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A Review: Influence of electrode geometry and process parameters on surface quality and MRR in EDM using Artificial Neural Network

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ABSTRACT

Electrical Discharge Machining (EDM) is a non conventional machining process, where electrically conductive materials are machined by using precisely controlled sparks that occur between an electrode and a work piece in the presence of a dielectric fluid. It has been a demanding research area to model and optimize the EDM process in the present scenario. Lots of efforts have been exercised to model and optimize the performance and process parameters of EDM process using ANN. To model ANN architectures, learning/training algorithms and nos. of hidden neurons are varied to accomplish minimum error, but the deviation is made in an arbitrary manner. Artificial Neural Network model should be generated for both electrode geometry and various electrode materials to compare the influence of both in EDM.

Keywords - Artificial Neural Network (ANN), MRR, Surface Roughness, Tool Geometry

I. INTRODUCTION

Electrical discharge machining (EDM) is a non-traditional machining method commonly used to produce die cavities with the erosive effect of electrical discharges. It uses thermoelectric energy sources for machining low machinability materials; a complicated intrinsic-extrinsic shaped job regardless of hardness has been its distinguishing characteristics. EDM founds its wide applicability in manufacturing of plastic moulds, forging dies, press tools, die castings, automotive, aerospace and surgical components. In EDM, a power supply delivers high characteristics. EDM has its wide applications in manufacturing of plastic moulds, forging dies, press tools, die castings, automotive, aerospace and surgical components. No direct contact is made by EDM between the electrode and the work piece. It annihilates mechanical stresses, chatter and vibration problems during machining. Various types of EDM process are available, but here it is Die-Sinking type EDM machine which requires the electrode to be machined in the exact contradictory shape as the one in the work piece.

II. EDM PROCESS

To overcome some specific advantages of conventional machining processes, an EDM process has been introduced. This method is especially effective in machining hard die steels, complex cavities and small work pieces. Die casting, injection molding, forging, extrusion, upset forging and power compaction dies are manufactured using EDM technology [1]. EDM, basically a thermo electric process, has the ability to machine any conducting materials regardless of their mechanical and chemical properties. As there is no contact between the tool and the work piece required, it is very efficient and effective in machining very hard and high strength materials. The recent trends in development of EDM process have focused on the production of micro-features [3]. It becomes a basic machining method for manufacturing industries viz. Aerospace, Automotive, Nuclear, Medical and Die-mold production etc [4].

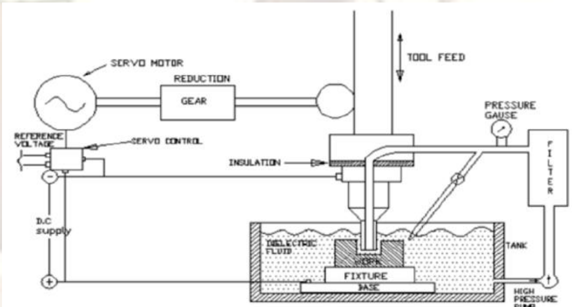


Fig. 2.1 Set up of Electrical Discharge Machining

In EDM, a power supply hands over high-frequency electric pulses to the electrode tool and the work piece. The gap between the tool and work piece is flushed with a flow of dielectric liquid. When an electric pulse is delivered from the electric supply, the insulating property of the die electric fluid is temporarily made ineffective. This permits a small spark to fly the shortest distance between the tool and work piece. A small pool of molten metal is shaped on the work piece and the tool at the point of discharge. A gas boils form around the discharge and the molten pools. As the electric pulse ends and the discharge disappears, the gas boil collapses. The wave of cool dielectric causes the molten metal to be ejected from the work piece and the tool, leaving small craters. This action is repeated no. of times each second during EDM processing. This removes material from the work piece in a shape corresponding to that of the tool [2].

Electrical discharge machining (EDM) processes are now gaining in popularity, since many complex 3D shapes can be machined using a simple shaped tool electrode. Depending on the kind of material used and other requirements, positive or negative polarity can be applied. When gap width between the tool and the electrode achieves the maximum sparking gap width, a micro-conductive ionized path appears and the electric spark occurs achieving temperatures up to 15,000 or 20,000°C [18].

Owing to the complex nature of the process involving physics of the EDM spark (plasma), it is difficult to observe the process experimentally and quantify the mechanism of material removal [17].

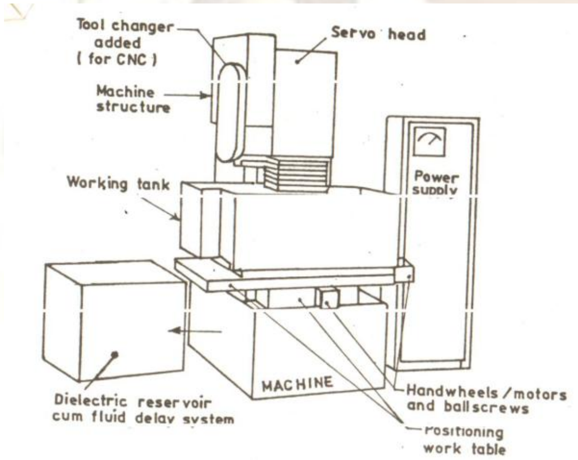


Fig. 2.2 Scheme of EDM Equipment

III. ELECTRODE GEOMETRY

To nurture the scope of further improvements in the process, the literature study works as a guide to run this analysis.

Kamlesh V. Dave et. al [1] reported that the tool electrode in EDM process is the means of providing electrical energy to the work piece. The contribution of Tool Geometry was found a significant factor on the Surface Roughness and Material Removal Rate (MRR). Copper was used as an electrode tool having different geometries such as Round, Square, Rectangle and Triangle. The work was carried out on AISI H13 Steel work piece.

Fig. 3.1 Practically processed specimens.

Fig. 3.1 shows the processed specimen of Ø 50 mm round bar of 6 mm thickness on which four geometry of tool electrode is grooved of 2 mm depth.

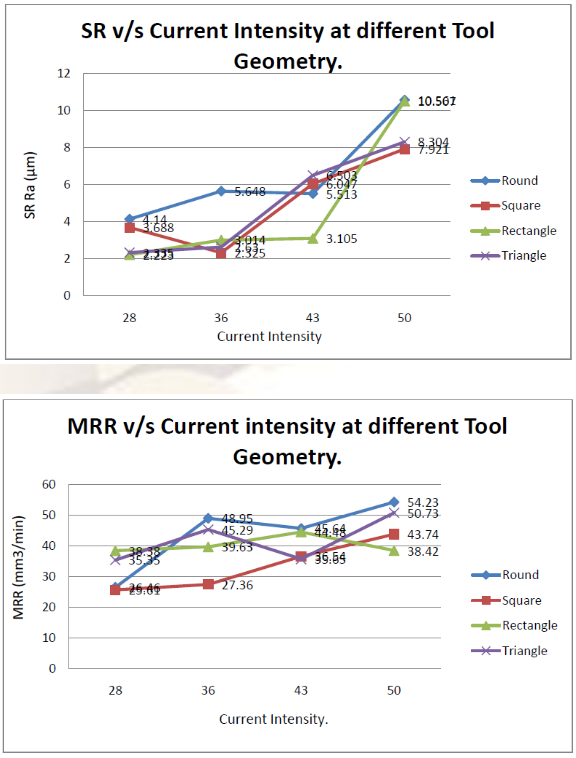


Fig. 3.2 Comparison of MRR and SR with current intensity at different tool geometry

Figure 3.2 shows that as current intensity increases, the MRR increases and so the Surface Quality decreases. Both the graphs show a same result that is the basic rule. But for current intensity 36 the results are different and the MRR is good and Surface Quality also good for Triangle and Rectangle Geometry.

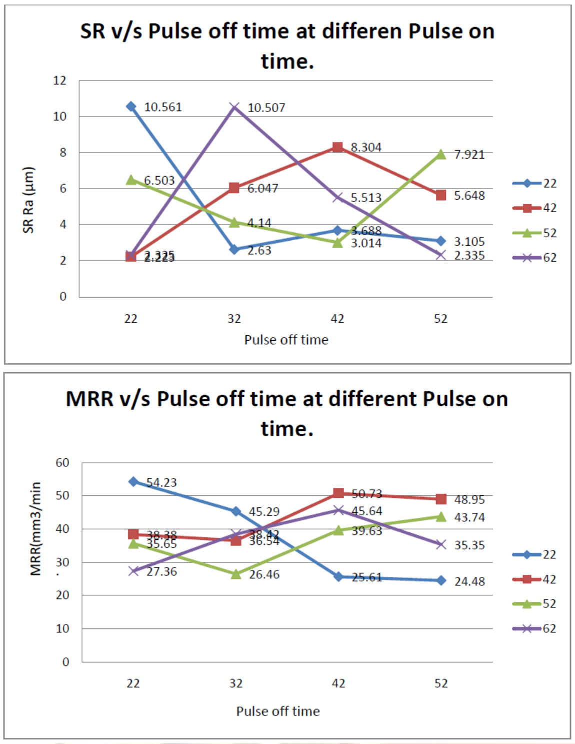


Fig. 3.3 Comparison of MRR and SR with pulse off time at different pulse on time

Fig. 3.3 shows that as the pulse on time and pulse off time difference increases the MRR and SR both give negative results that MRR decreases and SR increases. But as they come nearer to each other both the output parameter showing good results.

As per the S/N ratio and ANOVA the percentage contribution of the tool Geometry varies from 10% to 20% which shows that the geometry change improve MRR and SR up to certain extent.

Kamlesh V. Dave et. al [2] reported that designing and re-shaping of electrodes for each feature are time consuming and large number of electrodes are required. So to increase the productivity, quality and flexibility unvarying simple electrode shapes must be analyzed. Tool geometry is not the most significant factor that affects the performance measures the most but it is a significant factor that affects the performance measures. The Rectangle Geometry at 43 A current gives good results for both the performance measures.

B. B. Pradhan et. al [3] presents the attempts to optimize micro-EDM process parameters for machining Ti-6Al-4V super alloy which is possessing high strength, low weight, and outstanding corrosion resistance having applications in aerospace, automobile, chemical plant, power generation, oil and gas extraction, surgical instruments, and other major industries. High melting point of the tool material is required for machining difficult-to-cut materials. Out of copper, brass, and tungsten tools, the brass electrodes of 500 µm were used due to their high tensile stress compared to pure copper tools.

M. Kiyak et. al [4] studied that the EDM of 40CrMnNiMo864 tool steel on AISI P20 steel work piece provided important quantitative results for obtaining possible high surface finish quality and machining outputs. Increasing wear on electrode surface is unavoidable during EDM process which increases work piece surface roughness due to wear rate on electrode caused by pulsed current density.

Debabrata Mandal et. al [5] worked on EDM of C40 Steel with a copper (electrolytic grade) of cylindrical shape with a diameter of 12mm.

Ali Ozgedik et. al [6] presented that the tool wear problem is very critical in EDM since the tool shape degeneration directly affects the final shape of the die cavity. 1040 steel was used for the work piece. Tools were prepared by cutting round electrolytic copper rods of 22 mm diameter at 31.5mm length. The tools were then turned down to 20 mm diameter. For easier and even flushing purposes, a 4 mm diameter hole was drilled through the centre of the tool. The densities of the electrolytic copper tool and 1040 steel work piece specimens used in the experiments were 8.9 g/cm3 and 9 g/cm3, respectively.

Cao Fenggou et. al [7] reported that electrode zoom value has a major role to play with EDM, so that the discharge gap corresponding to the rough machining current peak value should not be less than the electrode zoom value. The experiment was carried out on the work piece S136 with an electrode of Ø 9.56 mm red copper rod.

Shing, S. et. al [8] performed the electric discharge machining of En-31 tool steel hardened and tempered to 55 HRc as a work piece with cylindrical copper, copper tungsten, brass and aluminium electrodes by varying the pulsed current at reverse polarity. Surface roughness depends on electrode material. The pulsed discharge current was applied in various steps in positive mode with four different electrode materials. The copper and aluminium electrodes achieve the best MRR with the increase in discharge current, followed by copper–tungsten electrode. Brass does not show significant increase in MRR with the increase in discharge current.

Copper gives the best MRR on En-31 work material. Brass electrode could not have effective machining rate and the mirror-shape of the tool electrode was found to be coated with a thin layer of the tool material. They concluded that for the En-31 work material, copper and aluminium electrodes offer higher MRR. Copper and copper–tungsten electrodes offer comparatively low electrode wear whereas aluminium electrode shows good results while brass wears the most. Cu and Al electrodes produce comparatively high surface roughness at high values of currents. Copper–tungsten electrode offers comparatively low surface roughness at high discharge currents giving good surface finish. Copper is comparatively a better electrode materials having better surface finish, low diametric overcut, high MRR and less electrode wear for En-31 work material and aluminium is next to copper in performance, and may be favored where surface finish is not essential.

H. Juhr et. al [10] reported that the cost of producing electrodes for the SEDM process is important, because electrodes wear out, and in most cases, several electrodes are required. The necessary number of tool electrodes is thereby a cost factor.

Angelos P. Markopoulos et. al [12] showed that the electrolytic copper of a rectangular work area 40×22 mm^2 was used for tool electrode of positive polarity on the work pieces of St 37, C 45, 100Cr6, Mic/al 1 and DP 1.

S. Assarzadeh et. al [13] reported that the BD3 steel and commercial copper were used as the work piece and tool electrode materials respectively. The bottom surface of the electrode is flat and parallel to the work piece surface. Also, the diameter of the cylindrical electrode was equal to the diameter of the round bar work piece of 12 mm.

Kesheng Wang et. al [14] suggested that the test was done on graphite electrode (size 2.9 × 9.8 mm) with nickel-base alloy work piece using an AGIE INNOVATION EDM machine.

G. Krishna Mohana Rao et. al [15] accounted that the experiments were carried out on Ti6Al4V, HE15, 15CDV6 and M-250 by varying the peak current and voltage and the corresponding values of hardness with use of copper tool electrode.

S. N. Joshi et. al [16] conducted the experiments on AISI P20 mold steel with use of Copper electrode and tried out an integrated approach to obtain the expected optimum performance of the EDM process.

S. N. Joshi et. al [17] described that work material AISI W1 tool steel was with an electrode material of graphite.

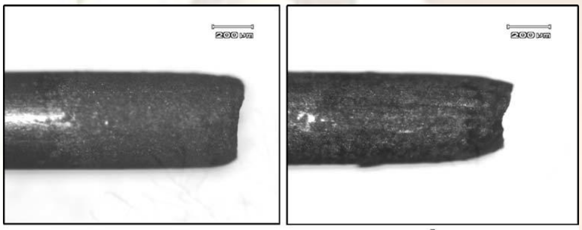
Narcis Pellicer et. al [18] reported that the experiment was carried out in H13 steel using different geometries of electrolytic copper electrodes such as square, triangle, circle and rectangle due to their simplicity and to their different machining contact area. The groove of 3 mm width and 1 mm depth was used as experimental target feature. They found the great impact of the tool geometry on the final feature accuracy and target width of 3 mm is nearly achieved by square electrodes and, in second term, by round and rectangle electrodes. Triangle electrodes do not do well and are not useful for complex geometries machining. Square and rectangle electrodes present better radial and axial wear ratios so, they are the best option for flexible tool electrode shape design.

IV. PROCESS PARAMETERS

Kamlesh V. Dave et. al [1] reported that when current intensity increases, the MRR increases and so the Surface Quality decreases. But for current intensity 36 the results are different and the MRR is good and Surface Quality also good for Triangle and Rectangle Geometry [Fig. 3.2]. They also described that as the pulse on time and pulse off time difference increases the MRR and SR both give negative results that MRR decreases and SR increases. But as they come nearer to each other, both the output parameters show good results [Fig. 3.3]. Gap Voltage, Current Intensity, Pulse on time, pulse off time are influential parameters to the common performance measures like MRR and Surface roughness. The rank was provided that which parameter affects the most to the least. For Surface roughness it is 1. Current intensity 2. Tool Geometry .3.Pulse off time 4. Pulse on time 5. Gap voltage and for MRR it is 1. Current Intensity 2. Pulse on time 3.Tool Geometry. 4. Pulse off time 5. Gap Voltage. The Rectangle Geometry at 43 A current gives good results for both the performance measures. Also, Pulse on time and Pulse off time range affect the MRR and SR. At P_{ON}=22 & P_{OFF} =22 hold good results but at P_{ON}=22 & P_{OFF}=62 the results are not friendly.

Kamlesh V. Dave et. al [2] accounted that to determine influential parameters for EDM groove machining, 24 experiments have been carried out based on Taguchi Orthogonal Array $OA_{16}(4^5)$ has been chosen in order to have representative data. The Taguchi method aims to find an optimal combination of parameters that have the smallest variance in performance. They concluded that p-value for B is less than others, so current intensity is the most significant factor.

B. B. Pradhan et. al [3] described that positive polarity i.e., work piece '+ve' and tool '-ve' was used during micro-EDM experimentation as tool wear is less in this case due to low sparking energy distribution at the cathode, i.e., tool as compared to reverse polarity and this helps in improving the micro-machining accuracy. Peak current (Ip), pulse-on-time (Ton), dielectric jet flushing pressure (Pr), and duty ratio (t) were considered as varying parameters by keeping other machining parameters constant. They took (i) Peak current (amp): 0.5 to 1.5, (ii) pulse-on-time: 1 to 20 µs, (iii) Duty factor (%): 60 to 90, (iv) Flushing pressure (kg/cm^2): 0.1 to 0.5. The dielectric used was kerosene so as to use conventional EDM machine. The experimental scheme has been designed based on L9 orthogonal array of Taguchi technique, which has nine rows corresponding to nine experimental runs with eight degrees of freedom on the basis of four input factors, i.e., peak current (Ip), pulse-on-time (Ton), flushing pressure (Pr), and duty factor (t), each factor having three levels. It is observed that there are weak effects of dielectric flushing pressure and duty factor on MRR.



a b

Fig. 4.1 Optical view of end of the tool after machining at a) 1.5 A, 1 µs, 0.5 kg/cm^2, 80%, b) 1.5 A, 20 µs, 0.3 kg/cm^2, 60%

They observed that Ton, the most influencing factor, has the maximum percentage of contribution on MRR, OC, and taper whereas peak current, I_p has the maximum percentage of contribution on TWR during micro-drilling of titanium alloy by EDM. Metal removal rate and tool-wear rate are found to increase with the increase in peak current due to higher discharge energy at higher value of I_p. Also MRR and TWR are found to increase when Ton increases from 1 to 10 µs but with further increase in Ton, MRR decreases. Flushing pressure and duty factor have no significant effect on both MRR and TWR. Overcut of the machined micro-hole is affected by the peak current and on time and increased with increase in I_p and Ton.

M. Kiyak et. al [4] studied that EDM-work piece material interaction is influenced by many process parameters and considered highly non-linear process. They concluded that Surface roughness increased with increasing pulsed current and pulse time. Low current and pulse time with high pulse pause time produced minimum surface roughness. High pulsed current and pulse time provide low surface finish quality. However, this combination would increase material removal rate and reduce machining cost. So, this combination should be used for rough machining step of EDM process. Rough and finish machining steps require different level of machine power. For rough EDM application, the machine power should be one fourth of the produced power with 16A of current, 6s of pulse time and 3s of pulse pause time. Finish machining should be carried out at one-half level of power at 8A of current and 6s of pulse time and 3 s of pulse pause time. Surface roughness of machined work piece would increase when surface quality of electrode decreases due to pulsed current density. For the same pulse pause time, the trends of surface roughness on the work piece and electrode are similar. Thus, there will be a relation between wear on electrode and increase of surface roughness from work piece with a view of surface quality.

Debabrata Mandal et. al [5] reported that as current decreases, MRR and TWR decreases but at that point of time T_{ON} decreases and T_{OFF} increases.

Ali Ozgedik et. al [6] found experimentally that increasing discharge current increases the work piece removal rate, tool wear rate, relative wear, front-surface wear rate and average surface roughness. The front-surface inclination angle increases with discharge current and decreases slightly for high settings of current. Inner and outer edge-wear radii increase rapidly against increasing discharge current.

The work piece removal rate increases with increasing pulse duration. The increase in tool wear rate with the increasing pulse duration is evident up to 50 µs. Further increase in pulse duration reduces the tool wear rate. The relative wear decreases with increasing pulse duration since the work piece removal rate increases at a faster rate than the tool wear rate. Work piece average surface roughness increases with increasing pulse duration due to the larger craters formed on the surface. Increasing pulse duration leads to an increase in the tool front-surface wear rate and front surface inclination angle, and it leads to a decrease in the outer and inner edge-wear radii. The best surface quality is obtained in injection flushing. The high front-surface wear rates are observed in injection flushing while the low values are obtained in the static condition.

Cao Fenggou et. al [7] presents a method that can be used to automatically determine the optimal nos. of hidden neuron and optimize the relation between process and response parameters of EDM process using GA and BP learning algorithm based ANN modeling. The ANN modeling was implemented to

establish relation between EDM process parameters such as current peak value (A), pulse width on (μs) ,processing depth (mm) with the response parameters
SR (μm), TWR(%), electrode zoom value (μm) and finish depth(mm). Good processing speed can be achieved under the premise of guaranteeing processing accuracy.

Shing, S. et. al [8] accounted that the copper and aluminum electrodes achieve the best MRR with the increase in discharge current, followed by copper–tungsten electrode. Brass does not point out significant increase in MRR with the increase in discharge current. Copper gives the best MRR on En-31 work material. The increase in MRR with the increase in discharge current is due to the fact that the spark discharge energy is increased to facilitate the action of melting and vaporization, and advancing the large impulsive force in the spark gap, thereby increasing the MRR. Copper electrode shows the most consistent overcut with the increase in current. Aluminium is also the best electrode material that shows low diametric overcut. Copper–tungsten and brass gave poor dimensional accuracy by resulting in higher diametric overcut. The diametric overcut is low due to the fact that at low current with reverse polarity, erosion is less. As spark energy is low at low current, the crater formed on the work material is small in depth and hence results in good dimensional accuracy. . Brass and aluminium show a considerable increase in the electrode wear with the increase in the discharge current. The EDMing has been done with reverse polarity, where the electrons strike the tool electrode surface liberating greater energy at this surface, and an electrode material with higher melting point wears less. Copper–tungsten gives low values of surface roughness at high discharge currents on En-31. It is also seen that copper and aluminium electrode results in poor machined surface at high currents due to the fact that higher MRR of Cu and Al metal electrodes is accompanied by larger and deeper craters, resulting in a greater surface roughness.

H. Juhr et. al [10] reported that for developing the continuous parameter generation technology the input parameters such as pulse current, discharge duration and duty cycle and response parameters as removal rate, wear ratio and arithmetic mean roughness were considered. In order to find levels of the pulse current I_e for the main experiments, the procedure is analogue, but in this case, the pulse current I_e is orthogonal projected onto the axis z.

Angelos P. Markopoulos et. al [12] showed that the process parameter to the ANN model were work piece material, pulse current and pulse duration at 3,4 and 4 levels respectively.

S. Assarzadeh et. al [13] reported that the current (I), period of pulses (T), and source voltage (V) were selected at 6, 4 and 4 levels respectively as network process parameters.

Kesheng Wang et. al [14] accounted that The surface roughness agrees with accepted trends indicating that good surface quality can be achieved for short on-time with low peak current (e.g. 10 A), hence with loss of productivity.

G. Krishna Mohana Rao et. al [15] presents the effects of current, voltage, machining time and type of material on hardness. Kerosene was used as dielectric medium. Current is the most influencing factor for surface roughness. From the sensitivity analysis it is concluded that type of material is having highest influence on all performance measures.

S. N. Joshi et. al [16] described that The recommended optimal values of process conditions are: discharge current of about 32 A, discharge duration 400 μs and duty cycle 80% for roughing operation. The intelligent process modeling and optimization approach developed in this work will provide a very effective tool to a process engineer to choose optimum process parameters for enhancing the productivity and finishing capability of the EDM process.

S. N. Joshi et. al [17] concluded that a multilayered feed-forward neural network with leaning algorithms such as gradient descent (GD), GD with momentum (GDA), Levenberg – Marquardt (LM), conjugate gradient (CG), scaled conjugate gradient (SCG) were employed to establish relation between input process conditions (discharge power, spark on time, and duty factor) and the process responses (crater geometry, material removal rate, and tool wear rate) for various work tool work materials. Important process parameters were identified and their effects on performance parameters were extensively studied.

Narcis Pellicer et. al [18] presented the influence of the main EDM process parameters and different tool geometries on basic process performance measures. A set of designed experiments with varying parameters such as pulsed current, open voltage, pulse time and pulse pause time are carried out in H13 steel using different geometries of copper electrodes. Results help to select appropriate EDM process parameters to machine parts depending on product requirements. Influence of different process parameters (pulse current, open voltage, pulse time and pulse pause time) as well as tool electrode shape on several performance measures (MRR, surface roughness, depth, width, slope, and DVEE) has been analyzed for copper electrode and AISI H13 steel work piece in sinking type EDM process using statistical tools. They concluded that the MRR and surface roughness increase with discharge current. Pulse-off variation affects MRR, but its behavior is not lineal due to the interactions with other process parameters.

V. ARTIFICIAL NEURAL NETWORK (ANN)

Debabrata Mandal et. al [5] presents the attempts to model and optimize the complex electrical discharge machining (EDM) process using soft computing techniques. Artificial neural network (ANN) with back propagation algorithm is used to model the process. A multi-objective optimization method, non-dominating sorting genetic algorithm-II is used to optimize the process. Experiments have been carried out over a wide range of machining conditions for training and verification of the model. Testing results demonstrate that the model is suitable for predicting the response parameters.

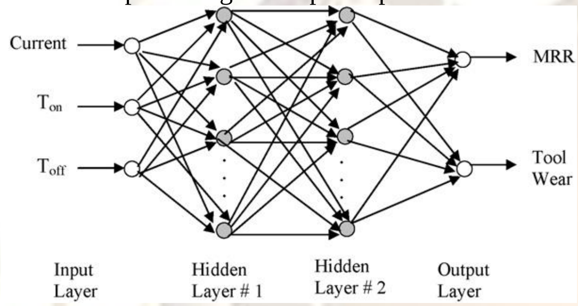


Fig. 5.1 Architecture of the neural network model

Neural network architecture of two hidden layers with three inputs and two outputs has been used to model the process, as shown in Fig. 5.1. AMSE is the least corresponding to momentum coefficient equals to 0.6 and it is taken as an optimal value. To find out the suitable architecture of the network for the above problem different architectures have been studied. The model with 3-10-10-2 architecture is found the most suitable for the task under consideration with learning rate as 0.6 and momentum co-efficient as 0.6. Out of 78 screened patterns, 69 have been used for training, and 9 have been used for testing of prediction capability of the model. The maximum, minimum and mean prediction errors for this network are 9.47, 0.0137 and 3.06%, respectively. Mean prediction error has been calculated by taking the average of all the individual errors, for all the testing patterns. They just concluded that the MRR and tool wear have been measured for each setting of current, pulse on time and pulse off time. An ANN model has been trained within the experimental data. Various ANN architecture have been studied, and 3-10-10-2 is found to be the best architecture, with learning rate and momentum coefficient as 0.6, having mean prediction error is as low as 3.06%. The MRR and tool wear have been optimized using a multi-objective optimization method, non-dominating sorting genetic algorithm-II.

Cao Fenggou et. al [7] present a method that can be used to automatically determine the optimal nos. of hidden neuron and optimize the relation between process and response parameters of EDM process using GA and BP learning algorithm based ANN modelling. The ANN modeling was implemented to establish relation between EDM process parameters such as current peak value(A), pulse width on(μs) ,processing depth (mm) with the response parameters

SR(μm), TWR(%), electrode zoom value(μm) and finish depth(mm).A three layer feed forward neural architecture was used to implement the ANN modeling in EDM process. The number of neurons at the middle layer was determined by GA and node deleting network structure optimization method. GA combined with node deleting network structure optimization method was implemented to find out the global optimal solution, since it is hard for GA based optimization method to find out the local optimal solution, a BP algorithm was finally implemented to converge on the global optimum solution. AS GA converged to global optimal solution quickly the training time is reduced now and as in the second phase BP algorithm was implemented the local optimal solution problem also solved now. Finally they concluded 8 nos. of hidden neuron were found to be optimal for ANN modeling with a desired processing precision and efficiency.

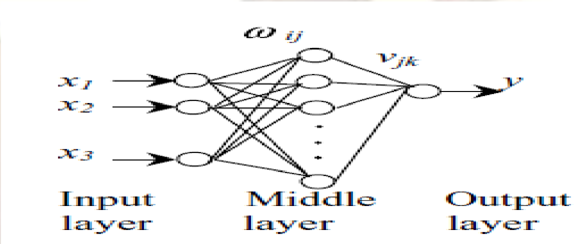


Fig. 5.2 Multi-layer feed-forward network structure model

Kuo-Ming Tsai et. al [9] took six neural networks and a neuro-fuzzy network model for modeling material removal rate (MRR) in EDM process and analyzed based on pertinent machine process parameters. The networks, namely the LOGMLP, the TANMLP, the RBFN, the Error TANMLP, the Adaptive TANMLP, the Adaptive RBFN, and the ANFIS have been trained and compared under the same experimental conditions for two different materials considering the change of polarity. The various neural network architectures that were used here for modeling were trained with the same Gradient descent learning algorithm. For comparisons among the various models various performance parameters like training time, *RMSE*, *R2* were used. On the basis of comparisons they found ANFIS model to be more accurate than the other models.

H. Juhr et. al [10] made a comparison between NRF (nonlinear regression function) and ANN for the generation of continuous parameter technology, which is a continuous mapping or regression. They found ANN's to much easier than NRF's. For modeling with ANN's, feed forward networks with three to five layers were used, which were trained with back- propagation with momentum term. For developing the continuous parameter generation technology they considered the input parameters as pulse current, discharge duration and duty cycle and response parameters as removal rate, wear ratio and arithmetic mean roughness. They used two major performance evaluation criteria sum of squared deviation and sum of relative deviation to evaluate the performance of the two mapping functions. At the end they just concluded that ANN shows better prediction accuracy than nonlinear regression functions.

Promod Kumar Patowari et. al [11] have applied ANN to model material transfer rate (MTR)
and layer thickness (LT) by EDM with tungsten copper (W–Cu) P/M sintered electrodes. They have used input parameters to the ANN model such as compaction pressure (CP), sintering temperature (ST), peak current (I_p), pulse on time (T_{on}), pulse off time (T_{off}) with target measures like MTR, and LT. A multilayer feed-forward neural network with gradient-descent learning algorithm with 5 nos. of neuron in hidden layer has been used to train the ANN model. Two activation functions tansig and purelin have been used in hidden and output layers, respectively. To evaluate the ANN model two performance measures average error percentage and MSE have been implemented. The performance measure MSE during training and testing of MRR were found to be 0.0014 and 0.0038, respectively. Another performance measure average error percentage during training and testing of MRR were found to be 3.3321 and 8.4365, respectively. While modeling LT, MSE during training and testing were found to be 0.0016 and 0.0020 respectively and average error percentage during training and testing were calculated to be 6.5732 and 3.1824 respectively.

Angelos P. Markopoulos et. al [12] implemented an ANN model for the prediction of SR in EDM. For this purpose they used Matlab® as well as Netlab®. The process parameter to the ANN model were work piece material, pulse current and pulse duration at 3, 4 and 4 levels respectively. They used back propagation algorithm for training with model assessment criteria as MSE and R. Finally they concluded that both Matlab® as well as Netlab® were found efficient for the prediction of SR of EDM process.

S. Assarzadeh et. al [13] presented a research work on neural network modeling and multi-objective optimization of responses MRR and SR of EDM process with Augmented Lagrange Multiplier (ALM) algorithm. A 3–6–4–2-size back-propagation neural network was developed to predict these two responses efficiently. The current (I), period of pulses (T), and source voltage (V) were selected at 6, 4 and 4 levels respectively as network process parameters. Out of 96 experimental data sets 82 data sets were used for training and residual 14 data sets were used for testing the network. The training model was trained with back propagation training algorithm with momentum term. Relative percentage error and total average percentage error were used to evaluate the models. From the results in terms of mean errors of 5.31% and 4.89% in predicting the MRR and Ra they concluded that the neural model can predict process performance with reasonable accuracy. Having established the process model, the augmented Lagrange multiplier (ALM) algorithm was implemented to optimize MRR subjected to three machining regimes of prescribed Ra constraints (i.e. finishing, semi-finishing and roughing) at suitable operating conditions.

Kesheng Wang et. al [14] have employed a hybrid artificial neural network and Genetic Algorithm methodology for modeling and optimization of two responses i.e. MRR and SR of electro-discharge machining. To perform the ANN modeling and multi-objective optimization they have implemented a two-phase hybridization process. In the first phase, they have used GA as learning algorithm in multilayer feed-forward neural network architecture. In the second phase, they used the model equations obtained from ANN modeling as the fitness functions for the GA-based optimization. The optimization was implemented using Gene-Hunter. The ANN model optimized error for MRR and SR were found to be 5.60% and 4.98% which laid a conclusion for these two responses to accept the model.

G. Krishna Mohana Rao et. al [15] described a work aimed on the effect of various machining parameters on hardness. The various input parameters that have been considered here are different types of materials (Ti6Al4V, HE15, 15CDV6 and M250), current, voltage and machining time. To correlate the machining parameters and response parameter they used a multi-layer feed forward neural network with GA as a learning algorithm. For this purpose they used Neuro Solutions software package. They used a single hidden layer with sigmoid transfer function in both hidden and output layer. And they found a maximum prediction error of 5.42% and minimum prediction error of 1.53%.

S. N. Joshi et. al [16] reported an intelligent approach for modeling and multi-objective optimization of EDM parameters of the model with less dependency on the experimental data. The EDM parameters data sets were generated from the numerical (FEM) simulations. The developed ANN process model was used in defining the fitness functions of non-dominated sorting genetic algorithm II (NSGA-II) to select optimal process parameters for roughing and finishing operations of EDM. While implementing NSGA-II for roughening operation only two contradicting objectives MRR and TWR were considered, while implementing for finishing operation best trade up was shared between 3 conflicting objective namely MRR, TWR and crater depth. Finally they carried out a set of experiments to validate the process performance for the optimum machining conditions and found successful implementation of their approach.

S. N. Joshi et. al [17] developed two models for the electric discharge machining (EDM) process using the finite element method (FEM) and artificial neural network (ANN). A two-dimensional axis symmetric thermal (FEM) model of single-spark EDM process was developed with the consideration of many thermo-physical characteristics to predict the shape of crater cavity, MRR, and TWR. A multilayered feed-forward neural network with leaning algorithms such as gradient descent (GD), GD with momentum (GDA), Levenberg – Marquardt (LM), conjugate gradient (CG), scaled conjugate gradient (SCG) were employed to establish relation between input process conditions (discharge power, spark on time, and duty factor) and the process responses (crater geometry, material removal rate, and tool wear rate) for various work tool and work materials. The input parameters and targets of the ANN model was generated from the numerical (FEM) simulations. To evaluate the model they used prediction error (%) and mean error (ME) and to improve the efficiency of model two BPNN architectures were tried out, viz. single-layered (4 –N – 4) and two-layered (4 – N1 – N2 – 4). They found optimal ANN model with network architecture 4 – 8 – 12 – 4 and SCG training algorithm to give very good prediction accuracies for MRR (1.53%), crater depth (1.78%), and crater radius (1.16%) and for TWR (17.34%).

VI. CONCLUSIONS

a) The electrode geometry and electrode materials are playing a greater role to affect the MRR and Surface Roughness with varying nature of process parameters which can be modeled and optimized with an ease of operation by ANN and GA.

b) The surface finish of work in the EDM process can be modeled and predicted successfully by the artificial neural network with reasonable accuracy even though the EDM process has been known for its stochastic nature.

c) Artificial Neural Network is a flexible tool for process parameters optimization. It is an effective tool to get the contribution of each parameter and to determine significant parameters which affect the performance characteristics.

d) ANN technique incorporates the relation between EDM process input parameters and the obtained S/N ratio absolutely.

e) The ANN-based process model can be used to select optimum process conditions to improve EDM process productivity and finishing capability. This will be the focus of our further research work.

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