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# Multiple-Objective Optimisation of Machining Operations Based on Neural Networks

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*Metal cutting plays an important role in manufacturing industries. Optimisation of cutting parameters represents a key component in machining process planning. In this paper, a neural network based approach to multiple-objective optimization of cutting parameters is presented. First, the problem of determining the optimum machining parameters is formulated as a multiple-objective optimization problem. Then, neural networks are proposed to represent manufacturers' preference structures. To demonstrate the procedure and performance of the neural network approach, an illustrative example is discussed in detail.*

**Keywords:** Cutting parameter optimisation; Neural networks; Machining operations; Metal cutting

## 1. Introduction

Since the Industrial Revolution, metal cutting has been a major machining process in manufacturing industries. One problem that confronted the manufacturing industries for nearly a century was the establishment of efficient metal cutting conditions for machining operations. Because of the dependency of machining process outputs upon cutting conditions, decisions on cutting conditions have a great influence on production rate, operation cost, and product quality. With wide applications of computer numerical control (CNC) and keen competition among manufacturers, the optimisation of cutting conditions becomes increasingly important.

There has been a considerable amount of research on machining process optimisation problems. In 1907, F. W. Taylor [1] recognised the problem of economic machining in the metal-cutting field in his seminal work. The majority of the pioneering work was concerned with the mechanism of chip formation and the emphasis was on the study of forces acting between cutting tools and workpieces. As the volume of machining operations increased, researchers began to investigate the cutting parameters that could improve production efficiency in machining processes. Quantitative methods for optimisation of machining operations based on a single objective such as minimisation of costs and maximisation of profit or production rate have been developed. Many paradigms have been proposed for single-objective optimisation of machining operations using various techniques such as differential calculus [2], regression analysis [3], linear programming [2], geometric programming [2, 4, 5], stochastic programming [6] and computer simulation [7].

In many real-world applications, manufacturers frequently face decision scenarios where multiple objectives have to be optimised simultaneously. These objectives are often conflicting and non-commensurate. The conflict arises when there is an improvement to one objective to the detriment of other objectives. The non-commensuration occurs when these objectives cannot be compared in the same scale or unit. In turning operations, for example, consider three non-commensurate objectives: minimising operation cost, maximising production rate, and maximising cutting quality. An increase in feedrate could result in an increase in production rate, but an increase in operation cost in terms of excessive tool wear and a decrease in cutting quality in terms of poor surface finish.

While the major efforts of previous work were concentrated on optimisation of a single objective, various multi-objective optimisation approaches have been proposed in recent years for optimising machining operations. Philipson and Ravindran [2, 8] apply goal programming techniques for machining process optimisation with multiple objectives. Ghiassi et al. [9] apply multiple-objective linear programming techniques and Mitwasi et al. [10] apply weighting techniques and interactive techniques such as the Zionts– Wallenius method for planning machining operations. Malakooti and Deviprasad [11] and Malakooti [12] develop other interactive approaches to multiple criteria decision making for metal cutting.

One major drawback of interactive approaches to machining process optimisation is that interactions with manufacturers are necessary for almost every different part. In an open job-shop production system, the lot size of manufactured items

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is usually small and product mix is usually diverse. Furthermore, in the dynamic global economy, the time-varying market value makes labour and material costs fluctuate. The diversity of product mix and the uncertainty of market value make interactive approaches to machining process planning inefficient owing to the extensive and frequent interactions with manufacturers for planning machining process. A global approach based on a preference model such as a multiattribute value function that represents a manufacturer's overall preference is more desirable.

During the past several years, artificial neural networks have manifested significant potential for solving complex problems. The application areas include, but are not limited to, associative memory, signal processing, pattern recognition, modelling, and optimisation, robotics and control. Recently, neural networks have been applied to some areas related to metal cutting. For example, Rangwala and Dornfeld [13] apply neural networks for learning and optimisation of machining operations. Rangwala and Dornfeld [14], Burke and Rangwala [15] propose neural network paradigms for tool wear monitoring.

In this paper, a multi-objective optimisation approach based on neural networks is presented for planning single-pass single-point turning operations. The purpose of this study is to demonstrate the potential of neural networks for machining process optimisation. The motivation of this study is to assess manufacturers' underlying value systems, via supervised learning of neural networks, that integrates multiple objectives into a single one.

The rest of this paper is organised as follows. In Section 2, a turning operation is formulated as a constrained multi-objective optimisation problem with three non-commensurate and conflicting objectives: production rate, operation cost, and cutting quality. All these objectives were represented as functions of cutting parameters such as cutting speed, feedrate, and depth of cut. In Section 3, a neural network approach is proposed for assessing a manufacturer's implicit multiattribute value function. A neural-network-based approach to cutting parameter optimisation for determining the most advantageous cutting conditions is described. The results of a simulation study are also discussed in detail.

## 2. The Cutting Parameter Optimisation Problem

### 2.1 Planning Scenario

In metal cutting, there are many factors related to process planning for machining operations. These factors can be classified as type of machining operations (turning, facing, milling, etc.), parameters of machine tools (rigidity, horsepower, etc.), parameters of cutting tools (material, geometry, etc.), parameters of cutting conditions (cutting speed, feed rate, depth of cut, etc.) and characteristics of workpieces (material, geometry, etc.). Among these factors cutting parameters (speed, feed rate, and depth of cut) are evidently dominating ones in a machining operation.

In turning operations, the cutting speed $v$ is defined as the rate at which the uncut surface of the workpiece passes the cutting edge of the tool. The feedrate $f$ is the distance moved by the tool in an axial direction at each revolution of the workpiece. The depth of cut $d$ is the thickness of metal removed from the workpiece measured in a radial direction.

For a given machining operation, determination of the optimum cutting conditions involves a conflict between maximising the metal removal rate and minimising the tool wear. By increasing the feedrate or spindle speed, the metal removal rate and hence the production rate can be increased; but this results in excessive tool wear, frequent tool changes and increased production costs. Therefore, there is an optimum set of cutting speed, feedrate and depth of cut which balances these conflicts and stays within constraints such as power consumption. The machining process optimisation is to determine the most advantageous cutting condition. That is, to determine optimal machine parameters such as $v$ (cutting speed, $f$ (feedrate), and $d$ (depth of cut) to optimise specified objectives such as production rate, operation cost, and cutting quality.

### 2.2 Objective Functions

The full development of machining process planning is based on optimisation of the economic criteria subject to technical and managerial constraints. The economic criteria are the objectives of machining operations in terms of costs, time, and quality.

The objectives considered in this paper are production rate to be maximised, operation cost to be minimised, and cutting quality to be maximised.

1. *Production rate*. Production rate is usually measured by the total time required to produce one item of product ($T_p$). It is a function of metal removal rate ($MRR$) and tool life ($TL$) [16]; i.e.

$$T_p = T_s + V(1 + T_c/TL)/MRR + T_i \tag{1}$$

where $T_s$, $T_c$, $T_i$ and $V$ are tool set-up time, tool change time, tool idle time, and volume to be removed respectively. To a certain operation, $T_s$, $T_c$, $T_i$, and $V$ are constant, hence $T_p$ is a function of $MRR$ and $TL$.

(i) *Metal removal rate* ($MRR$). By analytical derivation, $MRR$ can be expressed as the product of cutting speed, feedrate, and depth of cut; i.e.,

$$MRR = 1000\, vfd \tag{2}$$

(ii) *Tool life* ($TL$). The tool life is measured by the mean time between tool changes or resharpenings. The relationship between the tool life and machining parameters is given by the well-known Taylor's expanded tool-life equation [2, 17, 18];

$$TL = K_T/(v^{\alpha_T} f^{\beta_T} d^{\gamma_T}) \tag{3}$$

where $K_T$, $\alpha_T$, $\beta_T$, and $\gamma_T$ are non-negative constant parameters. This is an empirical formula and the constants are to be estimated statistically.

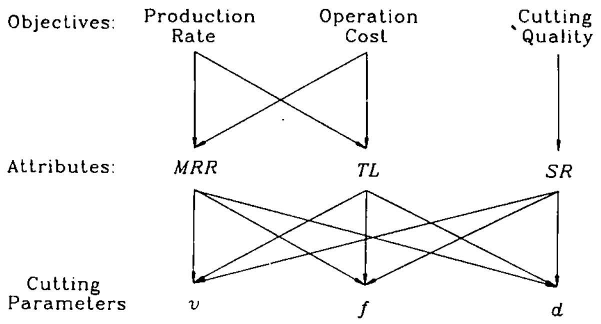


**Fig. 1.** A hierarchical structure of the objectives, attributes, and cutting parameters.

2. *Operation cost.* Operation cost can be expressed as cost per part ($C_p$). There are two terms in operation cost related to machining parameters: tool life $TL$ and time per piece $T_p$ [16].

$$C_p = (C_t/TL + C_l + C_o)T_p \tag{4}$$

where $C_t$, $C_l$ and $C_o$ are tool cost, labour cost, and overhead cost respectively. To a certain operation $C_t$, $C_l$ and $C_o$ are independent of machining parameters.

3. *Cutting quality.* There are many different methods for measuring cutting quality in terms of surface roughness and surface integrity, etc. The most important measure to be addressed is surface roughness. Two standard measurements for surface roughness ($SR$) are peak-to-valley height (i.e. the root-to-crest roughness value) and arithmetic centre-line average (ACLA) value which is based on a centre-line parallel to the general direction of the profile such that the areas of the profile above and below the centre-line are equal. The arithmetic centre-line average $H_p$ can be approximately expressed in some range as follows [9]:

$$H_p = SR = K_S v^{\alpha_S} f^{\beta_S} d^{\gamma_S} \tag{5}$$

where $K_S$, $\alpha_S$, $\beta_S$, and $\gamma_S$ are constants pertaining to specific tool-workpiece combination.

Based on the above discussion, a hierarchical structure of the objectives, attributes, and cutting parameters is depicted in Fig. 1.

### 2.3 Constraints

There are a number of factors such as power availability that constrain the cutting parameters. These factors originate usually from technical specifications and managerial considerations. The constraints considered in this study are summarised as follows:

1. *Explicit bounds on cutting parameters.* Owing to the limited capacity of machine tools and consideration for the safety of operators, the cutting parameters are usually constrained within lower and upper bounds.

$$v_{min} \le v \le v_{max} \tag{6}$$

$$f_{min} \le f \le f_{max} \tag{7}$$

$$d_{min} \le d \le d_{max} \tag{8}$$

2. *Implicit constraints due to machine capacity and workpiece characteristics.* Given a machine tool, its capacity is normally specified by its manufacturer. The machine capacity usually is represented by cutting power, cutting force, and so on. Similarly, given a workpiece material, its operating characteristics are dictated by its physical and mechanical properties.

(i) *Cutting power and force.* Cutting power ($P$) and force ($F$) are respectively the power and force used during a machining operation. The power consumption can be expressed as a function of cutting force and the cutting speed, i.e.

$$P = \frac{Fv}{6122.45\eta} \tag{9}$$

where $\eta$ is the mechanical efficiency and $F$ is given empirically by the following formula [2, 19]:

$$F = K_F f^{\beta_F} d^{\gamma_F} \tag{10}$$

Substitute equation (10) into equation (9), we have

$$P = K_P v f^{\beta_F} d^{\gamma_F} \tag{11}$$

where $K_p = K_F/6122.45\eta$.

Thus the constraints on cutting power and force are respectively,

$$P(v,f,d) \le P_{max} \tag{12}$$

$$F(v,f,d) \le F_{max} \tag{13}$$

(ii) *Cutting temperature.* The cutting temperature refers to the temperature on the internal surfaces of tool and workpiece caused by abrasion and thermal build-up. Cutting temperature can be empirically described as an exponential function of cutting parameters [16, 20, 21].

$$\theta = K_\theta v^{\alpha_\theta} f^{\beta_\theta} d^{\gamma_\theta} \tag{14}$$

where $K_\theta$, $\alpha_\theta$, $\beta_\theta$, and $\gamma_\theta$ are also constants, during normal operations, pertaining to specific tool–workpiece combination.

Because high temperature will result in excessive tool wear and low surface integrity, interface temperature is usually constrained by an upper bound; i.e.

$$\theta(v,f,d) \le \theta_{max} \tag{15}$$

In summary, the cutting parameter optimization problem can be formulated as the following multi-objective optimisation problem:

$$\min T_p(v,f,d) \tag{16}$$

$$\min C_p(v,f,d) \tag{17}$$

$$\min H_p(v,f,d) \tag{18}$$

subject to constraints (2), (3), (6)–(15).

## 3. A Cutting Parameter Optimisation Approach

### 3.1 Underlying Motivation

In the presence of the multiplicity of the non-commensurate and conflicting objectives, ideal solutions that optimise all objectives are rare and can be precluded. To evaluate the contribution and interaction of the multiple objectives and obtain a global perspective of a manufacturer's value system, it is often desirable to assess a multiattribute value function that represents the manufacturer's overall preference. A multiattribute value function is defined as a real-valued function that assigns a real value to each multiattribute alternative, according to the decision maker's preferential order, such that a more preferable alternative is associated with a larger value index than a less preferable alternative. One global approach to determination of the most desirable cutting parameters is by maximisation of the manufacturer's implicit multiattribute value function. Fig. 2 illustrates the proposed approach to cutting parameter optimisation for machining operation planning. The left-hand side of the block diagram is an objective entity concerning the data generation and objective formulation processes. The right-hand side is mainly subjective where the multiple objectives are mapped to a scalar value index that quantifies a manufacturer's overall preference.

The objective part of the optimisation approach shown in Fig. 2 can be modelled using a statistical method such as the least squares estimator [9, 16] using data generated from experiment or production. The main challenge in multiple-objective optimisation approaches to machining process optimisation lies in the difficulties in deciphering manufacturers' preferences. The currently dominant approaches to preference assessment rely on decomposition of a multiattribute value function into simple components based on some independence assumptions [22, 23]. The common decomposed multiattribute value functions are additive, multilinear, and multiplicative functions. Since in general or complex settings, a manufacturer's preference may not satisfy any independence assumptions, the decomposition approaches are not universally applicable.

Since the seminal work of Rumerhart et al. [24], supervised learning of artificial neural networks has been popularised. The essence of a supervised learning of neural networks is to construct their internal representations based on a finite set of training samples. Feed-forward neural networks, exemplified by the popular multilayer perceptron [24], have been proved to be universal approximators [25] and demonstrated to be applicable for modelling complex systems [26]. Wang and Malakooti [27] propose a feedforward neural network for multiple criteria decision making. Wang [28], Wang and Bender [29] discuss connectionist paradigms for representing decision makers' preference structures. These studies have laid a solid basis for developing a neural-network-based mutli-objective approach to machining process optimisation.

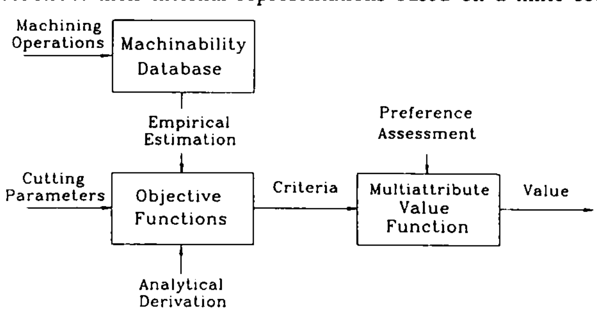


**Fig. 2.** A block diagram of the proposed approach to cutting parameter optimisation.

The motivation of this study is to represent the manufacturers' preference structures using neural networks via supervised learning. Specifically, we are interested in modelling manufacturers' implicit multiattribute value functions based on feedforward neural networks. Since multilayer neural networks are capable of approximating any functions, multilayer neural networks should also be able to represent any manufacturers' preference structures.

### 3.2 Modelling Procedure

In this context, the preference assessment process begins with determining a set of non-dominated sample alternatives and eliciting preferential information on these samples from the manufacturer concerned. A set of non-dominated alternatives is the set of alternatives in which each alternative is better than all the other alternatives in terms of at least one objective (criterion). The preference elicitation involves presenting a set of objective function values (criteria) associated with the samples for the manufacturers to evaluate. The elicited preferential information is in the form of holistic ratings. These samples paired with corresponding rating indices constitute a training set and a testing set as a basis for supervised learning. A feedforward neural network is to be trained based on the training set for representing the manufacturer's multiattribute value function. The testing set is to be used to verify and validate the resultant neural network from supervised learning. If the testing result is not satisfactory, e.g. the mean square testing error exceeds a prespecified tolerance level, then the neural network has to be retrained with a different starting weight configuration or larger training set. A constructed neural-network-based preference model represents the manufacturer's trade-offs among the objectives and long- or medium-range manufacturing strategies. After a neural-network-based multiattribute value function is constructed, if a migration of the manufacturer's preference is detected, a preference tracking is also needed. Since the preferences of manufacturers usually vary slowly in normal circumstances, the preference tracking based on an existing neural network configuration usually takes much less effort than completely retraining a neural network.

In assessing a multiattribute value function, the objectives ($T_p$, $C_p$ and $H_p$), instead of attributes ($MRR$ and $TL$), are to be used as arguments of the multiattribute value function. The main reasons for using objectives as arguments are twofold. First, if a multiattribute value function is assessed with objectives as arguments, then the differences in the time coefficients and volumes to be removed in equation (1) for different parts and the fluctuation of cost coefficients in equation (4) will have no effect on the multiattribute value function, in view of the fact that the preferences of manufacturers usually vary much slower than product mixes and costs. Therefore, the assessed multiattribute value function will be robust to the diversity of product mix and perturbation of labour and material costs. Consequently, changing products and updating cost coefficients will not entail reassessing the multiattribute value function. Secondly, the production rate and operation cost are more meaningful and comparable than material removal rate and tool life for manufacturers from a managerial point of view. The cognitive burden, hence the likelihood and magnitude of biases, can be substantially reduced in the preferential information eliciting phase.

For assessing multiattribute value functions, we can use the popular multilayer architecture of feedforward neural network. According to our preceding discussion, three objectives, $T_p$, $C_p$, and $H_p$, are used as inputs to a multilayer neural network. If the values of $T_p$, $C_p$ and $H_p$ are not in the same scale, the training data have to be normalised to avoid numerical imbalance. Since a neural network is to represent a real-valued mutliattribute value function, one output neuron is needed. To train the multilayer neural network, we propose using the adaptive learning algorithm [26]. Preference assessment approaches using different preference models, different neural network architectures, and different learning algorithms can be found in [27, 28].

Once a multiattribute value function is assessed and validated, the neural-network-based mutliattribute value function will be used to decipher the manufacturer's overall preference and the multiobjective optimisation problem will be reduced to a single-objective maximisation problem as follows.

$$\max_{v,f,d} y[T_p(v,f,d), C_p(v,f,d), H_p(v,f,d)] \tag{19}$$

subject to constrains (2), (3), (6)–(15), where $y$ is the output variable of the neural network. The most advantageous cutting parameters can be determined using a conventional mathematical programming technique.

Since the majority of conventional mathematical programming techniques rely heavily on the gradient of the objective function, the gradient of neural network output $y$ with respect to cutting parameters $(v,f,d)$, $[\partial y/\partial v, \partial y/\partial f, \partial y/\partial d]$, is derived as follows. Since $T_p$, $C_p$ and $H_p$ are inputs to the neural network $x_1$, $x_2$ and $x_3$ respectively, according to the chain rule,

$$\frac{\partial y}{\partial v} = \frac{\partial y}{\partial x_1}\frac{\partial T_p}{\partial v} + \frac{\partial y}{\partial x_2}\frac{\partial C_p}{\partial v} + \frac{\partial y}{\partial x_3}\frac{\partial H_p}{\partial v} \tag{20}$$

$$\frac{\partial y}{\partial f} = \frac{\partial y}{\partial x_1}\frac{\partial T_p}{\partial f} + \frac{\partial y}{\partial x_2}\frac{\partial C_p}{\partial f} + \frac{\partial y}{\partial x_3}\frac{\partial H_p}{\partial f} \tag{21}$$

$$\frac{\partial y}{\partial d} = \frac{\partial y}{\partial x_1}\frac{\partial T_p}{\partial d} + \frac{\partial y}{\partial x_2}\frac{\partial C_p}{\partial d} + \frac{\partial y}{\partial x_3}\frac{\partial H_p}{\partial d} \tag{22}$$

The partial derivatives of $T_p$, $C_p$ and $H_p$ with respect to $v$, $f$ and $d$ can be easily derived from equations (1)–(5). The partial derivatives of the neural network output $y$ with respect to the neural network input $x$, $\partial y/\partial x_1$, $\partial y/\partial x_2$, $\partial y/\partial x_3$, are further derived based on the chain rule as follows.

Let $L$ be the number of hidden layers, $v_{ij}$ and $u_{ij}$ be the output and input of the $j$th neuron in the $i$th hidden layer respectively, $w_{ij}^{(l)}$ be the connection weight between the $i$th neuron in the $l$th hidden layer and the $j$th neuron in the $(l+1)$th hidden layer (the $j$th input $x_j$ if $l = L$), and $l = 0$ for output layer (i.e. $v_{L+1,j} = x_j$ and $y = v_{01}$). Let the activation function be the sigmoid function $v = f(u) = 1/[1 + \exp(-u)]$. Thus $df(u)/du = f(u)[1-f(u)]$.

For $p = 1,2,3$;

$$\frac{\partial y}{\partial x_p} = \frac{\partial y}{\partial u_{01}}\frac{\partial u_{01}}{\partial x_p} = y(1-y)\sum_i w_{1i}^{(0)}\frac{\partial v_{1i}}{\partial x_p},$$

$$\frac{\partial v_{1i}}{\partial x_p} = \frac{\partial v_{1i}}{\partial u_{1i}}\frac{\partial u_{1i}}{\partial x_p} = v_{1i}(1-v_{1i})\sum_j w_{ij}^{(1)}\frac{\partial v_{2j}}{\partial x_p},$$

$$\vdots$$

$$\frac{\partial v_{Lk}}{\partial x_p} = \frac{\partial v_{Lk}}{\partial u_{Lk}}\frac{\partial u_{Lk}}{\partial x_p} = v_{Lk}(1-v_{Lk})\,w_{kp}^{(L)}.$$

### 3.3 An Illustrative Example

To demonstrate the detailed implementation procedure and operating characteristics of the proposed approach to machining operation optimisation, an illustrative example based on hypothetical data is discussed as follows.

*Illustrative Example.* Consider turning ferrous alloy bars using coated carbide tools on a CNC lathe. For simplicity, let us assume that the constant parameters in the objective functions and constraints have been estimated based on the data on tool life, surface roughness, cutting force and cutting temperature.

$$T_s = 0.12\,\text{min},\quad T_c = 0.26\,\text{min},\ T_i = 0.04\,\text{min},$$
$$V = 231376\,\text{mm}^3$$
$$C_t = \$13.55,\ C_l = \$0.31/\text{min},\ C_o = \$0.08/\text{min},\ \eta = 36\%$$
$$K_T = 1575134.21,\ \alpha_T = 1.70,\ \beta_T = 1.55,\ \gamma_T = 1.22$$
$$K_S = 1.17,\ \alpha_S = -0.25,\ \beta_S = 0.72,\ \gamma_S = 0.23$$
$$K_F = 1.38,\ \alpha_F = 0.00,\ \beta_F = 1.18,\ \gamma_F = 1.26$$
$$K_\theta = 26.23,\ \alpha_\theta = 0.36,\ \beta_\theta = 0.24,\ \gamma_\theta = 0.11$$
$$v_{min} = 4.0\,\text{m/min},\ v_{max} = 90.0\,\text{m/min}$$
$$f_{min} = 0.5\,\text{mm/rev},\ f_{max} = 75.0\,\text{mm/rev}$$
$$d_{min} = 1.0\,\text{mm},\ d_{max} = 5.0\,\text{mm}$$
$$F_{max} = 20\,\text{kg},\ P_{max} = 2\text{kW},\ \theta_{max} = 290°\text{C}$$

Accordingly, the three objective functions and constraints are as follows.

$$\min T_p = 0.16 + 231276\,(1 + 0.26/TL)/MRR$$
$$\min C_p = (13.55/TL + 0.39)T_p$$
$$\min H_p = 1.17v^{-0.25}f^{0.72}d^{0.23}$$
$$\text{s.t. } TL = 1575134.21v^{-1.70}f^{-1.55}d^{-1.22}$$
$$MRR = 1000vfd$$

**Table 1.** Randomized samples for training neural network.

| No. | $v$ (m/min) | $f$ (mm/rev) | $d$ (mm) | $T_p$ (min) | $C_p$ ($) | $H_p$ (μm) |
|---|---|---|---|---|---|---|
| 1 | 6.111881 | 0.797555 | 2.340617 | 20.430643 | 7.975532 | 0.958805 |
| 2 | 10.653035 | 27.179281 | 1.868801 | 0.588833 | 0.330964 | 12.030612 |
| 3 | 111.394638 | 15.183218 | 3.801355 | 0.202165 | 1.892841 | 7.547976 |
| 4 | 193.983826 | 21.109150 | 2.777154 | 0.190553 | 5.062711 | 9.463449 |
| 5 | 25.796320 | 52.867474 | 3.257393 | 0.216332 | 1.009139 | 19.083168 |
| 6 | 141.107452 | 57.829784 | 4.310526 | 0.182252 | 22.716995 | 19.676325 |
| 7 | 195.906494 | 16.957106 | 2.707206 | 0.194784 | 3.655530 | 8.081243 |
| 8 | 166.181458 | 34.327480 | 3.419019 | 0.184397 | 10.233696 | 13.472135 |
| 9 | 136.334366 | 45.478943 | 3.196722 | 0.184224 | 10.402867 | 16.562170 |
| 10 | 148.004639 | 9.046708 | 2.624805 | 0.231045 | 1.048726 | 5.169560 |
| 11 | 28.286631 | 50.844097 | 2.899594 | 0.219804 | 0.983298 | 18.520275 |
| 12 | 102.220772 | 42.819256 | 2.377972 | 0.191523 | 4.253696 | 15.950535 |
| 13 | 88.615616 | 52.608829 | 1.654805 | 0.198683 | 3.083999 | 18.552305 |
| 14 | 111.663200 | 48.912273 | 3.493606 | 0.183709 | 9.225237 | 17.523003 |
| 15 | 4.610370 | 59.541870 | 2.075716 | 0.567123 | 0.311246 | 21.517080 |
| 16 | 96.214729 | 29.491058 | 2.507248 | 0.199857 | 2.432417 | 12.209506 |
| 17 | 120.226692 | 45.760475 | 2.119297 | 0.190375 | 5.345912 | 16.677811 |
| 18 | 38.113590 | 60.887737 | 2.179968 | 0.211269 | 1.419678 | 20.961664 |
| 19 | 70.780602 | 31.148212 | 1.961699 | 0.219263 | 1.322238 | 12.777899 |
| 20 | 86.796715 | 4.571932 | 2.976379 | 0.358359 | 0.382672 | 3.196595 |

**Table 2.** Randomized samples for testing neural network.

| No. | $v$ (m/min) | $f$ (mm/rev) | $d$ (mm) | $T_p$ (min) | $C_p$ ($) | $H_p$ (μm) |
|---|---|---|---|---|---|---|
| 21 | 198.933929 | 27.133503 | 2.619678 | 0.188141 | 7.138271 | 11.332766 |
| 22 | 53.806206 | 57.360561 | 4.557482 | 0.184487 | 4.776284 | 19.942099 |
| 23 | 165.650436 | 47.683140 | 3.860317 | 0.182980 | 19.426577 | 17.069653 |
| 24 | 39.035248 | 42.439301 | 2.535691 | 0.219843 | 1.081714 | 16.156595 |
| 25 | 47.562119 | 52.460052 | 3.657186 | 0.192039 | 2.718086 | 18.746376 |
| 26 | 110.875824 | 10.291863 | 3.098087 | 0.230185 | 0.963589 | 5.705383 |
| 27 | 59.684071 | 59.715828 | 3.073794 | 0.189221 | 3.862165 | 20.485807 |
| 28 | 21.310099 | 69.956314 | 4.556017 | 0.198743 | 1.504644 | 23.436327 |
| 29 | 62.699303 | 25.650303 | 3.470901 | 0.206849 | 1.490136 | 11.137486 |
| 30 | 21.694632 | 73.623108 | 4.461654 | 0.197318 | 1.618100 | 24.305748 |
| 31 | 128.167603 | 58.333340 | 2.014679 | 0.187811 | 8.014126 | 19.837660 |
| 32 | 117.248085 | 10.463531 | 3.456862 | 0.219656 | 1.160988 | 5.767294 |
| 33 | 51.462387 | 41.477966 | 2.978210 | 0.202322 | 1.800933 | 15.804641 |
| 34 | 20.376232 | 64.044113 | 3.908536 | 0.209531 | 1.090228 | 22.012451 |
| 35 | 61.173374 | 51.565098 | 2.238563 | 0.199851 | 2.335288 | 18.422596 |
| 36 | 74.943329 | 57.154560 | 4.909787 | 0.181290 | 8.913015 | 19.759130 |
| 37 | 188.191406 | 18.840860 | 2.641407 | 0.193986 | 3.879806 | 8.725019 |
| 38 | 69.993225 | 66.923538 | 4.825312 | 0.180893 | 9.892230 | 22.166725 |
| 39 | 173.176300 | 19.980728 | 2.247108 | 0.198483 | 3.116219 | 9.117090 |
| 40 | 74.961639 | 4.409421 | 2.288614 | 0.467856 | 0.352066 | 3.123517 |

$$F = 1.38 f^{1.18} d^{1.26}$$

$$P = 0.000626 v f^{1.18} d^{1.26}$$

$$\theta = 26.23 v^{0.36} f^{0.24} d^{0.11}$$

$$4.0 \le v \le 90.0$$

$$0.5 \le f \le 75.0$$

$$1.0 \le d \le 5.0$$

$$F \le 20$$

$$P \le 2$$

$$\theta \le 290$$

In order to assess the manufacturers's implicit multiattribute value function, the preferential information has to be elicited. Listed in Tables 1 and 2 are, respectively, twenty training and testing samples. The cutting data were generated randomly within the specified lower and upper bounds, under the condition that the associated objective values are non-dominated. In this example, we assume that the manufacturer's implicit multiattribute value function is $v(T_p, C_p, H_p) = 0.42 \exp(-0.22T_p) + 0.36 \exp(-0.32C_p) + 0.17 \exp(-0.26H_p) + 0.05/(1 + 1.22T_p C_p H_p)$. The assumed multiattribute value function is used, only for the simulation purpose, to provide preferential data on behalf of the manufacturer and evaluate the performance of the trained neural network. Based on the implicit multiattribute value function, preferential ratings

**Table 3.** Preferential data given by the manufacturer and neural network.

| No. | $v\ [T_p, C_p, H_p]$ | $y\ (T_p, C_p, H_p)$ | $v - y$ | No. | $v\ [T_p, C_p, H_p]$ | $y\ (T_p, C_p, H_p)$ | $v - y$ |
|---|---|---|---|---|---|---|---|
| 1 | 0.165490 | 0.165510 | −0.000020 | 21 | 0.451121 | 0.451335 | −0.000214 |
| 2 | 0.713190 | 0.713435 | −0.000245 | 22 | 0.484552 | 0.483774 | 0.000778 |
| 3 | 0.633116 | 0.631448 | 0.001668 | 23 | 0.406823 | 0.407930 | −0.001107 |
| 4 | 0.492632 | 0.491931 | 0.000701 | 24 | 0.666175 | 0.666702 | −0.000527 |
| 5 | 0.670540 | 0.669414 | 0.001126 | 25 | 0.558644 | 0.559181 | −0.000537 |
| 6 | 0.405262 | 0.404750 | 0.000512 | 26 | 0.721960 | 0.716091 | 0.005869 |
| 7 | 0.541169 | 0.541706 | −0.000537 | 27 | 0.510904 | 0.509831 | 0.001073 |
| 8 | 0.423601 | 0.423983 | −0.000382 | 28 | 0.630082 | 0.629462 | 0.000620 |
| 9 | 0.419769 | 0.419912 | −0.000143 | 29 | 0.643813 | 0.643100 | 0.000713 |
| 10 | 0.720663 | 0.722399 | −0.001736 | 30 | 0.621741 | 0.620783 | 0.000958 |
| 11 | 0.672864 | 0.671789 | 0.001075 | 31 | 0.433018 | 0.434730 | −0.001712 |
| 12 | 0.500614 | 0.499743 | 0.000871 | 32 | 0.704319 | 0.702822 | 0.001497 |
| 13 | 0.540952 | 0.541394 | −0.000442 | 33 | 0.613048 | 0.615990 | −0.002942 |
| 14 | 0.425296 | 0.426046 | −0.000750 | 34 | 0.662616 | 0.660686 | 0.001930 |
| 15 | 0.706115 | 0.706117 | −0.000002 | 35 | 0.578212 | 0.580130 | −0.001918 |
| 16 | 0.580404 | 0.580410 | −0.000006 | 36 | 0.426607 | 0.427705 | −0.001098 |
| 17 | 0.472367 | 0.472279 | 0.000088 | 37 | 0.529609 | 0.528000 | 0.001609 |
| 18 | 0.635985 | 0.637361 | −0.001376 | 38 | 0.420349 | 0.421417 | −0.001068 |
| 19 | 0.651213 | 0.652430 | −0.001217 | 39 | 0.557094 | 0.554118 | 0.002976 |
| 20 | 0.813291 | 0.812391 | 0.000900 | 40 | 0.806748 | 0.811319 | −0.004571 |

$v[T_p, C_p, H_p]$ assumptively provided by the manufacturer for the generated training and testing data are listed in the second and sixth columns of Table 3.

The input–output samples 1–20 listed in Tables 1 and 3 were used as training samples. A multilayer neural network with four hidden neurons in one hidden layer was trained using an adaptive learning algorithm with line search capability. The initial connection weights and biasing thesholds of the neural network were generated at random uniformly over interval (0, 1). After 50000 epochs, the mean square training error was reduced to $0.5 \times 10^{-7}$. Fig. 3 illustrates the monotone decrease of the mean square training error versus epoch within a time window. Fig. 4 depicts the trained neural network that is to be used to represent the manufacturer's preference, where the values on the synaptic links are connection weights and values inside the circles are biasing thresholds for corresponding neurons. The trained neural network was tested based on the input–output samples 21–40. The mean square testing error is $2.5 \times 10^{-7}$ and the trained neural network was considered valid. The third and seventh columns of Table 3 record the output of the trained neural network for training samples and testing samples respectively. The fourth and eighth columns record the differences between expected and actual outputs of the trained neural network for all samples.

Based on the constructed multilayer neural network, a commercial software package was used to obtain the optimal cutting parameters started with an arbitrary initial solution. Table 4 records the optimum cutting parameters and corre-

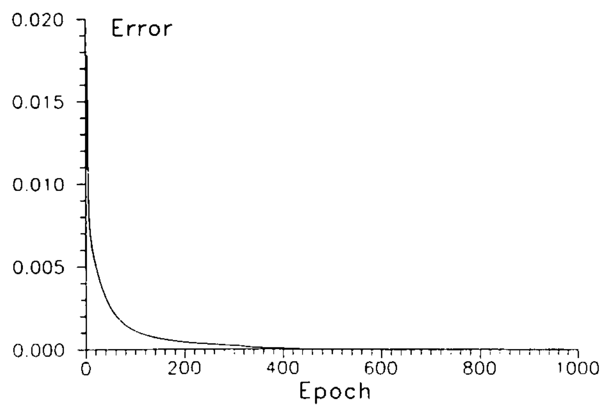


**Fig. 3.** Mean square training error versus epoch in the supervised learning.

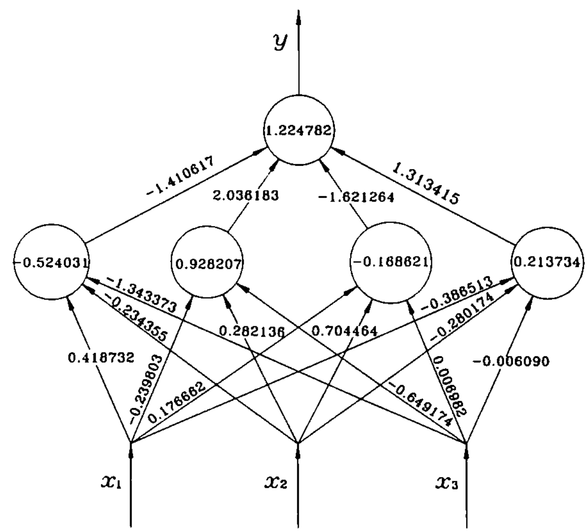


**Fig. 4.** Constructed multilayer neural network as a preference representation.

**Table 4.** Optimum cutting parameters, objective functions values, and process outputs.

| Basis | $v$ (m/min) | $f$ (mm/rev) | $d$ (mm) | $T_p$ (min) | $C_p$ ($) | $H_p$ (μm) |
|---|---|---|---|---|---|---|
| $v\,[T_p, C_p, H_p]$ | 90.000000 | 1.728503 | 5.000000 | 0.459051 | 0.317014 | 0.815663 |
| $y\,[T_p, C_p, H_p]$ | 90.000000 | 1.728491 | 5.000000 | 0.459053 | 0.317013 | 0.815659 |
| Basis | $MMR$ (mm³/min) | | $TL$ (min) | $F$ (kg) | $P$ (kW) | θ (°C) |
| $v\,[T_p, C_p, H_p]$ | 777826.196634 | | 45.078891 | 20.000000 | 0.816670 | 180.406892 |
| $y\,[T_p, C_p, H_p]$ | 777820.742366 | | 45.079381 | 19.999924 | 0.816663 | 180.406589 |

sponding values of objective functions and process outputs based on maximising both the assumed implicit multiattribute value function $v[T_p,(v,f,d),\ C_p(v,f,d),\ H_p(v,f,d)$ and the trained neural network $y[T_p(v,f,d),\ C_p(v,f,d),\ H_p(v,f,d)]$. Clearly, the neural-network-based optimisation approach provides a sufficiently accurate approximation to the true optimal solution.

## 4. Concluding Remarks

In this paper, a neural-network-based approach to cutting parameter optimisation for planning machining operations has been described. The proposed approach possesses many desirable features. It provides a global measure of a manufacturer's preference, hence relaxes the need for frequent and intensive interactions with the manufacturer to determine the optimum cutting parameters. It provides a robust representation due to the fault-tolerant nature of neural networks. It provides an automated paradigm for optimisation of cutting parameters since the proposed approach is easy to computerise. Although global preference modelling via supervised leaning may be computationally intensive, the proposed approach is more advantageous than interactive approaches, specially for the job-shop production systems where product mix is diverse and dynamic. Future work could be directed to application of other preference models and neural networks to machining process optimisation, implementation of the proposed approach to real-world problems, and extension of the proposed approach to adaptive control of machining operations for on-line adjustment of cutting parameters based on information from sensors.

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## Nomenclature

| | |
|---|---|
| $v$ | cutting speed (m/min) |
| $f$ | feed rate per revolution (mm/rev) |
| $d$ | depth of cut per pass (mm) |
| $T_p$ | total operation time per part (min) |
| $T_s$ | set-up time per part (min) |
| $T_c$ | tool change time (min) |
| $T_i$ | idle time per part (min) |
| $C_p$ | cost per part ($) |
| $C_t$ | cost of tool per piece ($) |
| $C_l$ | labor cost per unit time ($/min) |
| $C_o$ | overhead per unit time ($/min) |
| $V$ | volume to be removed per part (mm$^3$) |
| $MRR$ | metal removal rate (mm$^3$/min) |
| $TL$ | tool life (min) |
| $SR$ | surface roughness (μm) |
| $H_r$ | arithmetic centre-line average (μm) |
| $P$ | cutting power (kW) |
| $F$ | cutting force (kg) |
| $\theta$ | interface temperature (°C) |