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Process Optimization of Chemical Vapor Deposition-Based Boron Nitride Coatings on Floating Ball Valve Components Using a Teaching Learning-Based Optimization Algorithm

Rajmohan T¹, Nandakumar A¹, Vijayan D¹, Vijayabhaskar S¹

¹. Department of Mechanical Engineering, Sri Chandrasekharendra Saraswathi Viswa Mahavidyalaya (SCSVMV), Kanchipuram, IND

Corresponding author: Rajmohan T, rajmohanscsvmv@kanchiuniv.ac.in

Abstract

Floating ball valves are widely utilized as isolation devices in pipeline systems where minimal pressure drop is essential. These valves typically comprise a carbon steel body, spherical ball, seat ring, sealing elements, stem, and gaskets. Conventional metal-to-metal sealing between the ball and seat often leads to surface degradation, including cracking, peeling, scratching, and delamination-especially under high-temperature or corrosive service conditions. To address these issues, the present study explores the deposition of boron nitride (BN) coatings on the ball and seat components using the Chemical Vapor Deposition (CVD) technique. BN was selected for its superior wear resistance, chemical inertness, and thermal stability, making it ideal for demanding applications across energy, marine, and aerospace sectors. The CVD process parameters-deposition temperature, coating time, and film thickness-were optimized using a teaching learning-based optimization algorithm to enhance coating performance. The objective was to minimize surface roughness and porosity while maximizing hardness. The optimal CVD conditions were identified as a temperature of 950°C, a coating thickness of 11µm, and a deposition time of 20 hours. The optimized BN coating significantly improves the functional lifespan and sealing efficiency of floating ball valve components under adverse operating environments.

Categories: Advanced Materials, Chemical Process Optimization, Materials Engineering

Keywords: chemical vapor deposition (cvd), boron nitride, surface roughness, coating, porosity, hardness

Introduction

Chemical Vapor Deposition (CVD) has established itself as a pivotal technique in advanced materials processing, enabling the fabrication of high-purity, high-performance coatings and thin films. Choy [1] provides a comprehensive overview of the principles underpinning CVD, detailing the complex interplay of thermodynamics, kinetics, and transport phenomena that govern the process. CVD involves the reaction of gaseous precursors on or near a heated substrate to produce a solid film. This method is uniquely suited to applications requiring conformal coatings on intricate geometries, surpassing conventional line-of-sight techniques such as Physical Vapor Deposition (PVD) [2,3]. The flexibility in tailoring film morphology and microstructure has made CVD indispensable in sectors like microelectronics, aerospace, energy devices, and nanotechnology [4,5].

Numerous variants of CVD have emerged to expand its application scope and resolve challenges such as high temperature requirements or precursor instability. These include Plasma-Enhanced CVD, which allows lower processing temperatures suitable for organic materials [6]; Atomic Layer Deposition, known for its atomic-scale control of thickness [7]; and Metalorganic CVD, particularly useful for compound semiconductors like GaN and InP [8]. Recent advancements also include Aerosol-Assisted CVD and Flame-Assisted CVD, which enable open-atmosphere deposition and cost-effective manufacturing [9,10]. These variants demonstrate the method's adaptability to diverse functional requirements such as dielectric layers, wear-resistant coatings, superconductors, and nanostructured materials [11,12].

Complementing these theoretical advances, Gadhari and Sahoo [13] offer an experimental study on electrodeless Ni-P-TiO₂ composite coatings, which shares principles with CVD through its focus on surface chemistry and deposition control. Using the Taguchi design of experiments (DOE), the study identified annealing temperature and TiO₂ content as critical parameters influencing microhardness, achieving values above 1000 HV. Their findings align with the broader literature emphasizing the role of particle dispersion, precursor concentration, and post-deposition heat treatment in optimizing mechanical performance [14-16]. Although not strictly a CVD process, the study's approach to parameter tuning, characterization using Scanning electron microscope, Energy-Dispersive X-ray, and X-ray diffraction, and focus on tribological enhancement mirror many CVD goals and techniques.

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Together, these contributions illustrate the depth and breadth of research on vapor-phase coating technologies. While foundational works like those by Choy and Pierson [1,17] explore the fundamental mechanisms and system configurations, application-driven studies such as those by Gadhari and Sahoo [13] and Zhao et al. [18] highlight the real-world engineering potential of optimized coatings. The integration of advanced diagnostics, thermodynamic modeling, and surface science has made CVD a continuously evolving field with applications extending from nanoelectronics and Micro-Electro-Mechanical Systems devices to turbine blades and biomedical implants [19,20]. As materials demands grow increasingly complex, the role of CVD in precision coating technologies is poised to become even more vital.

Computational methods provide researchers with unprecedented ways to investigate material behavior and assess key properties across diverse applications, regardless of the time and length scales involved [21]. By simulating physical processes, scientists have been able to validate experimental findings and design advanced coatings that not only perform better but also introduce entirely new functionalities. For several decades, however, the optimization methods were constrained by simplistic techniques, mainly traditional stress-strain criteria, which limited their practical utility. Contemporary optimization is thus classified into two broad categories. The first, gradient-based approaches, can converge rapidly to an accurate solution in well-behaved problems; yet their performance suffers in highly nonlinear or multifaceted scenarios where derivatives become difficult or impossible to evaluate. As experimental challenges grow in complexity, the demand for more robust strategies has intensified. In response, the last ten years have seen the demand of numerous meta-heuristic algorithms drawn from natural and physical phenomena. One such method, the teaching-learning-based optimization (TLBO), models its heuristic on classroom dynamics: a knowledgeable instructor conveys a lesson while students independently share insights, adapting collectively as understanding deepens.

The algorithm unfolds in two sequential stages that researchers commonly refer to as the "teacher phase" and the "learner phase" [22]. The TLBO framework has found a wide range of applications aimed at improving the performance characteristics of plasma spray coatings. For example, Rao [23] successfully deployed TLBO to demonstrate constrained mechanical design problems, thereby underscoring the method's adaptability across various engineering disciplines. More recently, Mishra et al. [24] turned to TLBO for fine-tuning the coating properties of $\text{Al}_2\text{O}_3\text{-TiO}_2$ applied to superalloy substrates, a study that illustrated the algorithm's ability to meet strict material performance targets. In addition, Rajesh and Rao [25] further showcased TLBO's strength in handling multi-objective tasks; they aggregated several output metrics into a unified objective function during their investigations of plasma spray coatings.

The literature has repeatedly emphasized the significance of developing dependable predictive models that link the engineering characteristics of surface coatings to shifts in processing conditions. This is something the TLBO algorithm can address, as it generates optimized solutions grounded in rigorous mathematical formulations. Because TLBO natively accommodates multi-objective optimization (MOO) tasks, it fits neatly into environments where several performance metrics-like coating thickness, surface roughness, and material hardness-must be fine-tuned at the same time. Additionally, TLBO strengthens the overall robustness of the optimization process, seamlessly integrating user-defined preferences into the workflow and thereby elevating the final quality of the applied coatings.

Materials And Methods

Materials

In this work, the ball component of an industrial valve was made of carbon steel as the base material because of its high mechanical strength, machinability, and suitability for surface modification. To enhance the surface, the carbon steel ball was coated using the CVD process. The coating composition contains 8.4% of Boron (B), 0.03%-0.08% of Carbon (C), 0.08% of Manganese (Mn), and 0.1%-0.4% of Nitrogen (N), with the balance being Iron (Fe). The use of Boron and Nitrogen in the coating improves the material's surface hardness, reduces wear and porosity, and improves resistance to heat degradation. This coating composition was selected to meet the performance requirements of an industrial valve application operating under high pressure.

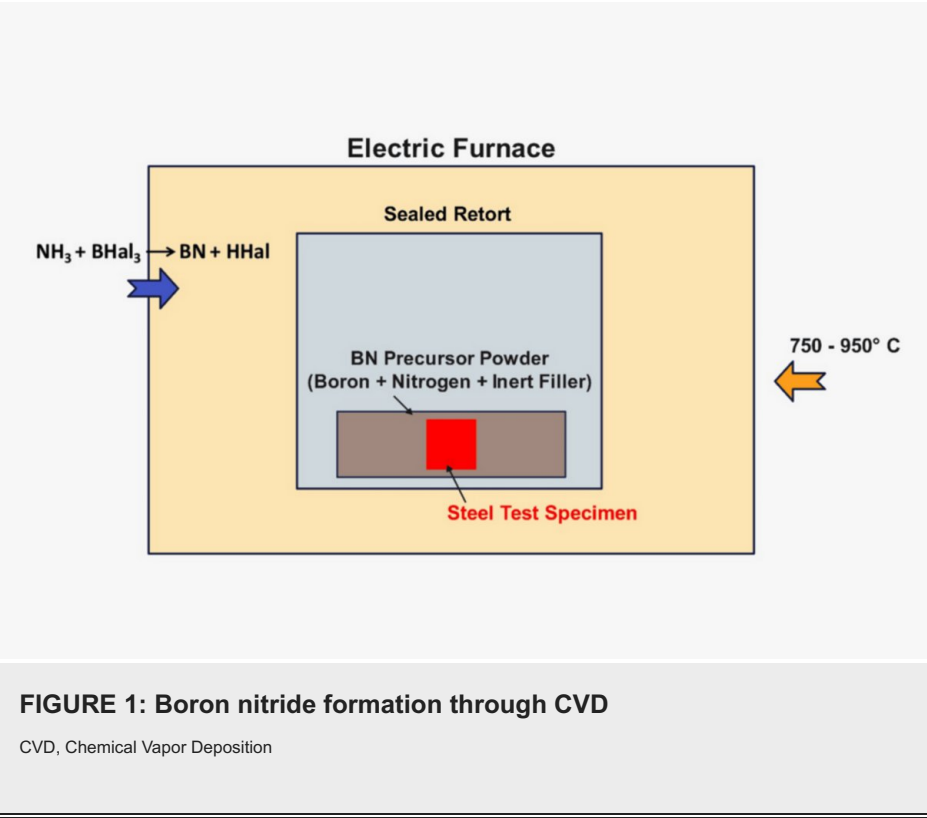
Experimental design

To study the combined and individual effects of key process parameters on the quality of BN coatings, a Central Composite Design (CCD) was adopted. CCD is a robust and widely used statistical DOE technique suitable for developing second-order (quadratic) models and optimizing multi-variable processes. The selected input variables for this study were temperature ($^{\circ}\text{C}$), time (hours), and coating thickness (micron), each considered at three principal levels: low (-1), center (0), and high (+1), as shown in Table 1. In addition to the factorial and axial points, CCD includes center point replications to estimate experimental error and improve model accuracy. This approach allows the development of a quadratic response surface model, capable of capturing nonlinear behavior and interactions among variables. The design enables effective prediction and optimization of critical coating responses such as porosity, microhardness, and

surface roughness, facilitating the identification of ideal process conditions for enhanced coating performance.

S. No	Factors	Unit	Levels		
			-1	0	1
1	Temperature	Degree Celsius	700	825	950
2	Time	Hrs	1	6	11
3	Thickness	Micron	5	12.5	20

TABLE 1: Factors levels



CVD coating

Figure 1 illustrates the fundamental sequence involved in the formation of boron nitride (BN)-based coatings through the CVD process. Initially, a powder mixture comprising a boron-containing salt (B-salt), a nitrogen-containing salt (N-salt), and an inert filler is combined with the substrate. Upon heat treatment, the B- and N-based salts decompose, releasing reactive gaseous species such as boron halides and ammonia. These gases diffuse and interact at the surface of the heated substrate, resulting in the simultaneous deposition of boron and nitrogen species. This reaction leads to the in-situ synthesis of a solid BN layer on the substrate surface, completing the coating formation. Figure 2 emphasizes the progressive transformation from solid-state precursors to gaseous intermediates and finally to a dense, solid BN coating.

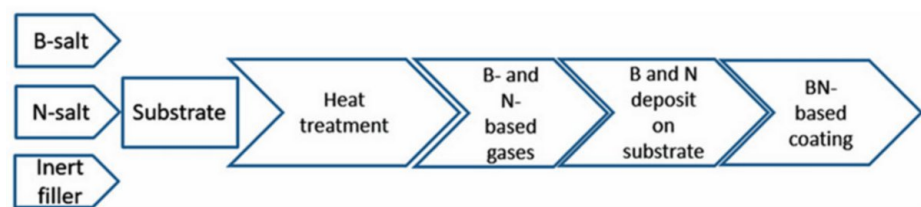


FIGURE 2: Principal schematic of coating formation

The BN coating experiments were conducted using an electric furnace equipped with a Nickel-Chromium (Ni-Cr) heating element, rated at 24kWh, capable of reaching a maximum coil temperature of 1000°C. The furnace chamber contained a retort made of stainless steel (SS 310) to withstand the high-temperature processing environment and to minimize contamination during diffusion reactions. The experimental setup is depicted in Figure 3 [2]. For temperature measurement of the test specimen, an L-shaped chromel-alumel (K-type) thermocouple housed in an Inconel sheath was positioned in proximity to the sample. To monitor and control the coil temperature with high precision, a second K-type thermocouple enclosed in a ceramic tube was employed. This setup ensured a measurement accuracy of $\pm 5^{\circ}\text{C}$, which is critical for consistent thermal diffusion and BN layer formation.



FIGURE 3: Electric furnace setup

Evaluation of surface roughness, microhardness, and porosity

Figure 4 shows the BN-coated samples. The surface roughness of the BN-coated samples was evaluated according to ASTM D7127-17 using a Mitutoyo Surf Test 301 surface roughness tester (Tokyo, Japan), which provides high-resolution measurement of surface topography. The roughness values were recorded in the normal direction to the surface. To assess the mechanical integrity of the coating, Vickers

microhardness (VHN) measurements were conducted in accordance with ASTM E384-2011 using a Vickers hardness tester. A load of 100g was applied for 15 seconds using a diamond indenter, and hardness readings were taken at three different locations on each sample to ensure consistency. For the evaluation of porosity and diffusion characteristics, a cross-sectional sample was prepared through standard grinding and polishing techniques following surface preparation before metallographic analysis. Vilella's reagent was used to etch the surface and reveal the coating microstructure. The diffusion depth and porosity features were examined under 200× magnification using an optical microscope equipped with image analysis capability, in compliance with ASTM B487-2002. The experimental values of responses are presented in Table 2.

Sl. No	Temp (°C)	Time (Hour)	Thickness (µm)	Porosity (%)	Hardness (VHN)	Roughness (Micron)
1	700	11	20	3.50832	1125	1.3386647
2	825	3	25	2.87725	1435	1.1222165
3	700	11	0.11345	2.05574	1400	1.2176237
4	825	1	5	6.21321	1044	1.3093414
5	950	1	12.5	11.8604	1750	0.9465483
6	825	6	5	4.25663	1444	1.2178646
7	825	6	12.5	3.10905	1503	1.2186566
8	700	1	12.5	1.09554	771	1.4829107
9	950	11	5	2.18744	1714	1.0054093
10	700	6	5	0.06785	1205	1.4377177
11	1035	6	20	2.23763	1955	0.9912021
12	825	6	12.5	3.10905	1344	1.1843283
13	825	6	12.5	3.10905	1298	1.1843283
14	825	6	0.11345	5.03904	1305	1.1830337
15	950	6	20	2.12586	1866	1.0696838
16	825	14.5	12.5	0.7556	1510	1.1908164
17	950	1	20	9.01743	1855	0.8770611
18	825	6	12.5	3.10905	1305	1.1843283
19	825	6	12.5	3.10905	1355	1.1843283
20	825	6	12.5	3.10905	1345	1.1843283

TABLE 2: Experimental responses



FIGURE 4: Boron nitride-coated samples

Results And Discussion

Multi objective optimization (MOO) using TLBO algorithm

The TLBO algorithm was employed to solve the optimization problem defined by the given cost function [25, 26]. The TLBO algorithm is a population-based metaheuristic inspired by the teaching-learning process in a classroom, where the interaction between a teacher and students, as well as among students themselves, drives the search for the optimal solution.

The TLBO algorithm was initialized with a population of 50 solutions (students), each randomly generated within the specified variable bounds:

Where, x_1 = temperature, x_2 = time, and x_3 = thickness. There are three factors in the present investigation namely temperature, time, and thickness. Hence, equal weightage has been given to each

factor, and therefore $w_1 = w_2 = w_3 = 0.3333$. These weightage values are applied to determine the multi-objective function and is given below:

$$MOO = -7.90242 + 0.01887 \times x_1 + 0.217915 \times x_2 + 0.153766 \times x_3 - 0.00027 \times (x_1 \times x_2) - 0.00012 \times (x_2 \times x_3) - 0.000009 \times x_1^2 - 0.00187 \times x_2^2 - 0.00178 \times (x_2^2)$$

The algorithm iterated for 1000 iterations, during which the population was updated through the teacher and learner phases. In the teacher phase, each student's position was updated based on the best solution found so far, simulating the influence of a teacher. The update is guided by a teaching factor, which determines the influence of the teacher on the students. The new position is calculated as:

$$new\ position = current\ position + rand \times (best\ solution - teaching\ factor \times mean\ position)$$

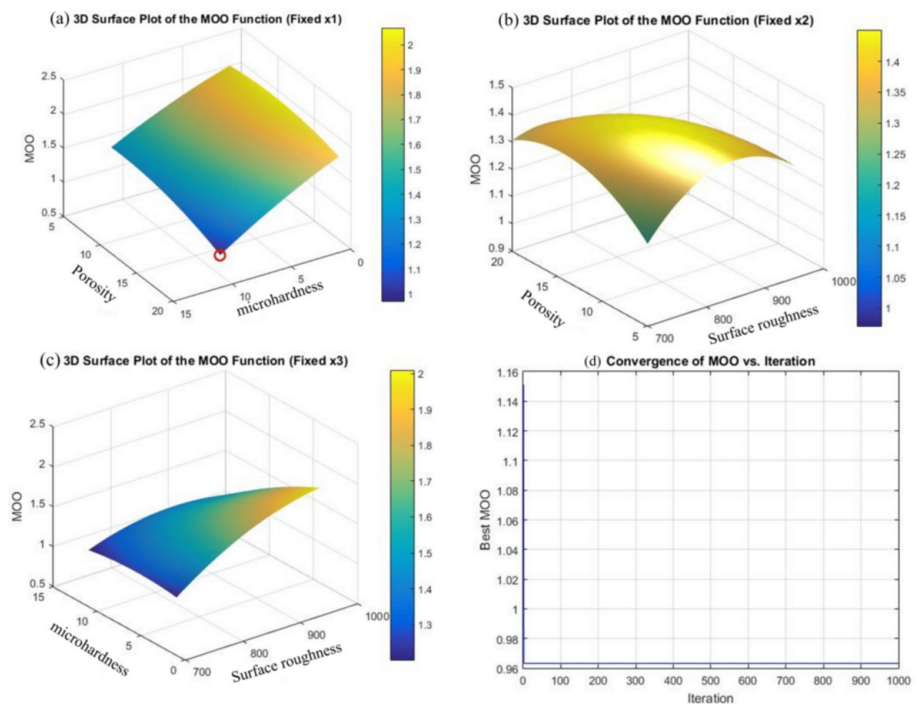
In the learner phase, students interacted with each other, updating their positions based on the difference between their solutions, simulating peer learning. If the selected student has a better solution, the update is:

$$new\ position = current\ position + rand \times (selected\ student\ position - current\ position)$$

If the selected student has a worse solution, the update is:

$$new\ position = current\ position - rand \times (selected\ student\ position - current\ position)$$

The new position is then evaluated using the cost function, and if it improves the current solution, it is accepted. The convergence of the TLBO algorithm was monitored by plotting the best MOO value against the iteration number. The convergence plot (Figure 5d) shows a steady decrease in the best MOO value over iterations, indicating the algorithm's effectiveness in exploring the solution space and converging toward the optimal solution. The plot provides insights into the rate of convergence and the stability of the algorithm. To visualize the optimization landscape, 3D surface plots were generated for different combinations of variables. Figure 5a, b, and c shows the 3D surface plot for x_1 and x_2 with x_3 value. These plots provide insights into the relationship between the variables and the objective function. The plots reveal the complex interactions between the variables and the objective function, showing how changes in one variable affect the overall coating performance.



MOO function on (a). Porosity vs. microhardness, (b). Porosity vs. Surface roughness, (c). microhardness vs. surface roughness, (d). Convergence of MOO vs. Iteration

FIGURE 5: The 3D surface plots. (a) Time (x2), thickness (x3) vs. MOO; (b) temperature (x1), thickness (x3) vs. MOO; (c) temperature (x1), time (x2) vs. MOO; (d) convergence plot vs. iteration

MOO, multi-objective optimization

The 3D surface plots for each factor such as temperature (x1), time (x2), and thickness (x3) are developed to understand the convergence performance of any two factors with respect to the multi-objective function. Considering equal weights, i.e., $w_1 = w_2 = w_3 = 0.3333$, the combined objective function is generated, and the TLBO algorithm is applied on the combined objective function with the optimum coefficient Z max being 0.963195 and the corresponding values of optimum input parameters are,

Temperature (C) = 950

Time (hrs) = 11

Thickness (Micron) = 20

Effect of process parameters on responses

The effects of process parameters such as deposition time, temperature, and coating thickness on the response variables are illustrated in Figures 6-8.

Surface Roughness

Surface roughness in thermally sprayed or CVD coatings is primarily governed by the interplay between droplet solidification, splat layering, and surface diffusion, all of which are influenced by temperature, time, and coating thickness. Figure 6 shows the 3D surface plots of process parameters on surface roughness. From the data, higher deposition temperatures (especially $\geq 950^\circ\text{C}$) tend to reduce surface roughness, likely due to improved particle melting, better wetting, and stronger adhesion to the substrate, which promote smoother surfaces. At lower temperatures (e.g., 700°C), insufficient melting may lead to irregular splat shapes, increasing surface roughness [27]. Similarly, shorter deposition times (1-3 hours) are associated with higher roughness in some samples, possibly due to incomplete surface coverage and uneven layer formation. In contrast, moderate to longer times (around 6 hours) favor more uniform coating buildup and thermal equilibrium, resulting in smoother finishes [28]. Interestingly, the roughness slightly decreases with increasing coating thickness up to a point, which may be due to improved layering,

though excessive thickness may cause internal stresses and surface undulations if not controlled [29]. In general, smoother surfaces are obtained when the deposition process ensures sufficient thermal input for proper spreading and flattening of particles on the substrate.

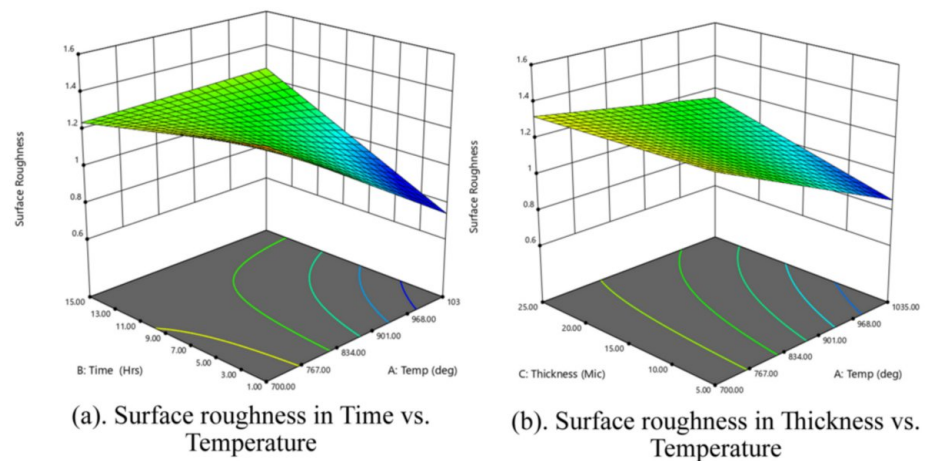


FIGURE 6: The 3D surface plots on surface roughness. (a) Surface roughness in time vs. temperature; (b) surface roughness in thickness vs. temperature

Effect of Process Parameters on Microhardness

Microhardness is a critical indicator of a coating's wear resistance and structural integrity, and it is closely affected by thermal input, deposition duration, and coating thickness. Figure 7 shows the 3D surface plots of process parameters on microhardness. It shows that, hardness increases with temperature, peaking around 1955 VHN at 1035°C and 1866 VHN at 950°C. This trend reflects enhanced densification and grain refinement due to more complete melting and better diffusion bonding at elevated temperatures [30]. However, temperatures that are too high may risk oxidation or phase transformation if not controlled. Time also plays a key role—durations around 6 to 14.5 hours yield the highest hardness values, suggesting that prolonged deposition allows for layer compaction and the development of a fine-grained microstructure through thermal cycling [31,32]. Extremely short deposition times may lead to partially bonded or underdeveloped structures, reducing hardness. Coating thickness contributes as well, where moderate-to-high thickness values (12.5–20 μm) correspond to high hardness, likely due to cumulative deposition of well-fused splats and reduced porosity [33]. Overall, achieving high hardness requires a balanced combination of thermal energy, time for structural development, and sufficient coating build-up to support densification and reduce defects.

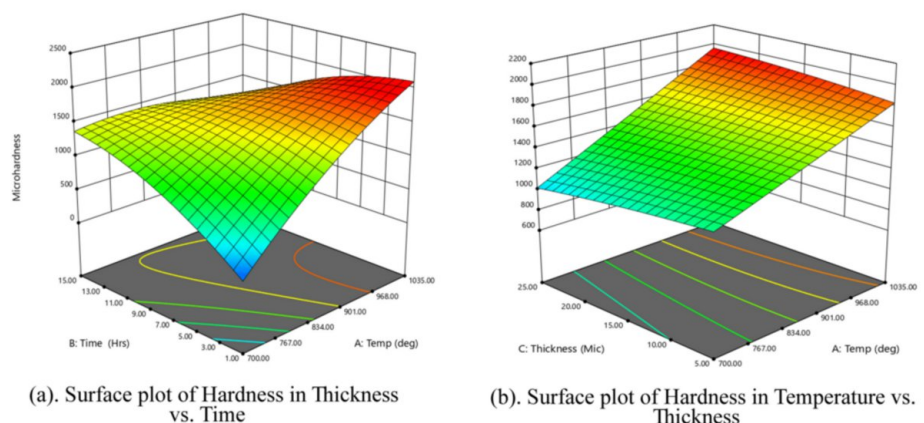


FIGURE 7: The 3D surface plots on microhardness. (a) Microhardness in time vs. temperature; (b) microhardness in thickness vs. temperature

Effect of Process Parameters on Porosity

The porosity of coatings in chemical vapor deposition or related thermal processes is significantly influenced by process parameters such as temperature, time, and thickness [34]. From Figure 8, it is evident that porosity tends to increase at elevated temperatures (particularly beyond 900°C), which can be attributed to accelerated vaporization, oxidation, and gas entrapment in the coating matrix due to overheating. Moderate temperatures around 825°C appear optimal for minimizing such effects [35]. In terms of duration, longer coating times (approximately 6 hours) consistently produce lower porosity, likely due to more complete melting, improved inter-splat bonding, and adequate time for gases to escape before solidification. Shorter durations (1-3 hours), on the other hand, lead to more variable and often higher porosity levels, potentially from insufficient deposition or rapid cooling. The influence of coating thickness on porosity is less direct but still relevant; excessively thin coatings may have fewer structural defects, while thicker coatings can suffer from stacking flaws, interlayer voids, or shrinkage stresses that trap pores [36]. Overall, optimizing temperature and time is critical for achieving dense, low-porosity coatings, while thickness-related porosity can be managed through precise process control.

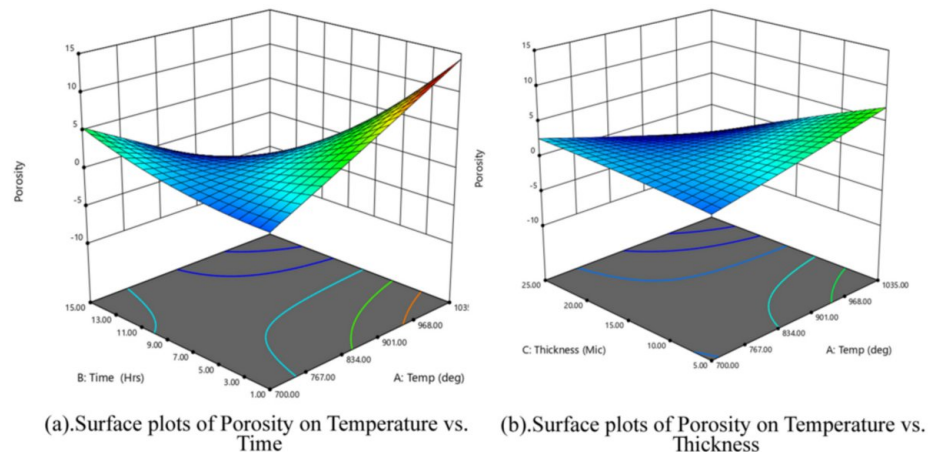


FIGURE 8: The 3D surface plots on porosity. (a) Porosity on temperature vs. time; (b) porosity on temperature vs. thickness

Conclusions

The application of BN coatings via CVD has demonstrated significant potential in enhancing the performance of floating ball valve components used in demanding service environments. By optimizing key CVD parameters using the TLBO algorithm, the study achieved coatings with reduced surface roughness and porosity, alongside increased hardness. The optimal deposition conditions, 950°C, 11µm coating thickness, and 20 hours deposition time, resulted in substantial improvements in sealing efficiency and operational durability. These findings confirm that BN coatings offer a viable and effective surface engineering solution to mitigate wear and degradation issues commonly encountered in conventional metal-to-metal sealing systems, particularly in high-temperature and corrosive applications. TLBO algorithm has proved its effectiveness in solving the MOO problems.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Vijayan D, Rajmohan T, Nandakumar A, Vijayabhaskar S

Acquisition, analysis, or interpretation of data: Vijayan D, Rajmohan T, Nandakumar A, Vijayabhaskar S

Drafting of the manuscript: Vijayan D, Rajmohan T, Nandakumar A, Vijayabhaskar S

Critical review of the manuscript for important intellectual content: Vijayan D, Rajmohan T, Nandakumar A, Vijayabhaskar S

Supervision: Vijayan D, Rajmohan T, Nandakumar A, Vijayabhaskar S

Disclosures

Human subjects: All authors have confirmed that this study did not involve human participants or tissue.

Animal subjects: All authors have confirmed that this study did not involve animal subjects or tissue.

Conflicts of interest: In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Intellectual property info:** Figure 3 is not a copyrighted photograph; it depicts our own facility. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

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