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CFNN-PSO: An Iterative Predictive Model for Generic Parametric Design of Machining Processes

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ABSTRACT
Every production process consists of a large number of dependent and independent variables, which substantially influence the quality of the machined parts. Due to the large impact of process variabilities, it is difficult to design optimal models for the machining processes. Mathematical or numerical models for production processes are resource driven, which are not cost effective approaches in terms of computation and economical production. In this paper, a new artificial neural network (ANN) based predictive model is introduced, which exploits particle swarm optimization (PSO) algorithm to minimize the root mean square errors (RMSE) for the network training. This approach can effectively obtain an optimized predictive model that can calculate precise output responses for the production processes. In order to verify the proposed approach, two case studies are considered from literature and shown to produce significant improvements. Furthermore, the proposed model is validated on abrasive water jet machining (AWJM) with industrial garnet abrasives and optimal machining conditions have been obtained with optimized responses, which are substantially improved while compared with gray relational analysis (GRA).

Introduction

Optimal designing of production processes gained tremendous interest from researchers in recent past. In industrial production scenario, it is not easy to obtain optimized conditions for production process since a large number of design variables are involved, which need to be correctly selected for improved responses. Interdisciplinary collaborative techniques are followed while producing complex engineering products (Cook and Chiu 1998). These require complicated design space due to the nonlinearities exist in mutual relationships among dependent and independent process variables. Therefore, it is a difficult process to frame these complex relationships in the form of mathematics (Afazov 2013). Accuracy of certain production

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process is subject to the expensive experimental machining data, which is correlated with machining costs, tool cost, labor costs, overhead costs, and scrap costs etc. Therefore, data driven models, machine-learning techniques, or meta-models could be appropriate in such scenarios (Gröger, Niedermann, and Mitschang 2012).

The complexities of production of engineering products increase with the number of dependent and independent process variables. These types of problems are also termed as NP-Hard or combinatorial problems, which could have many near optimal solutions (Bruzzone et al. 2012). For an example, CNC milling machining includes a number of process variables such as spindle speed, feed rate, depth of cut, tool diameter, surface roughness (Ra), applied cutting forces, tool wear, material removal rate (MRR) etc. For this type of problems, process specific optimization approaches are required and universal formulations or models are not prominently available in literature (Mukherjee and Ray 2006). Optimization of production process is practically the adjustment of the independent design variables in order to obtain better scores for performance indicators. The values of machining variables could be obtained from a predefined design space defined by the specifications and tolerance values of tools and machines.

Hence, the aim of this paper is to portray some suitable hybrid optimization approach, which is process independent and obtains optimal solutions promptly. To cater the purpose, artificial neural network (ANN) based predictive model is proposed, which requires a small amount of process data for the training purpose and a popular bio-inspired algorithm called particle swarm optimization (PSO) is coupled to fine-tune the proposed predictive model. The proposed hybrid algorithm takes various design parameters as inputs and produces optimally trained predictive model, which is capable of producing improved process output. Root mean square error (RMSE) is used as the performance metric for the predictive model. The proposed algorithm is tested and validated with three cases; out of which two cases (CNC micro milling and water-in-diesel emulsification processes) are collected from literature and the remaining one (abrasive water jet machining, AWJM) has been conducted in laboratory. Rest of the paper is divided as follows, a detailed literature survey discussed in section #2, proposed predictive model portrayed in section #3, experimentations and results are demonstrated in section #4, followed by conclusions in section #5.

Related Works

Automated machining processes have modernized the production companies drastically since past few decades. Traditional production jobs take the materials with limited tolerance conditions as inputs; whereas non-traditional techniques could process raw materials beyond this limitations.

Due to technological advancement, cutting tool materials have become harder with higher spindle speed and improved tool drive. Therefore, high speed and precision based machining has become possible these days. The result is improved MRRs with reduce Ra for the work piece. Thus, complex geometry could be achievable in inexpensive ways. Tool life has been considered as an important performance indicator for high speed machining. Hard machining is one of such machining processes that consider relatively hard materials (Velayudham 2007). CNC turning (Dureja et al. 2016), micro-milling (Beake et al. 2015), cylindrical grinding (Mitrofanov and Parsheva 2017), hard boring (Ngo, Chu, and Nguyen 2018), AWJM (Patel and Tandon 2015) etc. are examples of hard machining processes.

Parametric Design of Manufacturing Processes

Mostly the machining process variables are set based on user experience or guidance provided by process manual, which might not be the optimal settings to the machining. Consequently, the production volume decreases with inferior quality and increased waste. Therefore, the optimal level of parametric settings would be necessary for better production throughput. In this study, some of the critical machining processes are considered such as CNC drilling, micro-milling, and AWJM, and parametric designs of the said processes are discussed. Next few subsections present in-depth discussion on related works and the need of the predictive modeling for production process optimization.

Drilling Process

Drilling is a traditional cutting process of materials using drill bit as a cutting tool, which makes circular holes on the workpiece. The chosen tool rotates along the axis and often used as a multi-point tool, which put force against the work-piece while in rotation (100–10000 rpm). This phenomenon removes material as chips with certain rate while generating the desired shape. Drilling operation could create some low residual stresses around the cut hole and accumulate highly deformed material on the generated surface. Hence, a finish operation could be required after drilling operation to avoid corrosions (Anand et al. 2018). In general spindle speed, feed rate, and drill diameter are considered as important process parameters for drilling process, whereas Ra, MRR, thrust force, and torque generated during drilling process are most important performance indicators. Various design of experiments (DOE) methods such as factorial design, Taguchi's method, response surface method (RSM), and gray relational analysis (GRA) are applied yet for optimization of the drilling process (Anand et al. 2018; Onwubolu and Kumar 2006).

Micro-milling Process

Micro-milling process is exclusively developed to make tiny components with greater geometric complexities and highest level of precisions. Application of micro-milling could be seen in aerospace, electronics, biomedical, and robotics fields (Lu et al. 2018). This process considers end mill tool (diameter in the range of 90–450 μm) and edge radius (0–5 μm). In micro-milling, the overall machining is reduced from 100 μm/tooth feed rates and 1 mm depth of cut to 1 μm/tooth feed rates and 100 μm depth of cut due to the miniature models. Primarily the micro-milling and traditional milling follow similar physics however, they differ in the operational sizes (Wu et al. 2013). Optimization of micro-milling process is an important area of study that helps finding optimal performance indicators. Achieving minimum Ra in micro-milling is an essential objective. To attain optimal set of values for process parameters, different DOE methods such as RSM, full factorial design and Taguchi methods were practiced in past literature (Kuram and Ozcelik 2013; Vázquez et al. 2010; Wang, Kweon, and Yang 2005). Recently, Khalilpourazari and Khalilpourazary (2018) developed a hybrid algorithm called sine-cosine whale optimization algorithm (SCWOA), for parameter optimization problem of multi-pass milling process which minimizes total production time. The SCWOA utilizes local and global search abilities to achieve optimality. Analysis of cutting force signal is critical for micro-milling since smaller cutting force signals could be affected by moderately larger noise. Therefore, filtration of the force signal is required (Zhu et al. 2008). A large number of process parameters of micro-milling machining could influence tool wear, cutting force and Ra greatly, which are spindle speed, depth of cut (radial and axial), tool diameter, composition of workpieces, feed per tooth etc. (La Fe et al. 2018).

AWJM Process

AWJM is a rapidly growing technology, which could be practiced in industry for a large number of applications such as plate profile cutting and machining of various materials including glasses, ceramics, metals etc. Cutting of glasses generates surfaces and shapes that could be unattainable with other techniques. This type of machined glass material could be used in different glass works such as aesthetic design of tabletop insets, tainted glass designs, looking glasses, glass based jewelries, etc. (Momber and Kovacevic 2012). Due to the natural fragility of glass materials, the primary grooves are fabricated with low pressure (450–780 bars). This pressure is increased gradually with the cutting speed. Therefore, proportional pressure control mechanism is required, which is obtained using the intensifier pump . Armağan and Arici (2017) demonstrated the benefits of the AWJM process, which are as follows:

- molten or solidified material does not accumulate on the cutting surface due to the absence of the heat-affected zones
- assembly fixtures are unnecessary for holding of the material since cutting forces have no impact on the cutting tools
- due to the use of pressurized water and abrasive material mix it is fairly easy to obtain complex geometry with lesser efforts
- it is an eco-friendly process and the cutting surface has a two-step mechanism, which includes cutting wear and deformation wear zones.

As in the case of every machining process, the quality of AWJM cut is significantly affected by the process parameters. There are several process parameters such as size of abrasive (AS), abrasive concentration (AC), feed rate (FR), standoff distance (SOD), and water pressure (WP) are of great importance. The main performance indicators are MRR, kerf width (KW), Ra etc. In order to effectively control and optimize any of the machining processes discussed above, specially designed tools and techniques are required. In next subsection, works related to optimization methods for machining processes are discussed.

Optimization of Machining Process Parameters

In order to optimize the machining process parameters without having actual knowledge of solid mechanics, exact mathematical models or data driven models are practiced in past literature (Mukherjee and Ray 2006). These type of optimization problems are classified as NP-Hard problems in the theory of computer science as these problems could have many objectives and multiple near optimal solutions in polynomial time (Woeginger 2003). Statistical and soft computing based techniques are well suited for these type of problems and primarily classified as regression based response surface techniques, Taguchi's method based GRA, ANN-based algorithms and evolutionary bio-inspired methods etc. (Chandrasekaran et al. 2010).

Regression Based Technique

Regression-based methods successfully approximate the correlation among variables and performance indicators related to production processes. With the help of probability distribution function, it is possible to portray the variations of the design variables in close neighborhood of the state space for output variables. Regression based modeling of machining processes, is a heavily explored area (Srivastava and Garg 2017; Tosun and Ozlar 2002). Various DOE-based approaches are considered while designing the input space such as Taguchi's method, RSM, factorial design, etc. (Armağan and Arici 2017; Baligidad et al. 2018; Vellaiyan and Amirthagadeswaran 2016; Verma and Sahu 2017). Tangjitsitcharoen, Thesniyom, and Ratanakuakangwan (2017) proposed a multiple regression analysis model to estimate the surface quality for the ball-end milling machining, which exploits the ratio of cutting forces.

García et al. (2018) portrays regression models to approximate physical quality indicators in a tube extrusion process based on data collected from a manufacturing company. This model utilized k nearest-neighbor and support vector machine (SVM) regression technique, which accurately estimates the internal and external diameter of an extruded tube. Hadad (2015) demonstrates a predictive model for minimization of Ra and grinding force based on a new semi-analytical regression model. Full-factorial design is used as the DOE tool and regression equations were obtained successfully using RSM. The major drawback of regression-based techniques is, it is not suitable when non-linearity increases in the considered machining process. If the number of process parameters, is large and many objectives are considered, it is difficult to assume the functional relationships among objectives and design variables beforehand. Due to the limitations of DOE design space and increased costs of running pre-defined sets of experiments, other approaches such as GRA, evolutionary algorithms and deep learning techniques are preferred over these.

Gray Relational Analysis (GRA)

To overcome the shortcomings of regression-based techniques various other methods are considered in literature. DOE coupled GRA is one such technique. DOE tools such as Taguchi's method, Latin hypercube sampling, Box–Behnken design, etc., are essential for optimization of process parameters or experimental design variables, which holds the practice under control with some trade-off between process variation and product quality (Taguchi 1990). These approaches are being used in selection of machining parameters heavily since past few decades. These also reduce the number of experimental runs substantially. For that matter, a quality loss function could be employed, which controls the digression between the experimental and desired values of variables. This loss function is then converted into a signal-to-noise (S/N) ratio. These tools are suitable for single response or single objective design. For multi-objective design approach, the GRA has been developed, which has the ability to exploit the DOE design space (Deng 1989) and approximate the degree of the correlation between experimental runs using gray relational grade (GRG) (Lin 2004). Steps of GRA are as follows:

Step1: The data are normalized to reduce inconsistency, which transforms the data values to be restricted in the range {0, 1}. When the performance objective is to be minimized, smaller-the-better (equation 1) rule is applied, else larger-the-better (equation 2) rule is applied

$$y_i^*(x) = \frac{y_i^0(x)_{max} - y_i^0(x)}{y_i^0(x)_{max} - y_i^0(x)_{min}} \tag{1}$$

$$y_i^*(x) = \frac{y_i^0(x) - y_i^0(x)_{min}}{y_i^0(x)_{max} - y_i^0(x)_{min}} \tag{2}$$

where $i \in [1, m]$ and $x \in [1, N]$, m is the number of experimental runs and N is the number of response objectives. $y_i°(x)_{max}$ and $y_i°(x)_{min}$ are the largest and smallest values of $y_i°(x)$, normalized data and $y_i^*(x)$ is the original data.

Step2: Compute gray relational coefficient (GRC) using the following equation:

$$\varepsilon_i(x) = \frac{\delta_{min} - \varepsilon \times \delta_{max}}{\delta_i^0(x) - \varepsilon \times \delta_{max}} \tag{3}$$

where $\delta_i^0(x) = y_i^0(x) - y_i^*(x)$, $\delta_i°(x)$ is the deviation coefficient, $y_i°(x)$ is the normalized data and $y_i^*(x)$ is the original data.

Step3: Calculate GRG using the following equation:

$$\gamma_i = \frac{1}{N} \times \sum_{k=1}^{N} \varepsilon_i(x) \tag{4}$$

GRG depicts the overall quality index and the degree of correlation between the normalized data and the original data. The values of GRG determine the ranking of experimental runs and obtain optimal set of variables.

Step4: Calculate the analysis of variance to find out the sensitivity of the variables to the design process at 95% confidence level and obtain the response table. This includes ranks based on delta statistics, which compare the relative magnitude of effects. The delta statistic shows the difference between the largest and the smallest average for each variables. It finally indicates the most sensitive variables to the design process.

Jeyapaul, Shahabudeen, and Krishnaiah (2005) and Ghan, Hashmi, and Dhobe (2017) have presented exhaustive reviews on multi-response process optimization based on Taguchi's method. It is shown that the amount of research works done on multi-response process optimizations are not many till that time. Recently Deepanraj, Sivasubramanian, and Jayaraj (2017), Angappan, Thangiah, and Subbarayan (2017), Wojciechowski el al. (2018), Anand et al. (2018), and many other researchers are focusing on multi-response process optimizations using Taguchi's design coupled GRA approaches, which are proved to be very efficient tools.

In this paper, this approach is adopted to find the optimal set of design parameters for the industrial AWJM process optimization.

ANN-based Deep Learning Algorithms

ANN is considered as a highly capable computing system that provides a framework for various deep learning techniques to interact with each other while processing big data. Training can be delivered to the system for 'learning' or acquiring knowledge based on previous experience about the process. This ability of ANN is sufficient to 'learn' the nonlinearity of the machining processes and interactions among the design variables and process responses with precision. The simplest form of ANN consists of interconnections among an input layer of neurons that processes data or design variables to the network and output layer of neurons that produces responses, with one or more hidden layers in between for training. ANNs are illustrated using their topology functions, weight vectors, and activation functions among the hidden and output layer of neurons (Zurada 1992). In every iteration or epoch of learning, the ANN could be trained with a subset of data and validated with another subset of data while trying to minimize the mean square error (MSE) calculated using target responses and obtained responses. ANN is an ideal deep learning tool for predictive analysis or functional approximation (Zhang, Patuwo, and Hu 1998). A large number of ANN models have been developed since decades. Out of these, mostly explored models are the multi-layer perceptron (MLP) and redial basis function (RBF) for machining process modeling. The outputs obtained from any network need not be the functions of the process variables. More precisely, these are approximation toward target values. MLPs have sequence of interconnected layers consisting of a number of neurons in each layer. MLPs could be simple feed forward or cascading type. Sometimes MLPs use back propagation (BP) training algorithm (these often known as BPNNs). The RBF network consists of three layers: an input layer, a single hidden layer with nonlinear processing neurons, and an output layer. During training process, ANNs adjust their weights to minimize the MSE between the target and obtained outputs. ANNs are capable of handling complex nonlinear relationships among the process parameters and responses with higher precision. As a computing tool, ANNs are quick and easy to model.

ANN-based techniques are being used in machining process modeling since decades. Dagli (1994) has elaborated a comprehensive study on ANN-based intelligent process designs. Yarlagadda (2000) has proposed an ANN model to approximate the process parameters for the pressurized die casting process. This is an alternative way to replace expensive, time taking experimental approach to obtain the process parameters by examining a physical model of the pressurized die casting process. Recently, Shakeri et al. (2016) portrayed a regression-based process model and BPNN-based predictive model for wire electro-discharge machining (WEDM) to obtain better Ra and MRR. Process variables considered are pulse current, frequency of pulse, wire and servo speed. ANN-based method shows better performance. Arnaiz-González et al. (2016) demonstrated the ball-end milling process models using MLP and RBF. RBF is shown to obtain better predictive model than MLP achieving higher precision. Khorasani and Yazdi (2017) proposed a Ra monitoring system for milling process considering following input variables, cutting speed, rate of feed, cut depth, type of materials, and coolant fluid; and mechanical vibrations, white noise, and Ra as process responses. Thereafter testing and recall/verification procedures are utilized to achieve higher accuracy. Pfrommer et al. (2018) developed a surrogate-based optimization model and finite-element (FE) model for composite textile draping process. The ANN-based surrogate model is used as a prediction tool of the shear angle of textile elements. Xiang and Zhang (2016) depicted a prediction model based on BPNN and support vector machine (SVM) for milling process modeling, and proposed an optimization technique using SVM and NSGA-II. D'Addona, Sharif Ullah and Matarazzo (2017) developed applications of ANN and DNA-based computing (DBC) to model tool-wear. Tool-wear images are processed as data to train the ANN. The DBC can distinguish the image similarity or dissimilar. Recent research trend shows that the ANN-based methods are very popular and useful for predictive modeling and being used heavily by the researchers. However, very few studies are proposed on the development of predictive metamodels, or surrogate models that can be used as a replacement of empirical or mathematical functions for optimization.

Evolutionary and Bio-inspired Methods

In recent past, a number of review articles have appeared based on the evolutionary and bio-inspired techniques applied in production or machining process optimization (Chandrasekaran et al. 2010; Mukherjee and Ray 2006; Yusup, Zain, and Hashim 2012). These are exclusively genetic algorithms (GAs) (Cook, Ragsdale, and Major 2000; Dereli, Filiz, and Baykasoglu 2001; Sangwan and Kant 2017; Xiang and Zhang 2016; Zhou and Turng 2007), Tabu search (TS) (Kolahan and Liang 2000), simulated annealing (SA) (Asokan, Saravanan, and Vijayakumar 2003; Chen et al. 2010), ant colony optimization (ACO) (Kadirgama, Noor, and Alla 2010; Vijayakumar et al. 2003), PSO (Ciurana, Arias, and Ozel., 2009; Farahnakian et al. 2011; Zhou, Ren, and Yao 2017), artificial bee's colony (ABC) (Pawar, Vidhate, and Khalkar 2018), etc. These techniques are proven methods and particularly capable of attaining global best solutions within limited time frame. Evolutionary algorithms or bio-inspired techniques coupled with ANN-based approaches are substantially robust tools while achieving optimal predictive process models. Nevertheless, these type of approaches are seldom practiced for manufacturing process optimization except some (Farahnakian et al. 2011).

Hence, in this study, the multi-response machining process-based generic predictive model is developed, which utilizes MLP network. It has the ability to approximate outputs (performance indicators) from given inputs (process variables). It also uses a PSO-based optimization technique to fine-tune the obtained predictive model by minimizing the root mean square values (RMSE) (the error between target values and obtained values). Finally, the proposed optimal predictive model is analyzed based on three distinct cases, out of which, two are collected from past literature to training and testing. The third one is collected from industry, which is used for validation of the proposed iterative predictive model and successfully compared with GRA.

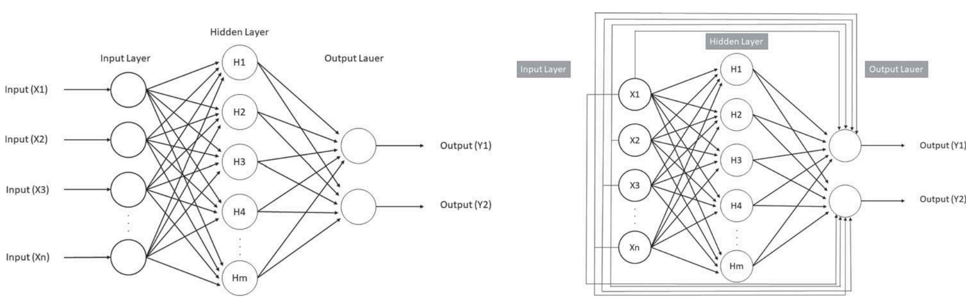
Research Approach

In this study, the focus is put on the MLP. The MLP networks are suitable for predictive modeling because of their natural ability of finding correlations among random inputs and outputs (Arnaiz-González et al. 2016). The default MLP architecture is also known as feedforward MLP ANN (FFNN) as depicted in Figure 1(a). It has n input neurons, m hidden layers neurons, and two output neurons.

The output equation of FFNN is

$$y_i = Z_i^{oa}\left(\sum_{j=1}^{m} w_{ji}^{oa} \times Z_k^{ha}\left(\sum_{k=1}^{n} w_{jk}^{ha} x_k\right)\right) \tag{5}$$

where Z_i^{oa} is denoted as activation function for i^{th} output y_i, w_{ji}^{oa} is the weight from j^{th} hidden layer neuron to i^{th} output node, $Z_k{}^{ha}$ is the activation function for j^{th} hidden layer neuron, $w_{jk}{}^{ha}$ is the weight from k^{th} input to j^{th} hidden layer neuron, and x_k is the k^{th} input signal. Furthermore, if some bias is added to input layer, Equation (5) can be written as



(a) Feed Forward ANN (FFNN) (b) Cascade Forward ANN (CFNN)

Figure 1. MLP architecture.

$$y_i = Z_i^{oa}\left(\beta_i + \sum_{j=1}^{m} w_{ji}^{oa} \times Z_k^{ha}\left(\beta_j + \sum_{k=1}^{n} w_{jk}^{ha} x_k\right)\right) \tag{6}$$

where β_i is the weight from bias to the i^{th} output layer neuron and β_j is the weight from bias to j^{th} hidden layer neuron.

Another variant of MLP network is known as cascade forward MLP ANN (CFNN) (Figure 1(b)), which has some additional direct connections among inputs and outputs. Equations (5) and (6) for CFNN can be written as

$$y_i = \sum_{k=1}^{n} Z_i^k \times w_j^k x_k + Z_i^{oa}\left(\sum_{j=1}^{m} w_{ji}^{oa} \times Z_k^{ha}\left(\sum_{k=1}^{n} w_{jk}^{ha} x_k\right)\right) \tag{7}$$

$$y_i = \sum_{k=1}^{n} Z_i^k \times w_j^k x_k + Z_i^{oa}\left(\beta_i + \sum_{j=1}^{m} w_{ji}^{oa} \times Z_k^{ha}\left(\beta_j + \sum_{k=1}^{n} w_{jk}^{ha} x_k\right)\right) \tag{8}$$

where Z_i^k is the activation function and w_j^k is the weight from inputs to outputs. The network weight in cascade forward network is approximated based on the neurons in the input layer. In this study, both types of MLP networks are used to obtain the predictive models.

Performance Metric

RMSE is used as the performance metric for the trained predictive models. RMSE is an improved metric, which accurately measures regression errors (Willmott 1981). If the model produces the output response y and the target response is t, the RMSE score is calculated using Equation (9).

$$RMSE = \frac{1}{N}\sqrt{\sum_i (y_i - t_i)^2} \tag{9}$$

where i is the sample data point index. These obtained MLP-based predictive models are further fine-tuned using PSO-based nature-inspired optimization algorithm, which is demonstrated in the next subsection.

Particle Swarm Optimization (PSO)

Eberhart and Kennedy (1995) first proposed PSO, which is a nature-inspired population based optimization technique. PSO mimics the behavior of bird flocking. PSO starts with a population of randomly generated pattern based solutions or particles (birds) and directs the searching of best solutions in the region of picks or downs for optima with multiple iterations. In PSO, the particles follow the best one in the swarm and fly through the problem space for convergence. Initially, the particles start flying across the solution space with randomly generated individual position and velocity. Positions are evaluated by the fitness function or objective function and objective values are stored. The velocity and position are updated using the following expressions:

$$v_i^t = w \times v_i^{t-1} + c1 \times \left[P_{best} - x_i^{t-1}\right] + c2 \times \left[G_{best} - x_i^{t-1}\right] \quad (10)$$

$$x_i^t = x_i^{t-1} + v_i^t \quad (11)$$

In every iteration, each particle is updated by two optimal values: the first one is the local best solution of the particle termed as *Pbest* and the other one is the best value obtained so far by the whole swarm known as the global best solution or *Gbest*. In this study, a novel PSO-based approach is considered, which efficiently obtains optimal predictive model based on MLP for machining process optimization. The proposed approach works in the following mode,

Step 1. The MLP-based initial models with fixed number of hidden layer neurons (number = 10) are trained using case data considered separately. Learning rate is considered as 0.1, Error target goal is set as 0, and number of epochs is set to 500. Machining process parameters are provided as inputs to the models. 70% test data are used for training purposes. The process responses are considered as outputs. Once the models are trained, remaining 30% data are used for testing and validation. This 70–30 rule for training, testing and validation is recommended by ANN researchers. The error between target and obtained responses are computed using RMSE (Equation 9).

Step 2. The proposed MLP-based predictive models are used as input solutions (particles) to the PSO. Initially an entire population of MLP-based predictive models are generated and trained. For every solution (MLP model), random velocity is generated. Each MLP-based model in swarm is utilized for testing and validation and obtained RMSE scores are stored against respective predictive models. Thereafter the model with lowest RMSE is selected from the swarm and marked as local best (*Pbest*) and global best solution (*Gbest*).

Step 3. In each iteration of the proposed PSO-based technique, the ANN models are modified using Equations (10) and (11). The velocity associated with each ANN model is updated using Equation (10). Thereafter the modifications to the ANN models are done in MLP training function with small change in the number of neurons in the hidden layers of the MLPs. RMSE scores are updated according to the modifications in the networks and the new smallest RMSE score is compared with previous *Pbest*. If the new RMSE score is better than *Pbest*, the associated ANN model with new RMSE score is stored as *Pbest*. The *Gbest* is updated in the similar way after each iteration. This update module is illustrated in the following pseudocode:

```
for h1 = 1: population_size
   Velocity = networks (h1).velocity + c1*rand*(localbestrmse – networks (h1).rmse) + c2*rand*(globalbestrmse – networks (h1).rmse);
 if velocity holds negative value
   net = cascadeforwardnet(5,'trainlm');
   net.trainParam.epochs = 500;
   net.trainParam.goal = 0;
   net.trainParam.lr = 0.1;
   net.trainParam.showWindow = false;
   [net, tr] = train(net,x',t');
   y11 = net(xt');
   t1 = tt';
   e1 = t1-y11;
   rmse_NN = sqrt(mse(e1));
   networks (h1).network = net;
   networks (h1).rmse = rmse_NN;
 else
   net = cascadeforwardnet(15,'trainlm');
   net.trainParam.epochs = 500;
   net.trainParam.goal = 0;
   net.trainParam.lr = 0.1;
   net.trainParam.showWindow = false;
   [net, tr] = train(net,x',t');
   y11 = net(xt');
   t1 = tt';
   e1 = t1-y11;
   rmse_NN = sqrt(mse(e1));
   networks (h1).network = net;
   networks(h1).rmse = rmse_NN;
 end
 if networks(h1).rmse ≤ localbestrmse
   localbestrmse = networks(h1).rmse;
   localbestnetwork = networks(h1).network;
 end
end
```

Step 4. The algorithm stops once the maximum number of iterations is reached. The final *Gbest* ANN model is the best ANN model selected with lowest RMSE score.

ANN Coupled PSO Pseudocode

(1) **START**
(2) **Set** values to *maxIT = 50, w = 0.5, c1 = c2 = 0.25,* $P_{size} = 50$,
(3) *Initial solution* is obtained as described in step 1 of subsection #3.2 and provided as an input to PSO
(4) The *initial solution* is the seed of the initial population called *P* of size P_{size}
(5) Along with initial solution, its velocity v is also generated randomly
(6) Fitness value of initial solution is computed using equation (9)
(7) **Set** *Gbest = Fitness (initial solution)*
(8) **Set** BestIndiv = initial solution
(9) **Generate** initial population P_{init} in the neighborhood of BestIndiv
(10) $i = 0$
(11) **While** $(i \neq P_{size})$
(12) $i = i + 1$
(13) **Do**
→ $Fitness\_P_{init}(i) = Fitness\ (P_{init}(i))$
→ $Pbest(i) = P_{init}(i)$
→ **If** $Fitness\ (P_{init}(i)) < Gbest$
→ **Set** BestIndiv = $P_{init}(i)$
(14) **Initialize** *fitnessVals* array
(15) **Set** $iter = 0$
(16) **While** $(iter \neq maxIT)$
(17) $iter = iter+1$
(18) **Do**
→ $i = 0$
→ **While** $(i \neq P_{size})$
→ $i = i + 1$
→ **Do**
⇒ *fitnessVals(i) = Fitness (P(i))*
⇒ **if** *min(fitnessVals) < Gbest*
⇒ **set** *Gbest = min(fitnessVals)*
⇒ **set** *BestIndiv* = ANN model *x* of *min(fitnessVals)*
→ $i = 0$
→ **While** $(i \neq P_{size})$
→ $i = i + 1$
→ **Do**
⇒ $v(i) = w \times v(i) + c1 \times w \times (pbest(i) - P(i)) + c2 \times w \times (BestIndiv - P(i))$
⇒ *update ANN model using step 3 in subsection #3.2*
→ *NewP = P*
⇒ *fitnessVals(i) = Fitness (NewP(i))*
⇒ **if** *min(fitnessVals) < Gbest*

⇒ **set** *Gbest* = *min(fitnessVals)*
⇒ **set** *BestIndiv* = ANN model *x* of *min(fitnessVals)*

(19) **STOP** with *Gbest* and *BestIndiv* as output

Results and Discussion

In this study, three different cases are considered for training, testing and validation of the proposed predictive models: (1) CNC micro-milling operation on Al7075 material with ball nose end mill (Kuram and Ozcelik 2013), (2) CNC drilling operation on CFRP composite (Krishnamoorthy et al. 2012), and (3) AWJM of commercial soda–lime–silica glass (experiments carried out in industry). All the cases are briefly described in the next subsections.

Micro-milling Operation

The experiments were carried out using a DECKEL MAHO DMU 60 PCNC milling machine. Al7075 material is used (Vickers hard-ness of 139) as a work piece material, which had a dimension of 15 × 10 × 20 mm^3.

The chemical compositions of material are given as Li < 0.0002 wt%, Si 0.92 wt %, Mn 0.348 wt%, $P < .001$ wt%, Sr <0.0001 wt%, Cr 0.093 wt%, Ni 0.057 wt%, Na 0.003 wt%, Al 89.0 wt%, Cu 1.71 wt%, Co <0.001 wt%, Ti 0.048 wt%, Be 0.0003 wt%, V 0.009 wt%, Fe 0.55, Pb wt%, 0.018 wt%, Mg 2.00 wt%, B 0.0017 wt%, Sn 0.008 wt%, Zn 5.22wt%, Ag 0.0022 wt %, Bi 0.0018 wt%, Ca 0.0027 wt%, Cd 0.0031 wt%, and Zr 0.0078 wt%. Spindle speed (SS) (5000–15000 rpm), feed per tooth (FPT) (0.5–1.5 μm/tooth) and depth of cut (DC) (50–100 μm) were considered as design parameters and tool wear (TW), cutting forces (Fx and Fy), and Ra were selected as process responses. For experimental design, Taguchi's L_9 orthogonal array is chosen and is displayed in Table 1.

Table 1. Input parameters and the performance characteristics for micro-milling (Kuram and Ozcelik 2013).

SS	FPT	DC	TW	Fx	Fy	Ra
10000	0.5	50	5.41	1.33	0.71	0.33
10000	1.0	75	13.51	1.63	0.86	0.47
10000	1.5	100	16.22	2.02	1.02	0.71
11000	0.5	75	27.02	1.62	1.08	0.32
11000	1.0	100	32.43	2.03	1.49	0.59
11000	1.5	50	14.86	2.65	1.52	0.58
12000	0.5	100	45.95	2.10	1.36	0.27
12000	1.0	50	27.03	2.99	1.66	0.35
12000	1.5	75	32.43	3.55	1.81	0.58

CNC Drilling Operation

The material used for experimentation is CFRP plates manufactured through hand layup process using carbon fiber and resin. The properties are described as follows: thickness of carbon fiber in the form of filaments is 0.050 mm, tensile strength (GPa) – 3.5, tensile modulus (GPa) – 230, density (g/ccm) – 1.75, and specific strength (GPa) – 2.00. Properties of the material EPON resin 8132 are described as follows: viscosity (poise) 5–7, weight per epoxide – 192–215, and density (lb/gal) – 9.2. The thickness of the plate is 3 mm and the holes to be drilled were all of a uniform diameter of 6 mm. The drilling tool used in experimentation was made of high-speed steel (HSS). The process parameters used here are as follows: spindle speed (SS) (rpm), point angle (PA) (°), and feed rate, (FR) (mm/min) chosen for this experimentation. The following five performance characteristics are chosen: thrust force (TF) (N), torque (Nm), entry-delamination factor (EnDF), exit-delamination factor (ExDF) and eccentricity (Ecc) (mm). For experimental design, Taguchi's L_{27} orthogonal array is chosen and displayed in Table 2.

Abrasive Water Jet Machining (AWJM)

Soda–lime–silica glass is the most prevalent type of glass used for window-panes, and glass containers for beverages, food, and some commodity items.

Table 2. Input parameters and the performance characteristics for CNC drilling (Krishnamoorthy et al. 2012).

SS	PA	FR	TF	Torque	EnDF	ExDF	Ecc
1000	100	100	99.69	0.73	1.3418	1.4378	0.0728
1000	100	300	165.2033	0.84	1.3759	1.6373	0.0619
1000	100	500	198.3633	1.12	1.4368	1.541	0.0609
1000	118	100	156.25	0.99	1.3921	1.2628	0.0517
1000	118	300	253.2933	1.34	1.44	1.4658	0.0431
1000	118	500	310.4667	1.37	1.5211	1.4137	0.0619
1000	135	100	155.4333	1.37	1.3398	1.1851	0.0437
1000	135	300	261.23	1.52	1.3587	1.3692	0.0302
1000	135	500	310.06	1.87	1.4756	1.2739	0.0251
2000	100	100	92.3667	0.48	1.39	1.4455	0.0623
2000	100	300	154.01	0.68	1.3439	1.51	0.0815
2000	100	500	192.8733	0.87	1.3817	1.3607	0.1113
2000	118	100	140.1767	0.57	1.4287	1.4	0.0652
2000	118	300	231.5233	0.92	1.43	1.4562	0.0821
2000	118	500	271.81	0.93	1.4474	1.3794	0.0799
2000	135	100	150.7533	0.64	1.4021	1.3296	0.0671
2000	135	300	234.78	0.94	1.3798	1.3585	0.0655
2000	135	500	299.1833	0.95	1.411	1.45	0.0671
3000	100	100	84.23	0.39	1.4287	1.41	0.0156
3000	100	300	152.3867	0.47	1.3974	1.3807	0.0322
3000	100	500	165.8133	0.6	1.36	1.1688	0.0588
3000	118	100	130.6167	0.4	1.4347	1.3534	0.0308
3000	118	300	191.8567	0.54	1.4098	1.51	0.0342
3000	118	500	270.3867	0.7	1.4224	1.4	0.0411
3000	135	100	143.6367	0.48	1.4601	1.44	0.0448
3000	135	300	226.0333	0.55	1.4264	1.51	0.0601
3000	135	500	283	0.78	1.4018	1.4774	0.077

Glass bake ware is often made of tempered soda lime glass. Soda lime glass accounts for about 90% of manufactured glass. Soda lime glass is relatively inexpensive, chemically stable, reasonably hard, and extremely workable. Since it is capable of being re-softened and re-melted numerous times, it is ideal for glass recycling. Soda–lime glass is prepared by melting the raw material, such as sodium carbonate (soda), lime, dolomite, silicon dioxide (silica), aluminum oxide (alumina) and small quantities of fining agents (e.g., sodium sulfate, sodium chloride) in a glass furnace at temperature locally up to 1650°C.

The temperature is only limited by the quality of the furnace superstructure material and by the glass composition. In this study, the experiments are carried out in industrial set up with AWJM Nanojet . A 60-HP pump was used to generate the required water pressure. The machining process was numerically controlled by Siemens controller (802D SL), garnet sand have been used as abrasive materials. In these experiments, AS, AC, FR, and SOD are considered as input process parameters. The Ra was measured by a non-contact profiler (Contour GT-I). The main performance indicators considered are MRR, top kerf width (TKW), bottom kerf width (BKW), and Ra. For experimental design, Taguchi's L_9 orthogonal array is selected and is displayed in Table 3.

Computational Experimentations

To analyze the proposed MLP-based PSO approach, abovementioned cases are considered. The proposed algorithm is programmed in MATLAB R2018a on Intel 8650U @1.90 GHz laptop. PSO parameters are set with the following values: $maxIT = 50$; $P_{size} = 20$; $c1 = 0.15$; $c2 = 0.25$; $w = 0.5$. Since two types of ANN models are used based on FFNN and CFNN, the results obtained are compared with each other and the best predictive model is elected. The results obtained using CFNN are shown to outperform the FFNN. Due to the NP-Hardn nature of the problem, attaining solution is not an easy task. Therefore, computational time is an important factor in this research. Computing time increases drastically with the size of population and number

Table 3. Input parameters and the performance characteristics for AWJM.

AS	SOD	AC	FR	MRR	TKW	BKW	Ra
100	2	120	80	2.09	1.94	0.89	9.11
100	5	180	120	2.29	1.81	0.85	9.42
100	8	240	160	2.35	1.79	0.85	9.48
150	2	180	160	1.54	1.69	0.76	9.86
150	5	240	80	2.11	1.95	0.90	9.09
150	8	120	120	2.19	1.91	0.86	9.54
200	2	240	120	1.52	1.89	0.79	9.54
200	5	120	160	1.75	1.77	0.80	10.05
200	8	180	80	1.95	2.05	0.90	9.17

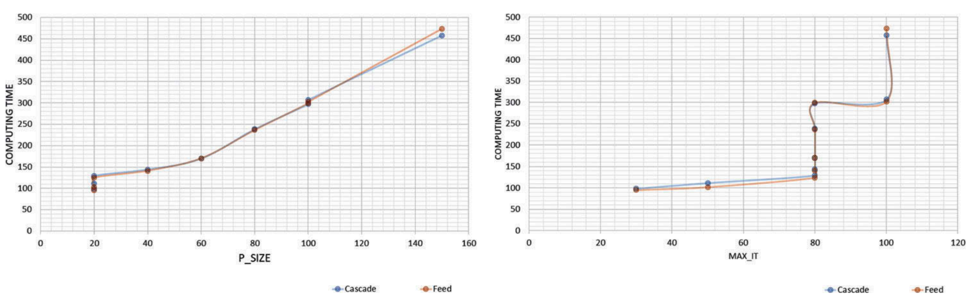
of iterations in PSO. Figure (2a,2b) demonstrates that computing time is exponentially related to the size of population and has some interesting relation with iteration numbers.

The complexity of the predictive models could increase with the number of design variables and responses of the machining processes. Table 4 presents the comparison among two predictive models and reveals that the CFNN-PSO is an improved model on the basis of RMSE scores. Based on computing time both the models exploit more or less equal time. It is hard to point out the fastest one.

Both the predictive models follow strict convergence properties as portrayed in Figure 3. Convergence plots also confirm that the CFNN-PSO model performed better than FFNN-PSO.

Therefore, the most near optimal ANN model, which is obtained using CFNN-PSO, is used further to obtain the optimal sets of parameters and responses for the considered cases. Fitted curves obtained using the CFNN model are portrayed in Figure 4–6 for each of the case studies. These curves visually portray the approximation capability of CFNN-PSO model. The new experimental design space is obtained using random function and predefined range for the process parameters.

For micro milling, the optimal published result is experimental run# 1 in Table 1. In this study, the most promising solutions, obtained using CFNN-PSO are as follows: (1) SS = 9373.596, FPT = 1.219, DC = 57.163, TW = 4.040, Fx = 2.799, Fy = 1.723, Ra = 0.198 and (2) SS = 11257.000, FPT = 0.153, DC = 86.430, TW = 4.494, Fx = 2.047, Fy = 1.863, and Ra = 0.181.



(a) (b)

Figure 2. Computational time curve with respect to PSO parameters (CNC drilling example).

Table 4. Comparison between ANN models.

Cases	RMSE		Computing time (s)	
	CFNN-PSO	FFNN-PSO	CFNN-PSO	FFNN-PSO
Micro-Milling Operation	0.4386	0.5622	106.09	94.97
CNC drilling Operation	3.9946	4.3849	86.47	94.49
AWJM Operation	0.0627	0.1271	71.74	81.01

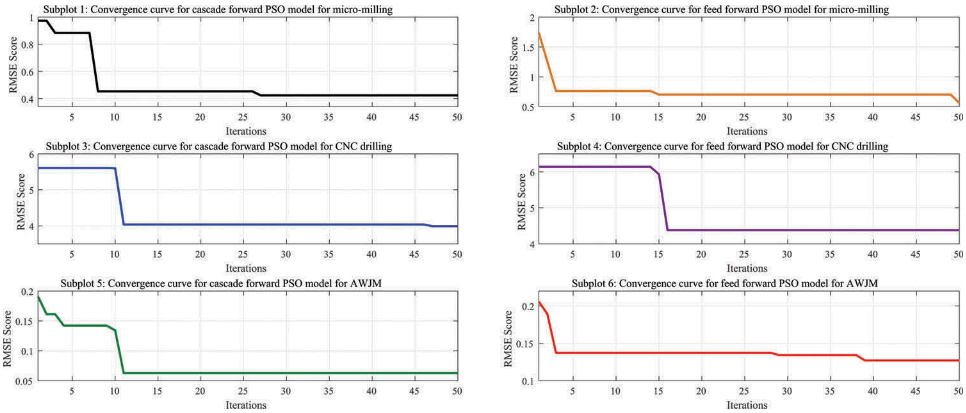


Figure 3. Convergence curves obtained for all the data.

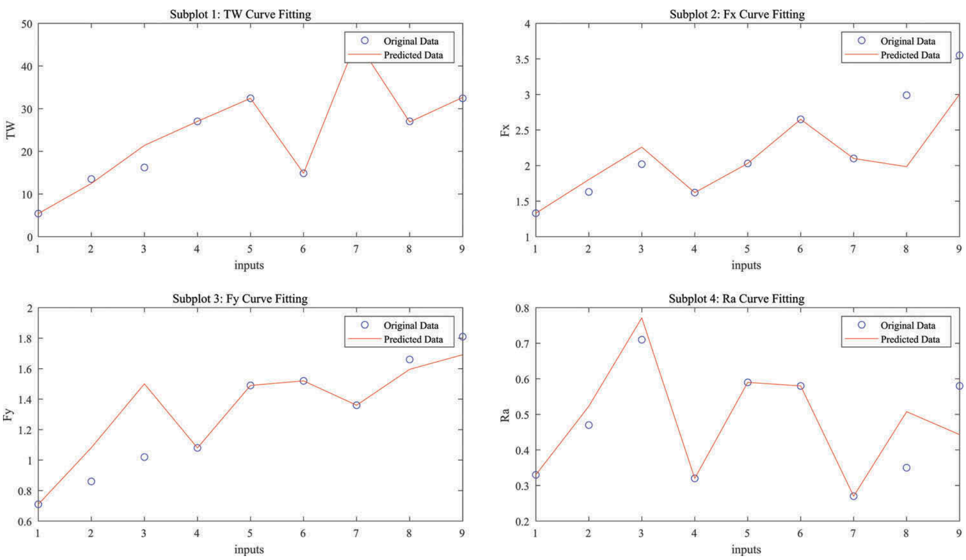


Figure 4. Curve fitting for micro-milling data.

For CNC drilling, the optimal published result is experimental run# 19 in Table 2. In this study, the most promising solutions, obtained using CFNN-PSO are as follows: (1) SS = 3834.203892, PA = 144.4841355, FR = 549.8807477, TF = 314.5818615, Torque = 0.092778617, EnDF = 1.376816667, ExDF = 1.55836835, Ecc = 0.003916968 and (2) SS = 1663.575273, PA = 141.8324067, FR = 118.9348359, TF = 163.5448858, Torque = 0.88063403, EnDF = 1.452188722, ExDF = 1.228260178, and Ecc = 0.010853929.

These results reflect that the CFNN-PSO has the ability to attain better solutions than the published one. This predictive model is used further to obtain optimal solutions for AWJM process and compared with the results obtained using GRA method. Factors (process parameters) and levels

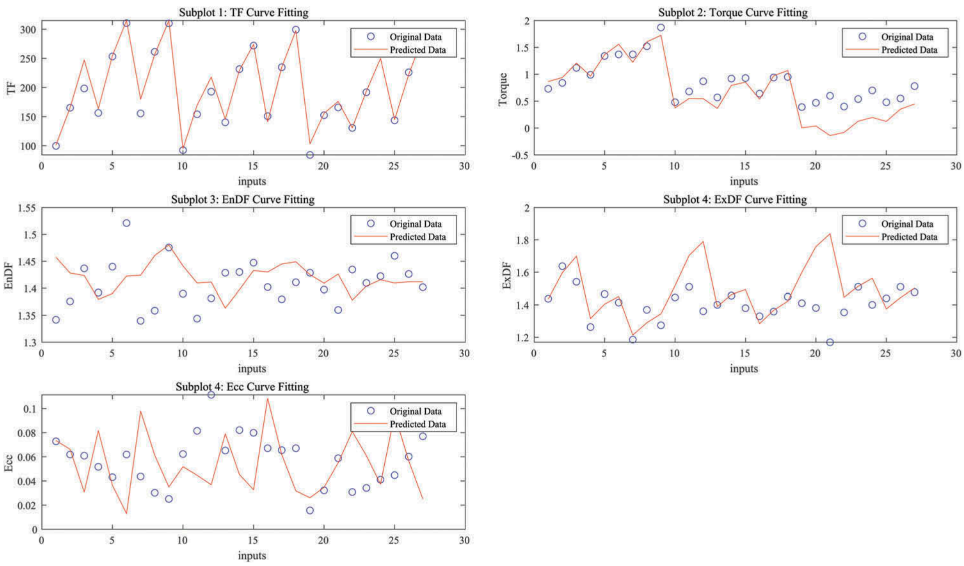


Figure 5. Curve fitting for CNC drilling data.

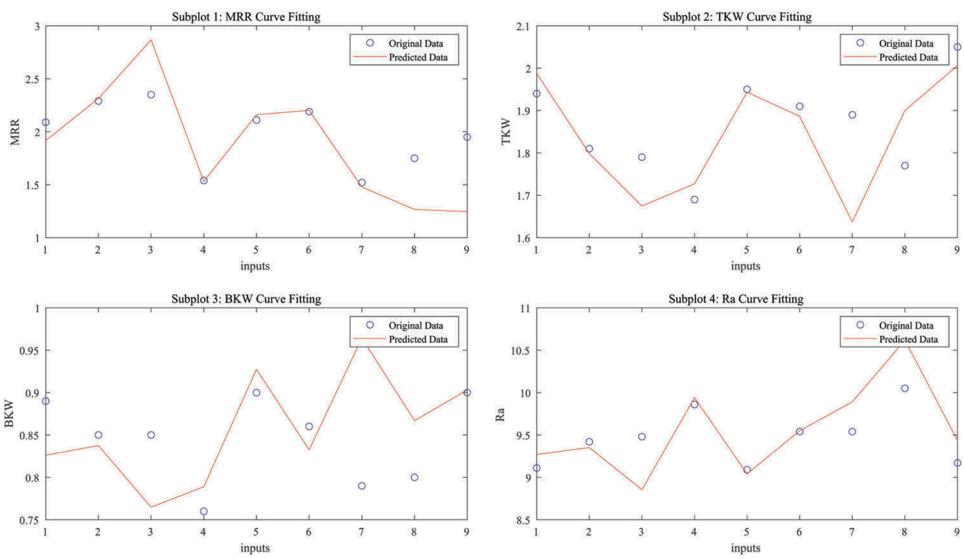


Figure 6. Curve fitting for AWJM data.

(values) for AWJM are portrayed in Table 5, where A = size of abrasive (AS), B = stand-off distance (SOD), C = abrasive concentration (AC), and D = feed rate (FR). L_9 orthogonal array is chosen to apply Taguchi's design. DOE and responses are portrayed in Table 3.

Using Equations (1)–(4), the GRA is performed on Ra, MRR, TKW, and BKW. Then GRC and GRG values are obtained for the trial runs for AWJM. The results are depicted in Table 6. The GRG response table (Table 7) portrays the

Table 5. Parameters and their levels for L_9 design.

Symbols	Abbreviation	Units	Level 1	Level 2	Level 3
A	AS	Grit	100	150	200
B	SOD	mm	2	5	8
C	AC	gram	120	180	240
D	FR	mm/min	80	120	160

mean of each response characteristic for each level of the parameters. It also depicts delta statistical analysis while comparing the relative importance of outcomes. It portrays the difference between the largest and the smallest means of the parameters. Ranks are allotted based on the obtained delta values. Using the level means in the response table, optimal set of levels of the parameters could be selected for optimal performance of AWJM.

According to Table 7, AS has the greatest importance and FR is the next most significant parameter, followed by AC and SOD. The main effect plot of Figure 7 shows that the optimal set of parameters are as follows: AS = 100, SOD = 2, AC = 180, and SOD = 160 (λ is prefixed to 0.5), respectively. Therefore, the optimal values of responses would be Ra = 9.728, MRR = 1.6796, TKW = 1.7372, and BKW = 0.7731. The proposed CFNN-PSO predictive model obtains at least two solutions that are better than the result produced by GRA for at least three objectives. Confirmatory tests were carried out based on the obtained results and the results are as follows: (1) AS = 127.5329695, SOD = 7.151323334, AC = 235.9500566, FR = 68.0973149, Ra = 9.090608246, MRR = 2.111026969, TKW = 1.950732338, BKW = 0.895640667 and (2) AS = 120.0688976, SOD = 7.802102857, AC = 235.5413261, FR = 58.7592643, Ra = 9.089430108, MRR = 2.110525813, TKW = 1.951125582, BKW = 0.895787245. Results obtained by CFNN-PSO have better Ra and MRR scores, which is desirable and this completes the validation of the proposed CFNN-PSO predictive model for parameter optimizations of machining processes.

Conclusions

This paper demonstrates an efficient iterative predictive modeling approach based on PSO and ANN, which has the ability to train itself with a small amount of experimental data obtained from machining process on shop floor. An effective PSO-based algorithm is also introduced, which is capable of optimizing the ANN models further while minimizing the RMSE score for the ANN models. This hybrid approach obtains a well-trained CFNN-PSO predictive model with very low RMSE score dedicated to the associated machining process. To verify the performance of the CFNN-PSO, three multi-response cases are portrayed. Out of these, two are collected from past literature based on micro-milling and CNC drilling processes. Training and validation of the

Table 6. GRA scores for the AWJM responses.

Original responses				Normalized responses				Deviation sequence				GRC				
Ra	MRR	TKW	BKW	Ra	MRR	TKW	BKW	Ra	MRR	TKW	BKW	Ra	MRR	TKW	BKW	GRG
9.11	2.09	1.94	0.89	0.985	0.688	0.308	0.042	0.015	0.312	0.692	0.958	0.971	0.615	0.419	0.343	0.587
9.42	2.29	1.81	0.85	0.659	0.925	0.664	0.331	0.341	0.075	0.336	0.669	0.595	0.869	0.598	0.428	0.623
9.48	2.35	1.79	0.85	0.598	1.000	0.726	0.345	0.402	0.000	0.274	0.655	0.554	1.000	0.646	0.433	0.658
9.86	1.54	1.69	0.76	0.201	0.022	1.000	1.000	0.799	0.978	0.000	0.000	0.385	0.338	1.000	1.000	0.681
9.09	2.11	1.95	0.90	1.000	0.713	0.286	0.025	0.000	0.287	0.714	0.975	1.000	0.635	0.412	0.339	0.596
9.54	2.19	1.91	0.86	0.528	0.812	0.410	0.272	0.472	0.188	0.590	0.728	0.514	0.726	0.459	0.407	0.527
9.54	1.52	1.89	0.79	0.528	0.000	0.440	0.749	0.472	1.000	0.560	0.251	0.515	0.333	0.472	0.666	0.496
10.05	1.75	1.77	0.80	0.000	0.270	0.773	0.697	1.000	0.730	0.227	0.303	0.333	0.406	0.688	0.623	0.513
9.17	1.95	2.05	0.90	0.916	0.523	0.000	0.000	0.084	0.477	1.000	1.000	0.856	0.512	0.333	0.333	0.508

Table 7. Response table for means of GRG.

Level	AS	SOD	AC	FR
1	0.6227	0.5881	0.5422	0.5641
2	0.6013	0.5772	0.604	0.5485
3	0.5058	0.5645	0.5837	0.6172
Delta	0.1169	0.0237	0.0618	0.0687
Rank	1	4	3	2

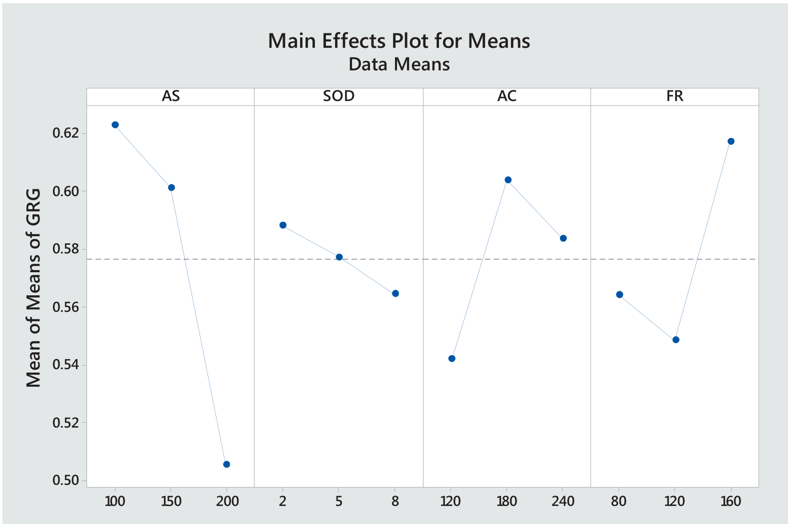


Figure 7. GRG Main effect plot for the parameters of AWJM.

proposed CFNN-PSO model prove that the model is capable of obtaining better results than the published one. Thereafter, the third case based on AWJM cutting of glass materials is collected from industry and the CFNN-PSO predictive model is tested on it. The results obtained are compared with the results obtained using GRA method. It is shown that the proposed CFNN-PSO technique could achieve at least two solutions, which are better than the GRA result for at least three objectives. This CFNN-PSO predictive model could be further extended as an objective function for many-objective optimization techniques such as NSGA III or MOEA/D in future.

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