PERFORMANCE EVALUATION OF EDM PARAMETERS USING GENETIC ALGORITHM AND RSM APPROACHES FOR INDUSTRIALS APPLICATION

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Abstract

This study explores the influence of spark current, pulse-on time, and duty cycle on material removal rate and surface roughness during the EDM process. The experimental design was developed using the Box-Behnken method, followed by analysis of variance (ANOVA) for evaluating the results.In this study, Inconel 625 superalloy was machined using the die-sink EDM method, with input parameters optimized through RSM and genetic algorithm techniques. The quadratic model demonstrated its precision for predicting MRR and SR, supported by an R^2 value close to 1. ANOVA analysis revealed spark current as the most significant parameter, with optimal settings of 40 A spark current, 60 µs pulse-on time, and 20% duty cycle achieving an MRR of 1.6 g/min and an SR of 5.41 µm, thereby enhancing process efficiency. Additionally, the application of a multi-objective genetic algorithm further improved MRR and minimized SR, with MATLAB-based 500 iterations yielding substantial results. The integration of RSM with the genetic algorithm proved effective in achieving the desired optimization.

Keywords: EDM, Inconel 625, MRR, SR, RSM, Genetic Algorithm.

1. Introduction

Fromcenturies in the past, people have strived to develop materials with advanced performance to satisfy their wishes. among diverse industries, aerospace has especially required materials which can withstand excessive temperatures and own wonderful energy, retaining their mechanical and thermal residences below harsh operating situations[1]. consequently, substances with excessive electricity, low density, and resistance to corrosive environments are extensively appropriate no longer only in the aerospace place however additionally in marine and chemical processing industries. all through records, humans have constantly aimed to create substances with great residences to fulfill evolving needs[2]. The aerospace company, particularly, calls for materials able to enduring intense temperatures and preserving their mechanical and thermal houses in annoying environments. As a end result, materials with immoderate electricity, low density, and robust resistance to corrosion are notably valued, now not exceptional in aerospace but moreover in marine and chemical

processing applications. EDM contribute about 22% of the machining phase internal advanced manufacturing, underscoring its significance in business applications[3]. This manner relies on thermal and electric mechanisms to eliminate material from the workpiece. This method is primarily based on thermal and electrical mechanisms to eliminate material from the workpiece. A brilliant advantage of EDM is the absence of direct physical touch among the electrode and the workpiece, which complements precision and minimizes mechanical stress for the duration of the machining technique. dangers which include mechanical loading, vibrations, and the formation of massive chips are correctly addressed by means of the EDM technique[4]. This method operates on an electro-thermal phenomenon, wherein excessive-power sparks melt and vaporize unwanted fabric from the workpiece. The erosion materials occur in the course of the pulse-on time, on the same time as the debris is flushed away during the pulse-off phase [5]. **Figure 1**illustrates the entire phenomenon of material erosion in the course of the machining system. Dielectric fluids at the side of hydrocarbon-primarily based oils, water, deionized water, and kerosene are employed to facilitate the technique by using manner of acting as an insulating medium among the device and the workpiece. The performance and effectiveness of

EDM are motivated by means of the use of several method parameters. Key method parameters consisting of pulse-on time (Ton), pulse-off time (Toff), duty cycle (DC), spark current (Is), and voltage significantly have an effect on the green machining of high-energy materials. The configuration of those parameters immediately influences the power consumption of the EDM system, which in turn impacts its normal sustainability [6].numerous researchers have focused on optimizing procedure parameters to enhance the overall performance of EDM when machining nickel-based super alloys, titanium-primarily based alloys, excessive-strength steels, and exceptional conductive and semi conductive substances. Optimization strategies which incorporates ANOVA and Taguchi-based desirability competencies were employed to decide the maximum dependable manner parameters. Given the complexity of EDM regarding multiple parameters, superior techniques like artificial neural networks and system studying algorithms have additionally been applied to achieve major parameter settings[7]. This study pursuits to explore the have an effect on of EDM technique parameters which includes pulse-on time (Ton) and contemporary, and to establish the connection among performance metrics like fabric removal rate and floor roughness. the subsequent phase opinions the literature on previous studies and summarizes the important thing findings applicable to the focal point of this work[8].

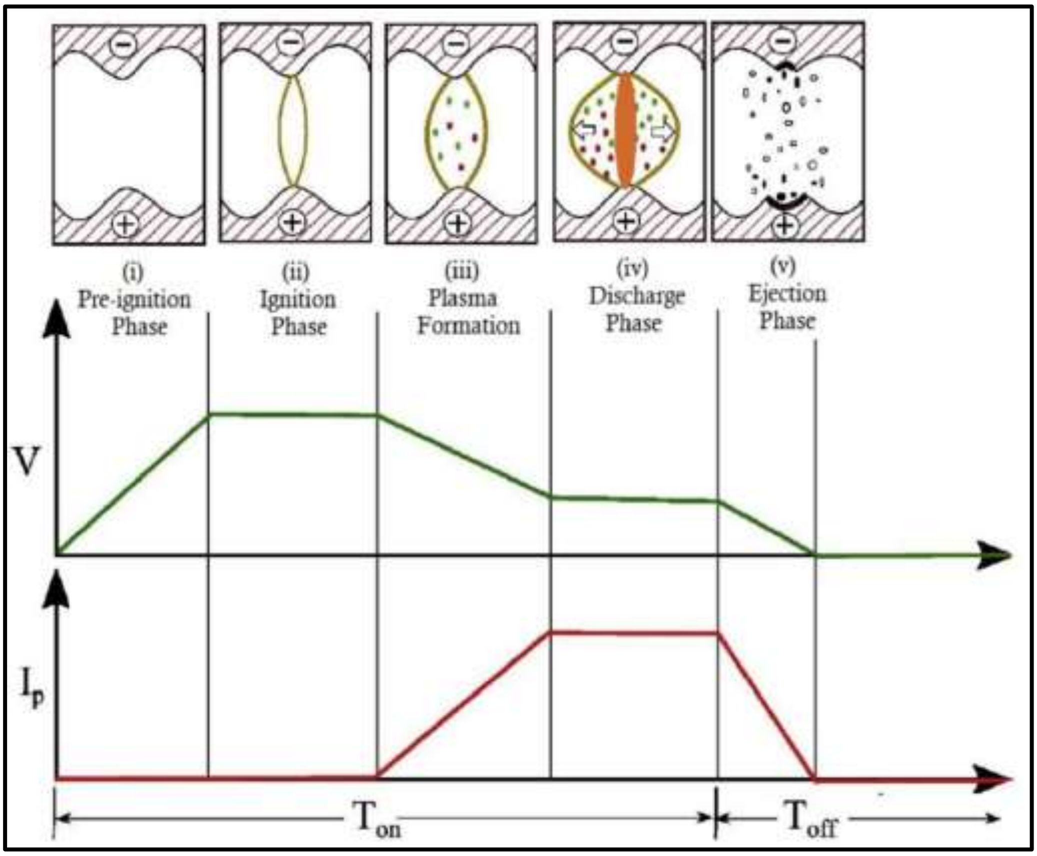

Figure 1: phenomenon of materials erosion [9]

1. Literature Survey

Sengottuvel et al. investigated the process parameters to set up the relationship among process and overall performance parameters. It was discovered that pulse-on time, spark modern, and duty cycle are the maximum influential parameters for achieving maximum material removal rate (MRR) and minimum surface roughness. The authors applied response surface methodology (RSM) and evaluation of Variance (ANOVA) techniques, revealing a strong correlation among method and performance parameters. additionally, fuzzy logic methods had been employed to investigate how spark cutting-edge impacts surface roughness and tool put on rate in electric Discharge Machining (EDM) [10].Magdalena et al. hired synthetic Neural Networks (ANN) and response surface method (RSM) to evaluate the validity and efficiency in their developed version. Their findings indicate that increasing the pulse-on time, rotational pace, and amplitude at some stage in the machining of Inconel 725 effects in better drilling pace, advanced velocity ratio, and reduced tool wear rate [1].Gopalakannan explored the machining of MMC 7075 composites the use of electrical Discharge Machining (EDM) with reaction surface method (RSM) and artificial Neural network (ANN) techniques. The study diagnosed tremendous input parameters of the EDM process to enhance the machining efficiency of MMC 7075 composites. among numerous non-traditional machining techniques, EDM was found to be the most superior method for correctly putting off undesirable fabric [11]. Junaid Mir systematically investigated the elimination of unwanted material from metal H11 using advanced Powder-mixed electric Discharge Machining (PMEDM) techniques. The study concluded that PMEDM is an powerful method for achieving a high material removal rate[11]. Junaid Mir systematically investigated the elimination of unwanted material from metal H11 using advanced Powder-mixed electric Discharge Machining (PMEDM) techniques. The study concluded that PMEDM is an powerful method for achieving a high material removal rate[2].Vinod Kumar hired twine electrical Discharge Machining (cord-EDM) to system Monel 400, a excessive-performance material. 4 input parameters including pulse-on time, pulse-off time, spark present day, and servo voltage had been selected to research floor roughness and device put on charge. The observe revealed that cloth elimination rate (MRR) progressed via 28% through optimization of method parameters the usage of response floor technique (RSM) and synthetic Neural network (ANN) strategies[12].Amit Kumar et al. applied grey Relational analysis to optimize the procedure parameters throughout the electric Discharge Machining (EDM) of M22 grade high-velocity metal. The have a look at recognized superior answers for kerf width, material removal rate, and tool put on charge, improving the general conductivity of the EDM procedure [13].Dutta et al. advanced a singular Adaptive Neuro-Fuzzy Inference machine (ANFIS) to predict the recast layer and surface roughness of machined workpiece at some point of the machining of Inconel 625. The have a look at discovered that the generated version is tremendously effective in reaching the desired output parameter values[14].Moreover, numerous authors have employed diverse strategies to decide the foremost output parameters for EDM-machined high-performance substances, that are widely applied in industries. table 1 offers their findings.

Table1: Key findings of previous research

Authors	Workpiece materials	EDM types	Optimizations techniques
Abbasadel et al. [15]	AI and silicon based composites	Die sinking EDM	RSM–COPRAS method
SapkalSagar et al. [16]	Titanium based alloy	EDM drilling methods	CCD based RSM techniques
Mandal et al. [17]	Monal 400 super alloy	Die sink EDM method	Dragonfly algorithm
Singh et al. [12]	Copper based alloy	EDM and hybrid EDM techniques	TLBO and genetic algorithm,
Bagal et. al. [18]	Stainless steel	Wire-EDM	TOPSIS AND MCDM mechanism

This work aims to optimize process parameters to enhance material removal rate and reduce tool wear rate using desirability functions and artificial neural network (ANN) tools. The sustainability of machining processes is also addressed through various techniques. A review of the literature reveals that significant efforts have been made to improve the machinability of materials, which contributes to the sustainability of the overall machining process. In this study, the machining of high-performance materials, commonly used in modern manufacturing sectors, is undertaken using electrical discharge machining (EDM). The selection of appropriate EDM parameters is critical for improving process efficiency, thereby enhancing productivity and sustainability. The literature survey also reveals that various tools, such as RSM-COPRAS, TOPSIS, MCDM, desirability functions, and the dragonfly algorithm, have been utilized to establish possible relationships between input and output parameters during the machining of nickel-based super alloys. These efforts contribute to improving process efficiency, promoting environmental friendliness, and advancing the concept of sustainability. Moreover, Advanced machine learning tools, such as ANN and desirability functions, are implemented to further optimize the process. The following sections will discuss the materials and methods employed in the proposed work.

3.Materials used and methods adopted

3.1 Materials details

Commercial utilized Inconel 625 superalloy has been used as a work material. Copper used as a tool material. Both materials have been purchased from Birla steel industries Gujarat. The work materials have been cut into dimension of 50 mm (length) * 50 mm (width) * 10 mm (thickness) for machining on die-sinking EDM setup. 12 mm diameter of copper electrode is considered for machining. EDM oil (hydrocarbon-based oil) used as a dielectric fluid. The specification of work material and tool material has been described in Table 2

Table 2: Specification of work material and tool material[8]

Inconel 625			
Melting point (C)	Tensile strength	Density	Modulus of Elasticity
1250 - 1350	550 MPa	8.15 m/cc2	207 GPa
Copper			
1084	200–250 MPa	8.96 g/cm³	110-130 GPa

3.2 Experimental work

Experiments has been carried out using an ENC-series Electric Discharge Machine. The machine is equipped with an RC pulse generator and machine equipment's with transverse and longitudinal displacement of 300 mm and 380 mm, respectively. A 10-micron paper filter is integrated into the system to efficiently remove debris. The complete EDM setup is illustrated in Figure 1. The work materialshave beensetup within the working tank for the experiments. Based on previous study, it was determined that the process parameters have significantly impact performance parameters. For this study, these process parameters were adjusted across three levels—low (-1), medium (0), and high (+1)—to thoroughly analyze their effects and interactions[19]. Table 3 outlines the levels and ranges of these parameters.In this study, MRR and SR were measured as output responses. MRR was calculated using the weight difference of the workpiece before and after machining, divided by machining time, while SR was determined using a Perthometer profilometer. Average values for both responses, based on five replicates, are presented in Table 5

Table 3: Levels and Ranges of Process Parameters

Parameter	**Description**	**Unit**	**Level -1**	**Level 0**	**Level 1**
A	Ton	µs	20	40	60

Parameter	Description	Unit	Level -1	Level 0	Level 1
B	Is	A	4	14	24
C	DC	%	10	40	70

Table 4: Constant Experimental Parameters in EDM Machining

Parameter	Value
Polarity	Straight
EDM oil	Hydrocarbon EDM oil
Flushing Pressure (MPa)	0.7
Gap Voltage (V)	40
Sensitivity (SEN)	50
EDM Machining Time (minute)	12

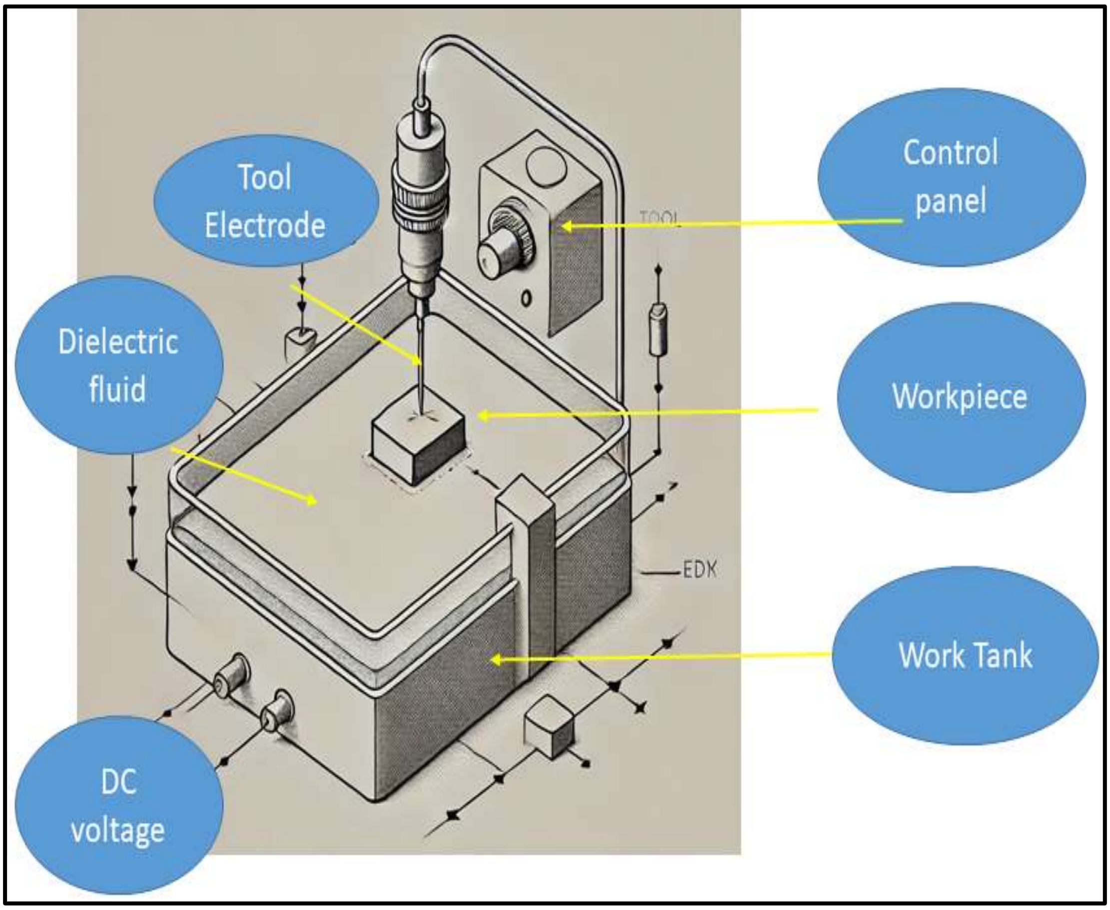

Figure 2: Schematic of EDM and its components [20]

3.3 Design of Experiments (DoE)

In this study, design of experiments (DOE) techniques was applied to determine the optimal relationship between input and output parameters. The experiments were designed using the Box-Behnken Design (BBD) method, resulting in a total of 17 experimental runs. Design Expert 13 software was used to structure the experimental design. A second-order polynomial equation was employed to model the process, as shown in Equation 1, which captures the linear, quadratic, and interaction effects between parameters. The surface morphology of the ED-machined surface, generated thru traditional, RSM-DF, and MOGA techniques, become analyzed using numerous characterization strategies[21].

$$y = \alpha_0 + \sum_{i=1}^{k} \alpha_i x_i + \sum_{i=1}^{k} \alpha_{ii} {x_i}^2 + \sum_{i=1}^{k} \sum_{j}^{k} \alpha_{ij\,(i<j)}\, x_i x_j + \varepsilon \qquad (1)$$

4. Results and Discussion

The results received from the experiments are provided in table 5. This segment discusses the development of a mathematical model and examines the effect of Ton, Toff, and duty cycle on MRR and SR. Moreover, the RSM-Desirability approach and multi-objective genetic set of rules were applied to perceive the most efficient parameter settings for reaching the best MRR and the lowest SR.Table 5 found out that the experimental 4 received the best of MRR, while experiment 5 acquired the lowest price of SR. This observe focus to obtained the most effective aggregate of enter values that intention to acquire the desired output. Inside the similarly phase, RSM and GA technique has been applied to obtained the desired consequences. This attempt also leads to revolution inside the challenging production sector.

Table 5: Box-Behnken design experimental obtained values

Sr. No	Ton (μs)	Is (A)	DC (%)	MRR (g/min)	SR (μm)
1	40	4	10	0.012	3.05
2	40	24	70	0.145	6.10
3	40	14	40	0.085	4.00
4	60	24	40	0.160	5.95
5	20	14	10	0.040	3.00
6	60	14	70	0.102	4.20
7	60	14	10	0.065	3.85
8	40	14	40	0.084	4.30
9	40	14	40	0.083	4.32
10	20	4	40	0.010	3.00
11	20	24	40	0.105	4.50
12	60	4	40	0.030	3.60
13	40	4	70	0.015	3.25
14	20	14	70	0.042	3.95
15	40	24	10	0.120	4.75
16	40	14	40	0.085	4.50
17	40	14	40	0.090	4.45

4.1 Process parameters influences on MRR

TheMRR and SR are notably influenced with the aid of Ton, Is, and DC. the best MRR (0.160 g/min) is observed at 60 µs Ton, 24 A Is, and 40% DC (Run 4), at the same time as the bottom (0.010 g/min) happens at 20 µs Ton, four A Is, and forty% DC (Run 10). MRR will increase with higher Is due to intensified strength discharge, improving fabric elimination. Ton additionally performs an important role, as longer intervals improve MRR by using growing surface heating, even though excessive ranges may also improve flushing performance.The interplay between Is and DC highlights that optimal combinations maximize MRR while retaining perfect SR ranges[22].Figure 2 suggests the three-D surface examine of various input parameters interaction with MRR. 3-D surface reveals that spark current is the most considerable input parameter to acquired the best MRR compared to pulse on time and duty cycle.

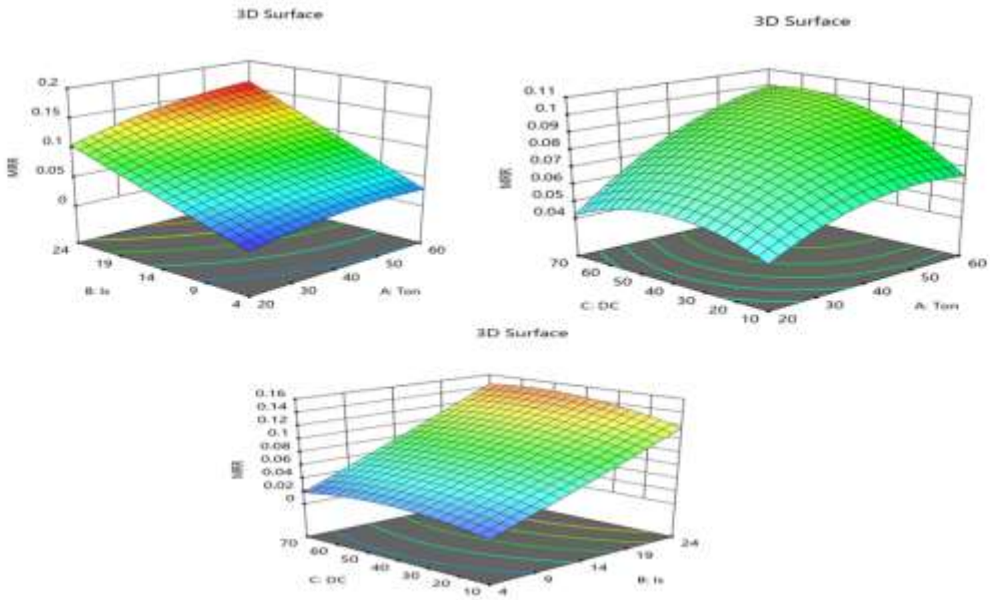

Figure 3: 3D illustrations of Ton, Is and DC with MRR

4.2 Process parameters influences on SR

SR turned into modeled effectively using a second-order quadratic equation, as confirmed with the aid of ANOVA analysis. The high F-value and p-value below 0.05 demonstrate the model's statistical significance. Key parameters such as Ton, Is, and DC significantly influence SR, with their interactions also contributing to the model's reliability. The coefficient of determination ($R^2 = 0.94$) and adjusted R^2 (0.91) reflect a strong correlation between process parameters and SR. Residual and regression plots indicate minimal error and align closely with the predicted values, validating the accuracy of the model and its precision in predicting SR trends[19].

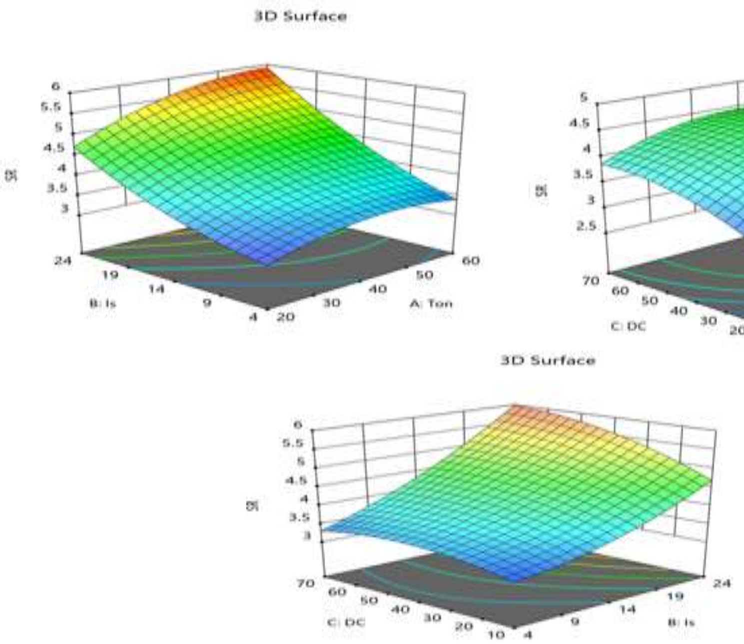

Figure 4: 3D illustrations of Ton, Is and DC with SR

4.3 Genetic algorithm based multi-objective optimization

The genetic algorithm was carried out to determine the satisfactory combination of input parameters for reaching preferred output parameters, especially MRR and SR. This technique is based on ideas which include genetic evolution, crossover, mutation, and natural selection. Pareto evaluation found out that all solutions aligned in an unmarried course, validating the feasibility of the choicest answer.By optimizing the parameters, this method successfully enhanced MRR and minimized SR, contributing to improved industrial performance[23]. After 500 iterations, the results consistently converged toward the optimal solution. Experiment number 4 recorded the highest MRR (1.64 g/min) and the lowest SR (5.9 µm).

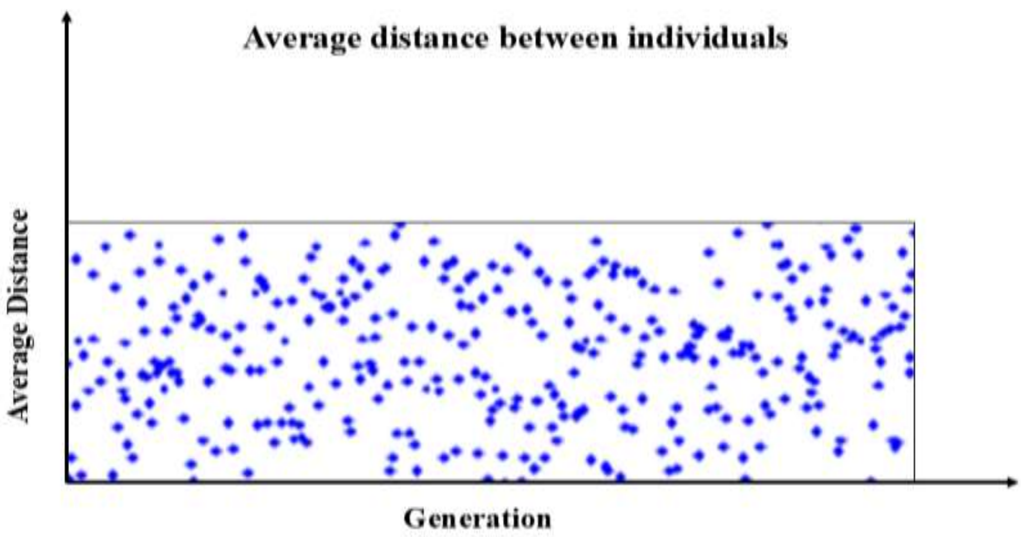

Figure 5: Individual average distance

5. Conclusions

In this study, Inconel 625 superalloy was machined using the die-sink EDM method. The input parameters were optimized using RSM and genetic algorithm techniques, and the obtained results are as follows:

1. The quadratic model provided accurate results for MRR and SR, confirming its suitability for predicting optimal performance. The R^2 value close to 1 highlights the model's precision and validity.
2. 3-D surface reveals that spark current is the most considerable input parameter to acquired the best MRR compared to pulse on time and duty cycle.
3. ANOVA analysis identified spark current as the most critical factor influencing MRR and SR. The optimal settings of 40 A spark current, 60 µs pulse-on time, and 20% duty cycle resulted in an MRR of 1.6 g/min and an SR of 5.41 µm, enhancing EDM process efficiency.
4. The application of a multi-objective genetic algorithm successfully improved MRR and minimized SR. Using MATLAB for 500 iterations demonstrated significant results. The integration of RSM with the genetic algorithm achieved the desired optimization.

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