

# INTELLIGENCE INTEGRATION OF PARTICLE SWARM OPTIMIZATION AND PHYSICAL VAPOUR DEPOSITION FOR TiN GRAIN SIZE COATING PROCESS PARAMETERS

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## ABSTRACT

Due to increasing complexity of industrial production, decisions regarding selection of coating parameters importantly influence the level of production, 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<sub>2</sub>), argon gas pressure (Ar), and Turntable Speed (TT), while thin film grain size of titanium nitride (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, a developed quadratic polynomial model equation which represents the process variables and coating grain size was used in order to optimize the coating process parameters, particle swarm optimization (PSO) was 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 response surface methodology (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, PSO could get the best lowest value for grain size than experimental data with reduction ratio of ≈6%.

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

## 1. INTRODUCTION

In high speed machining, temperatures on the cutting tip may exceed 800 °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 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].

Two main techniques in depositing coating on cutting tool are physical vapor deposition (PVD) and chemical vapor deposition (CVD). The main difference between the both processes is the vapour source. The PVD process uses a solid target as a source material which vapours in atom particle to be a thin film coating. However, the CVD process uses a chemical source as coating material. In the PVD coating process, the sputtered particle from harder material embedded on the cutting tool in presence of reactive gas. A process in PVD technique called magnetron sputtering is well-known technology used in hard coatings industry due to ability to sputter many hard materials such as titanium to be coated to cutting tool.

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 [5-9]. 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 [14-17], ANFIS [18] have been also used to predict coating performance, and Genetic algorithms (GAs) which have been used to optimize the process parameters for achieving the desired grain size fusion zone [19, 20]. However, some limitations of the approaches have been discussed. The Taguchi approach has difficulties detecting the interaction effect of a nonlinear process [21] and the full factorial method is only suitable for optimization purposes [22]. A neural network needs a large amount of training data to be robust [23], and a significant amount of data as well as powerful computing resources are necessary [24]. However, PSO is an effected technique which has been using widely in optimization. A brief summary of some previous related researches is indicated in Table 1 including modeling and optimization techniques.

Researchers use RSM to study relationships between measured response functions [25- 27]. RSM is a collection of mathematical and statistical methods used to model and analyze significant parameters that affect the output responses [28].

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, particle swarm optimization (PSO) has been adopted to minimize the coating grain size under the constraints of Argon pressure (Ar), Nitrogen pressure ( $N_2$ ) and Turntable speed (TT).

This paper is organized as follows: Sect. 2 includes experimental design and result characterization and analysis. Sect. 3 presents modeling methodologies, brief introduction and analysis to PSO algorithm, and The PSO optimization setup and programming. Optimization

result and discussion are provided in Sect. 4. Sect. 5 concludes the paper.

Table 1: Related Researches about Modeling and Optimization Techniques.

Technique	Summary
PSO	<ul style="list-style-type: none"> <li>- In turning operation: PSO model was found to be capable of better predictions of dimensional deviation within the trained range [29].</li> <li>- For the tool wear prediction in end milling, the average error of PSO model prediction equals 1.62 % for a learning base and 15.94 % for a testing base, which means that developed model is suitable for prediction of tool wear [30].</li> <li>- Maximal bonding strength of plasma spraying nanostructured Al<sub>2</sub>O<sub>3</sub>-13%TiO<sub>2</sub> (mass fraction) coating was optimized based on PSO algorithm. Result was significantly better than result of orthogonal optimization. It provided a clear basis for selecting the best process parameters of plasma spraying nanostructured [31].</li> <li>- PSO provided minimum values of surface roughness and the corresponding optimal machining parameters, namely, cutting speed, feed rate and depth of cut [32].</li> <li>- Sputtering and deposition Parameters Optimization of RF Magnetron Sputtering Process to produce the desirable ZnO thin film properties [33].</li> </ul>
PSO & GAs	<ul style="list-style-type: none"> <li>- It is found that PSO algorithm was the best implemented. Also, the PID controller parameters obtained from PSO algorithm gives better tuning result than the others [34].</li> <li>- In Ti coating processes it could increase hardness and resistance to corrosion and wear up to 17 % [35].</li> </ul>
PSO based ANNs (IPSONNOS)	<ul style="list-style-type: none"> <li>- The observed results have shown a good agreement between the predicted values by proposed IPSONNOS algorithm and experimental measurements, with 94% of correlation between experimental results and IPSONNOS targets [36].</li> <li>- Results of the PSO prediction show close matching between the model output and directly measured hardness [37].</li> </ul>
Combine full factorial DOEs, RSM (PSO)	<ul style="list-style-type: none"> <li>- Combined full-factorial DOEs with RSM modeling and PSO to optimize the parameters during turning of tungsten–copper alloy [38].</li> </ul>
ANNs	<ul style="list-style-type: none"> <li>- It could estimate (hardness of titanium thin-film layers as protective industrial tools) [39].</li> <li>- It could predict tool wear and surface roughness patterns [40].</li> </ul>
GSA	<ul style="list-style-type: none"> <li>- The algorithm performance was acceptable in optimizing the Parameter, and it could be serve as an improvement from the traditional practice in the fabrication process [41].</li> <li>- GSA indicated its capability in optimization end milling process through its speed and accuracy with minimal number of iterations [42].</li> </ul>
GA, Tagushi, ANNs	<ul style="list-style-type: none"> <li>- The performance of the integrated procedure is better than that of Taguchi methods and traditional approach [43].</li> <li>- Combining all methods possessing the functions of modeling and optimization for a thin film in the vacuum sputtering process can be used to solve the process parameters design problems [44].</li> <li>- The proposed procedure searched for the optimal process parameters for a TiO<sub>2</sub> thin film of the vacuum sputtering process. And can be used to solve the optimal process parameters design problem [45].</li> </ul>
ANNs, GA	<ul style="list-style-type: none"> <li>- NNs model can explain the processing effects of process variables in the ZnO:Ga thin films. The optimal process conditions are predicted using the GA for optimized recipes of ZnO:Ga thin film [46].</li> <li>- The techniques were proven to be an effective methods to optimize the properties of ITO/Al/ITO multilayer films [47].</li> </ul>
RSM, GA	<ul style="list-style-type: none"> <li>- The models were applied successfully in analyzing the effect and determining the optimum machining parameters on different surface roughness parameters [48].</li> </ul>

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. As shown in Figure 1, 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.

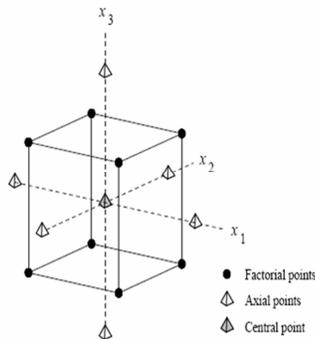


Figure 1: RSM Central Composite Design for Three Factors

Table 2: Extreme Operating Window for Respective Process Parameters.

	+Alpha	- Alpha
<b>N<sub>2</sub> pressure</b> [×10 <sup>-3</sup> mbar]	0.16	1.84
<b>Argon pressure</b> [×10 <sup>-3</sup> mbar]	3.66	4.34
<b>Turntable Speed</b> [r.p.m]	4.0	9.0

**2.2 Material and Method.**

The experiment was run in unbalanced PVD magnetron sputtering system made by VACTEC Korean model VTC PVD 1000 as shown in Figure 2. 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 3.

In this process, N<sub>2</sub> pressure, Ar pressure, and turntable speed were selected as variables.



Figure 2: PVD Magnetron Sputtering Machine.

**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. As shown in Figure 3, the AFM XE-100 model was used in characterizing and analyse the surface image for 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<sup>2</sup>) 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 4.



Figure 3: AFM XE-100 Model

Table 3: 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	°C	-	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 <sub>2</sub> pressure	×10 <sup>-3</sup> mbar	-	-	0.16-1.84	-
• Argon pressure	×10 <sup>-3</sup> 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 4: Experimental Run and Result of TiN Coating Grain Size.

Run	A:N <sub>2</sub> pressure [×10 <sup>-3</sup> mbar]	B:Argon pressure [×10 <sup>-3</sup> 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

**2.4 Effect of Parameters on TiN Coating grain size.**

**2.4.1 Turntable speed**

Figure 4 (a) and Figure 4 (b) show the AFM images of the grain size with different turntable speeds of 4.0 rpm and 9.0 rpm, respectively. As shown in Figure 4 (a), most of the grain size lengths are smaller compared to the grain size lengths in

Figure 4 (b). [49] Used Electron Beam-Physical Vapor Deposition (EB-PVD) to fabricate yttrium-stabilized zirconia films and reported that an increase of substrate rotation speed from 0 rpm to 20 rpm has increased the columnar grain size and thin film width. Besides that, an increase of rotation speed also increases the porosity of the grain size.

2.4.2 Argon pressure

The grain size changes is supported by the AFM images as indicated in Figure 5 (a) and Figure 5 (b), with Argon pressure at  $3.8 \times 10^{-3}$  mbar and  $4.2 \times 10^{-3}$  mbar, respectively. Most of the grain lengths as indicated in Figure 5 (a) are larger if compared to the grain lengths in Figure 5 (b). [50] In study of Argon pressure effect to Mo films using direct current pulse magnetron sputtering also reported that films sputtered at low Argon pressure had greater grain size and good crystallization. On the other hand, the grain size became smaller and bad crystallization in sputtering at high Argon pressure.

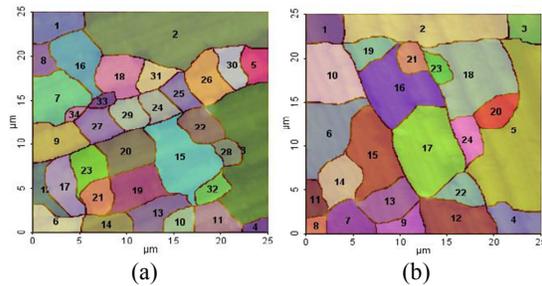


Figure 4: AFM Images of the Grain Size with Different Turntable Speeds (a) 4.0 Rpm, And (b) 9.0 Rpm.

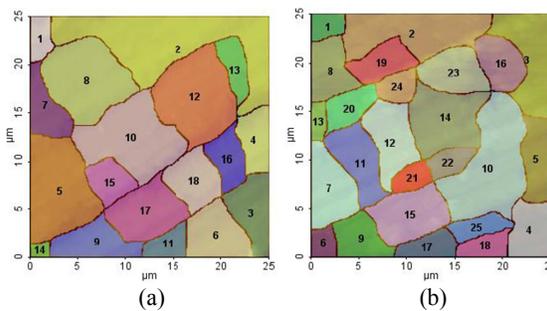


Figure 5: AFM Images of the Different Grain Size With Argon Pressure (a)  $3.8 \times 10^{-3}$  Mbar, And (b)  $4.2 \times 10^{-3}$  Mbar

3. MODELING METHODOLOGIES:

3.1 Determination of polynomial equation to Using RSM model of TiN coating grain size

(From our previous study in [51], 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 have been analyzed to select the appropriate model. Based on that, the quadratic polynomial equation may represents the

relationship of TiN coating grain size and input variables.

Initial ANOVA analysis for response surface quadratic model to grain size has been done and indicated that the developed quadratic model is not significant relative to the noise due to natural variation for that particular process such as the variability of the measuring instrumentation during the coating process. However, this insignificant term used to improve upon the insignificance of the model using the model reduction method with manual elimination method to get the significant model. By using ANOVA to improve response surface reduced quadratic model the model became strongly significant. 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:

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

where  $PN_2$  is nitrogen pressure,  $PAr$  is argon pressure, and  $\omega TT$  is Turntable Speed.

In the same previous study [51], a validation process was done using residual error and prediction accuracy. 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 [52-57]. Equation for residual error,  $e$  as the following:

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

where  $vp$  is predicted value and  $va$  is actual value.

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

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

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

The validation investigated 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 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 conclude that the model is good enough to predict the TiN coating grain size.

Figure 6 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.

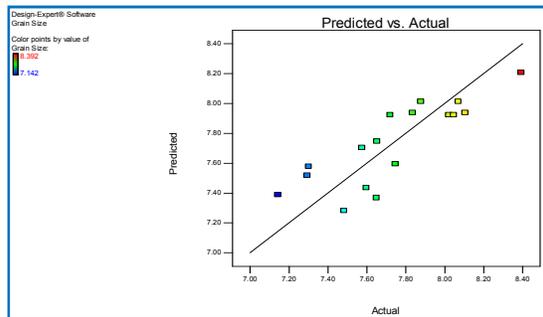


Figure 6: Plot Of Residual Versus Predicted Response for TiN Coating Grain Size.

### 3.2 Bio-inspired particle swarm optimization Algorithm

PSO is a Population based effective technique proposed by [58], it is a stochastic and heuristic algorithm inspired by social behavior of fish schooling or bird flocking. As a soft computing technique, POS is a computational method which has been used to optimize a various engineering problems by iteratively improving candidate solutions when a particles moving in problem space toward the best solution depending on a fitness mathematical formula while updating their

positions and velocities [37]. The solution starts with setting a population of random solutions and updating generations while searching for optima. The potential solutions (particles), fly through the problem space by following the current optimum particles [34]. Iterative movement for each particle is influenced by its local best known position, and compared with best known positions in overall search space (global), which are updated as better positions are found by other candidates particles resulting to move the swarm toward the best solutions [30].

PSO has many advantages and located on the top level of optimization pyramid as one of the most appropriate algorithms, high quality solution, calculation time is short, stable convergence characteristics [34], and can solve question expressed by real number. Compare to Genetic algorithms; PSO has fewer parameters make implementation easier and converges faster [59], evolutionary operators is not complicated such as crossover and mutation as in GAs. On the other hand, PSO is also considered superior to the standard backpropagation algorithm of feed forward artificial neural networks, as it does not require gradient information and the prescription of differentiable functions [60]. In general, in addition to improvement of solving capabilities for complex problems, PSO also has a high convergence speed and good generalization capabilities for a wide variety of problems [61]. The potential of the PSO approach has been demonstrated by its successful application to optimization problems such as function minimization [62-67].

It is demonstrated that PSO gets better results in a cheaper way compared with other techniques. One version, with slight variations. It can be used for approaches across a wide range of applications, as well as for specific applications with specific requirement [34]. As a result, PSO can be used to optimize problems that are irregular, noisy and changing over time.

#### 3.2.1 PSO (Algorithm analysis)

PSO does not create an optimal solution, but searches for it [68]. From PSO mechanism, two main points are important, position and velocity of each particle, the solution starts from creating initial particles with randomly positions with  $N$

decision parameters, these positions and velocity are defined as  $X_{i(n)} = (x_{i1}, x_{i2}, \dots, x_{in})$  and  $V_{i(n)} = (v_{i1}, v_{i2}, \dots, v_{in})$ , respectively. For each individual particle (*i-th* particle), the best tracking position in its history is defined as  $P_{i(n)} = (p_{i1}, p_{i2}, \dots, p_{in})$ , while the global position tracking among all particles is defined as  $P_{g(n)} = (p_{g1}, p_{g2}, \dots, p_{gn})$ . After finding the two best values (individual and global), the velocity and position of particle is updated as following:

$$v_{new} = w \times v_{old} + c_1 \times r_1(p_{in} - x_{in}) + c_2 \times r_2(p_{gn} - x_{in}) \quad (4)$$

where  $w$  is the inertia weight;  $r_1$  and  $r_2$  are random numbers between  $[0,1]$ ;  $c_1$  and  $c_2$  are called cognition and social constants, respectively [37]. Generally are learning factors;  $c_1$  refers to a self-recognition component coefficient;  $c_2$  refers to the social component coefficient,  $c_1$  and  $c_2$  are a positive constant which pull the particles toward the global best position.  $c_1$  and  $c_2$  as constants acceleration parameters, play important roles and pulling the particles toward the global best position. The inertia weight  $w$  are usually utilized in velocity equation as follow:

$$w = \frac{w_{max} - [(w_{max} - w_{min}) \times iter]}{iter_{max}} \quad (5)$$

where  $w_{max}$  is the initial weight, usually chosen as a large value less than 1;  $w_{min}$  is the final weight;  $iter$  and  $iter_{max}$  are the iteration numbers for current and the maximum iteration. A suitable value selection for the inertia weight  $w$  usually provides balance between global and local exploration abilities and consequently a reduction on the number of iterations required to locate the optimum solution. [69]. A global search is enabled by large  $w$ , whereas a small  $w$  enables a local search. Gradually decreasing the weight starting from large value get better global exploration of the search space, and linearly decreasing it to get more refined solutions, thus a time decreasing inertia weight value is used.

From Eq. (4), to keep a position tracking, a particles movement is done considering its own past experience, i.e., the memory of its last best local position, and the experience of the most successful particle in the swarm's population. The new particle position is then determined using the

previous position and the new velocity and can be written as

$$x_{in\_new} = x_{in\_old} + v_{new} \quad (6)$$

### 3.2.2 Grain size fitness (objective) function

A fitness function for PSO 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:

```
fitness_Grain=-72.8553-(4.9435.*init_sw(:,1))+(37.9109.*init_sw(:,2))+(2.4602.*init_sw(:,3))+(1.2360.*init_sw(:,1)).*init_sw(:,2)-(0.4413.*init_sw(:,2)).*init_sw(:,3)-(4.5898.*init_sw(:,2).^2)-0.04511.*init_sw(:,3).^2);
```

(7)

### 3.2.3 PSO parameters limitation constraints optimization for coating process

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

#### 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

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

### 3.2.4 Swarm optimization setup and programming

Using MATLAB, The optimization model has been implemented. Referring to experimental data (Table 4), Figure 7 summarizes description of model simulation parameters. In addition, Figure 8 and Figure 9 Explain the PSO algorithm simple flow chart and pseudocode [70], respectively.

## 4. OPTIMIZATION RESULT AND DISCUSSION

### 4.1 PSO Programming result

Considering Eq. (1), which is the optimization fitness function, the limitation constraints of the optimization Eq. (8-10), and the

PSO model parameters setting in Figure 7 under three different constraints ( $N_2$ , Ar, TT...), the next Figures (10 and 11) show the results of implementation using MATLAB toolbox to obtain the optimal value of grain size.

**Inputs**

- Initialize network parameters ( $N_2$ , Ar, TT).
- Initialize PSO parameters, Number of particles ( $N=10$ ), Learning factors ( $c1=c2=2$ ), Dimension of particles ( $D=3$ ), Stopping condition ( $Iter.=20$ ), Initial weight ( $wmax=0.9$ ), & Final weight ( $wmin=0.4$ ).

**Constraints**

- $N_{2min}=0.5$ ,  $N_{2Rmax}=1.5$ ;  $Armin=3.8$ ,  $Armax=4.2$ ;  $TTmin=5$ ,  $TTmax=8$ ;

**Main objective of algorithm**

- Finding the best optimized coating grain size under the constraints of  $N_2$ , Ar, and TT.

**Outputs**

- Given optimal solution best global fitness ( $min.grainsize$ ) and the best global position ( $N_2$ , Ar, and TT).

Figure 7: Model Of Minimize Coating Grain Size Programming

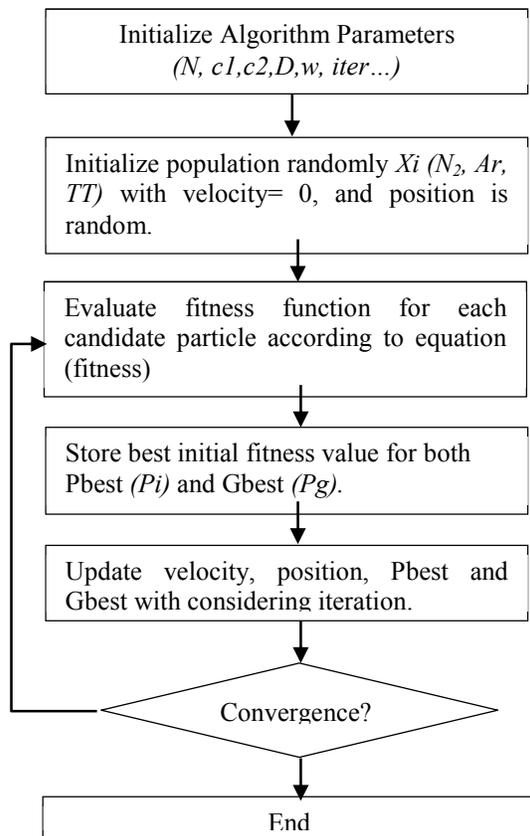


Figure 8: PSO Algorithm Simple Flow Chart.

- 1: Initialize PSO algorithm parameters, Number of particles ( $N=10$ ), Learning factors ( $c1=c2=2$ ), Particles dimension ( $D=3$ ), Stopping condition ( $Iter.=20$ ), Initial large weight ( $wmax=0.9$ ), & Final small weight ( $wmin=0.4$ ).
- 2: Initial populations of particles  $Xi = (N_2, Ar, TT)$  with random positions and zero velocities  $Vi$ .
- 3: Comparing and modifying the each particle position with constraints
- 4: **if** ( $Xi > \text{max. constraints}$ ) **then**
- 5:  $Xi = \text{max. constraints}$
- 6: **end if**
- 7: **if** ( $Xi < \text{min. constraints}$ ) **then**
- 8:  $Xi = \text{min. constraints}$
- 9: **end if**
- 10: Evaluate the initial fitness values  $f(Xi)$  of each candidate particle according to Eq. (1),
- 11: Store the best initial fitness value and both of Pbest ( $Pi$ ) and Gbest ( $Pg$ ).
- 12: **while**  $i < \text{iter}$  **do**
- 13:  $r1 = \text{rand}()$ ;  $r2 = \text{rand}()$ ;
- 14: Calculate  $w$  according to Eq. (5),
- 15: Update  $Vi$  according to Eq. (4),
- 16: Update  $Xi$  according to Eq. (6),
- 17: Comparing and modifying the position of each particle with constraints
- 18: Repeat steps 3 – 9
- 19: for each particle, Evaluate a new fitness values  $f(Xi)$ .
- 20: Compare each particle's fitness evaluation with the current particle's to obtain the individual best position.
- 21: Compare fitness evaluation with the population's overall previous best to obtain the global best position.
- 22: **end while**
- 23: Given optimal solution best global fitness ( $min.coating$ ) and the best global position ( $N_2$ , Ar, TT).

Figure 9: PSO Algorithm Pseudocode.

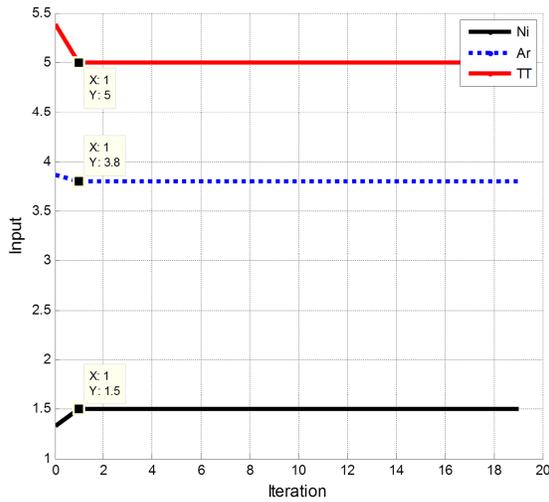


Figure 10: the Behavior of Constraint Parameters That Impact the Coating Grain Size

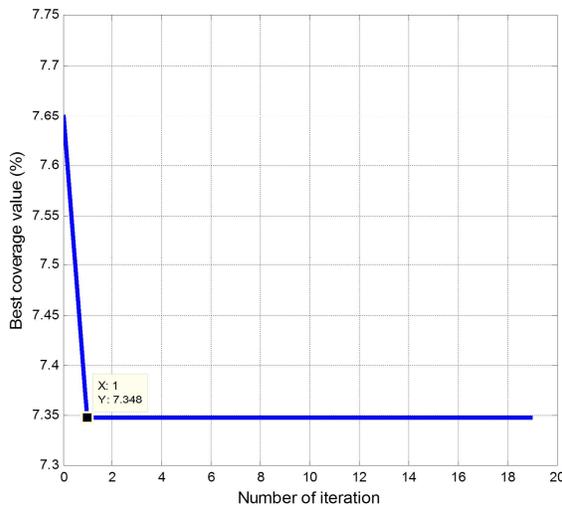


Figure 11: The Behavior of the Fitness Function-Grain Size With Change In The Constraint Parameters

Figure 10 indicates the impact of parameters on the coating grain size. The most important parameters for grain size, where the Ar and TT are minimum. However, when the N<sub>2</sub> value increases to maximum, the grain size also increases.

As discussed in section (3.1) The ANOVA analysis shows that only turntable speed term and quadratic term of Argon pressure are the significant factors. By using PSO, this paper has reported same analysis and put the nitrogen pressure as the lowest effecting parameter in coating grain size. We can reach the optimal minimum grain size value by setting the optimal coating condition values to  $1.5 \times$

$10^{-3}$  mbar at maximum Nitrogen pressure,  $3.8 \times 10^{-3}$  mbar at minimum Argon pressure, and 5 rpm for the minimum Turntable Speed. Figure 9 indicates the best fitness value is  $\approx 7.35 \mu\text{m}$ .

From above figures and discussion, we conclude that PSO optimization model has reduced the grain size from  $7.78 \mu\text{m}$  to reach  $7.35 \mu\text{m}$ , with reduction value =  $0.43 \mu\text{m}$  compared to the experimental dataset.

#### 4.2 PSO model validation.

The validation process was done by comparing the new optimal data to the experimental dataset. 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 PSO into this equation, and then we expect to get the same value between result using MATLAB and transformation process result.

Figure 10 indicates that we can reach the minimum grain size value by setting the optimal cutting condition values to  $1.5 \times 10^{-3}$  mbar for Nitrogen pressure,  $3.8 \times 10^{-3}$  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  $7.35 \mu\text{m}$ . By comparing this value with the MATLAB result in Figure 3 we can observe the two values are same.

From the experimental dataset we note that the lowest grain size result is  $7.29 \mu\text{m}$ , and the highest is  $8.39$ , within the average =  $7.78 \mu\text{m}$ . The lower and upper parameters values for the lowest grain size value are 0.5 for N<sub>2</sub>, 4.2 for Ar, and 8 for TT. For the highest grain size value; the parameters values are 0.5 for N<sub>2</sub>, 3.8 for Ar, and 8 for TT. The average values of parameters are 1 for N<sub>2</sub>, 4 for Ar, and 6.5 for TT.

As a result, the best optimized grain size value has been reached by using a PSO compare to the experimental dataset with ( $\approx 6\%$ ) of quite high ratio of percentage and it is very good range near the minimum value and is much better than the average point.

#### 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 Nitrogen gas pressure, Argon gas pressure and Turntable Speed. In this study, PSO algorithm was taken, the result proves high industrial significance since it can be easily integrated into the coating process for manufacturing.

The ability to predict coating process even before machining based on the input parameters, such as nitrogen pressure, Argon pressure, and turntable speed, will give manufacturers an advantage in terms of time savings and maintenance cost and less rejects.

Using particle swarm optimization, an objective fitness function for three parameters (Nitrogen Pressure (N<sub>2</sub>), 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, prediction interval, and optimized value validation with objective function. 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 PSO, even with a small amount of data.
- Optimal values for grain size have been developed using PSO with 7.35 $\mu$ m, 1.5  $\times$  10<sup>-3</sup> mbar for Nitrogen pressure, 3.8  $\times$  10<sup>-3</sup> mbar for Argon pressure, and 5 rpm for Turntable Speed.
- The results show that PSO are able to reduce the minimum value of coating layer grain size feature in the experimental data.
- The finding proved that the PSO can be used in manufacturing, obviating the need for trial and error and saving time, materials, efforts, and maintenance. Therefore, it has proven to be acceptable in the sputtering process parameter optimization

## ACKNOWLEDGEMENT

The authors are grateful to Universiti Teknikal Malaysia Melaka (UTeM) for grant no. PJP/2013/FTMK(14A)/S01218.

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