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MODELING AND OPTIMIZATION OF PHYSICAL VAPOUR DEPOSITION COATING PROCESS PARAMETERS FOR TiN GRAIN SIZE USING COMBINED GENETIC ALGORITHMS WITH RESPONSE SURFACE METHODOLOGY

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ABSTRACT

Optimization of thin film coating parameters is important in identifying the required output. Two main issues of the process of physical vapor deposition (PVD) are manufacturing costs and customization of cutting tool properties. The aim of this study is to identify optimal PVD coating process parameters. Three process parameters were selected, namely nitrogen gas pressure (N_2), argon gas pressure (Ar), and Turntable Speed (TT), while thin film grain size of titanium nitrite (TiN) was selected as an output response. Coating grain size was characterized using Atomic Force Microscopy (AFM) equipment. In this paper, to obtain a proper output result, an approach in modeling surface grain size of Titanium Nitrite (TiN) coating using Response Surface Method (RSM) has been implemented. Additionally, analysis of variance (ANOVA) was used to determine the significant factors influencing resultant TiN coating grain size. Based on that, a quadratic polynomial model equation was developed to represent the process variables and coating grain size. Then, in order to optimize the coating process parameters, genetic algorithms (GAs) were combined with the RSM quadratic model and used for optimization work. Finally, the models were validated using actual testing data to measure model performances in terms of residual error and prediction interval (PI). The result indicated that for RSM, the actual coating grain size of validation runs data fell within the 95% (PI) and the residual errors were less than 10 nm with very low values, the prediction accuracy of the model is 96.09%. In terms of optimization and reduction the experimental data, GAs could get the best lowest value for grain size then RSM with reduction ratio of ≈6%, ≈5%, respectively.

Keywords: *TiN, Grain Size, Modeling, Sputtering, PVD, RSM, Genetic Algorithms.*

1. INTRODUCTION

In high speed machining, temperatures on the cutting tip may exceed 800 ^{o}C. This leads to tool wear and reduces cutting tool performance. Thus, the cutting tool with high resistance wear is very important to deal with the crucial condition. A cutting tool with high resistance to wear promises better tool life and directly reduces machining cost. Reasons behind the associated difficulty includes knowledge of machining; empirical equations relating the tool life, forces, power, surface finish, and realistic constraints; and specification of machine tool capabilities [1, 2]. Machining cutting tool performance can be enhanced by implementing PVD coating process with the tools' features. In general, the implementation of PVD coating process leads to higher manufacturing and cutting tool properties customization costs [3]. Hard coatings such as Titanium Nitride (TiN) coating are

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usually used in metal cutting industry due to its coatings performance, including hardness and resistance to wear. The main purpose of coating is to enhance the surface properties while maintaining its bulk properties. A coated tool has been proven to be forty times better in tool wear resistance compared to an uncoated tool [4].

The benefits of coating process are obviously part of the main reason for the optimization process. From the above statements, a proper choice of coating parameters optimization is important because this better helps identify the output in terms of its nearer designed optimization objectives. Examples of positive effect of coating powder in an object cutting process include fewer mistakes, increased durability, and keeping an original polished look, [2]. The characteristic benefits of coating include less material usage, reduced trials in experiments, multi-purposes for the same process and material, and less required maintenance [3].

In PVD coating process, many factors are reported have significant influence to coating characteristics including coating grain size. Coating grain size is the average size (diameter) for individual grain particle in a metal. Smaller grains size in the thin film coating can improve the hardness of the cutting tool. Some done researches showed that N_2 pressure, Argon pressure, and Turntable Speed could have significant effect on the deposited coating grain size and surface morphology [5, 6, 7, 8, 9]. However, the study on the optimization among PVD sputtering process parameters is still needed.

Choosing correct optimal cutting parameters for every metal cutting process is not an easy task. Such parameters, which determine the cutting result quality, require accurate control. Generally, modern manufacturers manage to obtain such result quality level based on past experience and published researchers work's guidelines to determine the machining parameters, while a hand-out provides users with cutting parameters from the machining databases. But, the range that is given in these sources refers only to starting values, and not the optimal values. Therefore, coating parameters optimization is a crucial aspect to identify the output of chief importance.

Modeling is an adequate way to address the coating process issues such as cost and customization. A model may be used to predict the coating performance value and indicate the optimum combination of input parameters to find best result. Many techniques have been applied to model coating works. Experiment-based approaches such as Taguchi [10], full factorial, and RSM [11] have been reported in designing model with minimum experimental data [12]. Intelligence based approaches such as fuzzy logic [13], neural network [14, 15], and ANFIS [16] have been also used to predict coating performance. However, some limitations of the approaches have been discussed. The Taguchi approach has difficulties detecting the interaction effect of a nonlinear process [17] and the full factorial method is only suitable for optimization purposes [18]. A neural network needs a large amount of training data to be robust [19], and a significant amount of data as well as powerful computing resources are necessary [20].

Researchers use RSM to study relationships between measured response functions [21, 22, 23]. RSM is a collection of mathematical and statistical methods used to model and analyze significant parameters that affect the output responses [24]. Genetic algorithms (GAs) are among the common methods used to improve many solutions of optimization complex problems. It has provided an excellent insight to a large number of problems in the materials domain [25]. It has been demonstrated that GAs optimization are today's most implemented techniques in optimizing machining process parameters [26]. It have assisted surface roughness based machining coating researches for long ago, It have been also used to optimize the process parameters for achieving the desired grain size fusion zone [27, 26]. Algorithms are used to optimize the grain size and indicate the effect of process factors to the TiN coating grain size. Per recommendations, GAs are probed to gather less data with well-designed experiments; it can match and map out the input vs. output interaction in result forecasting [22], and give a better value of grain size when compared to the actual experimental data.

The objectives of this paper are to identify the most influence coating parameters to the coating grain size and to optimize the coating parameters in order to find the most suitable combination of parameters' values. In this paper, the RSM approach was used to identify the most significant parameters to the coating grain size, and optimization of the coating parameters was done using RSM-GAs technique.

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2. EXPERIMENT

2.1 Experimental Design.

In this study, the experimental matrix and data analysis were based on RSM center cubic design, using Design Expert version 8.0 software. It was designed based on 8 factorial points, 6 axial points, and 3 central points. In the experimental matrix, the extreme points (operating window) of the +/- Alpha value were designed as shown in

Table *2* Based on the defined extreme point values, the software then output the high and low settings for the factorial points. The purpose is to ensure that the characterization could be performed by covering the widest range of operating window.

2.2 Material and Method.

The experiment was run in unbalanced PVD magnetron sputtering system made by VACTEC Korean model VTC PVD 1000. The coating chamber was fixed with a vertically mounted titanium (Ti) target. The surface of tungsten carbide inserts were cleaned with an alcohol bath in an ultrasonic cleaner for 20 minutes. Tungsten carbide inserts were loaded in the rotating substrate holder inside the coating chamber. To produce the electron in the coating chamber for sputtering purpose, the inert gas Argon was used. The inserts were coated with Ti in presence of nitrogen gas. Detailed process for the coating is indicated in Table 1 In this process, N_2 pressure, Ar pressure, and turntable speed were selected as variables.

2.3 Atomic Force Microscopy.

A grain size value of the TiN coating was measured using the atomic force microscopy (AFM) method. The method determined the morphology of the surface based with less requirement of sample preparation and non-destructive testing. The AFM XE-100 model was used in characterizing coating grain size. The non-contact mode detection approach using a commercial cantilever was based on the Y-axis length in 25 µm × 25 µm (625 µm^2) scanning area. The average of the grain length for every area was calculated by dividing the total grain length with total number of grain in the scanning area. TiN coating grain size values from the seventeen experimental runs ranging from 7.14 µm to 8.39 and shown in Table 3 XEI software was used to analyse the surface image to obtain the grain size reading.

3. MODELING METHODOLOGIES:

3.1 The RSM Model in Predicting Tin Coating Grain Size

3.1.1 Diagnostic Plot For Tin Coating Grain Size Model

The analysis started with identifying the transformation requirement to the analysis. The analysis indicates that no transformation is needed because the ratio of minimum to maximum of the response range is 1.175, which is less significant effect if the power transform is applied. Transformation is required if the ratio is greater than 10. Besides that, the diagnostic plots of the developed grain size quadratic model in terms of normal probability plot of studentized residual, studentized residual versus predicted value plot and external studentized residual plot are also analyzed. The normal probability plot in Figure 1 demonstrates that the errors are distributed normally. This can be explained when the residual fall on the straight line. Therefore, no response transformation is required.

The plot of predicted response versus residual for coating grain size is shown in Figure 2. There are no obvious pattern and unusual formation of the data. In addition, no megaphone pattern has been identified, and the plot is scattered in random formation. This pattern also indicates that the response transformation is not required to improve the analysis. Figure 3 indicates the plot of residual versus run number for TiN coating grain size. The figure shows that the entire data plot falls between the ranges. Therefore, a study to find root cause of the outlier data is not required. In conclusion, a model or response terms transformation are not required due to structure and reasonable pattern as indicated on the graph plot. In addition, due to in range residual data in the plot, no revision to the experimental data is required.

3.1.2 Determination Of Polynomial Equation To Represent RSM Model Of Tin Coating Grain Size

Determination of suitable model to represent relationship of grain size and process factors is based on model analysis. Sequential model sum of square (SMSS) analysis, lack of fit test, and model summary statistic as indicated in Table 4 and Table 5 have been analyzed to select the appropriate model Table 4 shows that the linear, 2FI and quadratic terms have no significant p-values. However, the quadratic is suggested due to having the highest order polynomial compared to the

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others. Meanwhile, the p-value of the suggested quadratic model in lack of fit test is higher than 0.10 as shown in Table 5 This indicates that the lack of fit of the model is insignificant.

Based on analysis in Table 4 and Table 5, the quadratic polynomial equation may represent the relationship of TiN coating grain size and input variables.

In Sequential Model Sum of Squares [Type I], the highest order polynomial is selected where the additional terms are significant and the model is not aliased.

3.1.3 ANOVA Analysis Of The Response Surface Model For Coating Grain Size

The initial ANOVA analysis for response surface quadratic model to grain size has been indicated in Table 6 The table indicates that the developed quadratic model is not significant, with a p-value of 0.2421. The model F-value of 1.726 implies that the model is not significant relative to the noise. Values of "Prob > F" less than 0.1000 indicate model terms are significant. In this case C, B^2 are significant model terms. The value is greater than 0.1000 to indicate that the model terms are not significant. Noise is due to natural variation for that particular process such as the variability of the measuring instrumentation during characterization process and the variability of the substrate temperature during the coating process. There is a 24.21% chance that a model F-value may occur due to noise. Additionally, many insignificant terms do not represent the model, as shown in the same table. However, this insignificant term could be used in the next section to improve upon the insignificance of the model using the model reduction method.

The "Lack of Fit F-value" of 2.89 implies the Lack of Fit is not significant relative to the pure error. There is a 27.68% chance that a "Lack of Fit F-value" this large could occur due to noise. Non-significant lack of fit is good. The model should fit.

3.1.4 Model Reduction To Improve The Model For Coating Grain Size

A preferred way to improve the insignificant model term is the manual elimination method. In this method, we remove A^2 and AC, which contribute to the insignificance of the model. After removing, we found that the model became significant. The ANOVA to improve response surface reduced quadratic model is indicated in Table 7 The p-value of this model is 0.0788 to indicate that the model is strongly significant. The improvement is obvious when the model F-value is 2.76, and has only 7.88% chance that a model F-value this large could occur due to noise. The p-value of the lack of fit for this model is 0.3581 to show that the lack of fit for this model is not significant as desired. There is a 35.81% chance that a "Lack of Fit F-value" this large could occur due to noise. Non-significant lack of fit is good. The lack of fit F-value is 2.12 implies that the lack of fit is not significant due to pure error. Table 7 also indicates that only C and B^2 terms are significant factors to the model. This is indicated by the p-values less than 0.10 and F-values greater than 1. Therefore, the turntable speed and Argon pressure were identified as significant parameters with greater influence to the coating grain size.

Based on the modeling work, a quadratic polynomial equation as shown in Eq. (1) represents the relationship between input PVD coating process parameters and grain size is developed as the following:

$$\textbf{\textit{Grain Size}} = -72.8553 - 4.9435\, PN_2 + 37.9109\, PAr + 2.4602\, \omega TT + 1.2360\, PN_2\, pAr - 0.4413\, PAr\omega TT - 4.5898\, PAr\,^\wedge 2 - 0.04511\omega TT\,^\wedge 2; \quad (1)$$

where PN_2 is nitrogen pressure, PAr is argon pressure, and ωTT is Turntable Speed.

The next cube representation in Figure 4 shows the interaction behavior of ABC factors which are (N_2, Ar, and TT, respectively) relative to RSM. It is clear that the lowest grain size value is 7.37 for RSM model with 1.5 for N_2, 3.8 for Ar, and 5.0 for TT. The lowest value of grain size is the best for coating process. Thus, RSM model could be reduced the grain size value from 7.78µm to reach 7.37µm, with a reduction value = 0.41µm compared to the experimental dataset.

3.1.5 Validation Of Developed RSM Model

In validation process, the residual error as shown in Eq. (2) is used to measure the difference between the predicted and the actual value for each dataset. Residual error is the simple performance measure that used in many studies [28, 29, 30, 31, 32, 33] . Equation for residual error, *e* as the following:

$$e = \frac{vp - va}{vp} \quad (2)$$

where v_p is predicted value and v_a is actual value.

Besides that, performance of a developed predictive model is also measured In terms of the

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prediction accuracy as shown in Eq. (3). This performance measure is very important to see how accurate a model could predict the output performance when the input parameters are changed. Equation to calculate the prediction accuracy, A as the following:

$$A = \frac{1}{n}\sum_{i=1}^{n}\left(1 - \frac{|v_p - v_a|}{v_p}\right) \times 100\% \qquad (3)$$

where n is number of experimental data, v_p is predicted value and v_a is actual value.

Table 8 shows that the experimental values of the TiN coating grain size fall within the 95% prediction interval (PI). This means the model could predict the TiN grain size in accurate result. Besides, the table also shows that the highest percentage of residual error (RE) is 5.4%. The maximum error is less than 10% and indicates that the model predicts almost accurate result. The prediction accuracy of the model is 96.09% to show that the model is good enough to predict the TiN coating grain size.

Figure 5 shows that the plot of the TiN coating grain size for predicted versus actual values scatters around the mid-line. Disperse pattern of grain size value near with the mid-line shows that the RSM model is efficient to predict the TiN grain size result with less residual error. The nearest value from the line means that it has the lowest error. Therefore, when the value intersects the line; then, the error approaches to zero.

3.2 Combining Genetic Algorithms (Gas) With RSM Model And System Optimization

GAs are an Artificial Intelligence algorithms techniques for process optimization, and are capable of extracting some of strategies in the nature uses successfully, Then derived strategies can be changed and used into theories of mathematical optimization searching for a global optimum within a time space.

In the process, GAs in Figure 6 applies three fundamentals rules in its process of learning and search for global optimum within a time space. These are selection, crossover, and mutation.

An illustration for GAs methodology application in optimization process is given in Figure 7.

For implementation and based on existing literatures including [35] works, after assigning appropriate parameters for the GAs, the process parameters are encoded as follows:

i. First, encode the process parameters as genes by binary encoding.
ii. Combine a genes set for a chromosome that execute GAs basic operations (crossover and mutation).
iii. Crossover operation enables exchange between chromosomes to create new offspring.
iv. Apply mutation operation to create small randomness with a new chromosome.
v. Evaluate each chromosome by decoding parameters from other chromosome to predict machining performance measures.
vi. The fitness or objective function is a function needed in the optimization process and the selection of the next generation in the GAs.
vii. Derive optimal results of process parameters by comparing values of objective functions among all individuals after some GAs iterations.

3.2.1 Grain size fitness (objective) function

To combine GAs with RSM, a fitness function for GAs has been developed based on the previous RSM quadratic polynomial function in Eq. 1. Using the MATLAB toolbox, we have coded the new fitness function in a correct syntax as the following:

function g = grain(x)
g = -72.8553 - 4.9435 × x(1) + 37.9109 × x(2) + 2.4602 × x(3) + 1.2360 × x(1) × x(2) - 0.4413 × x(2) × x(3) - 4.5898 × x(2)^2 - 0.04511 × x(3)^2;
end (4)

where *g* is grain size, *x(1)* is Nitrogen pressure, *x(2)* is Argon pressure, and *x(3)* is Turntable Speed.

3.2.2 GAs parameters limitation constraints optimization for coating process

The limitation constraints for the optimization objective function of GAs for coating are subjected to the following:

$$N_{2min} \le N_2 \le N_{2max} \qquad (5)$$
$$Ar_{min} \le Ar \le Ar_{max} \qquad (6)$$
$$TT_{min} \le TT \le TT_{max} \qquad (7)$$

where N_2min, $Armin$, and $TTmin$ are the lowest value of Nitrogen pressure, Argon pressure and Turntable Speed of experimental design respectively, N_2max, $Armax$ and $TTmax$ are the highest values of Nitrogen pressure, Argon

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pressure and Turntable Speed of experimental design respectively.

In coating process, the basic formulas in Eq. (5-7) were used to formulate the GAs parameters limitation constraint in coating process. The following equations identify the limitation constraints for GAs parameters for coating.

Nitrogen pressure

$$0.16 \leq \text{Nitrogen Pressure } N_2 \leq 1.84 \quad (8)$$

Argon pressure

$$3.66 \leq \text{Argon Pressure Ar} \leq 4.34 \quad (9)$$

Turntable speed

$$3.98 \leq \text{Turntable Speed TT} \leq 9.02 \quad (10)$$

3.2.3 GAs Optimization Setting Up Parameters For Coating

To get the optimal solution using genetic algorithms, we take some criteria into consideration. Considering the flow of GAs to search about the optimal solutions given in Figure 6, include initial population size of GAs parameters, the selection function type, and rates of crossover and mutation. Per prior researches, there are no optimums setting values produced as a guideline for GAs parameter combination in order to reach the optimal result. In terms of optimization using MATLAB toolbox, many combinations choices to set values were validated to get the best solution, such as the selection function type (Stochastic uniform, Remainder, Uniform, Roulette).

Table ***9*** lists the best setting values of the GAs parameters to achieve the optimal solution [34].

3.2.4 GAs optimization result and discussion

Considering Eq. (4), which is the optimization fitness function, the limitation constraints of the optimization Eq. (8-10), and the GAs parameter combination of (

Table ***9***), the next Figures (8-10) show the results of implementation using MATLAB toolbox to obtain the optimal value of grain size.

From Figure 8, we can reach the minimum grain size value by setting the optimal cutting condition values to 1.5 × 10^{-3} mbar for Nitrogen pressure, 3.8 × 10^{-3} mbar for Argon pressure, and 5 rpm for the Turntable Speed. Figure 9 indicates the value of the mean fitness at 7.52 µm, with the best fitness value is 7.35 µm.

3.2.5 Evaluation Of Iteration Number For Gas In Coating

Figure 9 illustrates the number of progressive iteration which has been generated by GAs to obtain the minimum value of grain size. The grain size values have decreased sharply until generation number 8, and then fluctuated until 51th to get optimal results (iterations) depending on the parameters setting up the combination.

From above figures and discussion, we conclude that GAs optimization model has reduced the grain size from 7.78µm to reach 7.35µm, with reduction value = 0.43µm compared to the experimental dataset.

3.2.6 GAs model validation.

The validation process was done by comparing the new optimal data to the experimental dataset and analysing the number of progressive iterations for optimal solutions estimated by those approaches. The calculation for validating the results can be made by the previous Eq. (1). To evaluate and prove the results depending on the equation; we need to transfer the obtained values of optimum cutting parameters in GAs into this equation, and then we expect to get the same value between result using MATLAB and transformation process result.

Figure 3 indicates that we can reach the minimum grain size value by setting the optimal cutting condition values to 1.5 × 10^{-3} mbar for Nitrogen pressure, 3.8 × 10-3 mbar for Argon pressure, and 5 rpm for the Turntable Speed. After passing the obtained optimal parameters from MATLAB toolbox into Eq. (1), we found that the output is 7.35µm. By comparing this value with the MATLAB result in Figure 3 we can observe the two values are same.

4. GRAIN SIZE RESULT COMPARISON BETWEEN RSM, GAS, AND EXPERIMENTAL DATA

From the experimental dataset we note that the lowest grain size result is 7.29µm, and the highest is 8.39, within the average = 7.78µm. The lower and upper parameters values for the lowest grain size value are 0.5 for N_2, 4.2 for Ar, and 8 for TT. For the highest grain size value; the parameters values are 0.5 for N_2, 3.8 for Ar, and 8 for TT. The average values of parameters are 1 for N_2, 4 for Ar, and 6.5 for TT.

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Figure 11 compares the result between RSM, GAs, and experimental data. The best optimized grain size value has been reached by using a combined GAs and RSM compare to the experimental dataset with (≈6%) of quite high ratio of percentage and it is very good range near the minimum value and is much better than the average point. RSM has also reduced the grain size value with (≈5%) of quite high ratio of percentage.

5. CONCLUSION

Machining cutting tool performance can be enhanced by implementing the PDV coating process into the tools features. Achieving a great level of surface quality on polished surface requires sufficient engineering creativity for such operational processes to reach the desired specifications and results for the finished products. A proper choice of coating parameters optimization is so important because this better help identify the output of a complex piece of art to its nearer designed optimization objectives. TiN coatings were deposited using PVD sputtering process at different levels of N_2 gas pressure, Argon gas pressure and Turntable Speed. In this study, the experimental matrix was developed based on RSM technique.

Using genetic algorithms, an objective fitness function for three parameters (Nitrogen Pressure (N_2), Argon pressure (Ar), and Turntable Speed (TT)) has been passed and implemented. The results have been discussed and validated by using actual testing data in terms of residual error and prediction interval. The results indicate that the new models are better for grain size than actual data as follows:

- The collected data using CCD technique can be applied to develop the parameters for limitation constraints of genetic algorithms, even with a small amount of data.
- Optimal values for grain size have been developed using GAs with 7.35µm, 1.5 × 10-3 mbar for Nitrogen pressure, 3.8 × 10-3 mbar for Argon pressure, and 5 rpm for Turntable Speed.
- RSM new model could reduce the grain size values, reaching 7.37µm, 1.5 × 10-3 mbar for Nitrogen pressure, 3.8 × 10-3 mbar for Argon pressure, and 5 rpm for Turntable Speed.
- For modeling and optimizing the PVD magnetron sputtering coating process using RSM and GAs, the results show that both techniques are able to reduce the minimum value of coating layer grain size feature in the experimental data.
- The finding proved that the GAs can be used in manufacturing, obviating the need for trial and error and saving time, materials, efforts, and maintenance.

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Table 1: Process of the PVD Coating.

Variables	Unit	Experiment			
		Process 1	Process 2	Process 3	Process 4
		Alcohol Bath	Ion cleaning	TiN deposition	Cooling
• Equipment	-	Ultrasonic bath cleaner	PVD magnetron sputtering machine		
• Sputtering power	kW	-	-	4.0	-
• Substrate temperature	℃	-	300	400	400-60
• Ion source power	kV/A	-	0.24/0.4	0.24/ 0.4	0.24/ 0.4
• Substrate bias voltage	V	-	-200	-200	-200
• N_2 pressure	$\times 10^{-3}$ mbar	-	-	0.16-1.84	-
• Argon pressure	$\times 10^{-3}$ mbar	-	-	3.66-4.34	4.0
• Turntable speed	Rpm	-	4.0	4.0-9.0	4.0
• Duration	Min	20	30	150	60

Table 2: Extreme Operating Window For Respective Process Parameters.

	N_2 pressure [$\times 10^{-3}$ mbar]	Argon pressure [×10-3 mbar]	Turntable Speed [r.p.m]
- Alpha	0.16	3.66	4.0
+alpha	1.84	4.34	9.0

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Table 3: Experimental Run And Result Of TiN Coating Grain Size.

Run	A:N2 pressure [×10 -3 mbar]	B:Argon pressure [×10 -3 mbar]	C: Turntable Speed [rpm]	Grain Size [µm]
1	1.84	4	6.5	8.07
2	1	3.66	6.5	7.22
3	1	4.34	6.5	7.48
4	0.16	4	6.5	7.88
5	1.5	3.8	5	7.65
6	0.5	3.8	5	7.75
7	0.5	4.2	5	7.60
8	0.5	4.2	8	7.29
9	1.5	4.2	5	7.57
10	1	4	9.02	8.10
11	1.5	3.8	8	7.84
12	0.5	3.8	8	8.39
13	1.5	4.2	8	7.65
14	1	4	3.98	7.14
15	1	4	6.5	7.72
16	1	4	6.5	8.02
17	1	4	6.5	8.05

Table 4: Sequential Model Sum Of Squares (SMSS) Analysis For Grain Size Model [Type I].

Source	Sum of Squares	df	Mean Square	F-Value	p-value Prob > F	
Mean vs Total	1017.162	1	1017.162			Suggested
Linear vs Mean	0.467947	3	0.155982	1.584182	0.2409	
2FI vs Linear	0.263257	3	0.087752	0.863062	0.4916	
Quadratic vs 2FI	0.473769	3	0.157923	2.035894	0.1975	Suggested
Cubic vs Quadratic	0.460994	4	0.115249	4.21689	0.1334	Aliased
Residual	0.081991	3	0.02733			
Total	1018.91	17	59.9359			

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Table 5: Lack Of Fit Test For Grain Size Model.

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Linear	1.213992	11	0.110363	3.343384	0.2527	
2FI	0.950735	8	0.118842	3.600251	0.2355	
Quadratic	0.476966	5	0.095393	2.889889	0.2768	Suggested
Cubic	0.015972	1	0.015972	0.483864	0.5586	Aliased
Pure Error	0.066019	2	0.033009			

Table 6: ANOVA For Response Surface Quadratic Model Of The Grain Size [Partial Sum Of Squarestype [III].

Source	Sum of Squares	df	Mean Square	F-Value	p-value Prob > F	
Model	1.204972	9	0.133886	1.726015	0.2421	not significant
A-N_2	1.95E-06	1	1.95E-06	2.51E-05	0.9961	
B-Ar	0.105724	1	0.105724	1.362965	0.2812	
C-Turntable	0.362221	1	0.362221	4.66964	0.0675	
AB	0.122232	1	0.122232	1.57578	0.2497	
AC	0.000804	1	0.000804	0.010365	0.9218	
BC	0.14022	1	0.14022	1.807679	0.2207	
A^2	0.011108	1	0.011108	0.143196	0.7163	
B^2	0.34257	1	0.34257	4.416304	0.0737	
C^2	0.095909	1	0.095909	1.236434	0.3029	
Residual	0.542985	7	0.077569			
Lack of Fit	0.476966	5	0.095393	2.889889	0.2768	not significant
Pure Error	0.066019	2	0.033009			
Cor Total	1.747957	16				

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Table 7: ANOVA For Response Surface Reduced Quadratic Model [Partial Sum Of Squares - Type III].

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	1.193061	7	0.170437	2.764361	0.0788	significant
A-N_2	1.95E-06	1	1.95E-06	3.16E-05	0.9956	
B-Ar	0.105724	1	0.105724	1.714767	0.2228	
C-Turntable	0.362221	1	0.362221	5.874942	0.0384	
AB	0.122232	1	0.122232	1.982512	0.1927	
BC	0.14022	1	0.14022	2.274268	0.1658	
B^2	0.416315	1	0.416315	6.752316	0.0288	
C^2	0.127269	1	0.127269	2.06421	0.1846	
Residual	0.554897	9	0.061655			
Lack of Fit	0.488878	7	0.06984	2.115757	0.3581	not significant
Pure Error	0.066019	2	0.033009			
Cor Total	1.747957	16				

Table 8: PI And RE Of The TiN Coating Grain Size For RSM Model.

Input parameters			Grain Size						
A: N_2 pressure [$\times 10^{-3}$ mbar]	B: Argon pressure [$\times 10^{-3}$ mbar]	C: Turntable speed [rpm]	Predict (µm)	95% PI low (µm)	95% PI high (µm)	Actual (µm)	Error (µm)	Error (%)	Predictive Accuracy (%)
0.7	3.85	5.6	7.77	7.17	8.36	8.19	-0.42	5.4	96.09 %
1.1	3.95	7.4	8.01	7.42	8.61	7.88	0.13	1.62	96.09 %
0.9	4.05	6.2	7.86	7.25	8.46	7.49	0.37	4.71	96.09 %

Table 9: Combination of GAs parameter for coating parameters.

Setting Type	Setting Value / Function Type
Population size	100
Scaling function	Rank
Selection function	Roulette wheel
Crossover function	Heuristic
Crossover rate	0.8
Mutation function	Uniform
Mutation rate	1.0

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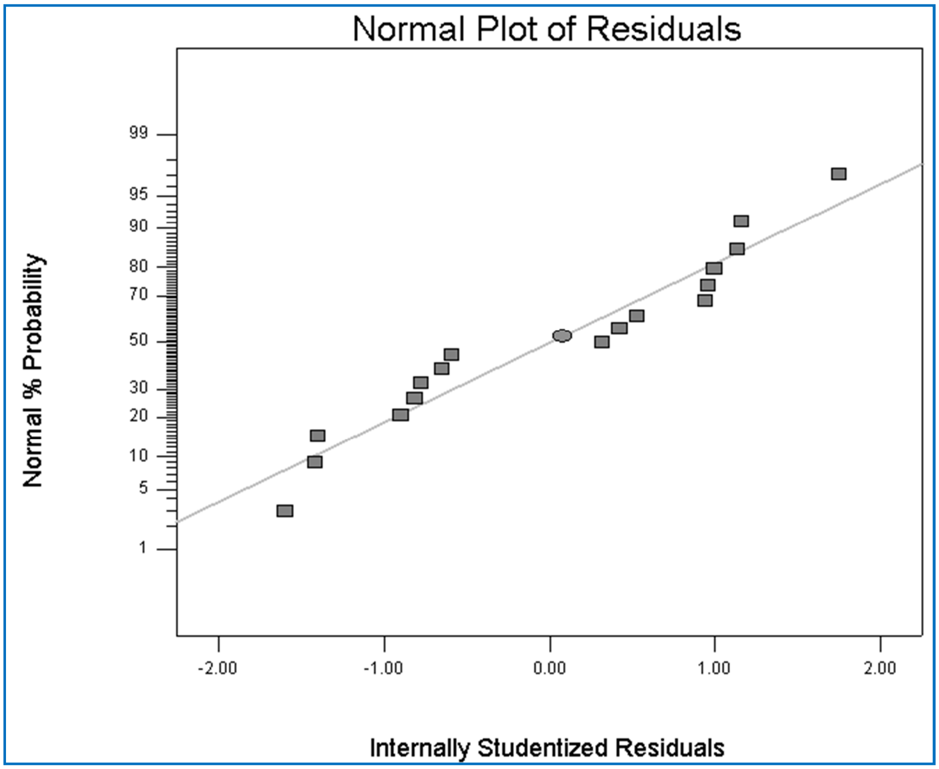

Figure 1: Normal Probability Plot Of Residual For TiN Coating Grain Size.

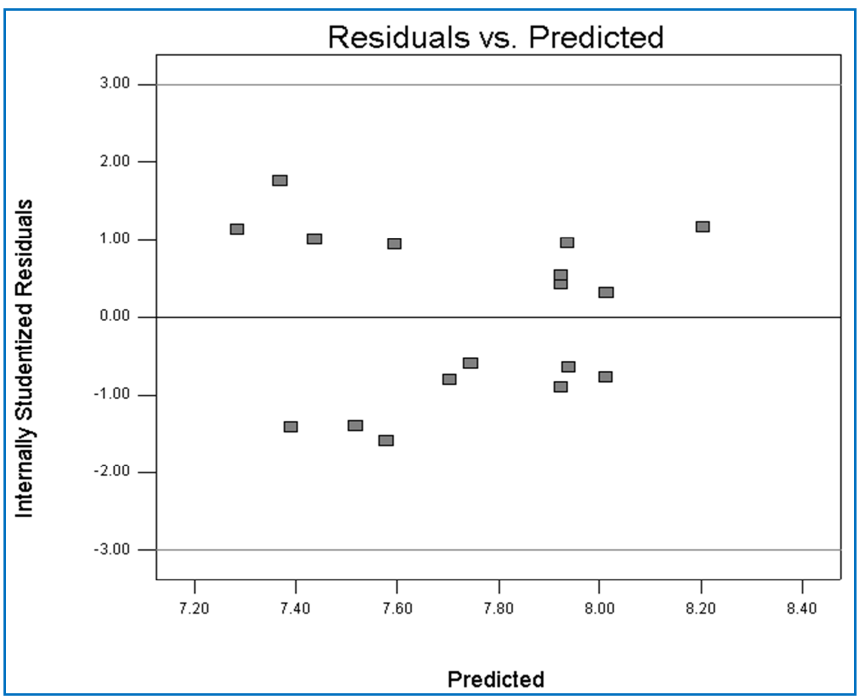

Figure 2: Plot Of Residual Versus Predicted Response For TiN Coating Grain Size.

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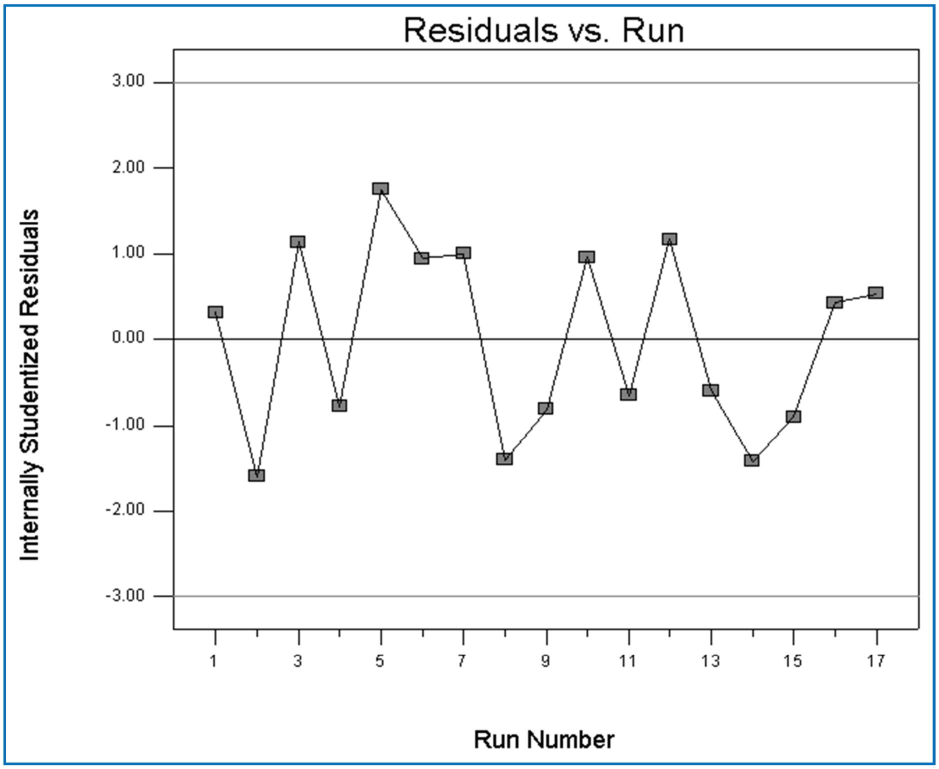

Figure 3: Plot Of Residual Versus Run Number For TiN Coating Grain Size.

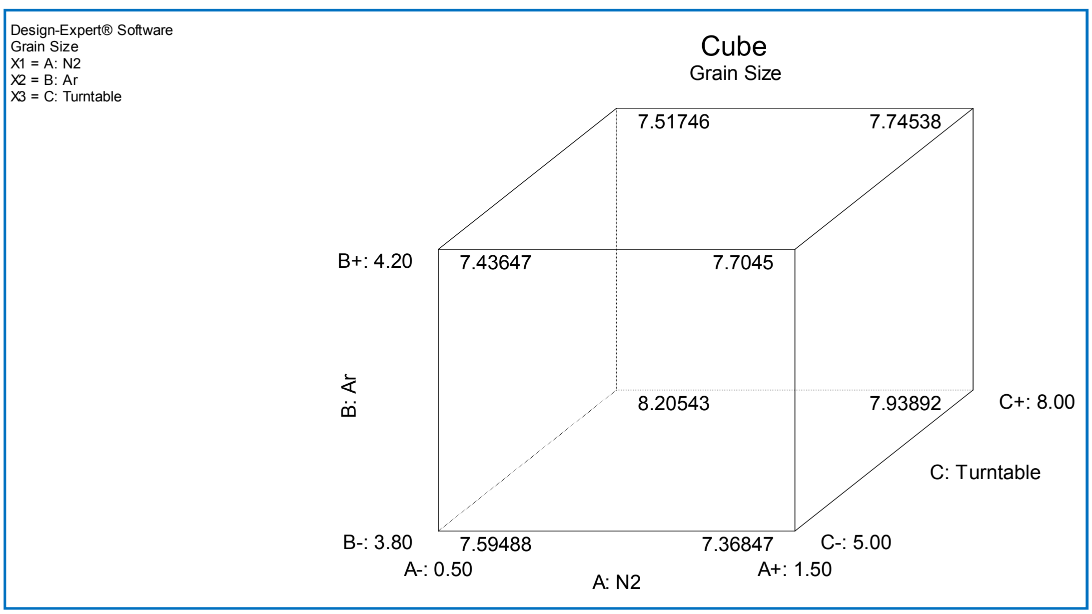

Figure 4: Behavior Of RMSE Relative To Interaction Of ABC Factors.

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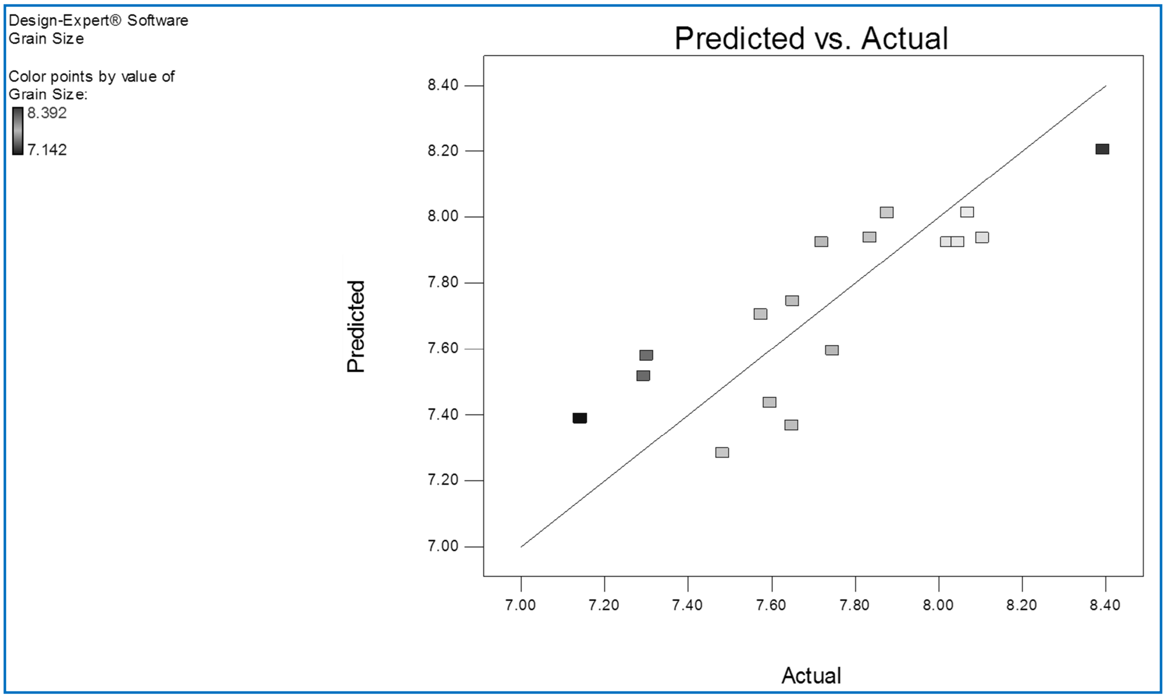

Figure 5: Plot Of Residual Versus Predicted Response For TiN Coating Grain Size.

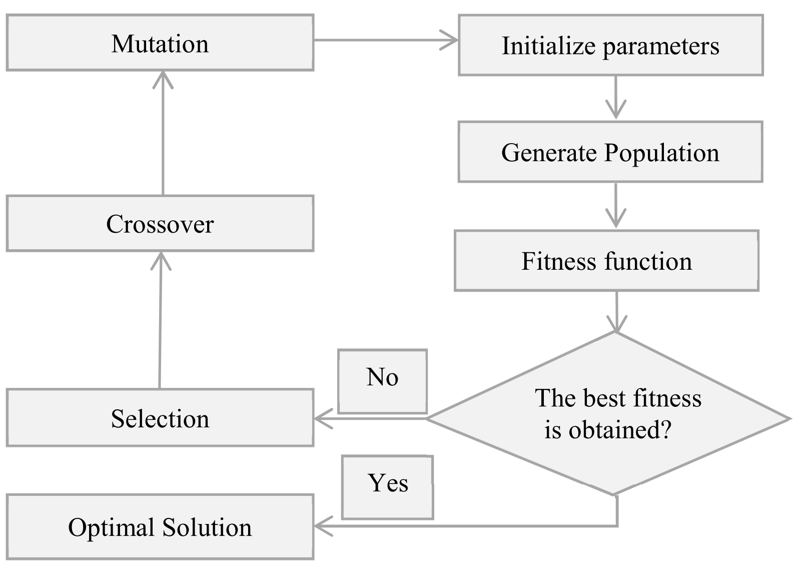

Figure 6: Flow Of Searching Optimal Solutions Of GAs [34].

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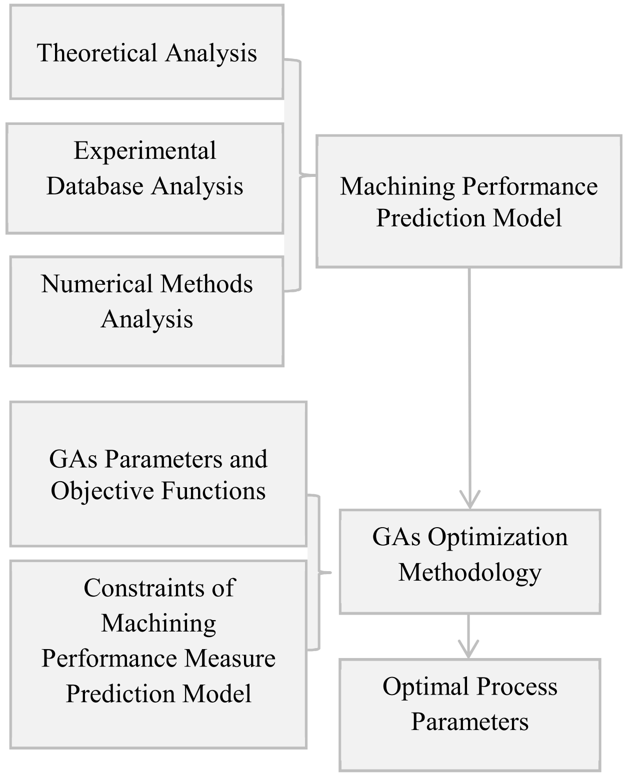

Figure 7: GAs Optimization Methodology.

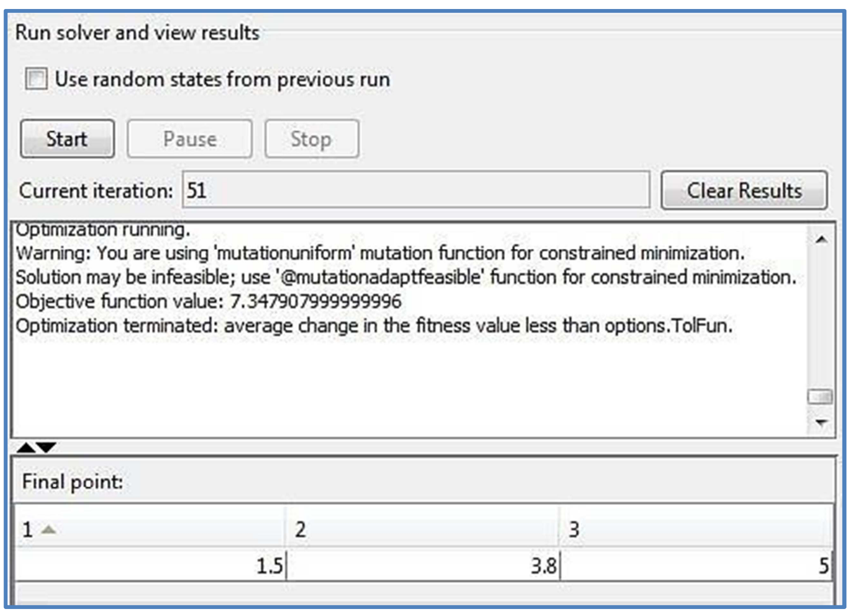

Figure 8: GAs Optimal Solutions For Grain Size.

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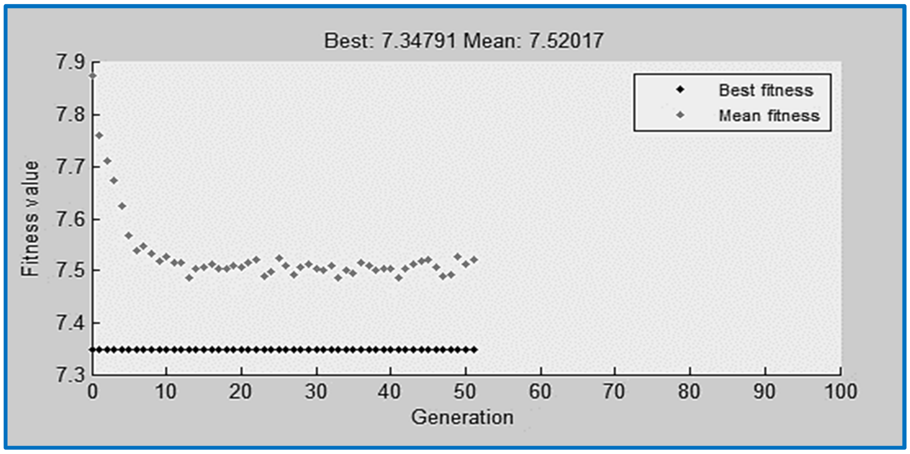

Figure 9: GAs Plot Functions For The Optimal Solution For Grain Size.

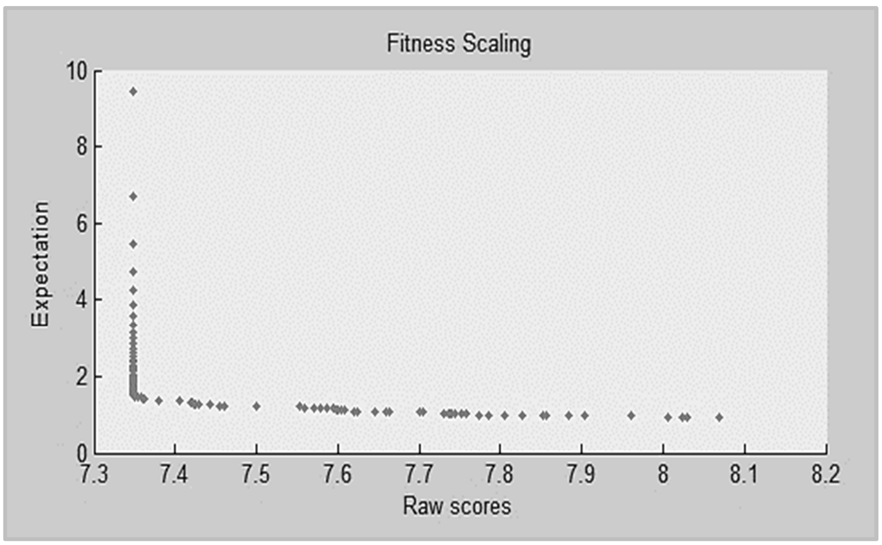

Figure 10: Fitness Scaling For Grain Size.

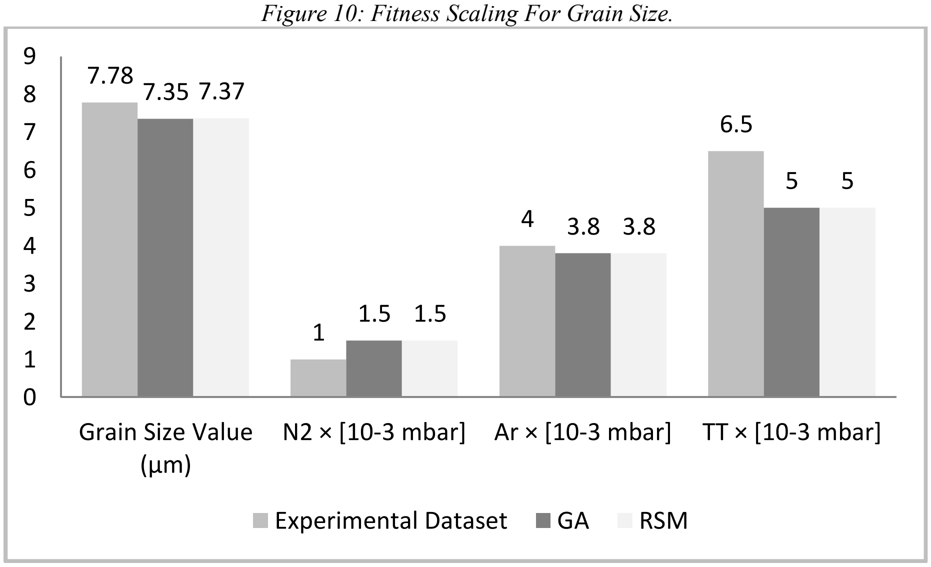

Figure 11: Result Comparison Values Between RSM, GAs, And Average Experimental Data.