MEREC-MABAC Based-Parametric Optimization of Chemical Vapour Deposition Process for Diamond-Like Carbon Coatings

Sellamuthu Prabhukumar[1], Jasgurpeet Singh Chohan[2], and Kanak Kalita[3(✉)]

[1] Department of Mechanical Engineering, Presidency University, Bangalore, India
prabhukumar.sellamuthu@presidencyuniversity.in
[2] Department of Mechanical Engineering, University Centre for Research and Development, Chandigarh University, Mohali, India
[3] Department of Mechanical Engineering, Vel Tech Rangarajan Dr, Sagunthala R&D Institute of Science and Technology, Avadi, India
drkanakkalita@veltech.edu.in

Abstract. This research paper presents an application of the Multi-attributive Border Approximation Area Comparison (MABAC) method combined with the Method based on the Removal Effects of Criteria (MEREC) for the parametric optimization of the Chemical Vapor Deposition (CVD) process in Diamond-like Carbon (DLC) coatings. A decision matrix is formulated using a case study from the literature. Four response parameters namely, Hardness (H), Young's modulus (E), Coefficient of Friction (COF), and Wear Rate (WR) are considered. The weight allocation for these response parameters is calculated using five different methods, namely MEREC, mean weight (Mean), Standard deviation (StDev), Entropy, and Criteria Importance Through Intercriteria Correlation (CRITIC) method. The MABAC method was employed to obtain the optimal parametric combination for the DLC coatings. Results showed a clear superior combination of the CVD process parameters can be achieved using the MEREC-MABAC methodology. Thus, the study successfully demonstrates the effectiveness of the MEREC-MABAC-based approach for the simultaneous optimization of multiple responses in the CVD process for DLC coatings.

Keywords: Diamond-like carbon coatings · Chemical vapor deposition · Parametric optimization · MABAC · MEREC · Multi-criteria decision making

1 Introduction

Diamond-like Carbon (DLC) coatings have been widely researched due to their exceptional properties, such as high hardness, low wear rate, and low coefficient of friction, which make them suitable for various applications in industries such as automotive, aerospace, and biomedical. The Chemical Vapor Deposition (CVD) process is commonly used to develop these coatings, but the quality of the coatings is significantly influenced by the process parameters. Among the numerous CVD parameter, the H_2

P. Vasant et al. (Eds.): ICO 2023, LNNS 855, pp. 414–422, 2024.
https://doi.org/10.1007/978-3-031-50158-6_41

flow rate, C_2H_2 flow rate and deposition temperature (T) are found to be some of the most significant ones. Therefore, optimizing these parameters is crucial to achieving coatings with desired properties.

In recent years, various research studies have been conducted to investigate the optimization of deposition parameters for DLC coatings using different techniques and methodologies. Ghadai et al. [1] employed a thermal CVD process and used input parameters such as temperature (T), H_2 flow rate and C_2H_2 flow rate to optimize hardness (H) and Young's modulus (E). Jatti et al. [2] investigated the optimization of H, E, and ID/IG ratio using the Inductively Coupled PECVD process. They considered input parameters like voltage (V), frequency (f), pressure (P), and gas composition. An L9 experimental design was used with nine experiments, and the Taguchi methodology was applied for optimization. Ghadai et al. [3] used the CVD process and input parameters V, f, P, and gas composition to optimize H, E, and ID/IG ratio. They employed an L9 experimental design with nine experiments and utilized the Grey fuzzy logic. Singh and Jatti [4] focused on the IC-PECVD process, optimizing H and E with input parameters like V, f, P and gas composition. They used an L9 experimental design with nine experiments and the Taguchi methodology for optimization. Ghadai et al. [5] used the PECVD process to optimize H with input parameters like T, H_2 flow rate, and C_2H_2 flow rate. They employed a CCD experimental plan with 20 experiments and utilized a single-objective GA for optimization. Ebrahimi et al. [6] employed a CVD process with input parameters T and H_2 flow rate to optimize the wear rate (WR) and the coefficient of friction (COF). They used a CCD experimental plan with 13 experiments and applied the desirability function approach for optimization. Ebrahimi et al. [7] utilized a CVD process and input parameters T, duty cycle, H_2 flow rate, and argon/methane flow ratio to optimize WR, wear durability, and H. They employed a CCD experimental plan with 23 experiments and used the desirability function approach for optimization. Kumar and Swain [8] used a thermal CVD process with input parameters T, H_2 flow rate, and N_2 flow rate to optimize H, E, and ID/IG ratio. Pancielejko et al. [9] used a modified cathodic vacuum arc method with input parameters V, argon pressure, coating thickness (t), and thickness of chromium interlayer (t_{cr}) to optimize H and WR. They employed an L9 experimental design with nine experiments and utilized the Taguchi methodology for optimization. Czyzniewski et al. [10] investigated the optimization of H, WR, adhesion, and H/E parameter using sputtering. They used input parameters like V, C_2H_2 flow rate, t, and t_{cr}. An L9 experimental design was employed with nine experiments, and the Taguchi methodology was applied for optimization.

From the literature review, it is found that several optimization methods have been applied in the literature for multi-objective problems. However, there is no application of newer methods like MEREC and MABAC in CVD process optimization. Thus, in this study, the Multi-attributive Border Approximation Area Comparison (MABAC) method, combined with the Method based on the Removal Effects of Criteria (MEREC) is employed for parametric optimization of the CVD process for DLC coatings. The main aim is to find the optimal CVD process parameters that yield the best compromise between Hardness (H), Young's modulus (E), Coefficient of Friction (COF), and Wear Rate (WR).

2 Methodology

2.1 MEREC

MEREC is a method for determining the weights of various criteria in multi-criteria decision-making (MCDM) problems [11]. MEREC focuses on the removal effect of each criterion on the alternative's performance. Criteria with higher effects on the performances receive greater weights. A logarithmic measure calculates alternatives' performances, and the absolute deviation measure identifies the effects of removing each criterion. The pseudo-code for MEREC is as follows:

1. Define the decision matrix (X) with elements x_{ij}.
2. Normalize the decision matrix (N) using nx_{ij}

$$n_{\mathrm{ij}}^{\mathrm{x}} = \begin{cases} \frac{\min_{\mathrm{k}} x_{\mathrm{kj}}}{x_{\mathrm{ij}}} \text{if} j \in B \\ \frac{x_{\mathrm{ij}}}{\max_{\mathrm{k}} x_{\mathrm{kj}}} \text{if} j \in C \end{cases} \tag{1}$$

   where B is the set of beneficial criteria and C is the set of non-beneficial (cost) criteria.
3. Calculate overall performance $\mathrm{S_i}$ for each alternative i using a logarithmic measure

$$\mathrm{S_i} = \ln\left(1 + \left(\frac{1}{\mathrm{m}} \sum_{\mathrm{j}} \left|\ln\left(\mathrm{n}_{\mathrm{ij}}^{x}\right)\right|\right)\right) \tag{2}$$

4. Calculate performance $\mathrm{S_{ij}}'$ of each alternative i by removing criterion j

$$\mathrm{S}_{\mathrm{ij}}' = \ln\left(1 + \left(\frac{1}{\mathrm{m}} \sum_{\mathrm{k,k \neq j}} \left|\ln\left(\mathrm{n}_{\mathrm{ik}}^{x}\right)\right|\right)\right) \tag{3}$$

5. Compute the summation of absolute deviations $\mathrm{E_j}$ for each criterion j

$$\mathrm{E_j} = \sum_{\mathrm{i}} |\mathrm{S}_{\mathrm{ij}}' - \mathrm{S_i}| \tag{4}$$

6. Determine the final weights $\mathrm{w_j}$ of the criteria

$$\mathrm{w_j} = \frac{\mathrm{E_j}}{\sum_{\mathrm{k}} \mathrm{E_k}} \tag{5}$$

2.2 MABAC

The MABAC method is an MCDM technique designed to evaluate, rank, and select the best alternatives among a set of decision alternatives based on multiple criteria [12]. MABAC is particularly effective in dealing with complex decision-making problems that involve conflicting criteria, as it incorporates the concept of border approximation area to determine the relative importance of each alternative. This approach facilitates the ranking of alternatives by comparing their proximity to an ideal solution, which is represented by a border approximation area. The pseudo-code for MABAC is as follows:

1. Develop the decision matrix (X) with m alternatives and n criteria. x_{ij} are the elements of X.
2. Normalize X to form the normalized matrix R (with elements r_{ij}) using the following rules

$$r_{ij} = \frac{x_{ij} - x_j^-}{x_j^+ - x_j^-} \text{ for benefit criteria} \quad (6)$$

$$r_{ij} = \frac{x_{ij} - x_j^+}{x_j^- - x_j^+} \text{ for cost criteria} \quad (7)$$

   x_j^+ and x_j^- are the maximum and minimum values of the J th criterion.
3. Compute the weighted normalized decision matrix V (with elements v_{ij})

$$v_{ij} = w_j \cdot \left(r_{ij} + 1\right) \quad (8)$$

   w_j is the weight of the J th criterion.
4. Compute the border approximation area (BAA) matrix B (with elements b_j)

$$b_j = \left(\prod_{i=1}^{m} v_{ij}\right)^{1/m} \quad (9)$$

5. Compute the distance matrix of alternatives (Q) from the BAA. q_{ij} are the elements of Q.

$$Q = V - B \quad (10)$$

6. Compute the criteria function (S_i) values and ranking the alternatives:

$$S_i = \sum_{j=1}^{n} q_{ij}, j = 1, 2, \ldots, n, i = 1, 2, \ldots, m \quad (11)$$

7. Rank the alternatives in descending order of S_i values.

3 Problem Description

In this work, the objective is to select the optimal CVD process parameters to develop an optimized DLC coating. The challenge is to find a suitable compromise solution wherein multiple responses are looked upon and optimized simultaneously. In the context of this study, four response parameters, namely Hardness (H), Young's modulus (E), Coefficient of Friction (COF) and Wear Rate (WR) need to be optimised simultaneously. The CVD deposition process parameters are H_2 flow rate, C_2H_2 flow rate and deposition temperature (T). Based on a central composite design of experiments, 15 experiments were conducted by Kalita et al. [13]. Those experiments are used as the decision matrix in this study for further analysis. Thus, in the context of this study, the decision matrix (D) iexpressed as,

$$D = \begin{array}{c} \\ A1 \\ A2 \\ A3 \\ A4 \\ A5 \\ A6 \\ A7 \\ A8 \\ A9 \\ A10 \\ A11 \\ A12 \\ A13 \\ A14 \\ A15 \end{array} \begin{bmatrix} H & E & COF & WR \\ 13.37 & 141.74 & 0.24 & 0.00084 \\ 20.56 & 272.73 & 0.14 & 0.00033 \\ 14.31 & 146.36 & 0.21 & 0.00072 \\ 23.22 & 289.65 & 0.074 & 0.00035 \\ 16.69 & 170.52 & 0.146 & 0.00065 \\ 39.35 & 350.24 & 0.06 & 0.00012 \\ 18.21 & 183.73 & 0.185 & 0.00056 \\ 20.11 & 250.36 & 0.159 & 0.00045 \\ 24.59 & 292.35 & 0.086 & 0.00031 \\ 22.48 & 283.75 & 0.105 & 0.000268 \\ 34.61 & 312.18 & 0.074 & 0.000132 \\ 21.05 & 275.48 & 0.16 & 0.00038 \\ 36.33 & 325.49 & 0.094 & 0.000128 \\ 23.22 & 287.77 & 0.142 & 0.00032 \\ 30.12 & 298.56 & 0.125 & 0.00025 \end{bmatrix} \tag{8}$$

As indicated earlier, in this paper, the MABAC method is used for multi-criteria decision-making. The weights for the four criteria are calculated using the MEREC method. However, for the sake of comprehensive comparison, the analysis is also carried out using other weight allocation methods namely, mean weight (Mean), Standard deviation (StDev), Entropy and Criteria Importance Through Intercriteria Correlation (CRITIC) method.

4 Results and Discussion

4.1 Multi-criteria Decision Making

Initially, the weights for the four criteria i.e., Hardness (H), Young's modulus (E), Coefficient of Friction (COF) and Wear Rate (WR) are calculated by using the five different weight allocation methods. Figure 1 shows the weights allocated by the various weight allocation methods. It is observed that StDev has almost the same allocation as the mean method. However, the Entropy method is seen to have allocated skewed weights with excessive weightage to WR response.

The MABAC calculations are carried out using all these weights and the Q-values are derived. The correlation between the solutions by the various weighted MABACs is shown in Fig. 2, which shows that there is a 100% correlation among the methods for this case study. This indicates that the parametric combination in the CCD-based CVD experiments is such that there is a clear superior combination.

Figure 3 shows the changes in the Q-values with respect to the various parametric combination in the CCD-based CVD experimental dataset. It should be noted here that the Q-value can be thought of as a 'combined proxy index' for the goal of simultaneous

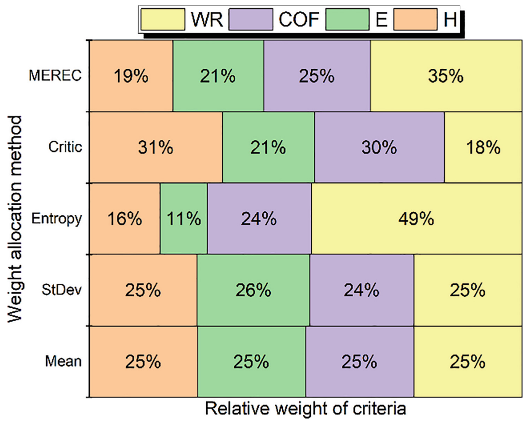

Fig. 1. Weights assigned to different criteria as per various weight allocation methods

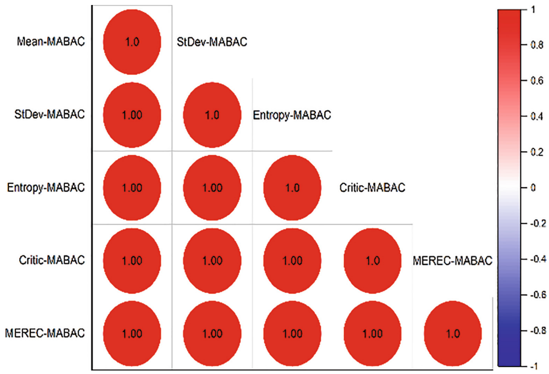

Fig. 2. Correlation among the various weight allocation methods

maximization of H and E while minimizing COF and WR. Thus, the higher the Q-value, the better the compromise solution. It is observed that irrespective of the weight allocation method, the Q-values follow a similar trend. Experiment number 6 is seen to be a clear winner that represents a good parametric combination. The various parameter value for this experiment is 60 sccm of H_2 flow rate, 2.5 sccm of C_2H_2 flow rate and deposition temperature (T) of 800 °C.

4.2 Parametric Optimization of CVD

The MABAC Q-values are aggregated level-wise for each of the three process parameters to find out the optimal parametric combination. A higher value of aggregated Q-value corresponds to a better parametric combination. Figure 4 shows the influence of the H_2 the flow rate on Q-values. It is observed that as the H_2 flow rate is increased the Q-values improve. However, at 80 sccm of H_2 flow rate and 95 sccm of H_2 flow rate, the Q-values are similar.

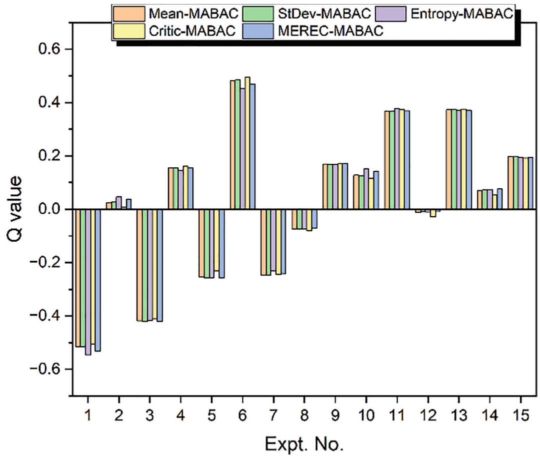

Fig. 3. Variation of MABAC Q-values with respect to CCD-based CVD experiments

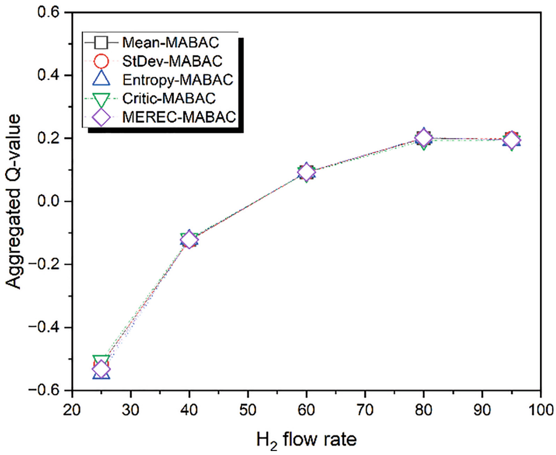

Fig. 4. Effect of H_2 flow rate on aggregated Q-values

Figure 5 shows the influence of the C_2H_2 flow rate on the MABAC Q-values. The Q-values monotonically decrease as the C_2H_2 flow rate increases. 2.5 sccm of C_2H_2 flow rate is found to be the most optimal. The drop in Q-value between 2.5 sccm of C_2H_2 flow rate and 9.5 sccm of C_2H_2 flow rate is 151.92%. This indicates the importance of choosing the optimal parameters for achieving the best performance from the DLC coatings.

Figure 5 shows the influence of the deposition temperature (T) on Q-values. A higher deposition temperature (T) is seen to be beneficial for achieving a better optimized DLC coating. Thus, as per the MEREC-MABAC analysis, a deposition temperature (T) of 900 °C is most beneficial in achieving the optimized DLC (Fig. 6).

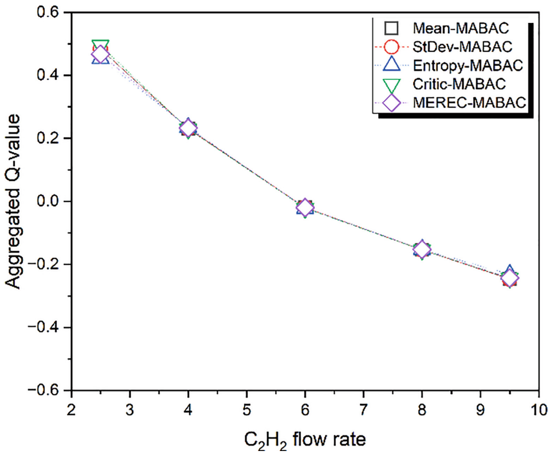

Fig. 5. Effect of C_2H_2 flow rate on aggregated Q-values

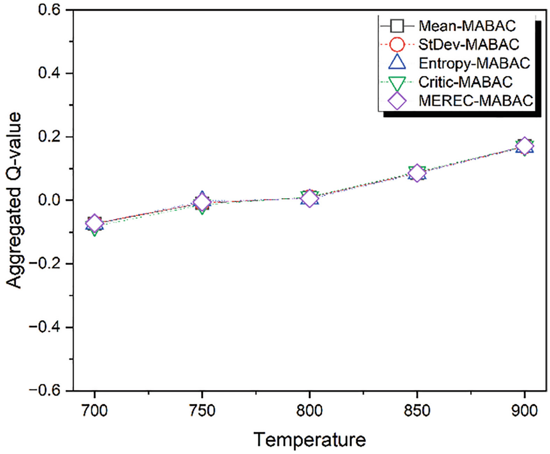

Fig. 6. Effect of deposition temperature (T) on aggregated Q-values

5 Conclusions

In this research, MEREC-MABAC-based approach was applied for the parametric optimization of the CVD process for DLC coatings. The optimal parametric combination for achieving the best compromise between Hardness (H), Young's modulus (E), Coefficient of Friction (COF) and Wear Rate (WR) was determined. The study demonstrated that irrespective of the weight allocation method used, the parametric combination in the CCD-based CVD experiments showed a clear superior combination, with experiment number 6 having the highest Q-value.

The analysis revealed that higher H_2 flow rate, lower C_2H_2 flow rate and higher deposition temperature (T) were beneficial for achieving the optimized DLC coatings. The results of this study can provide useful insights for researchers and practitioners in the field of DLC coatings. The proposed MEREC-MABAC-based approach can be extended to other multi-objective optimization problems in various fields.

References

1. Ghadai, R.K., Kalita, K., Mondal, S.C., Swain, B.P.: Genetically optimized diamond-like carbon thin film coatings. Mater. Manuf. Process **34**, 1476–1487 (2019)
2. Jatti, V.S., Laad, M., Singh, T.P.: Taguchi approach for diamond-like carbon film processing. Proc. Mater. Sci. **6**, 1017–1023 (2014)
3. Ghadai, R.K., Das, P.P., Shivakoti, I., Mondal, S.C., Swain, B.P.: Grey fuzzy logic approach for the optimization of DLC thin film coating process parameters Using PACVD technique. IOP Conf. Ser. Mater. Sci. Eng. 1–6 (2017)
4. Singh, T.P., Jatti, V.S.: Optimization of the deposition parameters of DLC coatings with the IC-PECVD method. Part Sci. Technol. **33**(2), 119–123 (2015)
5. Ghadai, R.K., Kalita, K., Mondal, S.C., Swain, B.P.: PECVD process parameter optimization: towards increased hardness of diamond-like carbon thin films. Mater. Manuf. Process. **33**, 1905–1913 (2018)
6. Ebrahimi, M., Mahboubi, F., Naimi-Jamal, M.R.: RSM base study of the effect of deposition temperature and hydrogen flow on the wear behavior of DLC films. Tribol. Int. **91**, 23–31 (2015)
7. Ebrahimi, M., Mahboubi, F., Naimi-Jamal, M.R.: Optimization of pulsed DC PACVD parameters: toward reducing wear rate of the DLC films. Appl. Surf. Sci **389**, 521–531 (2016)
8. Kumar, D., Swain, B.: Investigation of structural and mechanical properties of silicon carbonitride thin films. J. Alloys Compd. **789**, 295–302 (2019)
9. Pancielejko, M., Czyżniewski, A., Zavaleyev, V., Pander, A., Wojtalik, K.: Optimization of the deposition parameters of DLC coatings with the MCVA method. Arch. Mater. Sci. Eng. **54**(2), 60–67 (2012)
10. Czyzniewski, A.: Optimising deposition parameters of W-DLC coatings for tool materials of high-speed steel and cemented carbide. Vacuum **86**(12), 2140–2147 (2012)
11. Kalita, K., Ghadai, R.K., Chakraborty, S.: Parametric optimization of CVD process for DLC thin film coatings: a comparative analysis. Sādhanā **47**(2), 57 (2022)
12. Keshavarz-Ghorabaee, M., Amiri, M., Zavadskas, E.K., Turskis, Z., Antucheviciene, J.: Determination of objective weights using a new method based on the removal effects of criteria (MEREC). Symmetry **13**(4), 525 (2021)
13. Pamučar, D., Ćirović, G.: The selection of transport and handling resources in logistics centers using multi-attributive border approximation area comparison (MABAC). Expert Syst. Appl. **42**(6), 3016–3028 (2015)