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PARTICLE SWARM OPTIMIZATION ALGORITHM TO ENHANCE THE ROUGHNESS OF THIN FILM IN TIN COATINGS

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ABSTRACT

Nowadays, lots of disciplines require optimization to determine optimal parameters to accomplish top quality services which include parameters optimization of thin film coating. Modification of sharp tool characteristics and costs are two primary matters in the procedure of Physical Vapour Deposition (PVD). The purpose of this study is to figure out the optimal parameters in PVD coating process for better thin-film roughness. Three input parameters are chosen to describe the solutions over the target data, such as Nitrogen gas pressure (N2), Turntable speed (TT), and Argon gas pressure (Ar), although the surface roughness had been chosen being a result response of the Titanium nitrite (TiN). Atomic Force Microscopy (AFM) tools were applied to describe the roughness of coating layer. Within this research, a process of modelling using Response Surface Method (RSM) was applied for surface roughness of Titanium Nitrite (TiN) coating to get a best result. Particle Swarm Optimization (PSO) was applied as an optimization technique for the coating process to enhance characteristics of thin film roughness. In validation process, different experimental runs of actual data were conducted. It was found that residual error (e) is less than 10, to indicate that the model can accurately predict the surface roughness. Also, PSO could reduce the value of coating roughness at reduction of ≈ 48% to get a minimum value compared to actual data.

Keywords: optimization, modelling, PVD, PSO, roughness, RSM, TiN coating.

INTRODUCTION

When the cutting tip process starts in a high speeding machine the temperature reaches 800 °C. This situation will cause tool wear, therefore decreasing cutting tool execution. Therefore, high strength wear of cutting tool is required in order to trade with this essential situation, and to guarantee a much better tool life with minimizing the machine charge immediately. Thin film coating improves cutting tools performance. The most important aim of coated is always to increase the surface properties whereas keeping its bulks properties. To improve tool wear, coating tool is 40 times more efficient in tool wear impedance is definitely in comparison with the uncoated tool [1]. Like wear resistance, roughness of coatings as coating of Titanium Nitride (TiN), were typically chosen by metal cutting industry because they affect coating performances. Two prime methods of the depositing coating upon cutting tools become the physical vapor deposition (PVD) and chemical vapor deposition (CVD). The PVD strategy runs on a sturdy target a resource material where vaporizes an atom to form a thin film over the material. Nevertheless, the CVD employs a chemical resource for coating. In the PVD, particles from the rough materials are sputtered on the tool with helping of reactive gas. A magnetron sputtering strategy is a popular technology in PVD in the coatings industry; also it's qualified to separation several of solid items, like the titanium to coat cutting tools. In PVD coating operation, lots of aspects could be reported to get important effects in the coating properties, such as the thin film roughness [2] [3]. Coating roughness plays an important rule and determines the quality of machining performances. It influences the level of rubbing and tools pick up the conduct of cutting tool after sliding with workpiece materials [4] [5]. Many of studies reported that the Nitrogen gas pressure (N_2), turntable speed (TT), and argon gas pressure (Ar) significantly affect surface roughness and morphology [6]. Modeling is used to anticipate the value of coating performance and to signify the optimal formula in input parameters to get better results. Lots of strategies are being used in coating modeling. Taguchi [7], full factorial, and RSM [8] are an experimental based method reported in designing models with a lower limit of experimental data [9]. Fuzzy logic [10], neural network [11], and ANFIS [12] are Intelligence-based approaches applied for coating performance prediction. Nevertheless, some constraints of the techniques are discussed already. The Taguchi strategy has difficulties detecting the communication influence of a nonlinear procedure [13]; also, the total factorial technique will only be suitable with optimal purposes [14]. A neural network requires a high level of training data to become robust [15], and also significant volumes of data along with efficient computing resources are required [16]. RSM is applied to learn relationships and interactions among certain measured responses [17] [18]. RSM involves using different mathematical and statistical methods to perform analysis and designing significant parameters that play important roles in the output responses [19] [20].

However, optimization algorithms are important to solve complex problem [21] [22]. PSO is an efficient technique which has been widely used in solving machining and coating optimization problems [23] [24].

Accordingly, in this work, the PSO system is used to optimize the roughness of TiN coating surface.

In this paper, RSM approach was used to get the most significant parameters which affect the roughness of thin film coating. Optimization of the coating parameters was done using PSO algorithm. This research is prepared as follows: Section 2 contains experimental design and result characterization and analysis. Section 3 presents modelling methodologies, validation and its result. Brief introduction and analysis of PSO algorithm, experimental setup, and programming are introduced in Section 4. Optimization result and discussion is presented in Sect 5. Sect. 6 conclusion of the study.

EXPERIMENT

Materials and Methods

The experiment was run by VACTEC model VTC PVD 1000. In coating chamber, Ar gas was used for electrons generation. N2 pressure, Ar pressure and TT were determined as parameters of the PVD coating process.

Experimental Design

Using the version 8.0 of Design Expert software. Central Cubic Design (CCD) was intended based on eight factorial points, six axial and three central points. This is to ensure achieving a wide range from the operating windows.

MODELING METHODOLOGIES

Determination of Polynomial Equation Using RSM Model of Tin Coating Roughness

In the same study [25], a validation process was done using residual error and prediction accuracy. The leftovers error as shown in Eq. (2) has been used to degree the variation among the foretold and the real value for each dataset. Residual error is the simple performance measure that used in many studies [24] [26] [5]. Equation for residual error is stated thus the following:

$$\textbf{Roughness} = -1265.15 + 2145.43P_{N2} + 388.44P_{Ar} + 174.30\omega_{TT} - 569.10P_{N2}P_{Ar} - 333.37P_{N2}\omega_{TT} - 55.44P_{Ar}\omega_{TT} + 23.81P_{N2}^{2} + 2.68\omega_{TT}^{2} + 86.33\, P_{N2}P_{Ar}\,\omega_{TT} \quad (1)$$

where P_{N2}, P_{Ar} and ω_{TT} denote nitrogen pressure, argon pressure and Turntable Speed, respectively.

In the same study [25], a validation process was done using residual error and prediction accuracy. Residual error (e) in Eq. (2) is used to calculate the difference between the actual value and predicted value for each dataset. Residual error is the simple performance measure that used in many studies [5] [24] [26]. Equation for residual error, is e as the following:

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

where vp is predicted value and va is actual value.

Model Validation

To validate the resulted model (objective function), three set of statistics were showed in three dissimilar empirical runs. In authentication runs, the real flatness roughness fell within ninety percent forecast intervening period. The most significant variety of residual errors was quite low at 4.08 to 8.62 which means that the model could accurately predict the surface roughness of the thin film.

Experimental Result and Discussion

Coating roughness values from the seventeen experimental runs ranged from 44.83 nm to 104.92 nm detailed process for the coating is indicated in Table-1.

PARTICLE SWARM OPTIMIZATION ALGORITHM

PSO is considered as an efficient technique among other population-based effective [27]. It is a stochastic and heuristic algorithm inspired by social behaviours of fish schooling or bird flocking. As a soft computing technique, POS is a computational method which has been used to optimize various engineering problems by iteratively improving candidate solutions when particles move in problem space toward the best solution depending on a fitness mathematical formula while updating their positions and velocities [28]. The solution starts with setting a different solutions or group which are randomly selected, and upgrading generations along with looking for the optima. The possible solutions (particles), fly throw the problem space by following the recent optimal particles [29]. For each particle, an iterative movement is influenced by its local best-known position, and compared with the global position which is the best-known positions found by other candidates' particles in overall search space (global), resulting in moving 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, it also offers a professional solution, calculation time is short, stable convergence characteristics [29], and can solve questions expressed by real numbers. Compared to Genetic algorithms (GAs); PSO has fewer parameters, makes implementation easier and converges faster [31], evolutionary operators is not complicated such as crossover and mutation as in GAs. Compared to standard back propagation algorithm such as feed forward artificial neural networks, PSO is considered superior and does not require prescription of differentiable functions and gradient information [32].

Generally, in addition to improvement of solving capabilities for complex problems, PSO also has good generalization capabilities and high convergence speed for several types of problems. Also, PSO has been demonstrated as a potential algorithm by its successful deployment in solving different problems such as functions minimization [33].

It is proved that PSO provides a cheaper way with better results compared with other techniques. One version, with slight variations. It can be used across different aspects of applications; in addition, it can be used for specific applications with specific requirement [29]. As a result, PSO can be utilized for noisy, irregular, and changing over time problems.

PSO (Algorithm Analysis)

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:

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

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. 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. The inertia weight w is usually utilized in velocity equation as follow:

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

where w_{max}1 is the primary weight, normally selected as a large value lower than 1; $w_{min}$is the final weight after iteratively decrement in w_{max}; iter and $iter_{max}$ are the iteration numbers for current and the maximum iteration. A perfect value is chosen due to the weight w normally offers a balance between local and global exploration abilities and consequently a reduction in the number of iterations needed to find the optimal solution [34]. A global search is enabled by large w, whereas a small w enables a local search. Gradually decreasing the weight and linearly decreasing w provide more refined solutions.

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 [36-40]. The new particle position is then determined using the previous position and the new velocity and can be written as

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

Coating Roughness Objective Function

The objective function for PSO has been developed based on the previous RSM quadratic polynomial function in equation 1.

PSO Parameters Limitation Constraints

For coating process experiment, equations (3-5) are subjected the limitation constraints for the optimization fitness function of PSO as follows:

Nitrogen pressure

$$0.16 \leq \mathrm{N2} \leq 1.84 \quad (3)$$

Argon pressure

$$3.66 \leq \mathrm{Ar} \leq 4.34 \quad (4)$$

Turntable speed

$$3.98 \leq \mathbf{TT} \leq 9.02 \quad (5)$$

Swarm Optimization Setup

Using MATLAB, the optimization model has been implemented. Referring to experimental data, Figure-1 summarizes description of model simulation parameters. In addition, Figure-2 and explain the PSO algorithm simple flow chart [35] [41-43].

Optimization Result and Discussion

PSO Programming Result

Considering equation (1), which is the optimization fitness function, the limitation constraints of the optimization equations (8-10), and the PSO model parameters setting in Figure-1 under three different constraints (N_2, Ar, TT), the next Figures (3 and 4) show the results of implementation using MATLAB toolbox to obtain the optimal value of roughness. The setting was used as recommended by [24].

Figure-3 indicates the impact of parameters on the coating roughness. The most important parameters for roughness, where the N_2 and TT are maximum. However, when the Ar value decreases to minimum, the roughness decreases.

By using PSO, the optimal minimum roughness value can be reached by setting the coating process values to 1.84×10^{-3} mbar at maximum N_2, 3.66×10^{-3} mbar at minimum Ar, and 9.02 rpm for the maximum TT [44-48]. Figure-4 indicates the best fitness value is 23.35nm.

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Table-1. TiN coating roughness result by actual experiment.

Run	N_2 pressure [$\times10^{-3}$ mbar]	Ar pressure [$\times10^{-3}$ mbar]	Turntable Speed [rpm]	*Roughness* [nm]
1	1.84	4	6.5	83.03
2	1	3.66	6.5	69.35
3	1	4.34	6.5	75.17
4	0.16	4	6.5	81.19
5	1.5	3.8	5	79.57
6	0.5	3.8	5	80.67
7	0.5	4.2	5	100.92
8	0.5	4.2	8	73.43
9	1.5	4.2	5	44.83
10	1	4	9.02	81.54
11	1.5	3.8	8	50.8
12	0.5	3.8	8	67.91
13	1.5	4.2	8	104.92
14	1	4	3.98	83.22
15	1	4	6.5	67.41
16	1	4	6.5	54.64
17	1	4	6.5	56.09

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, Ar*max*= 4.2; *TTmin*= 5, TT*max*= 8;

Main objective of algorithm
- Finding the best optimized coating *Roughness* under the constraints of N_2, *Ar, and TT*.

Outputs
- Given optimal solution best global fitness (min.*Roughness*) and the best global position (N_2, Ar, and *TT*).

Figure-1. Model of minimize coating roughness programming.

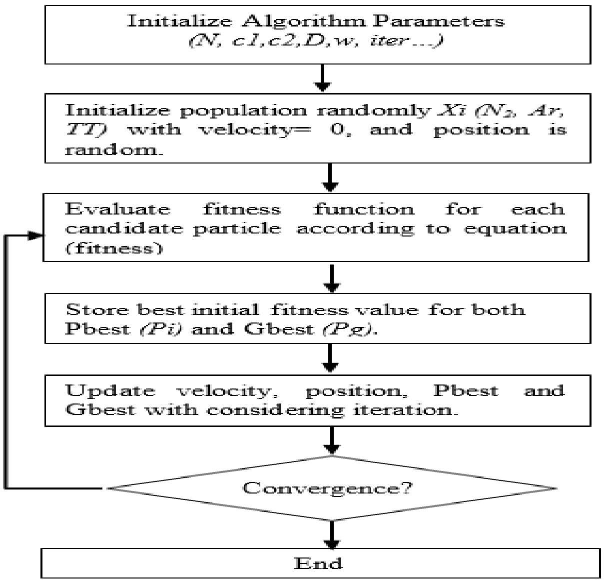

Figure-2. PSO algorithm simple flow chart.

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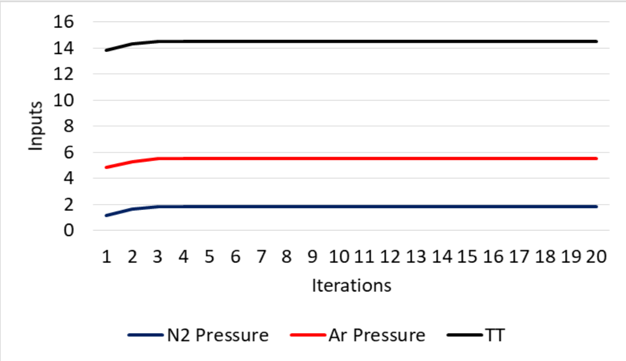

Figure-3. The behaviour of process parameters that influence the coating process.

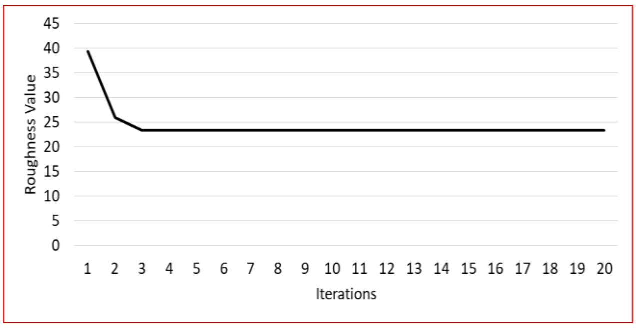

Figure-4. The behaviour of the objective function of coating roughness with changing the process parameters.

From the above figures and discussion, we conclude that PSO optimization algorithm has reduced the roughness from 44.83nm to reach 23.35nm, with reduction value = 21.48nm compared to the lowest value in the experimental dataset.

PSO Result Validation

For validation process of the result of PSO, the new optimal data was compared with the experimental dataset. This process was done by using the objective function as indicated in Eq. (1). For this reason, the values of the parameters by PSO are transferred into the equation, and the output value by the equation should be the same optimal value obtained by MATLAB. Figure-4 indicates that the minimum surface *Roughness* value could be reached by setting the parameters values to 1.84×10^{-3} mbar, 3.66×10^{-3} mbar and 9.02 rpm for N_2 pressure, Ar pressure and TT, respectively. After passing the optimal parameters that obtained by MATLAB into Eq. (1), it was found that the output value is 23.35nm. This result was then compared to the value from MATLAB as in Figure-3 and found the two values are the same.

As a result, the best optimized *Roughness* value has been reached by using a PSO compare to the experimental dataset with (≈48%) of quite high ratio of percentage and it is very good range lower the minimum value in the dataset.

CONCLUSIONS

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 performed using PVD process at different settings of N_2 pressure, Ar pressure and TT. In this paper, PSO optimization algorithm was applied, the result indicated that PSO can be easily used deployed and enhance manufacturing process in industrial field.

The ability to predict coating process even before machining based on the input parameters, such as N_2 pressure, Ar gas pressure, and TT will give manufacturers an advantage in terms of time savings and maintenance cost and less rejects.

Using particle swarm optimization, an objective function for three parameters which are N_2 gas pressure, Ar gas pressure, and TT has been passed and implemented. The results have been discussed and validated by using actual testing data in terms of residual error, and optimized value validation with objective function. The results indicate that the new models are better for Coating Roughness than actual data as follows:

- The developed model is applied to the parameters for limitation constraints of PSO, even with a small amount of data.
- Optimal values for Roughness have been developed using PSO with 23.35nm, 1.84×10^{-3} mbar for N_2 pressure, 3.66×10^{-3} mbar for Ar gas pressure, and 9.02 rpm for TT.
- The results show that PSO are able to reduce the minimize coating roughness in the experimental data.
- The finding proved that the PSO is efficient in industrial and manufacturing, reducing trial and error experiment, saving time, efforts, maintenance and materials. Therefore, it is recommended in the optimization process of sputtering.

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