F. Azadivar, G. Tompkins, “Simulation Optimization with Qualitative Variables and Structural Model Changes: A Genetic Algorithm Approach,” European Journal of Operational Research, v 113, n 1, February 1999, p 169-182.

21. Y. Yang, X. Shen, H. Shao, “Machining Parameter Optimization of Milling Process Based on Genetic Algorithms,” Ji Xie She Ji Yu Yian Jiu/Machine Design and Research, v 17, n 2, June 2001, p 9+60-62.

22. M. Brezocnik,M. Kovacic, “Integrated Genetic Programming and Genetic Algorithm Approach to Predict Surface Roughness,” Materials and Manufacturing Processes, v 18, n 3, May 2003, p 475-491.

23. Z. Khan, B. Prasad, T. Singh, “Machining Condition Optimization by Genetic Algorithms and Simulated Annealing,” Computers & Operations Research, v 24, n 7, July 1997, p 647-657.

24. R. Saravanan, P. Asokan, K. Vijayakumar, “Machining Parameters Optimization for Turning Cylindrical Stock into a Continuous Finished Profile Using Genetic Algorithm (GA) and Simulated Annealing (SA),” International Journal of Advanced Manufacturing Technology, v 21, n 1, 2003, p 1-9.

25. T.N. Wong, L.C.F. Chan, H.C.W. Lau, “Machining Process Sequencing with Fuzzy Expert System and Genetic Algorithms,” Engineering with Computers, v 19, n 2-3, 2003, p 191-202.

26. S. Ji, X. Li, Y. Ma, H. Cai, “Optimal Tolerance Allocation Based on Fuzzy Comprehensive Evaluation and Genetic Algorithm,” International Journal of Advanced Manufacturing Technology, v 16, n 7, 2000, p 461-468.

27. F. Cao, Q, Zhang, “Neural Network Modeling and Parameters Optimization of Increased Explosive Electrical Discharge Grinding (IEEDG) Process for Large Area Polycrystalline Diamond,” Journal of Materials Processing Technology, v 149, n 1-3, June 2004, p 106-111.

28. W.T. Chien, C.S. Tsai, “The Investigation on The Prediction of Tool Wear and The Determination of Optimum Cutting Conditions in Machining 17-4PH Stainless Steel,” Journal of Materials Processing Technology, v 140, n 1-3 SPEC., September 2003, p 340-345.

29. S. Sette, L. Boullart, L. L. Van P. Kiekens, “Optimizing the Fiber-To-Yarn Production Process with a Combined Neural Network/Genetic Algorithm Approach,” Textile Research Journal, v 67, n 2, February 1997, p 84-92.

30. S. Sette, L. Boullart, L.L. Van, “Optimizing a Production Process by a Neural Network/Genetic Algorithm Approach,” Engineering Applications of Artificial Intelligence, v 9, n 6, December 1996, p 681-689.

31. I.N. Tansel, S.Y. Yang, C. Shu, W.Y. Bao, N. Mahendrakar, Introduction to Genetically Optimized Neural Network Systems (GONNS), Smart Engineering Systems: Neural Networks, Fuzzy Logic, Evolutionary Programming, Data Mining, and Rough Sets, edited by Drs. Dagli, Akay, Buczak, Ersoy, and Fernandez, ASME Press, New York, 1999, pp.331-336.

32. S.Y. Yang, I.N. Tansel, C.V Kropas-Hughes, “Selection of Optimal Material and Operating Conditions in Composite Manufacturing. Part I: Computational Tool,” International Journal of Machine Tools & Manufacture, v 43, n 2, January 2003, p 169-173.

33. S.Y. Yang, V. Girivasan, N. R. Singh, I.N. Tansel, C.V Kropas-Hughes, “Selection of Optimal Material and Operating Conditions in Composite Manufacturing-II-Complexity, Representation of Characteristics and Decision Making, International Journal of Machine Tools & Manufacture, v 43, n 2, 2003, p 175-184.

34. D.E. Rumelhart, G. Hilton, R.J. Williams, Learning Internal Representations by Error Propagation, Parallel Distributed Processing: Explorations in the Microstructure of Cognition, v 1, Ed. E. Rumelhart, J.L. McClelland, MIT Press, 1986.

35. J.E. Dayhoff, Neural Network Architectures: An Introduction, Van Nostrand Reinhold, 1990.

36. R. Hecht-Nielsen, Neurocomputing, Addison-Wesley Publishing Company, Inc., 1990.

37. DARPA, Neural Network Study, AFCEA International Press, Fairfax, VA, v 23/1, 1988.

38. D.E. Goldberg, Genetic Algorithms in Search, Optimization and Machine Learning, Addison-Wesley, Reading, MA, 1989.

39. D.L. Carroll, "Chemical Laser Modeling with Genetic Algorithms," AIAA Journal, v 34, n 2, 1996, p 338-346.

40. G. Winter, P. Cuesta, J. Periaux, M. Galan, Genetic Algorithm in Engineering and Computer Science, John Wiley & Sons, 1996.

41. Scott Robert Ladd: Genetic Algorithms in C++, M&T Books, 1996.

42. Oberg, Jones, Horton, Ryffel, McCauley, Heald, and Hussain, Machinery's Handbook, 27th Edition, Industrial Press, New York, NY, 2004.

43. W.L.R. Ip, "Fuzzy Basis Material Removal Optimization Strategy for Sculptured Surface Machining Using Ball-Nosed Cutters," International Journal of Production Research, v 36, n 9, September 1998, p 2553-2571.

44. W.Y. Bao, I.N. Tansel, “Modeling Micro-End-Milling Operations--II: Tool Run-Out,” International Journal of Machine Tools & Manufacture, v 40, n 15, 2000, p 2175-2192.

45. Sandvik Coromant, Die and Mould Making with Sandvik Coromant, Tool and Methods, Tool Catalog, Sandviken, Sweden, 2002.

46. G.E.P. Box, W.G. Hunter, J.S. Hunter, W.G. Hunter, Statistics for Experimenters: An Introduction to Design, Data Analysis, and Model Building, Wiley-Interscience, Hoboken, NJ, 1978.

APPENDIX 1. The observed cutting forces at the test conditions

Table A.1.1. Observed maximum cutting forces with the 0.020" diameter end-mill.

Depth of cut (inch)	**Feed direction maximum cutting force** (N) **Feed rate** (ipm)		
	20	70	120
0.05	8.25	16.5	---
0.03	7.5	13.25	---
0.01	5	8.75	10

Table A.1.2. Observed maximum cutting forces with the 0.0625" diameter end-mill.

Depth of cut (inch)	**Feed direction maximum cutting force** (N) **Feed rate** (ipm)		
	30	65	100
0.15	23.5	30	70
0.1	16.25	24.5	42.5
0.062	14.5	20	37.5

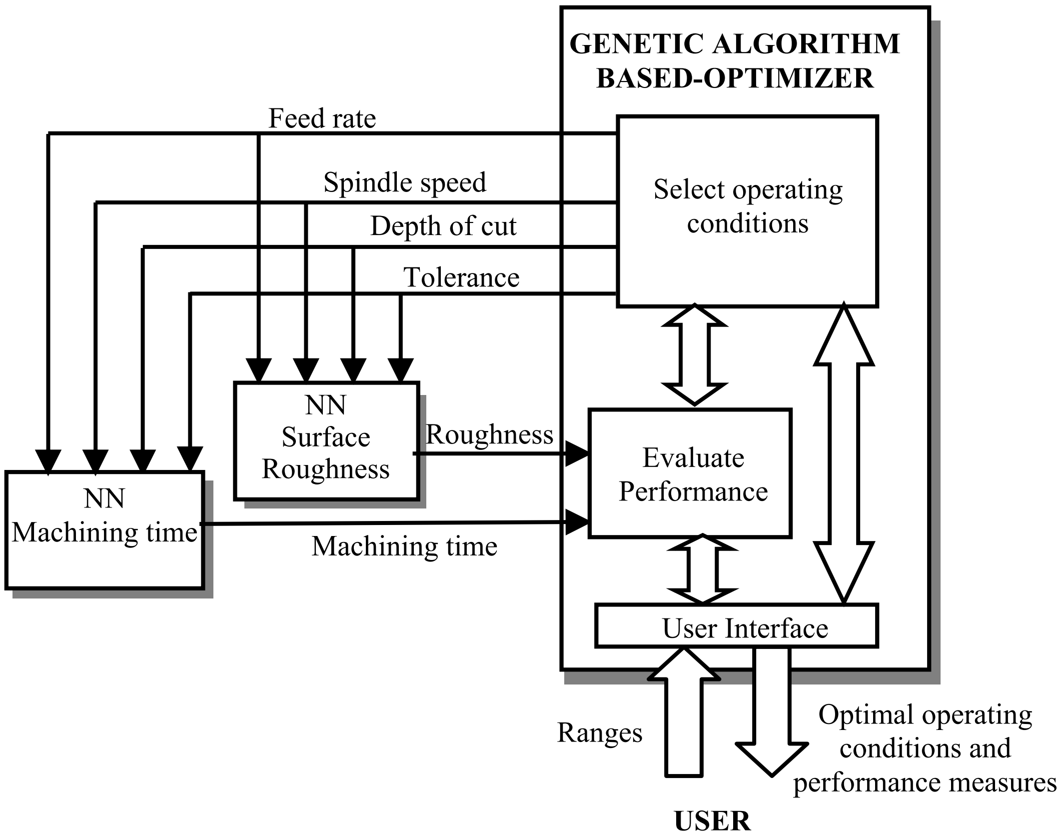
APPENDIX 2. The observed surface roughness at the test conditions
Table A.2.1. Measured surface roughness at the test conditions.

	Cutting speed	Feed Rate	Radial depth of cut	Tolerance	Average surface rough.	Machining time
Trail No	(m/min)	(mm/tooth)	(mm)	(mm)	(µm)	(min)
1	74	0.07	0.1	0.001	0.26	64
2	98.5	0.07	0.1	0.001	0.31	47
3	123	0.07	0.1	0.001	0.27	45
4	74	0.095	0.1	0.001	0.32	48
5	98.5	0.095	0.1	0.001	0.36	36
6	123	0.095	0.1	0.001	0.85	29
7	74	0.12	0.1	0.001	0.48	39
8	98.5	0.12	0.1	0.001	0.37	28
9	123	0.12	0.1	0.001	1.58	24
10	74	0.07	0.2	0.001	0.36	32
11	98.5	0.07	0.2	0.001	0.59	24
12	123	0.07	0.2	0.001	0.52	19
13	74	0.095	0.2	0.001	0.51	23
14	98.5	0.095	0.2	0.001	0.53	17
15	123	0.095	0.2	0.001	0.81	15
16	74	0.12	0.2	0.001	0.53	21
17	98.5	0.12	0.2	0.001	0.47	14
18	123	0.12	0.2	0.001	0.93	12
19	74	0.07	0.3	0.001	0.49	22
20	98.5	0.07	0.3	0.001	0.50	17
21	123	0.07	0.3	0.001	1.22	13.3
22	74	0.095	0.3	0.001	0.42	15.3
23	98.5	0.095	0.3	0.001	0.58	12
24	123	0.095	0.3	0.001	1.31	9
25	74	0.12	0.3	0.001	0.67	13
26	98.5	0.12	0.3	0.001	0.47	10
27	123	0.12	0.3	0.001	0.98	7.3
28	74	0.07	0.1	0.0055	0.37	64
29	98.5	0.07	0.1	0.0055	0.30	49
30	123	0.07	0.1	0.0055	0.37	48
31	74	0.095	0.1	0.0055	0.53	45
32	98.5	0.095	0.1	0.0055	0.47	37
33	123	0.095	0.1	0.0055	0.64	29
34	74	0.12	0.1	0.0055	0.65	39
35	98.5	0.12	0.1	0.0055	0.52	30.3

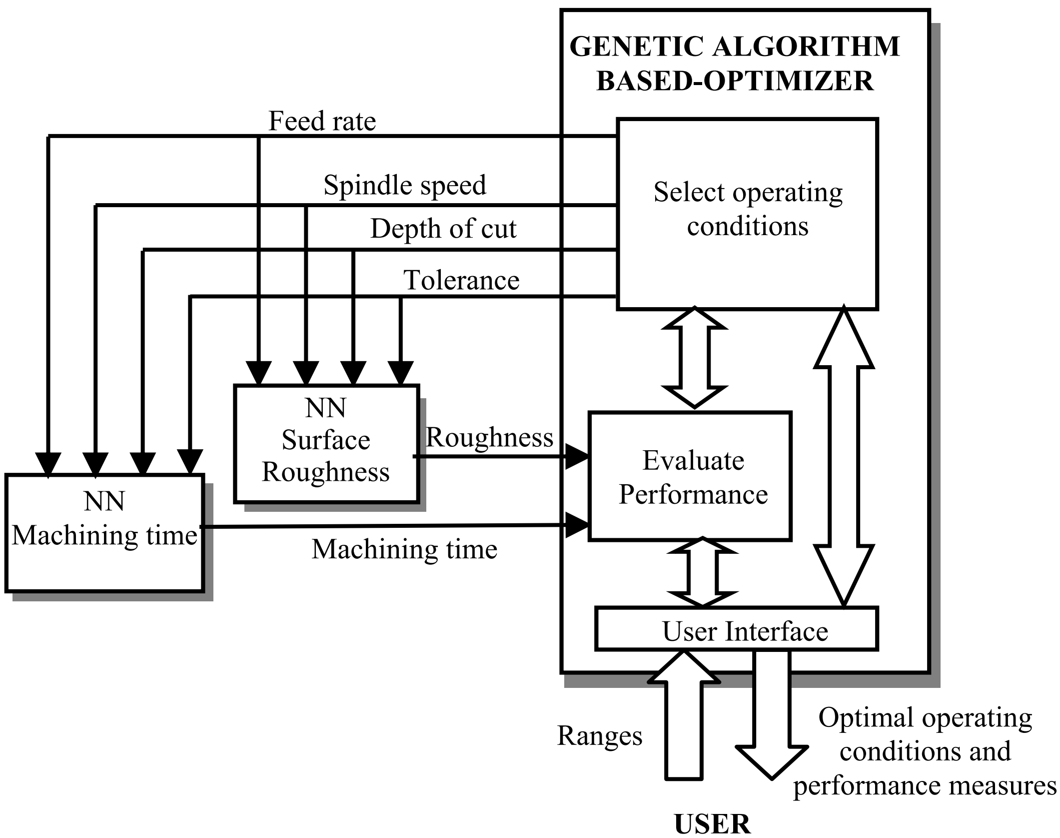
	Cutting Speed	Feed Rate	Radial Depth of Cut	Tolerance	Average Surface Rough	Machining Time
Trail No	(m/min)	(mm/tooth)	(mm)	(mm)	(µm)	(min)
36	123	0.12	0.1	0.0055	1.15	23.3
37	74	0.07	0.2	0.0055	0.49	33
38	98.5	0.07	0.2	0.0055	0.89	24
39	123	0.07	0.2	0.0055	0.71	20.3
40	74	0.095	0.2	0.0055	0.80	24
41	98.5	0.095	0.2	0.0055	0.66	29
42	123	0.095	0.2	0.0055	0.76	15
43	74	0.12	0.2	0.0055	0.58	20.3
44	98.5	0.12	0.2	0.0055	0.32	15
45	123	0.12	0.2	0.0055	0.77	12
46	74	0.07	0.3	0.0055	0.57	22
47	98.5	0.07	0.3	0.0055	1.22	16.3
48	123	0.07	0.3	0.0055	0.83	13.3
49	74	0.095	0.3	0.0055	0.69	16.3
50	98.5	0.095	0.3	0.0055	0.91	12.3
51	123	0.095	0.3	0.0055	0.90	9.3
52	74	0.12	0.3	0.0055	0.66	13
53	98.5	0.12	0.3	0.0055	0.73	10
54	123	0.12	0.3	0.0055	0.82	8
55	74	0.07	0.1	0.01	0.42	65
56	98.5	0.07	0.1	0.01	0.20	49
57	123	0.07	0.1	0.01	0.57	39
58	74	0.095	0.1	0.01	0.47	48
59	98.5	0.095	0.1	0.01	0.40	36
60	123	0.095	0.1	0.01	0.51	30
61	74	0.12	0.1	0.01	0.48	38
62	98.5	0.12	0.1	0.01	0.59	35
63	123	0.12	0.1	0.01	0.47	24
64	74	0.07	0.2	0.01	0.66	34
65	98.5	0.07	0.2	0.01	0.78	24.3
66	123	0.07	0.2	0.01	1.27	20
67	74	0.095	0.2	0.01	0.50	25
68	98.5	0.095	0.2	0.01	0.58	18
69	123	0.095	0.2	0.01	0.66	14
70	74	0.12	0.2	0.01	0.62	19

	Cutting speed	Feed Rate	Radial depth of cut	Tolerance	Average surface rough.	Machining Time
Trail No	(m/min)	(mm/tooth)	(mm)	(mm)	(µm)	(min)
71	98.5	0.12	0.2	0.01	0.60	15.3
72	123	0.12	0.2	0.01	0.62	12
73	74	0.07	0.3	0.01	0.58	23
74	98.5	0.07	0.3	0.01	0.70	17
75	123	0.07	0.3	0.01	0.71	13.3
76	74	0.095	0.3	0.01	0.68	18.3
77	98.5	0.095	0.3	0.01	0.72	12.3
78	123	0.095	0.3	0.01	1.05	10.3
79	74	0.12	0.3	0.01	0.85	9.3
80	98.5	0.12	0.3	0.01	0.61	10
81	123	0.12	0.3	0.01	0.62	8

PICTURES



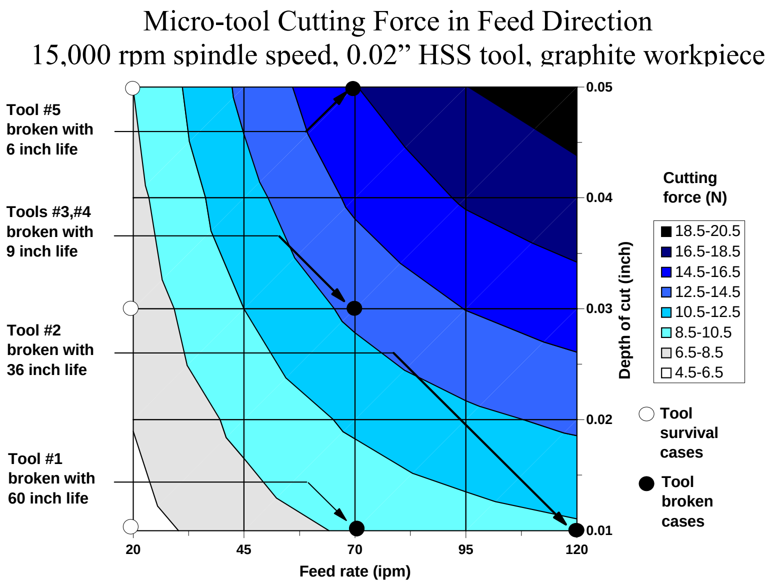
a) GONNS' architecture for the-end-milling operations.



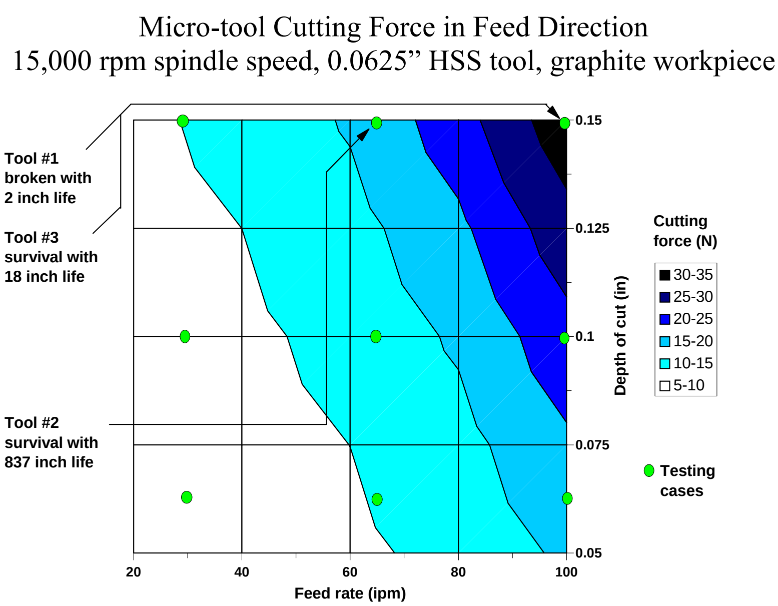
b) GONNS' architecture for mold making.

Figure 1. The architecture of the proposed GONNS.

Figure 2. The completed part after the machining operation.



a) Tool diameter is 0.02 inch.



b) Tool diameter is 0.0625 inch.

Figure 3. Some of the training cases, tool life and the typical feed direction cutting force