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Back-Propagation Artificial Neural Network Approach for Selection of a Rapid Prototyping Machine

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Abstract

A decade ago, rapid prototyping (RP) machine selection process was much easier since the breadth of choice was smaller, and the strengths of each technology were distinct and readily apparent. With advances in established technologies, materials and the introduction of new methods, selecting the right RP machine has become much more difficult. These advances have blurred the lines of distinction. The artificial neural network (ANN) research has opened a new dimension for scientific research and industrial/business applications. Although ANNs have been introduced for several years, their use in manufacturing area is quite recent and the applications to manufacturing problems are still very few. This paper attempts to demonstrate one of the potential applications of back-propagation ANN for selection of a Stereolithography apparatus (SLA) machine. The results of the study show the developed ANN model is capable of solving the RP machine selection problem with notable consistency and reasonable accuracy.

Introduction

Rapid prototyping (RP) refers to a variety of specialized equipment, software and materials capable of using 3D computer aided design (CAD) data input to directly fabricate geometrically complex objects. RP technologies have emerged as a key element of time compression engineering with their ability to shorten the product design and development process. This highly innovative and cost efficient technology has found applications in automotive, aerospace, and medical equipment manufacturing, replacing the commonly used slower and less accurate manual methods of fabricating prototypes [1]. With advances in established technologies, materials and the introduction of new methods, selecting the right RP machine has become much more difficult and is one of the most important decisions to be made when employing any particular RP technology. This is vital in minimizing build time and costs, and achieving optimal accuracy. When making this decision, designers and RP machine operators should consider a number of different process specific constraints. This may be quite a difficult and time - consuming task.

Presently available RP systems differ not only in cost, both of the equipment and materials, but also in capabilities in a very wide range. A choice of the RP machine, which meets the requirements of an industry in the best way, is not a trivial task. Each RP process has specific technological capabilities that have to be taken into account before a particular machine is selected. For example the following are major considerations that need to be taken into account in SLA machine selection [2]: laser configuration (type, wavelength and power), layer thickness, beam diameter, drawing speed, elevator configuration (resolution and repeatability), maximum part weight, capacity, maximum build envelope, operating system, size, weight and cost. Generally, selection in terms of these multiple attributes cannot be easily attained with usual programming tools. For this reason, the research studies in this field are progressively directed toward the use of new approaches and methods developed in the artificial intelligence (AI) world: knowledge-based systems, fuzzy logic, inductive learning, neural networks, and genetic algorithms. This paper describes the applicability of artificial neural network (ANN) approach to SLA machine selection problem. This tool, in fact, introduces an innovative approach fundamentally based on knowledge not directly visible by the user, but is able to be stored through a simpler and more intuitive training process. The reasons for using neural networks (NN) to solve the RP/SLA machine selection problem are: processing speed, processing order, abundance and complexity, knowledge storage, and processing control [3]. The paper provides the following: review of literature, the RP machine selection problem, results and discussion, conclusion and future research.

Review of Literature

During the last two decades, a number of developments have been reported in knowledge-based systems, fuzzy logic, inductive learning, neural networks and genetic algorithms [4]. ANN is one application of AI has achieved considerable success in recent years and opened a new dimension for scientific research and business applications. Evidently this approach has been applied to several areas in engineering and manufacturing. With the ready availability of high memory and affordable computers now, there is a considerable potential for the extension of ANN approach to solve challenging problems like RP machine selection. The purpose of this section here is limited to document some applications of ANN to manufacturing. However, interested readers can find basics of NN in some of the referenced sources [5-6].

ANN applications to manufacturing

Although ANNs have been introduced for several decades, their use in manufacturing area is quite recent and the applications to manufacturing problems are still very few. In the field of process planning, some studies have been carried out to test the behaviour of ANN in solving operations sequencing problem. Study of Dong et al. [7], illustrates the potential of ANN approach to solve the sequencing problem. A feedforward neural network was designed for each form feature in order to select the best sequence among a set of previously classified sequences. Another study [8] attempted the detection of the appropriate sequence of operations for machining holes. Sakakura and Inasaki [9] described an application of ANN for selection of grinding parameters. They developed a three-layer feedforward model to simulate the values of depth of cut and feed to be used in grinding, in order to obtain a given surface roughness. Li et al. [10] proposed an ANN model for selection of grinding wheel selection. The proposed network has five input neurons that correspond to the 'type of machine', the 'work piece material', the 'hardness', the 'surface roughness' and the 'severity' of the grinding operation; the output vector is formed by four elements, which represent the 'abrasive type', 'grade', 'grit size' and 'bond'. It is remarkable that the network was trained using a range of data directly taken from the manufacturer's catalogue. Further applications of ANN to manufacturing related problems are evidenced with selection of parameters of cutting tools [11], scheduling [12] and lot sizing [13]. The analysis of literature has revealed that the ANN approach has been applied to a wide variety of manufacturing problems.

However, a few attempts are also aimed to select general purpose machines. Some of the studies include Gopalakrishnan et al.'s [14] object oriented computer based software program, which is a prototype decision support system (DSS). They focused primarily on selection of vertical and horizontal machining centres with various options include high speed, productivity, machining complexity and machining accuracy to facilitate and satisfy production requirements. Arslan et al. [15] also proposed a DSS model for selection of knowledge intensive machining centres. It is evident that although DSS models have been developed to select general purpose machines, a specific AI based NN approach towards selection of RP machine is needed since the NN can have capability to solve problems that are difficult for human beings. This paper attempts to show the potentiality of ANN to RP/SLA machine selection problem through an illustration.

The RP Machine Selection Problem

Industries have been using RP techniques increasingly to reduce their product development cycle. An RP part should not only satisfy the quality requirements, but should also be built at the lowest cost and fastest speed. RP systems are controlled by a computer which uses the CAD representation that is translated into commands to build parts. For building a satisfactory part/prototype, it is an essential step towards the identification of the most suitable RP machine. It is therefore important to understand where the errors stem from, what are the issues associated with the RP equipment selection to minimize or eliminate the processing errors. Traditionally, designers are faced with three choices to select a right RP machine:

- relying on published literature such as books and articles and on personal experiences,
- relying on the experience of RP machine suppliers and
- appointing a consultant.

Designers relying on personal experience tend to select RP machines with which they are most familiar, however, the choice may not be the cost-effective machine. RP machine vendors have an inherent interest in selling their machinery, so their recommendations might sometimes be biased. On the other hand, consultants often charge substantial amounts for their recommendations and for the time they spend on evaluations. Thus, these traditional machine selection methods/options may not guarantee a cost-effective solution. The study of Gerrard [16] reveals that the role of engineering staff in authorization for final selection of machines is 6 per cent, the rest belongs to upper and middle management. It is evident that there is scope to apply ANN approach to RP machine selection problem, as it is time consuming and a knowledge intensive iterative process in addition to the following reasons:

- The range of RP applications increase as it improves the accuracy and reliability [17]
- RP techniques can guarantee great competitive advantages if applied to the production of tools and molds for the realization of technological prototypes [18]

- RP processes can be integrated with a variety of existing techniques to yield low-cost, high-speed methods to manufacture metal and composite parts [19]
- attempts have been made to apply ANN approach to several manufacturing applications [7-13] such as process planning, product design and analysis, process and machine diagnosis, analysis of grinding operations and machine maintenance analysis.

As mentioned before, the scope of the paper is limited to demonstrate the potential of ANN approach for the selection of SLA machine. Since SLA has established itself as one of the popular and reliable layer-additive processes to create prototypes in epoxy resin directly from computer aided design (CAD) data. The major steps of the proposed approach are:

- Construction of a three-layer feedforward back-propagation artificial neural network model
- Preparation of the training and testing samples
- Supervised learning and back-propagation training
- Testing of the output.

These steps are explained further in the following sections.

Construction of a three-layer feedforward back-propagation artificial neural network model

The ANN model used to select the SLA machine consists of an input layer, a hidden layer and an output layer, as shown in Figure 1. Each neuron or node in the input layer contains known information. The number of neurons (equal to 19) in the input layer is same as the set of parameters identified for the selection of a suitable SLA machine as given in Table 1. Lines represent weights which connect the input layer to the hidden layer. These weights are used to model the synaptic strength between neurons in the human brain, thus portraying the importance of one neuron's effect on the other of next layer. The hidden layer is also made-up of neurons, whose number is fixed on the basis of trial and error method, which is explained in the following sections. The output layer consists of four neurons only because four SLA machines are considered in the study for the purpose of illustration. An output node is used to represent each of the closest possible SLA machine. When the network is working correctly, the output node corresponding to the current SLA machine will have the values as given in Table 1. The activation of the neuron is computed by applying a Sigmoid function [5].

Preparation of the training and testing samples

Training patterns refers to the input data coupled with its desired outputs were prepared from the literature [2]. Generally, the selected training samples should be sufficient enough to cover the chosen characteristics of a typical SLA machine. The data of four SLA machines' information in the form of 24 samples along with the desired machines were used for training the network. When testing the network, various input data sets are applied to its input layer. The network generates the output. This output is used to determine the network performance and no back-propagation is carried out. The network's output is compared with the desired outputs. These input data sets and the desired outputs are collectively known as test samples. The input values have been coded with numerical values ranging between 0 and 1 in order to give a contribution to the network independent from their real absolute values.

Supervised learning and back-propagation training

Supervised learning is a process that incorporates an external teacher and/or global information. This process decides when to turn off the learning, how long and how often to present each association for training, and it also supplies performance error information. Supervised learning and back-propagation training algorithm proposed by Simpson [20] has been used in the study to adjust the weights of the network systematically such that the error between the output and the corresponding desired output is minimum. Also it maps new, never-before seen information entering the input layer to the nearest SLA machine at the output layer. The actual training of the network is accomplished by 'back-propagating' the error from the output layer to the hidden layer and finally to the input layer. The error is simply the difference between the desired output and the output calculated during training.

Network stability and optimality

As the proposed ANN has one hidden layer and the number of neurons in the hidden layer is initially set at 10. This number is arbitrarily fixed since there are no set rules to decide how many neurons should be used in a hidden layer [21]. However, there are a minimum number of hidden neurons that a network should have. A network with fewer hidden neurons will not train. In this study, the minimum number of hidden neurons is considered as a factor for system optimality, because in the case of hardware implementation of the network, a smaller number of neurons would mean less hardware.

The back-propagation algorithm selected in this study is a gradient descent type [20], in which the network weights are moved along the negative of the gradient of the performance function in an iterative manner. The weights involved in the network are adjusted in each of the iterations so as to reduce the error along a descent direction. In doing so, two parameters, called learning rate (η) and momentum factor (mf), are introduced in the literature [22] for controlling the size of weight adjustment along the descent direction and for dampening oscillations of the iterations. These two parameters have to be empirically chosen in the conventional back-propagation algorithm. In general, the 'mf' should be less than unity to stabilize the behavior of the algorithm. The selection of learning rate is also more arbitrary due to the fact that the error surface usually consists of many flat and steep regions and behaves quite differently from application to application [22].

The learning rate is set at 1.0 for the default network. A large learning rate is helpful for accelerated learning, when the weight search crosses a plateau. It can be set in between 0.0 to 4.0 [23]. A value 0.0 means that the weights will not change during training. As a result, the network will not train. A value 4.0 provides the network with large changes in weight values, which would mean fast training time. Therefore an efficient back-propagation algorithm should be capable of dynamically varying its learning rate and 'mf'.

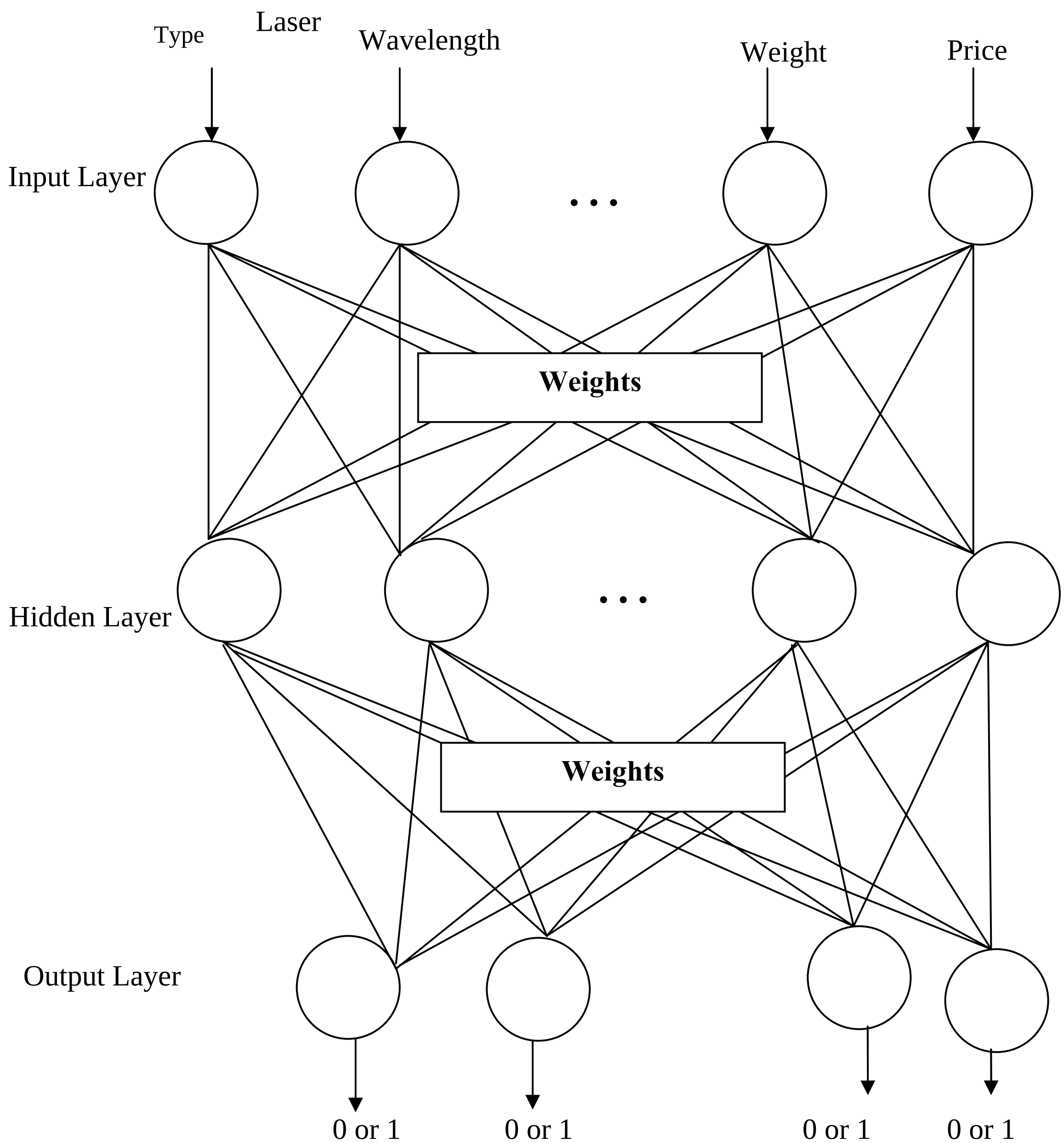

Figure 1: Feedforward Three-layer ANN Model for RP/SLA Machine Selection

Table 1: SLA Machine Parameters, Input and Output Neurons

Input Neuron ($N_{i = 1 \text{ to } 19}$)	Machine Parameter	
1	Laser Type	
2	Laser Wavelength	
3	Laser Power	
4	Layer Thickness	
5	Beam Diameter	
6	Drawing Speed	
7	Elevator Resolution	
8	Elevator Repeatability	
9	Maximum Part Weight	
10	Capacity	
11	Build Envelope in X-direction	
12	Build Envelope in Y-direction	
13	Build Envelope in Z-direction	
14	Operating System	
15	Size in X-direction	
16	Size in Y-direction	
17	Size in Z-direction	
18	Weight	
19	Price	
Output Neuron ($O_{i = 1 \text{ to } 4}$)	Machine	
	Study Code	Type
1	SL01	SLA0250
2	SL02	SLA3500
3	SL03	SLA5000
4	SL04	SLA7000

Network stability

The initial network with 19 input neurons, 10 hidden neurons and 4 output neurons is called the default network. The tolerance used for the default network is 0.10. For example, if a vector input corresponds to a desired output of 0 0 0 1 (SLA0250) and the network calculated an output of 0 0 0 (0.9 to 1.1), the training information is considered learnt. But an output below 0.9 and above 1.1 means the network has not yet learnt that particular training information. Reality is that the network has to learn all the training data before it is considered trained. Thus training tolerance must be considered in training the data, which translates to the minimum error allowed. There is a minimum training tolerance below which a network will fail to learn or converge. Also adding of the input noise to the input vectors causes the network for variations in training time. However, it helps the network to generalize and resulting network is a better predictor. For the default network, the input noise is set at 0.0.

Optimality

Once the default NN is trained, its parameters need to be optimized to yield an optimum performance. The changes made in the network parameters such as hidden neurons, input noise, learning rate and tolerance and the corresponding results obtained are shown in Table 2. The first step towards model optimality is changing the number of hidden neurons. Changing the number of hidden neurons subsequently changes the number of total weights. Hence they have to be reinitialized and the new network has to be trained. If the new network is trained and the hidden neurons are further reduced then the network needs to be retrained with the reduced number of hidden neurons. In this way an initial number of 10 in the default network are reduced to 2 hidden neurons. Next the input noise and the back-propagation learning rate are varied and experimentation continued. During the investigation the optimal network was found at the noise level of 0.1 and minimum tolerance of 0.08. The tolerance versus the number of iterations is plotted in Figure 2.

Table 2: ANN Model Optimality Results

Hidden Neurons	Input Noise	Tolerance	Learning Rate	Iterations
10	0.00	0.10	1	20
05	0.00	0.10	1	19
04	0.00	0.10	1	21
03	0.00	0.10	1	33
02	0.00	0.10	1	79
01	0.00	0.10	1	Does not train
02	0.05	0.10	1	79
02	0.05	0.01	1	4003
02	0.05	0.02	1	1073
02	0.05	0.03	1	512
02	0.05	0.04	1	309
02	0.05	0.05	1	212
02	0.05	0.06	1	159
02	0.05	0.07	1	127
02	0.05	0.08	1	106
02	0.05	0.09	1	85
02	0.1	0.01	2	1153
02	0.1	0.02	2	316
02	0.1	0.03	2	161
02	0.1	0.04	2	110
02	0.1	0.05	2	70
02	0.1	0.06	2	57
02	0.1	0.07	2	45
02	0.1	0.08	2	33

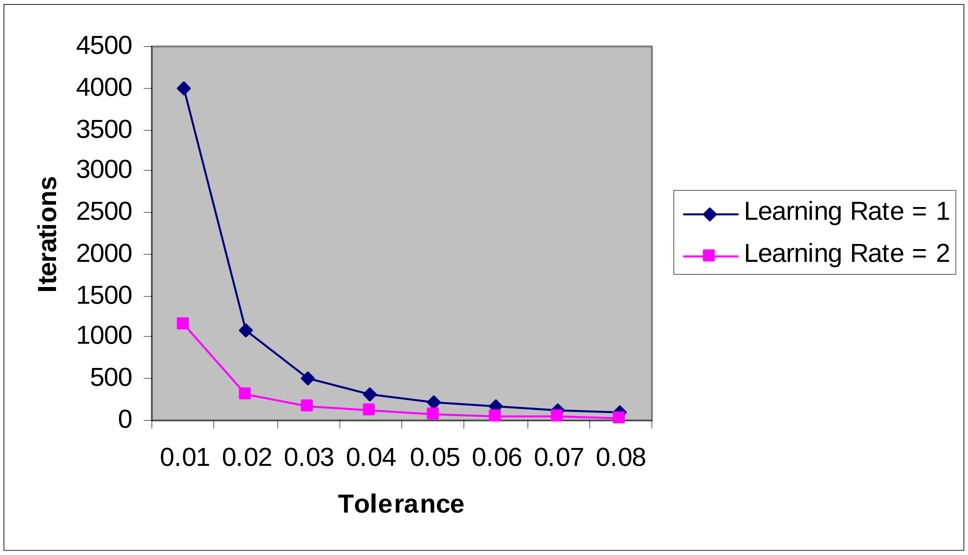

Figure 2: Tolerance versus Iterations

Testing of the model output

The flow chart for RP/SLA machine selection presented in Figure 3 has been used while developing the ANN model in ‘C’ language. The trained network for SLA machine selection has been simulated and tested for its validity. While testing the model, various samples, have been applied to the network. The output generated from the ANN model is compared to the desired output. The network output and the desired output against the respective sample numbers are listed.

Results and Discussion

In order to validate the capability of the trained neural network, 24 sets of test data are used. Based on the results some inferences can be drawn. Input neurons were set at an approximate activity levels in between 0 and 1 through normalization procedure to indicate the customer desired SLA machine specifications. In this study, four output neurons were used to select the possible or approximate an SLA machine. When the model is generating accurate output, the output neuron corresponding to the correct SLA machine has an activity of 1.0 and all others have any value in between 0 and 1.0, however, it depends on the noise level added to the input data and the set

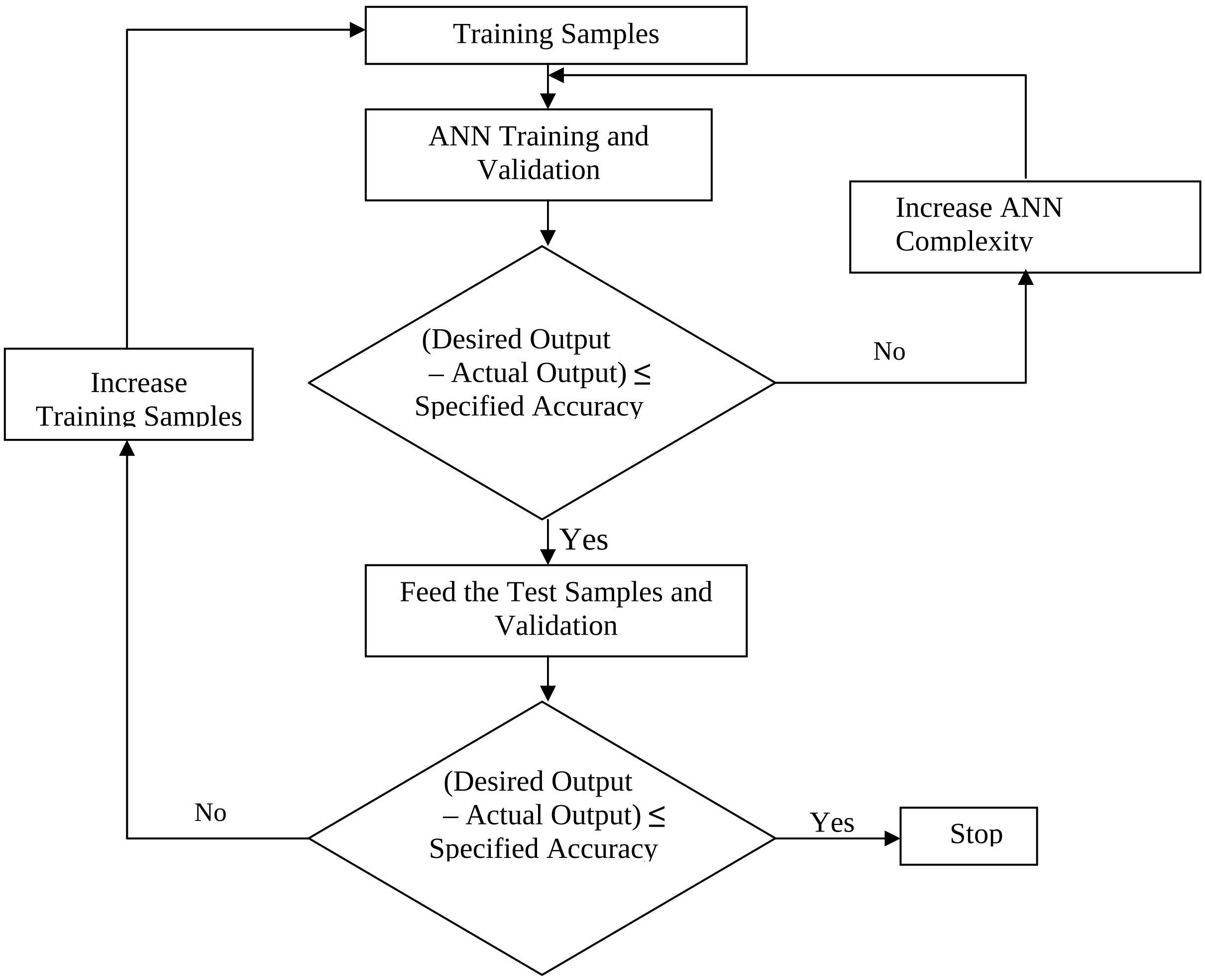

Figure 3: Flow Chart for RP/SLA Machine Selection Using ANN Approach

threshold levels. For two different combinations of noise levels the results were obtained and presented in Tables 3 and 4. All the 24 test samples, for threshold level of 0.9, mf of 0.9, learning rate of 2, tolerance of 0.08 and without any noise, the generated network output is coinciding with the desired output (Table 3). This shows that the ANN has been validated on a set of data, which has not been used in the training process. However, if the trained network performs poorly on the validating set, it is assumed that there is some important information in the validating data set, which the network was unable to learn. The samples with large deviations against their desired output are then added to the training set and the network is retrained using the new set of training samples. This process of training and validation is repeated until the performance of the trained network on the validating set is acceptable.

Table 3: Model Results without Input Noise

Sample #	Network Output				Desired Output			
1	0	0	1	0	0	0	1	0
2	0	0	1	0	0	0	1	0
3	0	0	0	1	0	0	0	1
4	0	0	0	1	0	0	0	1
5	0	0	1	0	0	0	1	0
6	0	0	1	0	0	0	1	0
7	0	1	0	0	0	1	0	0
8	0	1	0	0	0	1	0	0
9	0	0	0	1	0	0	0	1
10	0	0	0	1	0	0	0	1
11	1	0	0	0	1	0	0	0
12	1	0	0	0	1	0	0	0
13	0	1	0	0	0	1	0	0
14	0	1	0	0	0	1	0	0
15	1	0	0	0	1	0	0	0
16	1	0	0	0	1	0	0	0
17	0	0	0	1	0	0	0	1
18	0	0	1	0	0	0	1	0
19	0	0	0	1	0	0	0	1
20	0	1	0	0	0	1	0	0
21	0	0	1	0	0	0	1	0
22	0	1	0	0	0	1	0	0
23	1	0	0	0	1	0	0	0
24	1	0	0	0	1	0	0	0

Table 4: Model Results with Input Noise = 0.05

Sample #	Network Output				Desired Output			
1	0	0	0	0	0	0	0	1
2	0	0	1	0	0	0	1	0
3	0	0	0	0	0	1	0	0
4	1	0	0	0	1	0	0	0
5	0	0	0	0	0	0	0	1
6	0	0	1	0	0	0	1	0
7	0	0	0	0	0	1	0	0
8	1	0	0	0	1	0	0	0
9	0	0	0	0	0	0	0	1
10	0	0	1	0	0	0	1	0
11	0	0	0	0	0	1	0	0
12	1	0	0	0	1	0	0	0
13	0	0	0	0	0	0	0	1
14	0	0	1	0	0	0	1	0
15	0	0	0	0	0	1	0	0
16	1	0	0	0	1	0	0	0
17	0	0	0	0	0	0	0	1
18	0	0	1	0	0	0	1	0
19	0	0	0	0	0	0	0	1
20	1	0	0	0	0	1	0	0
21	0	0	0	0	0	0	0	1
22	0	0	1	0	0	0	1	0
23	0	0	0	0	0	1	0	0
24	1	0	0	0	1	0	0	0

Conclusion

Selecting a suitable RP/SLA machine for a given set of machine parameters is a complex problem since it can be affected by many factors. Identifying the correlation between selecting an appropriate SLA machine in accordance with its varying parameters is the key problem to be resolved. After reviewing the literature, laser configuration (type, wavelength and power), layer thickness, beam diameter, drawing speed, elevator configuration (resolution and repeatability), maximum part weight, capacity, maximum build envelope, operating system, size, weight and cost are chosen as SLA machine selection parameters to demonstrate the potential of the ANN model. Data of four SLA machines' information in the form of 24 samples along with the desired SLA machines' were used to achieve the optimum NN parameters. Results show that the developed ANN model has the capability of solving the SLA machine selection problem with two hidden neurons for noise level of 0.1 and tolerance of 0.08. When testing the network, 24 input data samples are used. Except in twelve data sets, the network displayed a robust performance for threshold level of 0.9, mf of 0.9, learning rate of 2, tolerance of 0.08 and with a noise level of 0.05 (refer Table 4). This outcome tells that the model needs to be validated with some additional SLA machine information, which has not been used in the earlier training process. Thus, the study has shown that a properly developed ANN model provides a valid alternative for solving the SLA machine selection problem. The ANN model demonstrated in this paper is an innovative approach fundamentally based on AI which is not directly visible to the user, but able to solve through a simpler and supervised feedforward back-propagation training process. This was carried out through training samples directly taken from the RP machine manufacturers' catalogues. The advantages of this approach, in comparison with other programming methods, are:

- There is no need to know the explicit function for selecting a suitable SLA machine for a user set specifications.
- Capability of accomplishing the selection of SLA machines in a short computing time.
- Capability of self-learning new data directly coming from RP machine manufacturers.
- Capability to easily update and adapt the training samples of the network to the actual requirements of the user.

Future Research

The potential of ANN as a SLA machine selection tool is usually based on a large sample size. The generalization capabilities of ANNs are highly dependent on the number of samples in the training process. Hence, there is scope to train and test the ANN model based on further larger sample size in the future. Also, it could be interesting to the researchers to compare the performance of ANN approach with other association rules or decision tree models especially to examine whether ANN approach has any superiority in solving SLA machine selection problem.

With respect to the other modeling tools for selection of the RP/SLA machine, IF-THEN rules often used in knowledge-based expert systems may have a remarkable advantage of representing the knowledge with simple and independent structures. Continuing research is now being directed towards the development of knowledge based neural system to demonstrate the potential of RP machine selection using several criteria such as build orientation, accuracy, and layer thickness.

References

[1] Rao, P.N., Lerner, Y. and Kouznetsov, V. Rapid Prototyping Applications in Metal Casting. Institution of Engineers Journal, Malaysia. Vol. 64, No.3, 2003, pp.1-7.

[2] Pham, D.T. and Dimov, S.S. Rapid Manufacturing: The Technologies & Applications of Rapid Prototyping & Rapid Tooling. Springer-Verlag, London, 2001.

[3] Arad, B. S., and El-Awawy, A. On Fault Training of Feedforward Neural Networks. Neural Networks, Vol.10, No. 3, 1997, pp. 539-553.

[4] Pham, D.T., and Pham, P.T. N. Computational Intelligence for Manufacturing. Computational Intelligence in Manufacturing Handbook, CRC Press, New York, 2000.

[5] Kronsjo, L. and Shumsheruddin, D.Advances in Parallel Algorithms. John Wiley and Sons, Inc., New York, 1992, pp.66-85.

[6] Negnevitsky, M. Artificial Intelligence – A Guide to Intelligent Systems, Second Edition. Addison-Wesley, Pearson Education Limited, Harlow, England, 2005.

[7] Dong, J. X., Tang, X. Q., and Wang, S.C. Inference Mechanism for CAPP Tool Based on Artificial Neural Network. Proceedings of 1st Congress on Intelligent Manufacturing, Puerto Rico, 1995, pp. 994 – 1002.

[8] LeTumelin, C., Garro, O., and Charpentier, P. Generating Process Plans Using Neural Networks. Proceedings of Second International Workshop on Learning in Intelligent Manufacturing Systems, Budapest, 1995.

[9] Sakakura, M., and Inasaki, I. A Neural Network Approach to the Decision-Making for Grinding Operations. Ann. CIRP, Vol. 41, No. 1, 1992, pp. 3453- 3456.

[10] Li, Y., Mills, B., Moruzzi, J. L., and Rowe, W. B. Grinding Wheel Selection Using a Neural Network. Proceedings of 10th National Manufacturing Research Conference Loughborough, 1994, pp. 597 – 601.

[11] Santochi, M. and Dini, G. Use of Neural Networks in Automated Selection of Technological Parameters of Cutting Tools. Computer Integrated Manufacturing Systems, Vol. 9, No. 3, 1996, pp. 137 – 148.

[12] Sabuncuoglu, I. and Gurgun, B. A Neural Network Model for Scheduling Problems. European Journal of Operational Research, Vol. 93, 1996, pp. 288 – 299.

[13] Gaafar, L.K. and Choueiki, M.H. A Neural Network Model for Solving the Lot-sizing Problem", Omega, Vol. 28, 2000, pp. 175 – 184.

[14] Gopalakrishnan, B., Yoshii, T. and Dappili, S.M. Decision support System for Machining Centre Selection. Journal of Manufacturing Technology, Vol. 15, No. 2, 2004, pp. 114-154.

[15] Arslan, M.C., Çatay, B. and Budak, E. A Decision Support System for Machine Tool Selection. Journal of Manufacturing Technology, Vol. 15, No.1, 2004, pp. 101- 09.

[16] Gerrard, W. Selection Procedures Adopted by Industry for Introducing New Machine Tools. In Worthington, B. (Ed.), Advances in Manufacturing Technology. Proceedings of Fourth National Conference on Production Research, Kogan Page, London, 1988, pp. 525-31.

[17] Gibson, I. Discussion on the Concept of a Flexible Rapid Prototyping Cell. Rapid Prototyping Journal, Vol. 2, No. 2, 1996, pp. 32-38.

[18] Gatto,A., Bassoli,E., Iuliano, L. and Violante, M.G. Rapid Casting in the Development of an Automotive Component: Evaluation of Dimensional Performances. Rapid Prototyping & Manufacturing Conference 2005, Dearborn, Michigan, Society of Manufacturing Engineers, 2005, TP05PUB49.

[19] Lyons, B. Manufacturing With 3DP, Examples of Casting. Composites and Thermal Spray, Manufacturing for Performance Conference & Exhibits 2006, Indianapolis, Indiana, Society of Manufacturing Engineers, 2006, TP06PUB2.

[20] Simpson, P. K. Artificial Neural Systems Paradigms and their Applications and Implementations, Pergamon Press, London, 1989.

[21] Shanker, M., Hu, M., and Hung, M. Effect of Data Standardization on Neural Network Training. Omega International Journal of Management Science., Vol. 24, No. 4, 1996, pp. 385-397.

[22] Yu, X-H., and Chen G-U. Efficient Back Propagation Learning Using Optimal Learning Rate and Momentum. Neural Networks, Vol. 10, No. 3, 1997, pp. 517- 527.

[23] Chaudhuri, S. P., and Sequeira, C. Neural Networks for Automatic Target Recognition. Working Paper, Electrical Engineering Department, University of Lowell, Lowell, Massachusetts, USA, 1992, pp 1-10.

Biography

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