A Survey on Soft Computing Methods used in Wire-EDM

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Abstract:

Wire-electrical discharge machining (WEDM) has been found to be an extremely potential electro-thermal process, which is used in machining of difficult-to-machine electrically conductive materials. Owing to high process capability, it is widely used in aerospace and automobile industries. Availability of the databases (for selection of optimum machining parameters), which are based on the manufacturer's in-house experimentation, is inadequate. Hence, proper modeling, control and optimization are required to select optimum set of machining parameters. Due to a large number of process variables, and complicated stochastic process mechanism, it is difficult to relate the input variables to the performance of the process by a mathematical model. Moreover, there is no perfect combination of process variables, which can simultaneously result optimum performance measures for multiple outputs. In order to obtain global optimum solutions, traditional mathematical techniques are not sufficient. Neural network (NN), Fuzzy logic (FL) and Genetic algorithm (GA) which are commonly known as soft computing techniques are being used to model, control and optimize such stochastic process. In this paper, a summary of such soft computing methods, which are being used in WEDM, is presented.

Keywords: Wire electrical discharge machining, stochastic process, soft computing technique

1. Introduction

Wire electrical discharge machining (WEDM) is a widely accepted non-traditional machining process used to manufacture components with intricate shapes and profiles. This process is unaffected by material hardness, no cutting force and the ability to achieve high accuracy. The wire-EDM metal removal process is characterized by nonlinear, stochastic and time varying characteristics. The material removal mechanism of wire-EDM is very similar to the conventional EDM process involving the erosion effect produced by the electrical discharges. Instead of using pre-shaped electrodes, which are commonly required in EDM, a thin 0.05-0.30 mm in diameter wire performs as the electrode in wire-EDM. A DC power supply delivers high frequency pulses of electricity to the wire and the work piece. The gap between the wire and work piece is flooded with deionized water, which acts as the dielectric. Material is eroded ahead of the travelling wire from the work piece by a series of discrete sparks [1]. Either the work piece or the wire can be moved to cause the wire to cut complex shapes. The gap between the wire and work piece gap usually ranges from 0.025-0.05 mm and is constantly maintained by a computer controlled positioning system. The organization of the paper is as follows: section 2 presents the modeling of WEDM process by neural network. Parameters optimization is presented in section 3. In section 4, controlling of process by FLC is presented.

2. WEDM Process Modeling

In WEDM the process features change drastically with the machining parameters. Even a skilled operator with the state-of-the art WEDM is rarely able to achieve the optimum performance due to its stochastic

material removal mechanism. Traditionally material specific (mostly for common steel grades) conservative machining data provided by the manufacturer are used to obtain best performance, which obviously produces inconsistent machining. As new materials come, this parameter setting provided by manufacturer will no more give optimum performance. One way to solve this problem is to correlate its controllable parameters to the performance measures [2]. The complex and stochastic nature of the process makes it difficult to make explicit mathematical model, correlating input and output of the process. As neural networks are highly flexible modeling tool with the ability to learn the mapping between input and output without knowing a prior relationship between them, many researchers had used neural networks for modeling of such random and complex process. Figure 2 shows a typical neural network model of WEDM process to predict various outputs for different controllable input parameters.

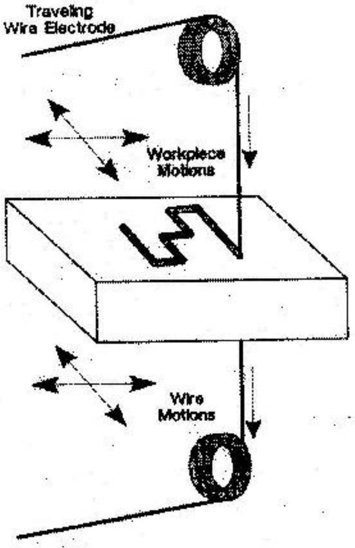

Fig. 1. Schematic diagram of WEDM process

Among different neural network models feed forward back propagation type neural networks were frequently used for modeling the wire-EDM process. The feed forward neural network [3] is composed of many nonlinear interconnected artificial neurons operating in parallel which are often grouped into input, hidden and output layers. The network function is largely determined by the connections between neurons. Commonly neural networks are trained, so that a particular set of inputs leads to a specific target output. The network is adjusted by interconnection weights during the learning stage using the back propagation-learning algorithm, which uses a gradient descent method to minimize the mean-square- error between the target and predicted output of the network. The important part of ANN is to find an optimum architecture which gives best fit for data as well provide better convergence in modeling within moderate period.

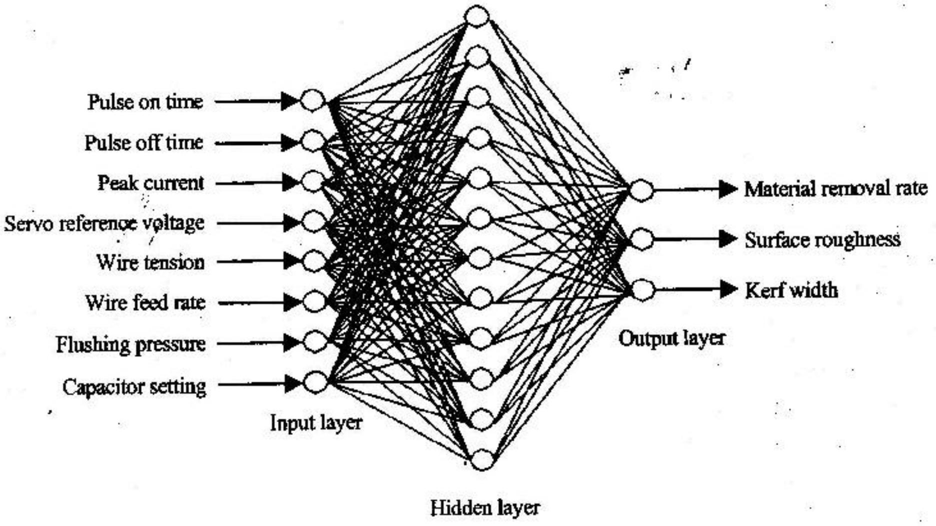

Fig. 2. Schematic diagram of a typical neural network model for WEDM process

Trang et al. [4] had adopted 8-14-2 feed forward neural network architecture to predict output parameters, namely machined surface roughness and machining speed with various controllable input parameters like pulse on-time, pulse-off time, peak current setting, no load voltage, servo reference voltage, capacitor setting and servo speed setting. They followed 2^{8-4} fractional factorial design of experiments on SUS-304 stainless steel to get training data. In order to obtain nonlinear relationship, different researchers used various transfer functions. Bhattacharyya et al. [5] used log-sigmoidal type transfer function to get 6-15-3 optimal architecture for predicting cutting speed, surface roughness and wire offset with the variation of pulse on time, pulse off time, peak current, servo reference voltage, wire tension and dielectric flow rate. Spedding et al. [6] adopted a hyperbolic tangent transfer function and used 4-16-3 architecture to model the process. Almost all researchers used single hidden layer, probably this is because it gives the best fit.

3. WEDM Process Parameters Optimization

Selection of optimum machining parameters for the best cutting performance is a challenging task. The wire-EDM process is controlled by several parameters. Any change in a parameter will cause random variation in the output as discussed earlier in section 2. Therefore, the variation in the output with respect to various controllable input parameters has to be understood completely. Among several measures of performance, cutting speed and surface roughness are considered by most of the researchers, as these parameters straightaway reflect the cutting performance of WEDM. The above two objectives are conflicting in nature and there is no single parametric combination which can allow simultaneous optimal solutions for the two objectives. Hence, this should be treated as a multi-objective optimization problem. Several researchers used conventional techniques to optimize machining parameters by considering it as a single objective optimization or constrained optimization problem. Bhattacharyya et al. [7] and Scott et al. [8] used adaptive models, based on signal to noise ratio and then optimized machining parameters by considering optimization of one objective (surface roughness or cutting speed) while the other objective was kept as a constraint. They have also used a program, based on graphical interpretation to obtain Pareto-optimal solutions from all possible parametric combinations. Liao et al. [9] obtained a mathematical model by regression and correlation analysis. Later they followed the feasible-direction method of non-linear programming to find out the optimum machining setting by considering it as a constraint optimization problem. Tarng et al. [4] used a simple weighting method to convert the cutting velocity and surface roughness into a single objective and arrived at the optimal parameters by simulated annealing. The obtained solution is obviously very much sensitive to the weight vector used in the scalarization process and demands the user to have a prior knowledge about the problem. The traditional techniques (such as simple weighting method) for optimization of single objective may provide a single Pareto-optimal point. But they are not sufficient, as in real situation user may require different alternative solutions. In wire-EDM sometimes we demand for better surface finish, when productivity is not so crucial or vice-versa. Depending upon the situation the weight factors have to be changed, and the same problem needs to be solved for number of times. Also, these methods fail when the objective function becomes discontinuous. Since genetic algorithm (GA) works with a population of points, it seems natural to use GA in multi-objective optimization problem to capture a number of solutions simultaneously. Shajan et al. [10] adopted non-dominated sorting genetic algorithm (NSGA) to optimize the machining parameters, considering surface roughness and cutting speed as the output. They have used multiple linear regression models to represent the relation between inputs and outputs.

NSGA varies from simple genetic algorithm only in the way the selection operator works. A shared fitness is used for selection. The crossover and mutation operators remain as usual. Before the selection is performed, the population is ranked on the basis of individual's nondomination as described, If obj.1 [i] < obj.1 [j] and obj.2 [i] < obj.2 [j], $i \neq j$ where, 'i' and 'j' are individual's number. Then, individual 'j' will be marked as nondominated point. The nondominated individuals present in the population are first identified from the current population. Then all these individuals are assumed to constitute first nondominated front in the population and assigned a large dummy fitness value. The remaining dominated individuals are again sorted to get second nondominated front. This process is repeated until the entire individual's in the whole population are ranked. The same fitness value is assigned to all individuals of a particular rank to give an equal reproductive potential. In order to maintain diversity in the population, these classified individuals are then shared with their dummy fitness value. The sharing function values $(sh(d_{ij}))$ for all individuals belong to a particular rank are calculated by the following formula [11]

$$(sh(d_{ij}) = \begin{cases} 1-\left(\dfrac{d_{ij}}{\sigma_{share}}\right)^2, & \text{if } d_{ij} < \sigma_{share} \\ 0, & \text{otherwise} \end{cases}$$

where, d_{ij} is Euclidean distance between two individuals i and j and σ_{Share} is maximum distance allowed between two individuals to become members of niche. The shared fitness of an individual belong to a particular rank is calculated as follows

$$F'_i = F_i \left[\sum_{j=1}^{n} sh(d_{ij})\right]^{-1}$$

where, F_i is dummy fitness, n is number of individuals belonging to a particular rank solution. After doing this, the second front individuals are assigned a new dummy fitness value, which is kept smaller than the minimum shared dummy fitness of the previous front. This process is continued until all the individuals get a shared fitness value. The next steps are reproduction which is based on shared fitness value, cross over and finally mutation to obtain new population. This process is repeated for several generations to obtain Pareto-optimal solutions for the wire-EDM process.

4. WEDM Process Monitoring and Control

Even today, the most advanced WEDM machine is not free from disturbances like wire breakage, wire lag, and unstable machining which reduce the machining efficiency and provide inadequate dimensional accuracy of machined products. In order to minimize those disturbances, an online monitoring and control of the process is required, which is based on some control algorithms. Classical control strategy and modern control technology based on analytical model are not applicable to wire-EDM process as it is complex and stochastic in nature. On the other hand, fuzzy logic controller (FLC), which does not require any explicit mathematical model, can be applied for monitoring and controlling of such complicated process. Over the last few years, several fuzzy logic controllers were developed due to its versatility and robustness. The basic concept of a FLC is to use the "expert experience" of a human operator to design a controller in controlling a process whose input-output relationship is described by a collection of fuzzy control rules (e.g., if-then rules) involving linguistic variables rather than a mathematical model. A typical fuzzy logic controller consists of four major parts: a fuzzification interface, a knowledge base, decision-making logic and a defuzzification interface. This section reports the various FLCs dedicated to reduce wire breakage, improve dimensional accuracy by reducing wire lag phenomena and provide stable machining by controlling gap condition.

4.1 Servo Control System

Since gap conditions directly control the machining speed and accuracy of the process, online monitoring of the gap condition and subsequent control is required. Usually it is done by comparing the instantaneous gap voltage with some reference servo voltage. But the selection of servo reference voltage depends upon the work piece height, flushing pressure and other parameters, which may be selected improperly by the operator. As a result, it can create unstable machining leading to wire breakage. Yan et al. [12] developed a control strategy based on fuzzy logic, which controls the servo mechanism but also adjust the servo reference voltage, if not selected properly. Figure 3 shows the schematic diagram of the proposed fuzzy logic controller.

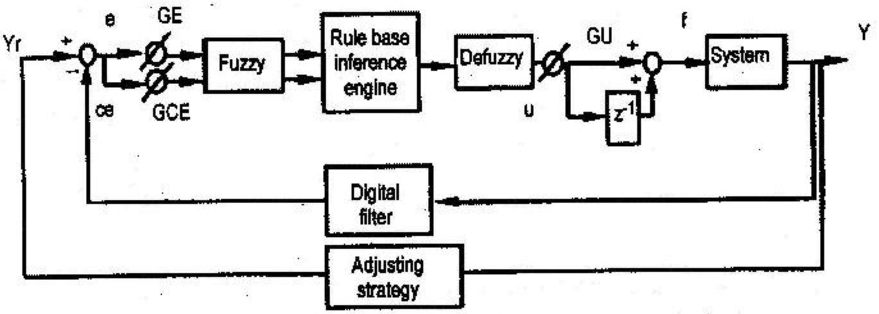

Fig. 3 Schematic diagram of a FLC for servo mechanism [12]

In the proposed controller, Yr and Y are respectively the reference voltage and gap voltage, e is voltage error [e=(Yr-Y)*GE], ce is change of voltage error [ce=[e(present)-e(previous)]*GCE], GE and GCE are scaling factors. Using this controller they claimed that steady machining could be obtained after a small transition period. Since the average gap voltage does not provide the detail information about the spark gap i.e., whether it is a normal discharge, or an arc discharge or in short circuit mode, the control system based on sensing average discharge voltage may become unstable. Keeping this is in mind, Liao et al. [13] developed a fuzzy logic controller which regulates the servo drives by sensing proportion of abnormal sparks and sparking frequency using a computer aided sparking frequency monitoring system. They investigated the relationship between these two sensing parameters and wire breaking phenomena, metal removal rate and surface roughness. The movement of servo drives was controlled by comparing the abnormal ratio with some predetermined reference value, keeping sparking frequency at a safety level which ensures higher material removal rate and no wire breakage. Similar type of work has been done by Woo et al. [14] but, they used changed in power consumption as input parameter for FLC to control servo mechanism keeping spark ratio and ignition delay time at a reference value.

4.2 Wire Breakage Control System

Wire rupture in the WEDM process not only increases the machining time but also reduces the machining accuracy and surface quality. Among the different causes for wire breaking several authors [15, 16] pointed out that sparking frequency increases abruptly and lasted for 5-40 milliseconds before wire rupture. Moreover, for WEDM process higher the material removal rate, higher will be the wire rupture as high material removal rate closely related to the high value of sparking frequency. Hence, the control system should maintain a high material removal rate while avoiding wire breakage. Yan et al. [17] developed a self-learning fuzzy control for wire rupture prevention. The reference sparking frequency was kept at a safety level which ensures high material removal rate and the difference between the reference frequency and the actual measured frequency was taken as input to the FLC which is controlled by regulating the pulse-off time in real time. Lee et al. [18] developed a gain self-tuning fuzzy controller for wire rupture prevention. The proposed tuning algorithms consist of three factors including the attraction causing factor, the over-shoot attenuating factor and the overloading factor. By regulating arc-off time and servo reference voltage, they controlled the time delayed and subsequently solved the wire breakage problem.

4.3 Wire Lag and Vibration Control System

During machining, the electrode wire experiences several forces due to sparking and other factors. The most influencing sources are electrostatic and electrodynamic forces resulting from sparking, and hydraulic forces from flushing. Moreover, these forces are varying with time and space due to the stochastic nature of the process. These forces are partially compensated by the axial tension of the wire. But due to its low rigidity the wire is deflected backwards just opposite to the cutting direction resulting wire lagging and subsequent vibration. The dimensional accuracy, particularly at corner points, is very much affected by the above phenomena. Hence proper controlling is required to minimize these effects. Chin et al. [19] developed a fuzzy logic controller to improve dimensional accuracy particularly when machining at corner points. From several past research works, they have pointed out that sparking force is closely related to cutting feed rate and it is being modified by controlling pulse-off time. By using this control system they claimed that 50% reduction in error at corner parts while machining time increases not more than 10% of normal value.

5. Conclusions

WEDM is a worldwide-accepted nontraditional manufacturing process, which is used to produce any intricate profile. With the advent of new materials having increasing hardness, strength and temperature resistance, conventional machines are almost incapable to machine them. Wire-EDM could be a suitable option for the manufacturing industries to deal with such materials. Lack of understanding of the process, problem with the wire breakage, inadequate control and improper optimization of the parameters make it difficult for the process to perform without any hitch to give better productivity. Out of the several research endeavors published in the field of WEDM, this paper has made an attempt to highlight the works covering three broad directions namely process modeling, parameter optimization and process control, all meant for improving the WEDM process. Authors believe that the present paper will be a guideline for the new researchers to focus their initiatives to enhance WEDM process and make it superior in the manufacturing field.

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