ScienceDirect

Materials Today: Proceedings

Available online 28 January 2023

In Press, Corrected Proof What's this?

Performance evolution in machining parameter of Al-Si (LM6) alloy using neural network

S. Arunkumar [a], N. Sriraman [b], R. Muraliraja [a], T. Vinod Kumar [a], V. Muthuraman [a]

Show more

Share Cite

https://doi.org/10.1016/j.matpr.2023.01.198

Get rights and content

Abstract

The global manufacturing age has increased competition in the manufacturing sector as markets become more agile and customer-focused. Because of the fierce rivalry, manufacturers are paying more attention to automation. In the last several decades, computer numerically controlled (CNC) machine tools have been utilized to achieve complete automation in machining. The artificial neural network theories are used in this research to train a solution for the problem of selecting machine setup settings for a turning operation. A collection of input and output values can be mapped out by an artificial neural network. A network may be used to anticipate output values for a certain set of input values once it has been trained. Process inputs like cutting speed, feed, depth of cut, and coolant flow rate can be generated by a trained program, as can their related process outputs like surface finish. Forward mapping of process inputs and outputs is accomplished using back propagation neural networks in this approach. The optimum machine setup parameter may then be selected interactively using these networks. To solve the model, a MATLAB program has been created. The experiment's findings are verified using a neural network.

Introduction

The machining settings are chosen to meet a variety of economic goals. These goals might include increasing output, lowering costs, and improving surface quality. Choosing the optimum mix of machine speed, feed, depth of cut, and coolant flow rate for a machining operation is known as parameter selection [1]. Traditionally, the settings were chosen based on experience and a lot of trial and error. Machine shops kept historical data on the metal cutting properties of workpiece tool combinations. These statistics are frequently used to configure a system. With the advent of newer materials, cutting tools, and machine equipment, these statistics frequently go out of date. Developing metal cutting characteristics for newer materials, cutting tools, and machine tools necessitate a large investment in time, machine, and human resources. Andersen et al., [2] describe neural Identification of behavioral trends as made possible by network modeling, a potent non-linear regression analytic technique. Predicting ferrite in arc welds as a function of composition was a challenge that this technology was used to solve. [3], [4]. Cook et al., [5] When modeling non-linear and highly correlated data sets, the neural network models mentioned above are excellent tools. GAs is efficient to search algorithms. The combination of a neural network model for prediction and a genetic algorithm for process optimization provides manufacturers with possible options to increase control and cut costs in their manufacturing process. Djurdjvc et al., [6] indicate that two feed-forward neural network models have been presented to predict the silicon modification level of W319 aluminum alloys using the Thermal Analysis parameters as inputs. The developed neural networks are a Multilayer Perception network [7]. Kanchana and Sarma [8] applied the Taguchi technique to optimize the software design process to enhance the software quality. They have considered the number of requirements per module [9], [10], [11]. Ranga Janardhan et al., [12] studied neural networks for the improvement of the quality of aluminum alloy castings developing a computer-based model using Artificial Neural Networks. The paper discusses the various details of the development of an Artificial Neural Network model for predicting the fracture pressure of liquid aluminum alloy and the tensile strength of the casting [13]. Soo Kima et al., [14] quoted In artificial intelligence (AI) research, ANNs are commonly used when a non-linear mapping between input and output parameters is necessary for approximating a function. [15]. To forecast the ideal bead width for robotic GMA welding, a multi-layer back-propagation network was used in this study to map the complicated and highly interacting process parameters pass number, welding speed, welding current, and arc voltage into the bead width. Vitek et al., [16]. To uncover behavioral trends, neural network modeling is a potent non-linear regression analysis technique. The issue of forecasting ferrite no in welds as a function of composition was tackled using this technique. Warren Liao et al., [17]. The ability to detect welding faults correctly is critical to the successful creation of an automated weld inspection system. Multilayer perception (MLP) neural networks achieve superior performance in detecting welding errors. [18]. To properly manage surface roughness, it is required to estimate the percentage contributions of factors such as cutting speed, feed rate, depth of cut, and coolant flow rate in this study effort.

Section snippets

Various restrictions for cutting conditions

The ultimate cutting conditions selection will need to adhere to a variety of limitations.

(a) Maximum feed limitation for machine tools: The maximum feed is chosen, and the appropriate speed is determined using the optimizing equations.

(b) Machine tool maximum speed restriction: The speed and feed are determined in the same manner as in a, but the speed determined is compared to the machine tool's maximum speed. If the former speed is less than the latter, it may be utilized; otherwise, the

The outcomes from the neural network

The networks projected the readings appear to be within an acceptable range. The percentage inaccuracy occasionally hovered around 10%. These inaccuracies can be considering that the real values are relatively small and even a slight divergence from the projected value can cause a bigger percentage of error, even though they can be viewed as unusual situations and ignored.

Training phase

Table 6 displays the 17 data sets that were used for training. The network is prepared for training when the network

Conclusions

The results were accurately anticipated by artificial neural networks. It took a lot of work to determine the ideal architecture. It was discovered that for a specific data pattern, there is a specific network design that may reduce the mistakes; this can be discovered via the trial-and-error approach and occasionally by experience. After a successful training period, the neural network model was more accurately able to predict the surface roughness. However, it should be emphasized that the

CRediT authorship contribution statement

S. Arunkumar: Conceptualization. **N. Sriraman:** Methodology. **R. Muraliraja:** Validation. **T. Vinod Kumar:** Investigation. **V. Muthuraman:** .

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Recommended articles

References (18)

D.F. Cook *et al.*
Combining a neural network with a genetic algorithm for process parameter optimization
Eng. Appl. Artif. Intel. (2000)

R. Amuthakkanan *et al.*
Reliability Analysis of Software Based Electro-pneumatic System Using Bayesian network

K. Andersen *et al.*
Artificial neural networks applied to Arc welding process modeling and control
IEEE Trans. Ind. App. (1990)

D. Benny Karunakar *et al.*

Modeling of green sand mould parameters using artificial neural networks
Indian Foundry J. (2003)

C.-C. Huang *et al.*
Parameter optimization in melt spinning by neural networks and genetic algorithms
Int. J. Adv. Manuf. Technol. (2006)

M.B. Djurdjevic, R. Francis, Application of Artificial Neural Networks in the prediction of the aluminum-silicon...

J.A. Freeman *et al.*
Neural Networks, Algorithms, Applications and Programming Techniques
(1999)

B. Kanchana, Sarma, Software Quality Enhancement Through Software Process Optimization Using Taguchi Methods, Indian...

Y. Liu *et al.*
Neural network based adaptive control and optimization in the milling process
Int. J. Adv. Manuf. Technol. (1999)

There are more references available in the full text version of this article.

Cited by (1)

DAO-LGBM: dual annealing optimization with light gradient boosting machine for advocates prediction in online customer engagement ↗
2024, Cluster Computing

View full text