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ORIGINAL ARTICLE

Expert systems in manufacturing processes using soft computing

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Abstract This paper presents a review on soft computing-based expert systems developed to establish input-output relationships of various manufacturing processes. To determine these relationships, both fuzzy logic- and neural network-based approaches were tried. Reasonably good results were obtained using the developed approaches. However, there is a chance of further improvement of the results. The scopes for future study have also been discussed.

Keywords Expert systems · Manufacturing processes · Soft computing · Forward mapping · Reverse mapping

1 Introduction

An expert system (also known as a knowledge-based system) is a computer program used to simulate human reasoning for solving a particular problem instead of simulating the problem domain itself (which is done in ordinary computer program). It uses heuristic methods only but not any algorithmic or statistical one. It consists of data base (DB), rule base (RB), inference engine, and some forms of user interface. A DB contains a set of numerical values used to represent some physical parameters. A RB consists of a set of rules, where each rule relates an output with the inputs using the information stored in the DB. The DB and RB of an expert system constitute its knowledge base (KB). An inference engine decides appropriate part of the KB to be activated in order to obtain the output for a set of inputs. Training is provided using optimization algorithm by taking the help of some collected data to develop an expert system for a process. If properly trained, an expert system may provide solutions, which are difficult to foresee beforehand.

To cope with increasing demands of today's dynamic and competitive market, manufacturing processes are to be automated, for which its input-output relationships are to be known in both forward and reverse directions. In forward mapping, outputs (that is, responses) of a process are expressed in terms of its input variables (also known as process parameters), whereas reverse mapping aims to determine a set of appropriate process parameters corresponding to a predefined set of responses. These input-output relationships are to be known in both the directions online to automate any process, and the associated tasks come under the umbrella of agile manufacturing systems.

Human beings have their natural thirst to know input-output relationships of any process or system. They first try to model the process using the principle of physics and mathematics. If the mathematical equation (say differential equation) is known, they solve it either analytically or using numerical methods to obtain input-output relationships of the process. It is important to mention that the above procedure can be applied, if and only if the problems are simple, whose inherent physics is known. Unfortunately, most of the real-world problems (say, the problems related to manufacturing processes) are so complex and ill-defined that they cannot be mathematically modeled due to our incomplete knowledge of their physics. Under these circumstances, statistical regression analysis [1] can be carried out based on the experimental data collected according to some designs of experiments, such as full factorial design, fractional factorial design, central composite design, Box-Behnken design, Plackett-Burman design,

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and others. It is to be noted that both linear and non-linear regression analysis can be conducted to determine input-output relationships of a process. However, the following difficulties may be faced with the regression analysis:

- It is carried out response-wise. Therefore, it may not be able to capture complete dynamics of a process.
- The problem of forward mapping can be solved efficiently using the regression analysis. However, it may not be always possible to solve the problem of reverse mapping using the obtained regression equations, particularly when the transformation matrix relating the outputs with the inputs becomes non-square and, hence, singular.

To overcome the above difficulties, soft computing-based approaches [2, 3] have also been used. Soft computing is a big family consisting of several members like fuzzy logic (FL) [4], neural networks (NNs) [5], genetic algorithms (GAs) [6], and others and their various combined forms, namely genetic-fuzzy system (GA-FL), genetic-neural system (GA-NN), neuro-fuzzy system (NN-FL), and genetic-neuro-fuzzy system (GA-NN-FL), in which precision is traded for tractability, robustness, ease of implementation, and a low-cost solution. It is important to mention that FL is a powerful tool for dealing with imprecision and uncertainty, NN is a potential tool for learning and adaptation, and GA is an important tool for search and optimization. Each of the above tools has its inherent merits and demerits. To remove their limitations and get the advantages of constituent tools, the above-combined techniques have been developed [3]. In the GA-FL, FL-based expert system is developed to predict input-output relationships of a complex process online, both in forward and reverse directions. Here, a GA-based tuning is provided to the fuzzy reasoning tool either off-line or online to develop its RB and DB (also known as KB). It is important to mention that Mamdani approach [7] and Takagi and Sugeno approach [8] are the most popular forms of fuzzy reasoning tool available in the literature. The former provides high interpretability, whereas the latter can obtain high accuracy in modeling. A genetic-neural system aims to evolve optimal neural network (NN) to be used for modeling input-output relationships of a process. In a GA-NN-FL, a fuzzy reasoning tool is represented using the structure of an NN and a GA is used to optimize the network.

This paper presents an extensive review of various soft computing-based expert systems developed in different fields of manufacturing science, such as casting, welding, metal cutting, unconventional machining, metal forming, and surface coating.

2 Expert systems in castings

Casting is one of the oldest manufacturing processes. To manufacture cast products, molten metal is poured into mould cavity and allowed to solidify. There exist a variety of casting methods, namely dry sand casting, shell mould casting, investment casting, die casting, centrifugal castings, and others. The quality of cast products depends on type of mould prepared, various phenomena associated with cooling, and others.

Researchers felt the need for development of input-output relationships of this process in order to get defect-free and good-quality castings. A few soft computing-based approaches were proposed by various investigators to determine input-output relationships of molding sand systems. Babu et al. [9] developed input-output models for a clay-bonded molding sand system. The parameters like amount of clay, amount of moisture, % of coal dust, and mulling time were considered as inputs of the model, and there were two outputs, namely green compression strength and permeability. The training and test data were collected through experiments. Both back-propagation neural network (BPNN) and neuro-fuzzy approach had been tried to solve the problem of forward mapping. Neuro-fuzzy approach was found to perform better than the BPNN. They developed the models separately for each output. Therefore, their model failed to capture the dependency of the above two outputs. Moreover, they did not solve the problem of reverse mapping. Moreover, Mandal and Roy [10] developed a BPNN model to determine compressive strength of a molasses-cement molding sand system as the function of amount of molasses and that of cement. They solved the problem of forward mapping only, in their study. Karunakar and Datta [11] suggested a model of green sand mould system, in which five input process parameters, namely grain fineness number, % of clay, % of moisture, mulling time, and hardness, were used, and five responses, such as green compression strength, green shear strength, permeability, dry compression strength, and dry shear strength, were considered. Reverse mapping problem was solved using BPNN and a GA separately. Although a better performance of GA was reported compared to the BPNN, they did not use a sufficient number of scenarios during the training of the latter. Moreover, a micro-GA used for this study might not be a good choice, as the accuracy in predictions was the main criterion to be fulfilled. Parappagoudar et al. [12] modeled a clay-bonded green sand mould system by considering four inputs (such as grain fineness number, % of clay, % of water, number of strokes) and outputs (namely permeability, compression strength, hardness, bulk density) each. Both forward and reverse mapping problems were solved successfully using BPNN and a genetic-neural system (GA-NN) separately. The GA-NN was found to outperform the BPNN. During the training of the networks using a back-propagation (BP) algorithm, error minimization was done using a steepest descent method, whereas this optimizer was replaced by a GA in the GA-NN approach. Being a steepest descent method, BP algorithm may get stuck at the local minima, whereas the chance of GA solutions for being trapped into the local minima is less. The better performance of GA-NN compared to the BPNN could be due to this reason. However, there is no guarantee that GA-NN will be able to perform better than the BPNN always. Their performances are dependent on the nature of error surfaces tackled during optimization [3]. Similar studies were also carried out using the BPNN and GANN models on forward and reverse mappings of cement-bonded and sodium silicate-bonded (carbon dioxide gas hardened) molding sand systems separately by Parappagoudar et al. [13, 14].

Although a few trials were made to capture input-output relationships of various molding systems using NNs, no significant study had been reported on the similar problems using FL techniques. It could be due to an inherent problem of developing suitable KB of the fuzzy reasoning tool particularly for the problems involving a large number of variables.

3 Expert systems in welding

Welding is one of the most popular joining processes. Various welding processes are in use nowadays, namely arc welding, gas welding, resistance welding, thermit welding, ultrasonic welding, laser beam welding, electron beam welding, and others. It is a complex process comprising a number of complicated natural phenomena, and consequently, its input-output relationships are expected to be non-linear in nature.

Several attempts were made to capture input-output relationships of this process using the principle of soft computing. Cook et al. [15] developed NN-based approach to capture input-output relationships of a laser welding process in both forward and reverse directions. The parameters, such as torch standoff, forward current, reverse current, and travel speed, were considered as inputs to determine the outputs, namely crown width and root width of weld beads. A BPNN was used to develop the model, and an incremental mode of training was adopted, although it was implemented off-line using some pre-collected data. Li et al. [16] modeled submerged arc welding (SAW) process using self-adaptive offset neural (SAON) networks. They considered three inputs in their model, namely current, voltage, and welding speed, and five bead geometric parameters, such as bead height, bead width, bead penetration, fused area, and deposited area, were taken as the outputs. They tackled the problem of forward mapping, and the SAON network was found to perform better than conventional multilayer perceptron networks. Tay and Butler [17] used a Gaussian radial basis function neural network (GaRBFNN) to model non-linear dynamics of a metal inert gas (MIG) welding process having five inputs, namely travel speed, wire feed rate, gun angle, voltage and standoff distance, and three outputs, such as bead penetration, width, and height. Experimental data were collected using the Taguchi method and with the help of which, the GaRBFNN was trained utilizing a gradient descent method. Thus, the problem of forward mapping was solved, but reverse mapping was not tackled by them.

Juang et al. [18] carried out forward mapping of tungsten inert gas (TIG) welding process using both BP and counter-propagation networks. Five inputs were used in their model, such as speed, wire speed, cleaning, gap, and current, and four bead geometric parameters, namely front height, front width, back height, and back width, were considered as the outputs. The counter-propagation NN was seen to show better learning ability compared to the BPNN, whereas the latter showed better generalization ability than the former. Later on, the said problem was also solved by Dutta and Pratihar [19] using the BPNN and GA-NN approaches. The GA-NN was seen to outperform the BPNN in most of the test cases. The same problem was also tackled by Mollah and Pratihar [20] using radial basis function neural network (RBFNN) trained by the back-propagation (BP) algorithm and GA, separately. The GA-tuned RBFNN was found to perform better than the BP-trained RBFNN. The BP-algorithm might have local minima problem, as it works based on a steepest descent algorithm. On the other hand, the chance of GA solutions for getting stuck into the local minima is less. Tarng et al. [21] used a BPNN of 5-8-6-3 type to establish the relationships between the inputs (namely arc gap, inert gas flow rate, welding current, speed, % cleaning) and outputs (such as front depth, back height, back width) in forward direction of a TIG welding process. Once the NN model was trained, simulated annealing [22] was utilized to search for the process parameters corresponding to optimal weld pool geometry in order to obtain appropriate weld strength. A fuzzy c-means algorithm [23] was then used to classify the weld quality. Nagesh and Datta [24] developed a BPNN model to predict weld bead geometries for depositing mild steel electrodes on cast iron plates. The process parameters like electrode feed rate, arc power, arc voltage, arc current, arc length, and arc travel rate were considered as the inputs of their model, and bead geometric parameters, namely bead height, bead width, depth of penetration, and area of penetration, had been used as the outputs. The main drawback of their model lies in the fact that some of the inputs were dependent on each other (for example, power, voltage, and current of the arc). They solved the problem of forward mapping only. An intelligent system for determining the welding parameters in pipeline welding was proposed by Kim et al. [25]. It was composed of four components: (i) a database and finite element method (FEM) model, (ii) a BPNN model for welding parameters, (iii) a BPNN model for welding quality, and (iv) a corrective neural network (CNN). The database and FEM model determined the number of pass required according to primary input parameters, namely material thickness, groove angle, material type, wire type, and diameter. The first BPNN estimated the appropriate welding parameters, such as welding current, arc voltage, and welding speed for each pass of welding and the welding position. The second BPNN was used to predict the bead geometry and weld quality. If the predicted bead geometry did not match with the target one, a CNN model was utilized to calculate corrective coefficient in order to maintain a proper match between the predicted and target geometries.

Mishra and DebRoy [26] developed a bidirectional model of gas tungsten arc (GTA) welding by coupling a NN with a real-coded GA to tackle the problem of reverse mapping also. They could determine a set of desired input process parameters corresponding to target weld bead geometry. Three inputs, namely arc current, voltage, and welding speed, and two outputs, such as bead penetration and width, had been considered in their model. Once trained, their model could yield the set of input parameters in order to get the desired weld bead much faster compared to the heat transfer and fluid flow model. Moreover, multiple sets of input variables could be obtained to ensure a set of outputs, as expected. Amarnath and Pratihar [27] could successfully solve the problems of both forward and reverse mappings using RBFNN, whose structure and parameters were optimized utilizing a GA. To decide the structure of the network, they used the concept of clustering. In their study, the number of hidden neurons of the network had been kept equal to that of clusters made by the input-output data points. More recently, Dey et al. [28] could develop BPNN- and GA-NN-based approaches separately, in order to successfully predict weld bead profiles. The problems of forward and reverse mappings of electron beam welding process were tackled by Dey et al. [29] using the RBFNNs. The performance of RBFNN depends on its architecture, which, in turn, is dependent on the number of hidden neurons. In their study, the input-output data of the process were clustered based on similarity using three clustering algorithms, and the number of hidden neurons was kept equal to that of the clusters obtained. A batch mode of training was adopted using the BP algorithm. A GA was utilized to determine the optimal values of the parameters related to clustering and BP algorithms. It is to be noted that reasonably good predictions were obtained by them in both forward and reverse mappings. Attempts were made by Malviya and Pratihar [30] to develop both multilayer feed-forward and RBFNNs separately, in order to carry out forward and reverse mappings of MIG welding process. The networks were optimized using particle swarm optimization (PSO) algorithm [31] only first and, then, a combination of PSO and BP algorithms. In their approach, six process parameters of MIG welding (such as welding speed, arc voltage, wire feed rate, gas flow rate, nozzle-to-plate distance, and torch angle) and three responses (namely, bead height, bead width, and bead penetration) were considered. The hybrid approach was found to perform better than the single approach.

A lot of research had been carried out to establish input-output relationships in different welding processes. Although the forward mapping problems had been solved by various investigators, the problems of reverse mapping did not receive much attention, till date. Both feed-forward multilayer NNs and RBFNNs had been extensively used for the above purposes. However, recurrent NNs (which can capture the dynamics of the process efficiently) had not been utilized to tackle these problems to the best of the author's knowledge. Moreover, no significant study had been reported on applications of FL-based expert systems to solve these problems. It could be due to the reasons discussed above.

4 Expert systems in machining

In machining, excess material of workpiece is removed in the form of chips in order to get finished product. Machining processes include turning, milling, drilling, grinding, and others. Besides these conventional machining processes, there are some unconventional processes, namely electro-discharge machining (EDM), electro-chemical machining (ECM), abrasive jet machining (AJM), ultrasonic machining (USM), etc. The present survey covers the developed expert systems on some of the above machining processes, as described below.

4.1 Expert systems in turning

Turning of a cylindrical job is carried out on a Lathe in order to reduce its diameter. A number of soft computing-based expert systems had been developed to model input-output relationships in turning. Some of these studies are discussed here.

Viharos and Monostori [32] developed an ANN-based approach for input-output modeling in plate turning. The parameters like feed, depth of cut, and speed were used as inputs of the model, which had only one output, that is, surface roughness. Thus, the problem of forward mapping only was attempted in their study. In order to establish the relationships between inputs and outputs during high-speed turning of nickel-based Inconel 718 alloy, an NN model was designed by Ezugwu et al. [33]. The parameters like speed, feed rate, depth of cut, cutting time, and coolant pressure were the inputs of the model, and there were seven outputs, such as tangential cutting force, feed force, spindle motor power consumption, machined surface roughness, average flank wear, maximum flank wear, and nose wear. A feed-forward NN with two hidden layers was used for this modeling, which was trained using Levenberg-Marquardt algorithm combined with Bayesian regularization. A set of experimental data was used for its training, and once trained, its performance was tested on some new test cases. They could obtain a good accuracy in predictions of the outputs. However, the problem of reverse mapping was not attempted by them. Wang et al. [34] proposed a hybrid NN approach to model tool wear progression in turning process. The hybrid approach was developed by combining a conventional NN with an analytical model of the turning process. The parameters like feed rate, cutting speed, depth of cut, bias value, cutting time, iterative time interval, and current flank wear length were used as the inputs of NN, and its outputs like average normal stress and temperature along the tool-workpiece interface were determined first. Those outputs of the NN were then fed to the analytical model to predict the tool wear length in the next time interval. Extended Kalman Filter (EKF) algorithm was used to train the NN. It is to be noted that the EKF could provide the training to the network using a less amount of training data and at a higher speed compared to the well-known BP algorithm. The developed hybrid NN could provide a reasonably good solution to the problem. Chavoshi and Tajdari [35] studied the effects of hardness and spindle speed on surface roughness in case of hard turning of AISI 4140 using CBN cutting tool using both multiple regression analysis and artificial NN. A better prediction accuracy of NN model compared to the regression analysis was also reported. They solved the problem of reverse mapping also using NN. However, a good accuracy in predictions was not obtained in the reverse mapping and it could be due to a mapping from one input to two outputs (through a 1-5-2 network).

An attempt was made by Nandi and Pratihar [36] to relate surface finish in ultraprecision turning with the cutting parameters, namely cutting speed, feed, and depth of cut using a GA-tuned fuzzy basis function network (FBFN). They developed an approach for automatic tuning of membership function distributions of the variables (that is, DB), rule base, and weighting factors indicating the strength of the rules to ensure minimum deviation in prediction. The GA-trained FBFN was able to yield reasonably good predictions of the surface finish of the machined component. Reddy et al. [37] developed adaptive neuro-fuzzy inference system (ANFIS) [38] to model input-output relationships in turning of aluminum alloys using carbide cutting tool. In their forward mapping model, surface roughness was expressed as the function of input variables, namely cutting speed, feed, and depth of cut. The performance of ANFIS was compared with that of response surface methodology (RSM). The former could outperform the latter. The problem of reverse mapping was not solved by them.

Both NN- and FL-based expert systems were designed and developed to establish input-output relationships for turning operation.

4.2 Expert systems in milling

Milling is a machining process utilized to manufacture various types of shapes by using multipoint cutting tools. Slab milling, slot milling, form milling, and face milling are a few examples of this machining process. There exist a few soft computing-based expert systems used to establish input-output relationships of milling processes. Two of such expert systems are discussed below.

Razali et al. [39] developed a fuzzy reasoning model (based on Mamdani approach) for peripheral end-milling process. They considered three inputs, namely hardness, radial depth of cut, and tool diameter, and two outputs, such as cutting speed and feed. Triangular membership functions were used for the inputs and outputs, and the rules were designed accordingly. The developed model could predict the input-output relationships of the process. However, the KB of the fuzzy reasoning model was not tuned using any optimizer. So, there is a chance of further improvement of the performance of their model. Surface roughness in end-milling process was modeled as the function of some parameters, namely spindle speed, feed rate, and depth of cut by Sharkawy [40]. He used three intelligent systems, such as RBFNN, ANFIS, and GA-FL. The RBFNN was found to perform better than the other two in terms of accuracy in prediction and computational complexity. The performances of ANFIS and GA-FL are dependent on the selection of membership function distributions of the variables and rule base and their proper tuning using an optimizer. On the other hand, the RBFNN can capture the non-linearity of a process due to the use of non-linear radial basis function as its activation function.

To the best of the author's knowledge, no significant study had been reported on reverse mapping of the process.

4.3 Expert systems in drilling

Drilling is one of the most popular hole making operations. It uses a two-point cutting tool, popularly known as drill bit. Some of the expert systems used to model its input-output relationships are described below.

Gill and Singh [41] developed an ANFIS model to establish relationship between material removal rate and the parameters like depth of penetration, time for penetration, and penetration rate in case of ultrasonic drilling of sillimanite ceramic. The predictions of the developed model were compared with some actual practical results and found to be satisfactory. Gajate et al. [42] used a transductive neuro-fuzzy inference system (TNFIS) to model direct and inverse dynamics of a drilling process. In the TNFIS, local models are derived for controlling the process using the concept of online clustering of its training data set. Clustering is done based on similarity among the data points, which is measured in terms of their Euclidean distances. The TNFIS uses Mamdani-type inference method and Gaussian membership function distribution representing each cluster. They developed a single-input and single-output model, where the feed rate and cutting force were considered as the input and output, respectively, in case of forward mapping. In inverse model of the process, cutting force and feed rate were taken as the input and output, respectively. A BP algorithm was used to train the TNFIS model.

The TNFIS model was seen to perform better than ANFIS model.

4.4 Expert systems in grinding

Grinding is a finishing operation carried out by using some abrasive particles like aluminum oxide, silicon carbide, boron carbide, etc. These abrasive particles are held using bonding material in the form of a wheel popularly known as grinding wheel. During operation, the grinding wheel rotates at a high speed and it is in contact with the job surface. Thus, the excess material is removed from the job. Various grinding processes are in use, such as surface grinding, form grinding, cylindrical grinding, and others. Some expert systems had been reported in the literature to represent its input-output relationships.

Nandi and Pratihar [43] developed a GA-FL to establish the relationships between the set of inputs (such as RPM of wheel, RPM of work, feed rate) and that of outputs (namely, surface finish and power requirement) in grinding. As the performance of fuzzy reasoning tool depends on both the membership function distributions of the variables (that is, DB) and its rule base (RB), a GA was used to tune both of them simultaneously with the help of some experimentally collected data. Both linear (that is, triangular) and non-linear (that is, second- and third-order polynomials) membership function distributions were used for the variables. The third-order polynomial membership function was able to capture the non-linearity of the process more accurately. The developed model was seen to predict the outputs accurately for some experimentally obtained test cases. It is to be noted that the problem of reverse mapping was not tried in their study. Baseri and Alinejad [44] designed an ANFIS model to relate surface roughness in grinding with its three input parameters, namely dressing speed ratio, dressing depth, and dresser cross-feed rate. Results of the ANFIS model had been compared with some experimental values and found to be satisfactory. Moreover, the ANFIS model was seen to outperform the BPNN model.

4.5 Expert systems in unconventional machining processes

To be in competitive market, modern manufacturing processes should have high productivity, ensure good accuracy, and be able to machine low machinability materials. Conventional machining processes may not be able to fulfill all the above requirements, and consequently, some unconventional machining processes, namely electro-discharge machining (EDM), electro-chemical machining (ECM), ultrasonic machining (USM), abrasive jet machining (AJM), and others, are in use. In EDM, excess material is removed from the job by erosion due to a series of electric sparks. The principle of electrolysis is used in ECM in order to remove the excess material. The USM is used for machining of electrically non-conducting, brittle materials. The tool vibrates in ultrasonic range, and a flow of abrasive slurry is maintained in the job-tool gap. AJM is suitable for brittle and fragile material. Abrasive particles move with high speed in air or gas and fall on the job surface. There will be brittle fracture, and consequently, wear particles will be generated and washed away by the jet. Some of the expert systems developed to model unconventional machining processes are discussed below.

A FL-based expert system was developed using the knowledge of skilled EDM operator by Yilmaz et al. [45]. Fuzzy if-then rules were designed to establish input-output relationships of this process according to Mamdani approach of fuzzy reasoning tool. The problem of forward mapping was solved only by considering three inputs (namely, discharge current, pulse duration, and pulse interval) and three outputs, such as electrode wear, surface roughness, and erosion rate. The membership function distributions of the input and output variables were assumed to be triangular. The performance of the developed expert system was found to be satisfactory on some experimental data. However, there is a chance of further improvement of its performance, as no optimizer was used in their model to determine its optimal KB. Moreover, the problem of reverse mapping was not attempted in their study. Labib et al. [46] designed two fuzzy logic controllers (FLCs) to monitor and control two outputs, namely feed rate and flow rate (valve position) separately of ECM drilling process. In both the controllers, measured current and flow rate were considered as the inputs. However, it would have been more practical to develop only one FLC to model both the outputs of the process simultaneously. The membership function distributions of the input and output variables were assumed to be linear. Mamdani approach of FLC was used in their study. No attempt was made in their model to determine optimal KB of the FLC.

Caydas et al. [47] developed an ANFIS model to establish input-output relationships of wire electro-discharge machining (WEDM) process. Two responses, namely surface roughness and white layer thickness obtained in the WEDM process, were modeled as the functions of four input process parameters, such as pulse duration, open circuit voltage, dielectric flushing pressure, and wire feed rate. The performance of the ANFIS model was found to be satisfactory on some experimental data. It is to be noted that the problem of reverse mapping was not solved by them. Maji and Pratihar [48] used a GA-tuned ANFIS model to carry out both forward and reverse mappings of EDM process. They considered both linear (that is, triangular) and non-linear (that is, bell-shaped) membership function distributions of the input variables, such as peak current, pulse on time, and pulse duty factor. Two outputs, namely material removal rate and surface roughness of the EDM process, were predicted in their model for conducting forward mapping. Results of both forward and reverse mappings were compared with some experimental data and found to be satisfactory. The said model with nonlinear membership function distributions of the variables could perform better than that with linear membership functions.

5 Expert systems in metal forming

Metal forming is one of the most important manufacturing processes, in which excess material of a workpiece is displaced (but not removed) through plastic deformation in order to achieve the desired product. Manufacturing processes like rolling, forging, extrusion, etc. come under the umbrella of metal forming. A number of expert systems had been developed by various researchers in forming, and some of those models are discussed below.

Kim and Kim [49] utilized a three-layer NN trained using a BP algorithm to model hot forging process. The aim was to determine optimal initial billet size and design suitable die geometry in order to satisfy the complete filling of die cavity. Both the training and test data were obtained through finite element (FE) analysis. The trained NN was found to predict the results of FE analysis accurately. A few expert systems on laser forming had also been reported in literature. Cheng and Lin [50] used three supervised NNs, namely BPNN using hyperbolic tangent activation function, that utilizing a logistic function as the activation function and RBFNN for developing models in order to predict bending angle in laser forming process. The parameters, such as laser power, scan speed, spot diameter, thickness, and length of workpiece, were considered as inputs to the networks, and bending angle was taken as the output. The performances of those NNs were verified with some experimental data. The RBFNN was found to outperform the other networks. Casalino and Ludovico [51] used a BPNN for selecting process parameters in laser bending under both temperature gradient and buckling mechanisms in order to achieve bending angle. The performance of the developed model was tested on some experimental data and found to be good. This approach could be thought of as an alternative to the time-consuming FE analysis.

Shen et al. [52] developed an ANFIS for modeling bending angle in laser forming as the function of laser power, beam diameter, scanning velocity, and thickness of the plate. The performance of the ANFIS model was optimized by varying both the type and number of membership functions. Its performance was verified with some experimental data and found to be satisfactory. Sharma et al. [53] suggested a model of forward mapping for hot extrusion process using a neuro-fuzzy approach popularly known as ANFIS model. The physical problem was to extrude a transmission shaft from CK-45 steel billet. In their study, they considered three input process parameters, namely die angle, coefficient of friction, and temperature of billet, and one output, that is, extrusion (punch) force. The training data were collected through FE analysis, and the performance of the developed model was tested on FE-predicted results. Reverse mapping was not implemented in their study. FE analysis was carried out using ANSYS package to determine forging load and axial stress developed for handling axisymmetric component by Gangopadhyay et al. [54]. Both forging load and axial stress were found to be dependent on flow stress and die-blank interface friction significantly. As the FE analysis took a considerable amount of time, an attempt was made by the authors to develop an expert system based on GA-FL to establish the said input-output relationships. It is to be noted that the training data of the expert system were obtained beforehand using the ANSY S package. The developed expert system could predict the outputs for a set of inputs within a fraction of a second, whereas the FE analysis took a few hours time to determine the same. The expert system could help the shop floor people to get the input-output relationships of this process well before the actual production starts.

Both FL- and NN-based expert systems had been developed to establish input-output relationships in forming processes. However, reverse mapping for this process was not been attempted by the researchers.

6 Expert systems in surface coating

The purpose of providing coating over a metal surface is to improve its quality in terms of hardness, wear resistance, roughness, and others. Attempts were made to develop soft computing-based expert systems in order to determine input-output relationships in surface coatings. Some of those studies are stated below.

Duan et al. [55] developed fuzzy reasoning tool to establish relationships between the process parameters (such as arc current, total flow rate, argon/helium ratio, sound peak ratio) and two responses, namely anode condition and average length of the plasma jet separately for an argon/helium plasma spray process. It is to be noted that coating porosity could be related to an average length of the plasma jet. In their model, membership function distributions of the variables were assumed to be Gaussian in nature. It is also important to mention that their approach might not be able to capture full dynamics of the process, as the two responses were modeled separately. Moreover, they did not try to implement reverse modeling of the process. Input-output modeling was done for atmospheric plasma spraying process carried out using alumina-titania powder. Forward modeling of this process was conducted using a feed-forward NN [56]. In their model, porosity level of coating was expressed as the function of five inputs, namely arc current, total plasma gas flow rate, hydrogen ratio, carrier gas, and powder feed rate. Two hidden layers were used in their NN model, which could provide good accuracy in predictions. Jean et al. [57] carried out experiments on partially stabilized zirconia plasma spraying coatings using eight process parameters, namely number of sprayed layers, accelerating voltage, arc current intensity, traverse speed, spraying standoff distance, powder feeder rate, carrier gas flow rate, primary plasma gas flow rate, and one output, that is, coating thickness. Analysis of variance was conducted on the collected data, and three process parameters, such as accelerating voltage, spraying standoff distance, and carrier gas flow rate, were identified as the significant ones. Fuzzy reasoning tool was developed based on Mamdani approach [7] by considering triangular membership function distributions for the input and output variables. The performance of the developed FL-based tool was found to be good. However, there was a chance of further improvement of its performance. Moreover, the problem of reverse mapping was not attempted by them. Hayati et al. [58] developed an adaptive neuro-fuzzy inference system (ANFIS) to establish a relationship between grain size of nanocrystalline nickel coatings and the process parameters, namely current density, saccharin concentration, and bath temperature. The performance of ANFIS model was compared with that of an artificial NN, and the former was found to be more accurate and reliable compared to the latter.

Input-output relationships of plasma spray coating process had been determined by Datta et al. [59] in both forward and reverse directions using multilayer feed-forward NN and RBFNN. The process parameters, namely primary gas flow rate, standoff distance, powder flow rate, and arc current, were taken as the inputs, and thickness, porosity, and micro-hardness of coating were considered as outputs of the NNs. During the training of the networks, BP algorithm, GA, and PSO algorithm were used. To decide the architecture of the RBFNN, the concept of clustering was utilized. The number of hidden neurons of the RBFNN was kept equal to that of clusters formed in the input-output training data set. The problems of both forward and reverse mappings were efficiently solved by the NNs. In another study, Datta et al. [60] attempted to tackle the problem of forward mapping only using ANFIS model also. To reduce the number of rules and, hence, computational complexity of the model, a hierarchical ANFIS architecture was adopted in their study. Tuning of the ANFIS model was done utilizing a GA and PSO algorithm separately. A good accuracy in prediction was obtained. However, their model was not used for reverse mapping, as the responses could not be sorted out in terms of their importance.

Several attempts were made by various investigators to carry out forward mapping for this process using both FL- and NN-based approaches. However, the problem of reverse mapping could not attract much attention of the researchers, till date.

7 Discussion and scope for future study

Input-output relationships of manufacturing processes are difficult to determine, as the physics is not fully known, and consequently, their mathematical modeling cannot be done accurately. Under these circumstances, input-output modeling is to be carried out based on some experimental data, which may not be always precise in nature. Statistical regression analysis can be conducted to establish input-output relationships of manufacturing processes, but it has its inherent limitations particularly in case of reverse mapping, as discussed above. As the experimental data are associated with imprecision and uncertainty, soft computing-based approaches may be suitable to obtain input-output relationships of manufacturing processes in both forward and reverse directions.

Both FL- and NN-based approaches have been developed to establish input-output relationships of various manufacturing processes, which are mainly non-linear in nature. Moreover, the degree/extent of non-linearity may not be the same over the entire ranges of the variables. Therefore, all the data points belonging to the search space may not be similar at all. The data points may form a few clusters depending on their similarities among one another. Clusters are formed based on the principle that similar data points should belong to the same cluster, and two dissimilar data should lie on two different clusters. For a manufacturing process, input-output data points may form a few clusters based on their similarities. Expert systems can then be developed cluster-wise [61, 62] to improve the accuracy in predictions in both forward and reverse directions. We, human beings, can visualize only up to three dimensions. In order to visualize the clusters involving higher than 3-D data points, some dimensionality reduction techniques [63, 64] are to be used. The performances of soft computing-based expert systems, clustering algorithms, and dimensionality reduction techniques depend on a set of parameters. A method of intelligent data mining may be adopted in order to determine these parameters, so that input-output predictions can be obtained accurately in both forward and reverse directions.

Reverse mapping determines a set of inputs to be selected in order to achieve a set of desired outputs in a manufacturing process. A closed-loop control system is to be adopted to automate any manufacturing process. A feed-back system is to be provided to compensate the deviation (if any) from the targets. A suitable hardware for the feed-back circuit of this process is to be designed and developed, so that it can be controlled accurately, online.

Recurrent NN consists of both feed-forward and feed-back circuits, and consequently, it may be a better tool to capture the dynamics of a manufacturing process. It may also be tried, in future, to develop suitable expert systems for manufacturing processes.

To develop soft computing-based expert systems for carrying out forward and reverse mappings in manufacturing processes, human intelligence is also used to extract their KBs. For example, considerable efforts are made to select the type of soft computing-based approaches (say FL techniques, NNs, or their combined approaches) to be used and their associated parameters. Human intelligence may be integrated with soft computing-based approaches to make the knowledge extraction process more efficient [65].

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