CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

The ample application of the wire electrical discharge machine in the manufacturing field attracts plenty of researchers towards it for various research works. The fundamentals of EDM were founded from the year 1907 onwards, when English chemist Joseph Priestly discovered the erosive effect of sparks Singh & Bhardwaj (2011). While analysing the literature associated with wire electric discharge machining process, the tendency of the researchers is inclined towards the use of various optimisation techniques like genetic algorithm, artificial neural network and regression analysis for modeling process and response parameters. Then the effects of input process parameters on output response parameters are endorsed by the modeling technique since wire electrical discharge machining is a complex process of highly directed input process parameters such as machining depth, pulse on time, pulse off time, discharge current etc., and output parameters like material removal rate, tool wear rate and surface quality Danial et al (2013). Mathematical modeling using artificial intelligence was one of the main modeling techniques used by several researchers. Kavis and Sara (2007) novel techniques dealt with incorporating other machining principles either conventional or unconventional with wire electrical discharge machining to improve its efficiency. In this chapter, the important literatures relevant to WEDM processes were studied carefully and segregated under the headings
like review based on the various modeling and optimisation techniques to relate the effects of process parameters and operating parameters, review based on the various workpiece materials and the review based on the modeling using artificial neural network.

2.2 OPTIMISATION TECHNIQUES ON WEDM

In WEDM, the output response parameters like material removal rate, surface roughness and tool wear are based on the various input process parameters. These process parameters play a vital role and the effect of these process parameters was studied by several researchers. Various optimisation techniques were used to identify the relationship between the input process parameters and the output operating parameters Manpreet Singh et al (2013).

Shabgard et al (2009) presented an experimental investigation to consider the machining characteristics in the EDM process of FW4 welded steel and reported that the regression technique was an important tool for representing the relation between machining characteristic and EDM input process parameters and the attained arithmetical models representing the complete relationship between them.

Mahapatra et al (2006) carried out experimental studies on Robofil100 WEDM with D2-Tool steel. They found a relationship between control factors and responses like metal removal rate and surface finish by using nonlinear regression analysis. GA was employed to optimise the WEDM process with multiple objectives.

Kamlesh Dave et al (2012) accounted that to determine influential parameters for EDM groove machining, 24 experiments were carried out based on Taguchi Orthogonal Array OA16(45) 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 was less than others, so current intensity was the most significant factor.

Kamlesh Dave et al (2012) reported that, when current intensity increases, the MRR increases and hence the surface quality decreases. But for current intensity with a value of 36, the results were different and the MRR was good and surface quality was also good for triangle and rectangle geometry. They also describe that, as the pulse on time and pulse off time difference increases, it resulted in decreased MRR and increased SR. But as they come nearer to each other, both the output parameters showed good results Singh and Garg (2009). Gap voltage, current intensity, pulse on time, pulse off time are influential parameters to the common performance measures like MRR and surface roughness. Esme et al (2009) studied the effects of the parameters from higher to lower, the order was provided for the parameters. For surface roughness it was current intensity, tool geometry, pulse off time, pulse on time, gap voltage and for MRR it was current intensity, pulse on time, tool geometry, pulse off time and gap voltage. The rectangle geometry at 43A current gave good results for both the performance measures. Also, pulse on time and pulse off time range affect the MRR and SR. For the 22 value, pulse on and pulse off results are good, but for the same value, pulses on and pulses off, the results are not friendly.

Pradhan et al (2008) described that positive polarity, i.e., workpiece ‘+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 to improve the micro-machining accuracy. Peak current, pulse-on-time, dielectric jet flushing pressure and duty ratio 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) dielectric flush pressure (kg/cm$^2$): 0.1 to 0.5. 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, pulse-on-time, flushing pressure, and duty factor, each factor having three levels Scott et al (1991). It was observed that there were weak effects of dielectric flushing pressure and duty factor on MRR. They observed that pulse on time as the most influencing factor, had the maximum percentage of contribution on MRR and taper, whereas peak current had the maximum percentage of contribution on TWR during micro-drilling of titanium alloy by EDM. Metal removal rate and tool-wear rate was found to increase with increase in peak current due to higher discharge energy at higher values of IP. Also MRR and TWR are found to increase when $T_{on}$ increases from 1 to 10 μs but with further increase in $T_{on}$, MRR decreases. Flushing pressure and duty factor have no significant effect on both MRR and TWR. Overcut of the machined micro-hole was affected by the peak current and on time and increased with increase in Ip and $T_{on}$.

Kiyak et al (2007) found that EDM-workpiece material interaction was influenced by many process parameters and as a 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. Though this permutation would increase material removal rate and reduce machining costs, this permutation should be used for the rough machining step in the EDM process. Rough and finish machining steps require different levels 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. One-half level of power at 8A of current and 6s of pulse time and 3s of pulse pause time should be carried out at finish machining. Due to pulsed current density, the surface quality of the electrode decreases and surface roughness of the workpiece increases. For the same pulse pause time, the trends of surface roughness on the workpiece and electrode are similar. Thus, there will be a relation between wear on electrode and increase of surface roughness from workpiece with a view of surface quality.

Debabrata Mandal et al (2007) reported that as current decreases, MRR and TWR decreases but at that point of time $T_{\text{ON}}$ decreases and $T_{\text{OFF}}$ increases.

Ali Ozgedik et al (2006) found experimentally that increasing discharge current increases the removal rate of the workpiece, electrode tool wear rate, top-surface wear rate and normal surface roughness. The top-surface preference angle increases with discharge current and decreases slightly with high settings of current. Inner and outer edge-wear radii increase rapidly against increasing discharge current. The removal rate of the workpiece increases with increasing pulse duration. The increase in rate of electrode tool wear with the increasing pulse duration was evident up to 50 $\mu$s. Further increase in pulse duration reduces the tool wear rate. The average surface roughness of the workpiece increases with increasing pulse duration due to the larger craters formed on the surface. Increasing pulse duration leads to an increase in the tool top-surface wear rate and top surface preference angle, and it leads to decreased wear radii in the outer and the inner edge. The finest surface quality was attained in injection flushing. The high front-surface wear rates are observed in injection flushing while the low values are obtained in the static condition.

Shing et al (2004) accounted that copper and aluminum electrodes achieve the best MRR with an increase in discharge current, followed by
copper–tungsten electrode. Brass did not point out a 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 increase in discharge current was due to the fact that the spark discharge energy was increased to facilitate the action of melting and vaporisation and advancing the large impulsive force in the spark gap, resulting in the increased MRR. Electrode made from copper showed the most consistent overcut with the increase in current. Aluminium was also the best electrode material that showed low diametric overcut. Copper–tungsten and brass gave poor dimensional accuracy by resulting in a higher diametric overcut. The diametric overcut was low due to the fact that at low current with reverse polarity, erosion was less. As spark energy was low at low current, the crater formed on the work material was small in depth and hence resulted in good dimensional accuracy.

Brass and aluminium showed a considerable increase in electrode wear with the increase in discharge current. The EDM work 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 gave low values of surface roughness at high discharge currents on En-31. It was also seen that copper and aluminium electrode result in poor machined surface at high currents due to the fact that higher MRR of Cu and Al metal electrodes was accompanied by larger and deeper craters, resulting in a greater surface roughness.

Juhr et al (2004) reported that for developing the continuous parameter generation technology, the input parameters such as pulse current, discharge duration and duty cycle, and output response parameters such as material removal rate, wear ratio and mean of surface roughness were taken to find levels of the pulse current for the main experiments, the procedure was
analogue, but in this case, the pulse current was orthogonal projected onto the z-axis.

Assarzadeh et al (2008) reported the current (I), period of pulses (T) and source voltage (V) were selected at various levels and levels were identified as network process parameters.

Kesheng Wang et al (2003) showed that the surface roughness agreed 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.

Krishna Mohana Rao et al (2010) presents the effects of current, voltage, machining time and type of material of hardness. Kerosene was used as dielectric medium. Current was the most influencing factor for surface roughness. From the sensitivity analysis, it was concluded that type of material was having the greatest influence on all performance measures.

Joshi & Pande (2011) described that the recommended optimal values of process conditions are: discharge current of about 32 A, discharge duration 400 $\mu$s and duty cycle 80% for roughing operation. The intelligent process modeling and optimisation 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.

Joshi & Pande (2009) 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 and the process responses for various work
tools and work materials. Important process parameters were identified and their effects on performance parameters were extensively studied.

Narcis Pellicer et al (2011) presented the influence of the main EDM process parameters and different tool geometries on basic process performance measures. Experiments with varying parameters like current pulse, voltage, pulse on time and pulse pause time were carried out on H13 steel using different geometries of copper electrodes. The results help to select appropriate EDM process parameters to machine parts depending on product requirements. Influence of different process parameters like pulse current, open voltage, pulse time and pulse pause time as well as tool electrode shape on several performance measures like MRR, surface roughness, depth, width and slope have been analysed for copper electrode and AISI H13 steel workpiece 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 behaviour was not linear due to the interactions with other process parameters.

Ho et al (2004) found that the ON time wave, the frequency of discharge, the voltage open circuit, the servo voltage, capacity charge, speed tables and the intensity of current in the discharge ions affect the ability to cut jobs, such as surface roughness and cutting speed while the wire speed, wire tension and rate of flow of the medium with electrical resistance minimal impact.

Lin et al (2001) developed a control strategy based on the fuzzy logic to improve the machining accuracy and concentrated sparking at corner parts without affecting the cutting feed rates. During the WEDM of pure titanium, wire breakage occurs when the wire comes in contact with non-conducting particles.
Gokler & Ozanozgu (2000) conducted experiments on Sodic Mark XI A500 EDW WEDM as machine tool and 1040, 2379 and 2378 steel as workpiece materials in order to investigate the effect of cutting and offset parameters on surface roughness in WEDM process. From the results it was concluded that, the balanced parameters do not influence the surface roughness and with the same result with cutting parameters. If the thickness of the workpiece increases, the average feed rate decreases.

Shunmugam & Shanjan Kuriakose (2004) carried out experiments on Ti-6Al-4V with Robofil 310, 5-Axis CNC WEDM as machine tool. The process parameters of the WEDM process were time between two pulses, pulse duration, servo voltage, servo speed variation, wire speed, wire tension and injection pressure. The experiments were planned as per Taguchi's L18 orthogonal array. The machining was performed with zinc coated and uncoated brass wire of 0.25mm diameter. Taguchi's and ANOVA methods were effectively employed to find out the influence of process parameters. For uniform surface characteristics the coated wires were preferred over the uncoated wires. The time between two pulses was the most sensitive parameter that influences the formation of a layer consisting of mixture of layers.

Sarkar & Bhattacharya (2005) conducted experiments on ELECTRA SUPERCUT 734, SERIES-200 CNC WEDM machine using γ-titanium aluminide alloy as workpiece material and then created a model to predict the cutting speed, surface finish and dimensional deviation as the function of different WEDM parameters. Both surface roughness and dimensional deviation were independent of pulse off time. So that pulse off time can be varied as per requirement to achieve better stability and accuracy without affecting the dimensional deviation and surface finish significantly. They determined the optimum process parameters by applying the constrained
optimisation technique in which one performance characteristic was optimised considering other as constraints.

Atul Kumar & Singh (2012) carried out experiments on SKD 61 alloy with five axis CNC Wire Cut EDM (CHMER- CW64GS) machine. The objective of the machining process was to find out the optimal process parameters of the machining method. The input process parameters were spark on time, spark off time, voltage, feed rate, servo voltage, wire tension and dielectric flushing pressure. The output response parameters were cutting speed, surface roughness and deviation in dimensions. The experiments were conducted as per Taguchi's L18 Orthogonal array. From the results it was concluded that the cutting speed increases with the increase in pulse on time and decrease with increase in pulse off time and open voltage. The effects of feed rate, wire feed, servo voltage, wire tension and dielectric fluid pressure on cutting speed were not very significant.

2.3 WORKPIECE MATERIAL AND TOOL ELECTRODE

In WEDM machining process, the wire electrode is an important factor even though there is no direct contact between the workpiece and wire electrode. Various research has been done on the study of the effects of the wire electrode on the workpiece.

Tzeng et al (2001) studied the effects of various powder characteristics of several materials on the efficiency in electro-discharge machining of SKD-11 tool alloy. The result shows that the size, the concentration and the density of the particle, the electrical resistivity and the thermal conductivity are significant factors affecting the EDM performance.

Sivaganga and Rao (2013) determined the effect of the input parameter i.e. thickness of the job on output parameters such as discharge
current, cutting speed, spark gap/over cut, metal removal rate and surface roughness value of high carbon high chromium steel, a die steel cut by wedm. They also concluded that the power requirement is increasing with increment in thickness. With increase in thickness, the material to be removed will be more which demands more energy. The energy will be supplied by increasing the machining current, in turn power. This may a reason for the increase in power. However the machine will have its own limitation of power input which is again a limitation of size of the work piece to be machined.

Lok and Lee (1997) machined 10 samples of Sailon material, 40mm thick under pre-set conditions, evaluated MRR as 4.5-6.0 mm3/min. The authors compared the machining rate of Sailon with that of SKD11 steel and found that sailon’s machinability is poor. It was also revealed that the material removal rate increased with increase in machining current to some extent and then decreased.

Pradhan et al (2008) presented the attempts to optimise micro-EDM process parameters for machining Ti-6Al-4V super alloy which possessing elevated strength, stumpy weight, and excellent resistance to corrosion having applications in automotive, power generation, oil and gas extraction, aerospace, chemical plant, surgical instruments and further major industries. High melting point of the tool material was required for machining hard to machine materials. Among the copper, brass and tungsten tools, normally the brass electrodes of 500 µm were used due to their high tensile stress compared to pure copper tools. Kiyak & Cakir (2007) showed that the EDM of 40CrMnNiMo864 tool steel on AISI P20 steel workpiece provided important quantitative results for obtaining possible high surface finish quality and machining outputs. Increasing wear on the electrode surface was unavoidable during the EDM process which increases workpiece surface roughness due to wear rate on electrode caused by pulsed current density.
Debabrata Mandal et al (2007) worked on the EDM of C40 Steel with a copper (electrolytic grade) of cylindrical shape with a diameter of 12mm.

Ali Ozgedik & CanCogun (2006) showed that the tool wear problem was very critical in EDM since the tool shape degeneration directly affects the final shape of the die cavity. 1040 steels were used for the workpiece. 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 center of the tool. The densities of the electrolytic copper tool and 1040 steel workpiece specimens used in the experiments were 8.9 g/cm$^3$ and 9 g/cm$^3$, respectively.

Cao Fenggou & Yang Dayong (2004) 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 workpiece S136 with an electrode of diameter 9.56 mm red copper rod.

Shing et al (2004) performed the electric discharge machining of En-31 tool steel hardened and tempered to 55 HRc as a workpiece 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 achieved the best MRR with an increase in discharge current, followed by copper–tungsten electrode. The brass does not show a significant increase in MRR with increase in discharge current. Copper gives
the best MRR on En-31 work material. Brass electrode could not have effective machining rates 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. Rao and Sarkar (2008) also studied Copper–tungsten electrode which offers comparatively low surface roughness at high discharge currents, giving a good surface finish. Copper was comparatively a better electrode material having a better surface finish, low diametric overcut, high MRR and less electrode wear for En-31 work material, and aluminium was next to copper in performance, and may be favoured where surface finish was not essential also reported by Choi et al (2008).

Anishkumar (2012) understood that in WEDM the cutting is done by brass wire having tensile strength of 900 N/mm². The occurrence of wire rupture would result in a great increase of machining rate, decrease of machining accuracy and the deterioration of quality of machined surface. In addition, since the spark gap is too narrow, a portion of discharging energy was absorbed by wire electrode. Hence the surface of wire melts is due to the induced high temperature. Seigi et al (2001) studied WEDM system core is wire which is used to receive a stable electrical discharge. So, the wire electrode is one of the important factors contributing the overall WEDM performance.

Juhr et al (2004) reported that the cost of producing electrodes in the WEDM process was more important because tool electrodes wear out and several electrodes are necessary in several cases. The required number of wire electrodes was thereby a cost factor.
Angelos Markopoulos et al (2008) showed that the electrolytic copper of a rectangular work area 40×22 mm\(^2\) was used for tool electrode of positive polarity on the workpieces of St 37, C 45, 100Cr6, Mic/al 1 and DP 1. S. Kern et al (2007) founded that wire rupture is a serious problem associated to WEDM process and wire electrode. This problem affects surface finish quality and accuracy, limits cutting speed and increases machining time. Dauw et al (1994) concluded in fact, wire breakage poses a constant threat to WEDM productivity, but WEDM operators can avoid wire breakage and keep their operations running smoothly and efficiently with some knowledge about the wire-EDM process, wire rupture causes and the behavior of wire and work pieces materials when they are subject to the process.

Assarzadeh & Ghoreishi (2008) reported that BD3 steel and commercial copper were used as the workpiece and tool electrode materials respectively. The bottom surface of the electrode was flat and parallel to the workpiece surface. Also, the diameter of the cylindrical electrode was equal to the diameter of the round bar workpiece of 12 mm.

Kesheng Wang et al (2003) suggested that the test was done on graphite electrode (size 2.9 × 9.8 mm) with nickel-base alloy workpiece using an AGIE INNOVATION EDM machine.

Liao et al (2002) identified the problem when cutting with WEDM is wire break and instability cutting. These are major factors resulting in reduced performance for cutting WEDM especially, when we look at cutting variable thickness workpiece. Mu-Tian and Pin-Hsum (2004) traditional methods to determine the appropriate value for the cut is to select a value that is used for cutting the thickness of the smallest parts. This method will allow reducing the possibility of the wire break and the lack of stability in cutting. However, the cutting speed is reduced dramatically.
Kinoshita et al (1982) studied the wire breakage in wire cut electronic discharge machine. This wire breakage was prevented by developing a control method and monitoring the pulse frequency. Hsue W.J et al (1999) performed the work on corner cutting. The concept of discharge angle was introduced by studying the geometric properties of WEDM. A mathematical expression was derived for the same by analytical geometry of WEDM. Krishna Mohana Rao & Hanumantha Rao (2010) accounted that the experiments were carried out on materials like Ti6Al4V, 15CDV6, HE15 and M-250 by varying the peak current and voltage and the corresponding values of hardness with the use of copper tool electrode.

Narcis Pellicer et al (2011) reported that the experiment were carried out in H13 steel using different geometries of electrolytic copper electrodes such as square, triangle, circle and rectangle due to their simplicity and in their different machining contact area. The groove of 3 mm width and 1 mm depth was used as an experimental target feature. They found the greatest impact of the tool geometry on the final feature accuracy and target width of 3 mm was nearly achieved by square electrodes and, in the second term, by round and rectangle electrodes. Triangle electrodes did not perform well and were not useful for complex geometries machining. Square and rectangle electrodes present better radial and axial wear ratios. Hence, they conclude that square and rectangle were the best options for flexible tool electrode shape design.

Luo et al (2013) identified that there are different factors leading to wire breakage such as high wire tension, thermal load, electrical discharge impact and poor flushing. When the developed stresses in wire are more than wire strength, the wire rupture will occur. The developed stresses in wire increase by changing in wire properties and characteristics, cross-section
reduction and the increase in wire temperature. Yan et al (2005) noted the factors such as high temperature, work piece varying thickness and process parameters influence the wire strength that affects the wire rupture. Patil and Brahmkar (2010) revealed that wire breakage was found to pose limitations on the material removal rate in the machining of MMCs.

2.4 ARTIFICIAL NEURAL NETWORKS APPLIED AS AN OPTIMISATION TECHNIQUE

Sivanandam et al (2006) reported that the artificial neural network (ANN) was a data processing system that was motivated by the way the biological nervous system (brain) processes information and ANN has high flexibility in fitting a data set and therefore they are utilised very often in creating inexact models. Vasudevan et al (2011) studied the characteristics of ANN such as robustness, tolerance against error, parallel accomplishment and ability to map the non-linear relationships and interactions of process parameters make it a promising tool for modeling many of the manufacturing problems. ANN has gained importance as a prediction tool among the researchers of WEDM as the data involved is complex.

Spedding & Wang (1997) performed experimental studies on AISI 420 steel to optimise process parameters in combinations by modeling the process using ANN and characterised the WEDM machined surface by a time series technique.

Spedding & Wang (1997) attempted to optimise process parameters in combinations by modeling the process using ANN and RSM. A RSM model used in central composite rotatable experimental design and 4-16-3 size BPNN was used. They worked with the pulse width, time between two pulses, wire mechanical tension and injection point as process parameters and
cutting speed, surface roughness and surface waviness were output responses. From the results, both of the models predicted the process performance, such as cutting speed, surface roughness and surface waviness within a reasonable large range of input parameter factor level and the ANN model was found to fit the data better and higher predictive capability to Ra and cutting speed Sean (2009).

Debabrata Mandal et al (2007) carried out research to model and optimise the highly complex electrical discharge machining process using soft computing techniques. Artificial neural network with back propagation algorithm was used to model the process. A multi-objective optimisation method, governing, organising genetic algorithm-II was used to optimise and model the method. Trials were carried out over a wide range of machining conditions for testing and verification of the model. Testing results demonstrate that the model was suitable for predicting the response parameters.

Choudhury and Bartarya (2003) Neural network architecture of two hidden layers with three inputs and two outputs were used to model the process. AMSE was the least corresponding to momentum coefficient equals to 0.6 and it was 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 was 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. A mean prediction error has been calculated by taking the average of all the individual occurred errors, for all the testing trial patterns. They 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 tested within the experimental data. Various artificial neural network architectures have been studied and 3-10-10-2 was found to be the best architecture with thrust coefficient and learning rate as 0.6, having at least 3.06% of mean prediction error. The MRR and tool wear have been optimised using a multi-objective optimisation method, non-dominating sorting genetic algorithm.

Basheer and Hajmeer (2000) suggested that an ANN is composed of a large number of simple processing units called neurons which are fully connected to each other through adoptable synaptic weight. In the training process, weights are adjusted to minimise the error between actual output and desired output.

Cao Fenggou & Yang Dayong (2004) present a method that can be used to automatically determine the optimal numbers of hidden neuron and optimise 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). A three layer feed forward neural architecture was used to implement the ANN modeling in EDM process. The number of neurons in the middle layer was determined by the GA and node deleting network structure optimisation method. GA combined with node deleting network structure optimisation method was implemented to find out the global optimal solution, since it was difficult for GA based optimisation method to find out the local optimal solution, a BP algorithm was finally implemented to converge on the global optimum solution. Testing time was reduced as GA converged to the global optimal solution quickly. In the
second phase, BP algorithm was implemented and hence, the local optimal solution problem also solved. Finally, they concluded that 8 numbers of hidden neuron were found to be optimal for ANN modeling with a desired processing precision and efficiency.

Kuo-Ming Tsai & Pei-Jen Wang (2009) took six neural networks and a Neuro-fuzzy network model for modeling material removal rate (MRR) in EDM process and analysed based on pertinent machine process parameters. The various networks have been tested and evaluated 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 tested with the same Gradient descent learning algorithm. For comparisons between the various models various performance parameters like training time, root mean square error, $r^2$ were used. On the basis of comparisons they found ANFIS model to be more accurate than the other models.

Cancki et al (2009) have studied the most important feature of artificial neural networks is their ability as automatically generating, forming and discovering new knowledge without any help just as the human brain.

Juhr et al (2004) made a comparison between nonlinear regression function (NRF) and ANN for the generation of continuous parameter technology, which was a continuous mapping or regression. They found ANN was much easier than NRF. For modeling with ANN, feed forward network with three to five layers were used, which were trained with back-propagation. For developing the continuous parameter generation technology they considered the input process parameters such as spark current, discharge time, task cycle and output response parameters as material removal rate, electrode tool wear ratio and arithmetic mean surface roughness. They used two major performance evaluation criteria sum of the squared deviation and
sum of the 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.

Pramod Kumar Patowari et al (2010) 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 in the ANN model such as compaction pressure (CP), sintering temperature (ST), peak current (IP), pulse on time (Ton), pulse off time (Toff) with target measures like MTR, and LT. A multilayer feed-forward neural network with gradient-descent learning algorithm with 5 units of neurons in hidden layer has been utilised 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 were implemented. The performance measure MSE during training and testing of MRR were found to be 0.0014 and 0.0038, respectively. An additional 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 the average error percentage was calculated during training and testing to be 6.5732 and 3.1824 respectively.

Angelos P Markopoulos et al (2008) implemented an ANN model for the prediction of SR in EDM. For this purpose they used MATLAB as well as NETLAB packages. The process parameter to the ANN model was workpiece 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 was found efficient for the prediction of SR of EDM process.
Nasr and Badr (2003) founded the experimental results which is use as target output during training all networks. Both input and output values are normalized between 0.1 and 0.9 by equation 1 as neural network was found to be perform better in this range. Tsai and Wang (2001) 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 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, $r^2$ were used. On the basis of comparisons they found ANFIS model to be more accurate than the other models.

Assarzadeh & Ghoreishi (2008) presented a research work on neural network modeling and multi-objective optimisation 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 in 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 the 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 optimise 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 (2003) employed a hybrid artificial neural network and Genetic Algorithm methodology for modeling and optimisation of two responses i.e. MRR and SR of electro-discharge machining. To perform the ANN modeling and multi-objective optimisation they have implemented a two-phase hybridisation 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 optimisation. The optimisation was implemented using Gene-Hunter. The ANN model optimised error for MRR and SR were found to be 5.60% and 4.98%, which proposed a conclusion for these two responses to accept the model.

Krishna Mohana Rao & Hanumantha Rao (2010) described a work aimed at the effect of various machining parameters on hardness. The various input parameters that have been considered for materials like Ti6Al4V are 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 neuron solutions software package. They used a single hidden layer with sigmoid transfer function in both hidden and output layers. And they found a maximum prediction error of 5.42% and minimum prediction error of 1.53%.

Joshi & Pande (2011) reported an intelligent approach for modeling and multi-objective optimisation of EDM parameters of the model with less dependence on the experimental data. The EDM parameter 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 objectives 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.

Joshi & Pande (2009) 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 predict the shape of crater cavity, MRR, and TWR. A multilayered feed-forward neural network with learning 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 like discharge power, spark on time and duty factor. The process responses were 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 were 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 an 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%).

Panda and Bhoi (2005) has developed an ANN model (using feed forward neural architecture) using Levenberg-Marquardt learning algorithm and logistic sigmoid transfer function to predict the material removal rate.
Here they have considered the process parameters gap voltage, pulse duration and pulse interval. To evaluate the performance of ANN model sum square error and $r^2$ coefficients were used and the validity of the neural network model was checked with the experimental data. In conclusion they concluded that a 3-7-1 feed forward neural model for EDM provides faster and more accurate results.

Katz & Tibbles (2004) investigated the effects of micro EDM model was proposed along with numeric simulation and experimental proof. This work aimed at relating input/output constraints towards the establishment of a possible process model. It makes use of dimensionless groups connected and relevant to micro electro discharges and their effect on metal removal during the process. The reasons for their selection are discussed and problems related to micro discharges are explained. An electric circuit used for the controlling of the discharge was presented and explained.

Tian et al (2012) studied process monitoring and control of micro wire EDM process by developing a new pulse refinement and control system. This system functions by detecting 4 major gap states classified as open circuit, normal spark, arc discharge, and short circuit by detecting the characteristics of gap voltage waveforms. The effect of pulse interval, machining feed rate, workpiece thickness on the normal ratio, arc ratio and short ratio were considered for the study. It could be concluded from the experiment that a longer pulse interval would result in increase of short ratio at a constant machining feed rate. A high machining feed rates as well as increase of workpiece height results in increase of short ratio.

Prohaszka et al (1996) proposed some requirement of the materials used for WEDM electrodes that will lead to the improvement of WEDM performance. Experiments had been conducted regarding the choice of
suitable wire electrode materials and the influence of the properties of these materials on the machinability in WEDM. He discussed in this paper that the material requirements for fabricating WEDM electrodes for improving WEDM performance. Experiments were carried out regarding the choice of suitable wire electrode materials and the effect of the material properties of the wire on the machinability in WEDM being presented. He evaluated the influence of the various materials used for the fabrication of wire electrodes on the machinability during WEDM, a series of boring experiments had conducted on a standard Electro Discharge Machine-unit. Negative polarity rods of pure magnesium, tin and zinc and of a diameter of 5.0 mm were used as the tool electrodes. The workpiece (anode) was annealed non alloyed steel with low carbon content. The operational parameters were kept constant during the whole series of experiments.

Prasad & Krishnan (2012) proposed that electrical discharge machining (EDM), researchers had explored a number of ways to progress and optimise the MRR including some unique experimental models that depart from the traditional EDM sparking singularity. Despite a range of different styles, all the research work in those area segments, the same objectives of reaching more efficient material removal rate (MRR) coupled with a decline in the tool wear rate (TWR) and improved surface quality. Their approach resulted with the outcome that the best suitable dielectric fluid for a given workpiece and tool material in order to increase MRR and reduce TWR.

Scott F Miller et al (2005) investigated the effects of wire electrical discharge machining (EDM) of the cross-section with minimum thickness and acquiescent mechanisms was studied. Effects of EDM process considerations, particularly the spark cycle time and $T_{on}$ on thin cross-section cutting of Nd–Fe–B magnetic material, carbon bipolar plate, and titanium were investigated.
An envelope of feasible wire EDM process parameters was created for the commercially pure titanium. The application of such cover to select suitable EDM process parameters for micro feature generation was established. Applications on thin cross-section EDM cutting for the manufacture of compliant mechanisms were discussed. In their research, the effects of spark cycle and $T_{on}$ of wire EDM micro structures were investigated. Tests were conducted on various materials for minimum thickness wire EDM cutting. The research presented the needs of meticulous thermal and electrostatic stress modeling for micro EDM, particularly for components with miniature feature size. Although the results presented were machine-dependent, this research delivers the guidelines and techniques for the development of wire EDM process to manufacture minute features on advanced engineering materials.

Kansala et al (2008) proposed a simple and easy reasonable model for an axi-symmetric two-dimensional model for powder mixed electric discharge machine (PMEDM) using the FEM. The model utilises several important features such as temperatures sensitive material properties, shape and size of the heat source (Gaussian heat flux distribution), the % distribution of heat among tool, workpiece and dielectric fluid, pulse on/off time, material discharge efficiency and phase change (enthalpy) etc. to forecast the thermal behaviour and material removal mechanism in PMEDM process. The developed model first calculates the temperature dispersal in the workpiece material using ANSYS software and then material removal rate (MRR) was predicted from the temperature profiles. The effect of various process parameters on temperature circulations along the radius and depth of the workpiece was reported. Finally, the model has been validated by relating the theoretical MRR with the experimental one attained from a newly designed experimental setup industrialized in the laboratory.
Banerjee et al (1993) described the application of wire-cut EDM process used in industry for the production of strategies such as punches, dies, stripper-plates of very hard metals and alloys. However, the frequent existence of rupture of the wire was one of the most serious production restraints in wire EDM cutting Anand and Shankar (2010). The marvel restricts the cutting speed, increases the machining time and affects the surface finish and accuracy adversely. The probable causes foremost to wire rupture are failure under thermal load, failure through short-circuiting and wire vibration, the most significant among these being the thermal load. It was, therefore, essential to be able to predict wire failure under extreme thermal loads, so that this situation can be avoided in actual operation and the performance efficiency thus improved.

The main objective of this study was to decide the temperature distribution in the material of the wire and thereby to expect failure due to thermal load. In this study, a simple computational model was established which will give the temperature values for varying magnitudes of factors, viz., input power, $T_{on}$, wire velocity and wire diameter. The main objective of this study was to control these parameters optimally, so that it would help in preventing thermal failure and thus obtaining better consumption of the process. A finite difference thermal model to predict the temperature distribution along the wire for the wire-EDM procedure in the zone of the discharge channel was proposed.

Mahapatra & Patnaik (2007) presented wire electrical discharge machining used for rough cutting operation in WEDM. It was treated as an interesting one because improvement of more than one machining performance measures viz. metal removal rate (MRR), surface finish (SF) and kerf width are seeking to obtain a precision work. Using Taguchi’s parameter design, it had been detected that a combination of factors for optimisation of
each enactment measure was different. In this study, the association between control factors and responses like MRR, SF and kerf are recognised by means of nonlinear regression investigation, resulting in a valid mathematical model. Finally, genetic algorithm, a popular evolutionary method, was employed to enhance the wire electrical discharge machining method with multiple objectives. The study established that the WEDM process parameters can be familiar to achieve better MRR, surface finish and cutting width simultaneously.

Lee & Li (2001) discussed about the wire rupture in the WEDM process which was a thoughtful problem for manufacturers. A new computer-aided pulse taste system based on the characteristics of voltage waveform during machining was established. With the use of this system, a large amount of sparking frequency data during wire split process, and under normal working conditions were collected and investigated. Two symptoms of wire rupture were known: the excess of arc sparks and a rapid rise of the total sparking frequency. The governing mechanisms of these two types of wire rupture were established from the SEM and EDX analyses of the split wire electrode. Also, an index to monitor wire breaking was recognised and its relationships with the metal removal rate and machining parameters were established. Based on the results obtained, a control strategy to thwart wire from rupturing while at the same time improving the machining speed was proposed.

Cao Fenggou & Yang Dayong (2004) presented a method, that can be used to automatically determine the optimal numbers of hidden neuron and optimise 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 machining speed can be achieved under the premise of guaranteeing processing accuracy.

2.5 SUMMARY

From the literature review, it was found that much research has been carried out on the wire cut electrical discharge machining by analysing the effect of electrode geometry and the effect of various parameters like peak current, pulse on time, pulse off time, servo voltage, wire feed rate on material removal rate and surface roughness. Some research has been done on the estimation of corrosion of the cemented carbide and on wire breakage; some models were developed to control and monitor the breakage of the wire.

There are also some studies regarding the effect of discharge angle, wire tension and wire feed rate of the wire electrical discharge machine. Few studies have been done on the effect of electrode material on machinability in the WEDM. Some studies on the development of mathematical models using various algorithms and tool for optimising the machining parameters for various materials. There were lots of research work regarding the optimisation and modeling of input machining parameters, but research and literature lacks much to say about the setting of input parameters without trial and error for machining materials for WEDM. So the need has been felt towards highlighting the process with the goal of achieving mathematical models to select the process parameters for maximum utilisation of WEDM with improved process machining performance.