APEM journal Advances in Production Engineering & Management 5 (2010) 3, 139-150
ISSN 1854-6250 Scientific paper

PROCESS PARAMETERS MODELING AND OPTIMIZATION OF WIRE ELECTRIC DISCHARGE MACHINING

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Abstract:
Wire electrical discharge machining (WEDM) is a widely accepted non-traditional material removal process used to manufacture components with intricate shapes and profiles. Due to many parameters and the complex and stochastic nature of the process, achieving the optimal performance is a very difficult task. The objective of this present work is therefore to discover the relationship between the performance measures of the process and its controllable input parameters and subsequently to find the optimal combination of the input parameters to achieve the maximum process performance. A mathematical model using response surface modeling (RSM) approach is developed for correlating the inter-relationships of various wire electric discharge machining (WEDM) parameters with performance measures. A non-traditional optimization technique, known as particle swarm optimization (PSO), is then applied to find the optimal combination of process parameters with an objective to achieve maximum machining speed for a desired value of surface finish. It is observed that the results of optimization obtained by using PSO algorithm show significant improvement over those obtained using traditional optimization technique. Also the results obtained are in good agreement with those obtained through practical experimentation. The mathematical model developed in this work will help the practitioners to simulate the process performance on any WEDM machine. Moreover, the optimization using PSO algorithm will help EDM users to achieve significant improvement in process performance than by using traditional optimization algorithms and handbook recommendations.

Key Words: Wire electric discharge machining, Response surface modeling, Particle swarm optimization

1. INTRODUCTION

In recent years an increasing demand for machining of complex shapes made of hard and difficult-to-machine materials with exact tolerances and surface finish resulted in the development of many advanced machining processes based on chemical, electro-chemical, thermal, electro-thermal, mechanical and other means of material removal. Wire electric discharge machining (WEDM) is one of the widely accepted advanced machining processes used to machine components with intricate shapes and profiles. It is considered as a unique adaptation of the conventional EDM process which uses an electrode to initialize the sparking process. As shown in Figure 1, WEDM utilizes a continuously travelling wire electrode made of thin copper, brass or tungsten. On application of a proper voltage, discharge occurs between the wire electrode and the workpiece in the presence of a flood of deionized water of high insulation resistance. The material is eroded ahead of the wire through a series of repetitive sparks between electrodes, i.e. workpiece and the wire.

WEDM has been gaining wide acceptance in modern tooling applications, machining of advanced ceramic materials and modern composite materials due to the following reasons [1]:

- As the wire diameter is small (0.05–0.3 mm), the process is capable of achieving very small corner radii.
- The wire is kept in tension using a mechanical tensioning device reducing the tendency of producing inaccurate parts.
- During the WEDM process there is no direct contact between the workpiece and the wire, eliminating the mechanical stresses during machining.
- WEDM process is able to machine exotic and high strength and temperature resistive (HSTR) materials and eliminate the geometrical changes occurring in the machining of heat-treated steels.

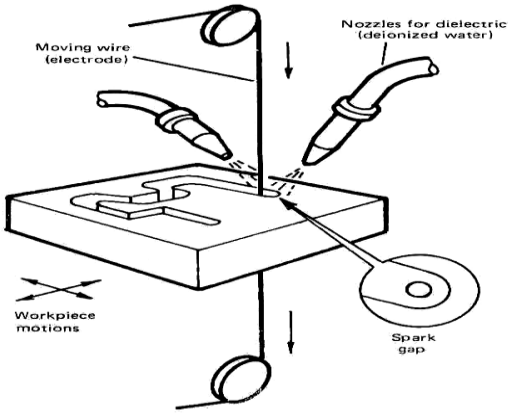

Figure 1: Basic sheme of wire EDM process.

Wire EDM manufacturers and users always want to achieve higher machining productivity with a desired accuracy and surface finish. Performance of the WEDM process, however, is affected by many factors such as servo feed setting, peak current, pulse on time, pulse off time, wire tension, etc. and a single parameter change will influence the process in a complex way. Because of many parameters and the complex and stochastic nature of the process, achieving the optimal performance, even for a highly skilled operator with a state-of-the-art wire EDM machine is rarely possible. An effective way to solve this problem is to discover the relationship between the performance of the process and its controllable input parameters by modeling the process through suitable mathematical techniques and optimization using suitable optimization algorithm. In the present work response surface methodology is used to model the process whereas the optimum parameter setting is achieved through an advanced optimization algorithm known as particle swarm optimization (PSO) algorithm.

The next section presents a brief review of the past research work done on the modeling and optimization of wire electric discharge machining process parameters.

2. REVIEW OF PAST RESEARCH WORK

Scott et al. [2] used a factorial design requiring a number of experiments to determine the most favourable combination of the WEDM parameter. They found that the discharge current, pulse duration and pulse frequency are the significant control factors affecting the material removal rate (MRR) and surface finish, while the wire speed, wire tension and dielectric flow rate have the least effect. Tarang et al. [3] employed a neural network system with the application of a simulated annealing algorithm for solving the multi-response optimization problem. It was found that the machining parameters such as the pulse on/off duration, peak current, open circuit voltage, servo reference voltage, electrical capacitance and table speed are the critical parameters for the estimation of the cutting rate and surface finish.

Anand [4] used a fractional factorial experiment with an orthogonal array layout to obtain the most desirable process specification for improving the WEDM dimensional accuracy and surface roughness. Liao et al. [5] proposed an approach of determining the parameter

settings based on the Taguchi quality design method and the analysis of variance. The results showed that the material removal rate and surface finish are easily influenced by the table feed rate and pulse on-time, which can also be used to control the discharging frequency for the prevention of wire breakage. Spedding and Wang [6] optimized the process parameter settings by using artificial neural network modeling to characterize the WEDM workpiece surfaces. Konda et al. [7] classified the various potential factors affecting the WEDM performance measures into five major categories namely the different properties of the workpiece material and dielectric fluid, machine characteristics, adjustable machining parameters, and component geometry. In addition, they applied the design of experiments (DOE) technique to study and optimize the possible effects of parameters during process design and development.

Gokler and Ozanozgu [8] studied the selection of the most suitable cutting and offset parameter combination to get a desired surface roughness for a constant wire speed and dielectric flushing pressure. Huang and Liao [9] presented the use of Grey relational and S/N ratio analyses to demonstrate the influence of table feed and pulse on-time on the material removal rate. Tosun et al. [10] investigated the effect of the pulse duration, open circuit voltage, wire speed and dielectric flushing pressure on the workpiece surface roughness. It was found that the increasing pulse duration, open circuit voltage and wire speed increases with the surface roughness, whereas the increasing dielectric fluid pressure decreases the surface roughness.

Tosun et al. [11] presented an investigation on the optimization and the effect of machining parameters on the kerf and the MRR in WEDM operations. The simulated annealing algorithm was then applied to select optimal values of machining parameters for multi-objective problem considering minimization of kerf and maximization of MRR. Hewidy et al. [12] developed a mathematical models based on response surface methodology for correlating the inter-relationships of various WEDM machining parameters of Inconel 601 material such as peak current, duty factor, wire tension and water pressure on the metal removal rate, wear ratio and surface roughness. Kuriakose and Shunmugam [13] presented a multiple regression model to represent relationship between input parameters and two conflicting objectives i.e. cutting velocity and surface finish. A multi-objective optimization method based on a Non-Dominated Sorting Genetic Algorithm (NSGA) is then used to optimize Wire-EDM process.

Sarkar et al. [14] presented an approach to select the optimum cutting condition with an appropriate wire offset setting in order to get the desired surface finish and dimensional accuracy for machining of γ-titanium aluminide alloy. The process has been modeled using additive model in order to predict the response parameters i.e. cutting speed, surface finish and dimensional deviation as function of different control parameters such as pulse on time, pulse off time, peak current, servo reference voltage, wire tension and dielectric flow rate. Kanlayasiri and Boonmung [15] developed a mathematical model using multiple regression method to formulate the pulse-on time and pulse-peak current to the surface roughness.

Although various researchers have considered the effect of different process parameters on various performance measures, these efforts needs to be further extended by considering more performance measures and more input parameters. Machining speed and surface finish are considered to be very crucial and important performance measures for WEDM, hence the same are considered in the present work. A mathematical model relating these performance measures with four important process parameters namely, pulse on time (T_{on}), pulse off time (T_{off}), peak current (I_p) and servo feed setting (F), is developed using a second order response surface modeling technique, as first-order models often give lack-of-fit [16]. Furthermore, it is revealed from the literature that mathematical programming techniques like method of feasible direction, Taguchi methods etc. had been used to solve optimization problems in wire electric discharge machining process. However, these traditional methods of optimization do not fare well over a broad spectrum of problem domains. Moreover, traditional techniques may not be robust and they also tend to obtain a local optimal solution. Considering the drawbacks of traditional optimization techniques, attempts are being made to optimize the machining problem using evolutionary optimization techniques. These

methods use the fitness information instead of the functional derivatives making them more robust and effective. These methods thus avoid the problem of getting trapped in local optima and enable to obtain a global (or nearly global) optimum solution. Efforts are continuing to use more recent optimization algorithms, which are more powerful, robust and able to provide accurate solution. Particle swarm optimization developed by Kennedy and Eberhart [17] is one of the recent algorithms and reported to be the better algorithm for continuous optimization as well as discrete optimization problems [18]. Hence, the same is considered in the present work.

The next section describes the development of a mathematical model for wire electric discharge machining process.

3. RESPONSE SURFACE MODELING (RSM)

Response surface modeling (RSM) is a collection of statistical and mathematical methods that are useful for the modeling and optimization of the engineering science problems. RSM quantifies the relationship between the controllable input parameters and the obtained responses. In modeling of manufacturing processes using RSM, the sufficient data is collected through designed experimentation. An experiment is designed with 2^k (where, k = number of parameters, in this study k =4) factorial with central composite-second order ratable design is used. This consists of number of corner points =16, number of axial points=8, and a centre point at zero level =4. The axial points are located in a coded test condition space through parameter 'α'. For the design to remain rotatable, 'α' is determined as $(2^k)^{1/4} = 2$. Thus the coded level for the axial points is at 2. The center point is repeated four times to estimate the pure error. The coded value corresponding to actual value for each process parameter is derived using following formula:

$$\text{Coded test condition} = \frac{\text{Actual test condition} - \text{mean test condition}}{\text{Range of test condition}/2} \tag{1}$$

As an illustration, if actual test condition of 'pulse on time (T_{on})' is 5 then, the corresponding coded value is [5-((4+8)/2)] / [(8-4)/2] = -0.5.

The coded numbers are thus obtained from following transformation equations:

$$x_1 = \frac{T_{on} - T_{on_0}}{\Delta T_{on}} \tag{2}$$

$$x_2 = \frac{T_{off} - T_{off_0}}{\Delta T_{off}} \tag{3}$$

$$x_3 = \frac{I_p - I_{p_0}}{\Delta I_p} \tag{4}$$

$$x_4 = \frac{F - F_0}{\Delta F} \tag{5}$$

Where, x_1, x_2, x_3 and x_4 are the coded values of the parameters T_{on}, T_{off}, I_p, and F respectively. T_{on0}, T_{off0}, I_{p0}, and F_0 are the values of pulse on time, pulse off time, peak current, and servo feed setting at zero level. ΔT_{on}, ΔT_{off}, ΔI_p and ΔF are, the intervals of variation in T_{on}, T_{off}, I_p, and F respectively. The experimental set up details are given below:

- Machine type/make: CNC-WEDM, Elektra ELPULSE-30

- Wire material: Brass
- Wire diameter: 0.25 mm
- Wire tension: 8 N
- Dielectric fluid: Deionised water
- Workpiece specification: Rectangular, cavity of size: 60x110x12 mm, OHNS
- Surface roughness measuring device: Hommel tester T-500

Table I shows coded values of process parameters. Table II shows the experimental matrix.

Table I: Coded values of process parameters.

Coded values	**-2**	**-1**	**0**	**+1**	**+2**
Pulse on time	2	4	6	8	10
Pulse off time	6*	10	20	30	40
Peak current	65	90	115	140	165
Servo feed	20	30	40	50	60

*although the coded value is ‘0’ by using equation (1), the minimum possible value is ‘6’.

Table II: Design of experiments and the results.

S.N.	T_{on} **(µs)**	T_{off} **(µs)**	I_p **(Amp)**	***F***	V_m**(mm/min)**	R_a **(µm)**
1	-1	-1	-1	-1	1.15	1.6
2	1	-1	-1	-1	1.5	2.5
3	-1	1	-1	-1	0.93	1.5
4	1	1	-1	-1	1.16	1.8
5	-1	-1	1	-1	1.54	2.2
6	1	-1	1	-1	1.58	2.3
7	-1	1	1	-1	1.13	1.7
8	1	1	1	-1	1.3	2.0
9	-1	-1	-1	1	1.58	2.3
10	1	-1	-1	1	1.9	3.7
11	-1	1	-1	1	1.05	1.5
12	1	1	-1	1	1.48	2.4
13	-1	-1	1	1	1.9	3.1
14	1	-1	1	1	1.57	2.4
15	-1	1	1	1	1.1	1.5
16	1	1	1	1	1.28	2.1
17	0	0	0	0	1.55	3.4
18	0	0	0	0	1.55	4.0
19	0	0	0	0	1.56	3.5
20	0	0	0	0	1.56	3.5
21	2	0	0	0	1.75	3.3
22	-2	0	0	0	1.13	1.6
23	0	2	0	0	1.35	1.8
24	0	-2	0	0	1.95	2.6
25	0	0	2	0	1.6	1.2
26	0	0	-2	0	0.81	3
27	0	0	0	2	1.7	1.6
28	0	0	0	-2	0.95	3.7

To study the effect of process parameters i.e. T_{on}, T_{off}, I_p, and F, on performance measures i.e. machining speed (V_m) and surface roughness (R_a), a second-order polynomial response is fitted into the following equation.

$$y = b_0 + \sum_{i=1}^{k} b_i x_i + \sum_{i=1}^{k} b_{ii} x_i^{\ 2} + \sum_{j>1}^{k} b_{ij} x_i x_j \tag{6}$$

Where 'y' is the response and the x_i (1, 2… k) are coded level of k quantitative parameters. The coefficient b_0 is the free term, the coefficients b_i are the linear terms, the coefficients b_{ii} are the quadratic terms, and the coefficients b_{ij} are the interaction terms. Equation (7) and equation (8) are then derived by determining the values of the coefficients using the least square technique for the observations collected as shown in Table 2, for machining speed (V_m) and surface roughness (R_a) respectively.

$$\begin{aligned} V_m &= 1.555 + 0.1095x_1 - 0.187x_2 + 0.0929x_3 + 0.1279x_4 + 0.0393x_1x_2 - 0.0793x_1x_3 - 0.01188x_1x_4 \\ &- 0.01688x_2x_3 - 0.0493x_2x_4 - 0.0606x_3x_4 - 0.03219x_1^2 + 0.02031x_2^2 - 0.0909x_3^2 - 0.06094x_4^2 \end{aligned} \tag{7}$$

$$\begin{aligned} R_a &= 3.6 + 0.2979x_1 - 0.2979x_2 - 0.1479x_3 - 0.03542x_4 + 0.021875x_1x_2 - 0.2031x_1x_3 + 0.04062x_1x_4 \\ &+ 0.01562x_2x_3 - 0.1531x_2x_4 - 0.1031x_3x_4 - 0.3182x_1^2 - 0.3807x_2^2 - 0.4057x_3^2 - 0.2682x_4^2 \end{aligned} \tag{8}$$

To test whether the data are well fitted in model or not, the calculated S value of the regression analysis for machining speed and surface roughness are obtained as 0.148 and 0.644 respectively, which are smaller and R value for both the responses are 0.89 and 0.71, respectively. The R value is moderately high for machining speed and is moderate for surface roughness. Hence, the model fits the data.

Now an advanced optimization method based on PSO algorithm is used to optimize Wire-EDM process parameters. The next section briefly describes the algorithm.

4. PARTICLE SWARM OPTIMIZATION (PSO)

Particle swarm optimization (PSO) is an evolutionary computation technique developed by Kennedy and Eberhart [17]. It exhibits common evolutionary computation attributes including initialization with a population of random solutions and searching for optima by updating generations. Potential solutions, called particles, are then "flown" through the problem space by following the current optimum particles. Each particle keeps track of its coordinates in the problem space, which are associated with the best solution (fitness) it has achieved so far. This value is called 'pBest'. Another "best" value that is tracked by the *global* version of the particle swarm optimization is the overall best value and its location obtained so far by any particle in the population. This location is called 'gBest'. The particle swarm optimization concept consists of, at each step, changing the velocity (i.e. accelerating) of each particle toward its 'pBest' and 'gBest' locations (global version of PSO). Acceleration is weighted by a random term with separate random numbers being generated for acceleration toward 'pBest' and 'gBest' locations. The updates of the particles are accomplished as per the following equations.

$$V_{i+1} = w * V_i + c_1 * r_1 * (pBest_i - X_i) + c_2 * r_2 * (gBest_i - X_i) \tag{9}$$

$$X_{i+1} = X_i + V_{i+1} \tag{10}$$

Equation (9) calculates a new velocity (V_{i+1}) for each particle (potential solution) based on its previous velocity, the best location it has achieved ('*pBest*') so far, and the global best location ('gBest'), the population has achieved. Equation (10) updates individual particle's position (X_i) in solution hyperspace. The two random numbers 'r_1' and 'r_2' in equation (9) are independently generated in the range [0, 1].

The acceleration constants 'c_1' and 'c_2' in equation (9) represent the weighting of the stochastic acceleration terms that pull each particle towards 'pBest' and 'gBest' positions. 'c_1' represents the confidence the particle has in itself (cognitive parameter) and 'c_2' represents the confidence the particle has in swarm (social parameter). Thus, adjustment of these constants changes the amount of tension in the system. Low values of the constants allow particles to roam far from target regions before being tugged back, while high values result in abrupt movement toward, or past through target regions [18, 19]. The inertia weight '*w*' plays an important role in the PSO convergence behaviour since it is employed to control the exploration abilities of the swarm. The large inertia weights allow wide velocity updates allowing to globally explore the design space while small inertia weights concentrate the velocity updates to nearby regions of the design space. The optimum use of the inertia weight "*w*" provides improved performance in a number of applications. The effect of w, c_1 and c_2 on convergence for standard numerical benchmark functions is provided by Bergh and Engelbrecht [20].

Unlike genetic algorithm, PSO algorithm does not need complex encoding and decoding process and special genetic operator. PSO takes real number as a particle in the aspect of representation solution and the particles update themselves with internal velocity. In this algorithm, the evolution looks only for the best solution and all particles tend to converge to the best solution. In the implementation process, particles randomly generated at the beginning or generated by internal velocity during the evolutionary process usually violate the system constraints resulting in infeasible particles. Therefore, the handling of system constraints, particularly nonlinear equation constraints, and the measurement and evaluation of infeasible particles is very important. To cope with constrained problems with evolutionary computation, various approaches such as rejection of infeasible individuals, repair of infeasible individuals, replacement of individuals by their repaired versions, and penalty function methods can be adopted. Among them, the penalty function methods are particularly promising as evidenced by recent developments [19].

Wire EDM process is discussed in the next section to demonstrate and validate the proposed particle swarm optimization algorithm with constant values of inertia weight and acceleration coefficients.

5. EXAMPLE

Now to demonstrate and validate the PSO algorithm, an example is considered for the optimization of wire electric discharge machining process parameters, based on the model developed in section 3.

5.1 Objective function

Maximize V_m (as given by equation (7))

5.2 Constraint

Constraint is to ensure that the surface roughness value (R_a) should not exceed permissible surface roughness (R_{per}) as specified by equation (11) below.

$$R_{per} - R_a \geq 0 \tag{11}$$

Where, R_a is the surface roughness value as specified by equation (8).

5.3 Parameters and parameter bounds

The four process parameters considered in the present work are Pulse on time (T_{on}), Pulse off time (T_{off}), Peak current (I_p), Servo feed setting (F).The upper and lower bound values for these parameters are as given below.

$$4 \leq T_{on} \leq 8 \ \mu s \tag{12}$$

$$10 \leq T_{off} \leq 30 \ \mu s \tag{13}$$

$$90 \leq I_p \leq 140 \text{ amp} \tag{14}$$

$$30 \leq F \leq 50 \tag{15}$$

Now, the PSO algorithm is applied to solve the above optimization problem. The optimum selection of operating parameters of the algorithm like acceleration constants 'c_1' and 'c_2' as well as inertia coefficient 'w' is very essential for convergence of the algorithm. To ensure the convergence of PSO algorithm, the condition specified by equation (16) must be satisfied [20].

$$\max (|\lambda_1|, |\lambda_2|) < 1 \tag{16}$$

Where, λ_1 and λ_2 are the eigen values given by equations (17) and (18).

$$\lambda_1 = (1 + w - \phi_1 - \phi_2 + \gamma) / 2 \tag{17}$$

$$\lambda_2 = (1 + w - \phi_1 - \phi_2 - \gamma) / 2 \tag{18}$$

$$\text{and } \gamma = [(1 + w - \phi_1 - \phi_2)^2 - 4w)]^{1/2} \tag{19}$$

Also, $\phi_1 = r_1 * c_1$ and $\phi_2 = r_2 * c_2$

Considering the feasible range for the value of '$\phi_1 + \phi_2$' as 0 to 4 and that for 'w' as 0 to 1, it can be observed that for convergent trajectories the relation given by equation (20) must be satisfied.

$$w > 0.5 (\phi_1 + \phi_2) - 1 \tag{20}$$

Now, in the present study the following values of 'w', 'c_1' and 'c_2' are used.

- Inertia weight factor (w) = 0.65
- Acceleration coefficients: c_1 = 1.65 and c_2 = 1.75

Considering the extreme possibility of random number as 'r_1'=0.95 and 'r_2'=0.95, the right hand term in equation (20) is 0.5*(0.95*1.65 + 0.95*1.75) –1 = 0.61, which is less than 0.65 thus satisfies the equation (20). Hence, the values of 'w', 'c_1' and 'c_2' selected in the present work are appropriate for convergence of the algorithm.

Table III shows the optimum values of process parameters for various values of surface roughness as per the customer requirement.

Table III: Results of optimization using PSO for various permissible values of R_a.

R_{per} (μm)	T_{on} (μs)	T_{off} (μs)	I_p (Amp)	F	V_m (mm/min)	R_a (μm)
2.0	8	30	132.52	50	1.422	2.0
2.1	4	21.65	140	50	1.465	2.1
2.2	4	19.68	140	50	1.522	2.2
2.3	4.1	10	140	50	1.827	2.3
2.4	4	10	135.75	50	1.835	2.4

For R_{per} = 2.0 μm, Optimality of the above mentioned solution could be confirmed from the Figures 2 to 5. Figure 2 shows the variation of machining speed and constraint with pulse on time. As shown in Figure 2, the machining speed increases with increase in pulse on time; hence higher value of pulse on time is desired. Thus the selection of upper bound value of pulse on time T_{on} = 8 μs is appropriate. It is also observed that the surface roughness initially increases and then decreases with pulse on time. Hence, the constraint is initially violated beyond value of $T_{on} \cong$ 5.3μs, however, it is satisfied again at T_{on} = 8μs. Variation of machining speed and constraint with pulse off time is shown in Figure 3. As shown in Figure 3, machining speed decreases but surface finish increases with the increase in pulse off time. Thus, from machining speed point of view, lower value of pulse off time is desired. However, upper bound value (30 μs) of pulse off time is selected as for any value below 30 μs, surface roughness constraint is violated.

Figure 4 shows variation of machining speed and constraint value with peak current. The machining speed initially increases slightly with peak current up to certain value (≅107 amps) and then decreases with increases in peak current. Values of peak current up to 107 amp can't be selected as for these values the constraint is violated. From this point of view lower value of peak current should be selected. As the value selected for peak current of 132.52 amp is the lowest value at which the constraint is satisfied, is appropriate. Figure 5 shows variations of machining speed and constraint value with servo feed setting. It is observed from Figure 5, that servo feed setting has less effect on machining speed, but affects the surface roughness significantly. Better surface finish can be achieved for higher value of servo feed setting. From this point of view, selection of upper bound value of servo feed setting (=50) is appropriate.

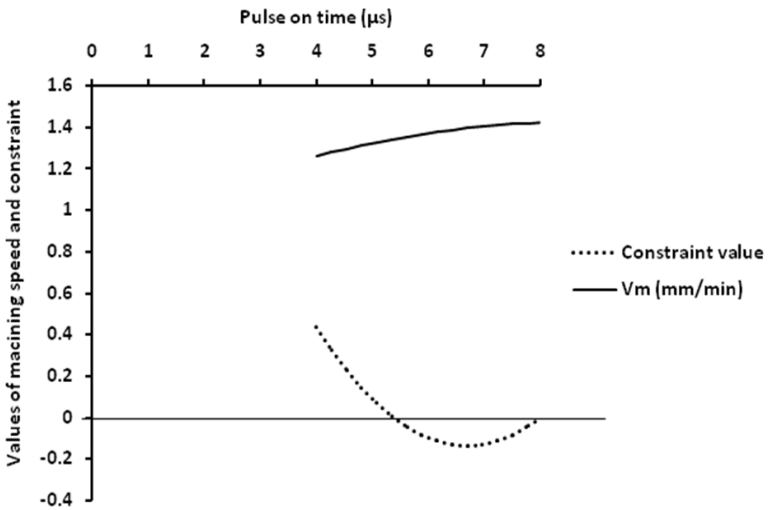

Figure 2: Variation of machining speed and constraint value with pulse on time.

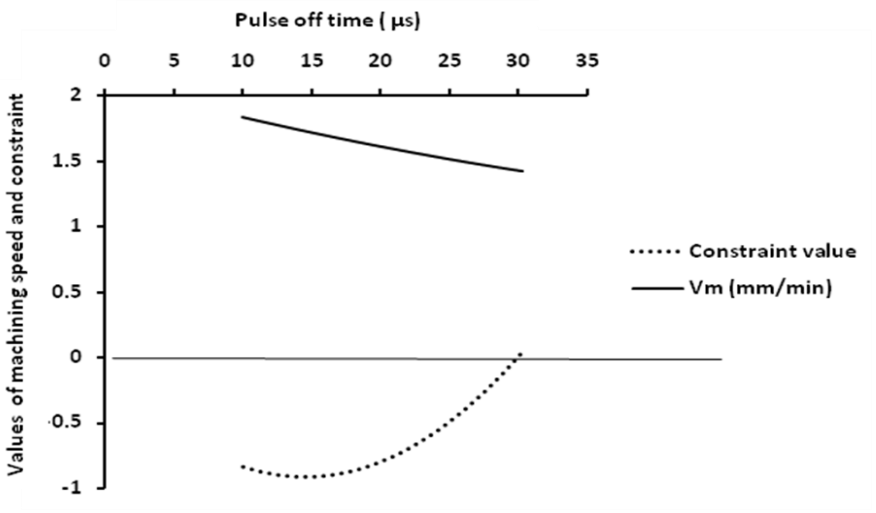

Figure 3: Variation of machining speed and constraint value with pulse off time.

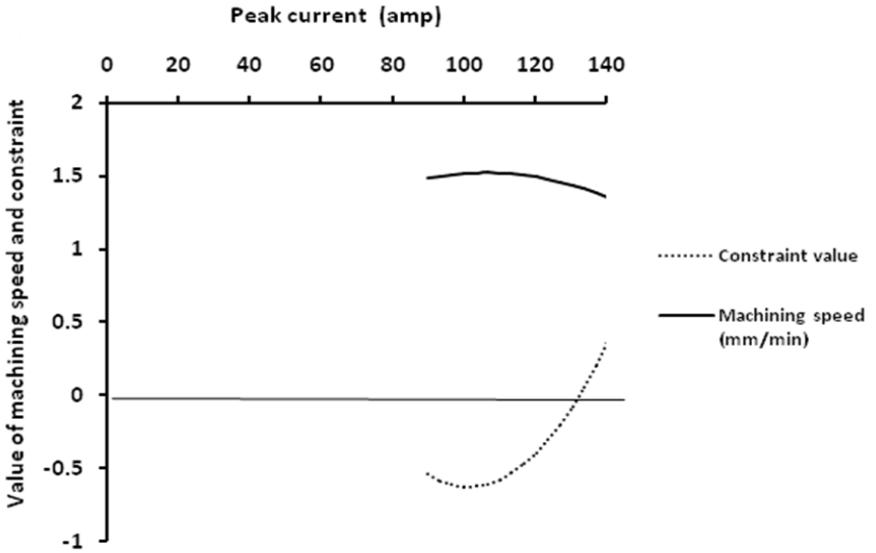

Figure 4: Variation of machining speed and constraint value with peak current.

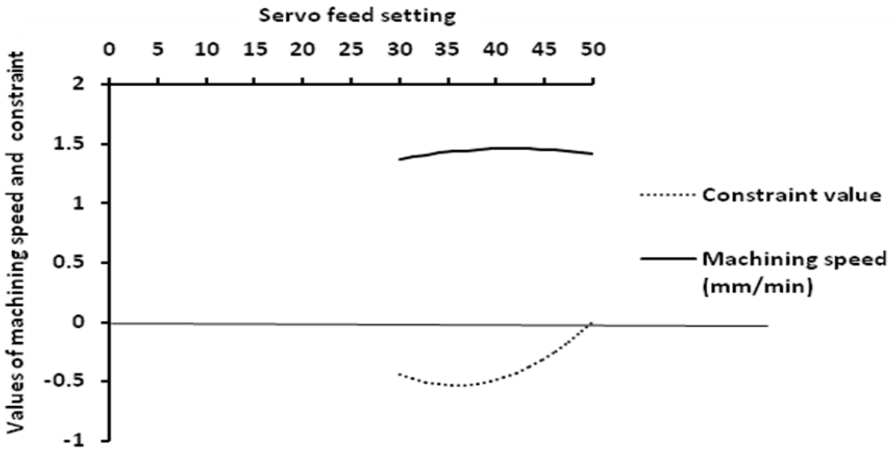

Figure 5: Variation of machining speed and constraint value with servo feed setting.

The model formulated in this work is highly multi-modal as it has number of local optima. As an illustration, for desired value of R_a = 2.1μm, one of the local optimum solution is: T_{on}=4, T_{off} = 10, I_p=90, and F = 31 with corresponding value of V_m=1.106 mm/min and constraint value zero thus showing no scope for further improvement. However, the global optimum solution obtained using PSO provides V_m=1.465 mm/min, showing about 32% improvement over the local optimum solution which is generally obtained by using traditional methods of optimization. This clearly justifies the use of non-traditional optimization algorithm like PSO as in present study, to solve such multi-modal problem.

6. CONCLUSIONS

Modeling and optimization aspects of wire electric discharge machining process parameters are considered in the present work. The objective considered is maximization of machining speed subjected to constraint of surface roughness. Mathematical models have been developed based on RSM approach for correlating the combined effects of pulse on time, pulse off time, peak current and servo feed setting on machining speed and surface roughness. The optimum setting of the process parameters is then obtained using a non-traditional optimization technique namely, particle swarm optimization. Compared to other non-conventional optimization methods, few trials are required to predict the best and worst operating parameters of particle swarm optimization algorithm. Furthermore, the particle swarm optimization algorithm requires only 30 to 40 iterations for convergence to the optimal solution. The algorithm can also be easily modified to suit optimization of process parameters of other non-traditional machining processes such as electro-chemical machining, laser beam machining, plasma arc machining, etc.

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