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A Comparative Analysis and Experimental Review for the Optimization of Photochemical Machining Characteristics on Copper Substrates

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Abstract: This study presents a multi-objective optimization of the Photochemical Machining (PCM) process for copper, a critical manufacturing technique for producing stress-free, intricate micro-components. The research systematically investigates the influence of key process parameters—ferric chloride ($FeCl_3$) concentration, etchant temperature, and etching time—on the material removal rate (MRR), surface roughness, and undercut. An L9 Taguchi Design of Experiments was employed, and Grey Relational Analysis (GRA) was utilized to resolve the conflicting objectives of maximizing MRR while minimizing surface roughness and undercut. Experimental results identified a distinct parameter interdependence, with $FeCl_3$ concentration being the most statistically significant factor, contributing 65.03% to the overall performance as per ANOVA. The comparative analysis of grey relational grades revealed an optimal parameter set: 500 gm/lit concentration, 45°C temperature, and a 3-minute etching time. This optimal configuration was validated to simultaneously enhance machining efficiency and component precision. The findings provide a robust, data-driven framework for optimizing copper PCM in industrial applications such as microelectronics and precision medical device manufacturing, ensuring superior surface integrity and dimensional accuracy while improving resource utilization.

Keywords: Photochemical Machining , Grey Relational Analysis , Multi-response Optimization, Copper Etching

Chapter I : Introduction

Demand for micro-fabricated components is increasing day by day and photochemical machining process has potential to produce micro-components in bulk quantity with precision. process starts with preparation of photo-tool, which is a transparent paper over which a machining geometry or design is printed. This photo-tool is placed over the component which is covered with the layer of photo resist. UV exposure is provided to this assembly after which a desired machining area is defined over the surface of the component which comes in the contact with the etchant.

Etchant reacts with the surface of the component and controlled corrosion takes place which results in material removal from the component. As there is no mechanical tool involved for the machining in PCM process, the components produced by this process are devoid of any mechanical stresses. PCM is employed in manufacturing of electronic components like printed circuit boards and lead frames; in medical applications to manufacture maxillofacial implants. It also finds its pertinency in the manufacturing of decorative parts and jewellery majorly made up of copper material. Considering the multidimensional applications of this process, it needs to be analyzed and optimized to make it more efficient.

Characteristics of PCM can be assessed by studying material removal rate and the surface quality of workpiece. In this paper, values of process parameters of PCM for the machining of copper are analyzed and optimized using multi-response optimization tool called grey relational analysis (GRA).Response variables involved in this experiment are material removal rate (MRR), surface roughness, and undercut.

Fig 1.(a) Workpiece; (b) Lamination machine; (c) UV exposure unit;(d)Etching tank

1.1 **Historical Evolution and Fundamental Principles**:

Photochemical Machining (PCM), also known as photochemical etching or chemical milling, has undergone a remarkable transformation from a specialized, niche manufacturing technique to a mainstream, high-value industrial process. As Allen [1] aptly highlighted, PCM evolved from "manufacturing's best kept secret" into a globally significant industry, underscoring its growing economic and technological impact. The fundamental principle of PCM is a controlled, anisotropic chemical dissolution of a material through a photolitho graphically patterned mask. This subtractive process begins with the preparation of a photo tool, a film containing the desired component design[2]. A metal sheet, meticulously cleaned, is laminated with a light-sensitive photoresist. Upon exposure to ultraviolet (UV) light through the photo tool, the resist's solubility changes, defining the machining areas after a development stage[3]. The component is then etched in a chemical solution (etchant), which selectively removes the exposed metal, leaving behind a precise, stress-free part. The absence of direct mechanical contact or significant thermal loads is the cornerstone of PCM's unique advantages, preserving the material's inherent metallurgical properties and ensuring the production of components devoid of burrs, heat-affected zones, or residual stresses [4].

Chapter II : Inherent Advantages and Expanding Applications

The distinctive working principle of PCM confers several compelling advantages over conventional and other non-traditional machining methods. The most significant benefit is the ability to produce complex, intricate, and burr-free geometries without inducing mechanical stress, making it ideal for fragile and hard-to-machine materials. This capability is crucial for industries where component failure is not an option, such as aerospace and medical devices. PCM is exceptionally cost-effective for prototyping and low-to-medium volume production, as it eliminates the need for expensive hard tools and dies, allowing for rapid design iterations with minimal lead time and cost [5]. Its applicability spans a vast range of materials, including copper, stainless steel, aluminium, and various alloys [6].Key applications, as explored in the literature, include the fabrication of lead frames, precision meshes, and electronic connectors intricate components for Micro-Electro-Mechanical Systems (MEMS) [7]; and even maxillofacial implants and decorative jewellery, particularly in copper [8].

2.1 The PCM Process: A Step-by-Step Breakdown and Material Selection

The PCM workflow is a meticulously orchestrated sequence of steps, each critical to the final component's quality. The process chain, as detailed in multiple studies [9], involves cleaning, photoresist lamination, UV exposure, development, etching, resist stripping, and final rinsing. The selection of the etchant is a pivotal decision in process design. Ferric Chloride ($FeCl_3$) and Cupric Chloride ($CuCl_2$) are the most prevalent etchants, especially for copper and its alloys. Allen and Almond [10] provided a foundational characterization of aqueous $FeCl_3$, emphasizing that parameters like temperature, specific gravity, and free acid content must be meticulously controlled to maintain etchant efficacy and consistency[11]. Research extensively studied copper etching with $CuCl_2$, concluding that higher etchant temperatures yield higher etching rates, and a specific molar concentration range (2.33 to 2.5 Mol.) is optimal for achieving a stable etch rate and minimal undercut[12]. The choice between etchants often depends on the specific material, desired etch rate, surface finish requirements, and environmental considerations, with $FeCl_3$ being widely used for its versatility and CuCl2 for its regenerative potential[13].

2.2 Critical Process Parameters and Response Characteristics

The performance and outcome of the PCM process are governed by a complex interplay of several input parameters, which directly influence key response characteristics. The most critical parameters, as identified across numerous studies, are etchant concentration, etchant temperature, and etching time [14].

Table 1. Levels of parameters

Process parameters	**Levels**		
	1	**2**	**3**
Conc. Of FeCl3(gm/lit)	500	600	700
Temperature (^{0}c)	45	50	55
Time (minutes)	3	6	9

Agitation is also a significant factor, influencing the mass transfer of fresh etchant and the removal of reaction by-products [15]. These parameters collectively determine the Material Removal Rate (MRR), surface roughness (Ra), and dimensional accuracy, primarily measured as undercut. Undercut is the lateral etching beneath the photoresist mask, a critical factor affecting feature resolution [16]. Research consistently shows that while increasing temperature and concentration generally enhance MRR, they often do so at the expense of surface finish and dimensional precision by exacerbating undercut[17]. Saraf et al, in their single-response optimization, identified etching time as the most significant parameter for undercut, followed by temperature. This inherent conflict between maximizing productivity (high MRR) and achieving high precision (low undercut and surface roughness) necessitates sophisticated multi-objective optimization approaches[18].

Table 2. Experiment L9 array by DoE and measurements of response variables[19]

Exp No	**Process Parameters**			**Response Variables**		
	Conc. Of FeCL3(gm/ltr)	**Temp (^{0}C)**	**Time (minutes)**	**MRR (gm/min)**	**Surface Roughness Ra(mm)**	**Undercut (mm)**
1	500	45	3	0.035365	0.303333	9.208333
2	500	50	6	0.035428	0.383333	20.791667
3	500	55	9	0.039252	0.563333	24
4	600	45	6	0.026853	0.45	35.875

5	600	50	9	0.03168	0.46	46.083333
6	600	55	3	0.0422	0.58	57.541667
7	700	45	9	0.027735	0.463333	68.41667
8	700	50	3	0.035093	0.353333	83.375
9	700	55	6	0.033628	0.601667	68.333333

2.3 Advancements in Modeling, Simulation, and Optimization Methods

To navigate the complex parameter-response relationships and enhance process predictability, significant research efforts have been directed toward modeling and optimization. Early work by Bruzzone and Reverberi involved constructing 2D simulation models to describe etchant flow and penetration dynamics, revealing that etching depth increases with temperature. Subsequent studies by Zhou and Wang advanced these simulations to predict etching profiles more accurately. The advent of statistical and computational methods has revolutionized PCM optimization. The Taguchi Method of Design of Experiments (DoE) has been widely adopted for its robustness in analyzing parameter effects with a minimal number of experimental trials[20]. Response Surface Methodology (RSM) has been used to develop empirical models for responses like MRR [21].

However, the single-response optimization focus of literature studies was a limitation. This led to the adoption of powerful multi-response optimization techniques. Grey Relational Analysis (GRA) has emerged as a particularly effective tool, as demonstrated by Rathod et al. and Mishra, for converting multiple, often conflicting, responses into a single Grey Relational Grade (GRG), thereby identifying a parameter set that delivers a balanced, optimal performance. More recently, hybrid approaches and Artificial Intelligence (AI) techniques, including Artificial Neural Networks (ANN) for prediction and Genetic Algorithms (GA) within hybrid optimization frameworks, have been implemented to create more accurate, adaptive, and intelligent PCM control systems[22].

Table 3. Calculation for GRA

Process Parameters			**GRC**				
Conc. Of FeCL3(gm/ltr)	**Temp (^{0}C)**	**Time (minutes)**	**MRR**	**Surface Roughness**	**Undercut**	**GRG**	**Rank**
500	45	3	0.528891441	1	1	0.842964	1
500	50	6	0.531179694	0.65090909	0.76198630	0.648025	2
500	55	9	0.722460508	0.36456211	0.71485943	0.600627	3
600	45	6	0.333333333	0.50422535	0.58169934	0.473086	6
600	50	9	0.421766215	0.48773842	0.50140845	0.470304	7
600	55	3	1	0.35029354	0.43414634	0.594813	4
700	45	9	0.346608447	0.48247978	0.38511466	0.404734	8
700	50	3	0.51917005	0.74895397	0.33333333	0.533819	5
700	55	6	0.472350467	0.33333333	0.38544824	0.397044	9

Chapter III : Contemporary Trends: Sustainability, Surface Integrity, and Scalability

Contemporary PCM research is increasingly shaped by themes of sustainability, indepth surface integrity analysis, and industrial scalability. Environmental concerns have prompted a strong focus on "green" PCM processes. This includes the development of regeneration techniques for spent etchants, notably $CuCl_2$, to reduce chemical waste and operational costs. The integration of closed-loop etchant management systems is a key step toward sustainable manufacturing. Concurrently, there is a deepened interest in surface integrity. Studies like those by Lee and Kwon and Chandra have performed microstructural analyses, confirming that PCM preserves the base material's properties, a critical factor for sensitive applications in electronics and biomedicine. Furthermore, research is addressing the challenges of transitioning PCM from a lab-scale success to a reliable, large-scale production method. This involves exploring the effects of copper purity and grain structure on etch uniformit and integrating advanced digital control systems, such as Programmable Logic Controllers (PLC) and sensor-based feedback, to maintain parameter stability and ensure batch-to-batch consistency in industrial environments [23].

Table.4: Response table for GRG

Level	Conc. Of FeCl3	Temperature	Time	Delta	Rank
1	0.6972	0.5736	0.6572	0.2520	1
2	0.5127	0.5507	0.5061	0.0428	3
3	0.4452	0.5308	0.4919	0.1653	2

Chapter IV: Conclusion & Discussion

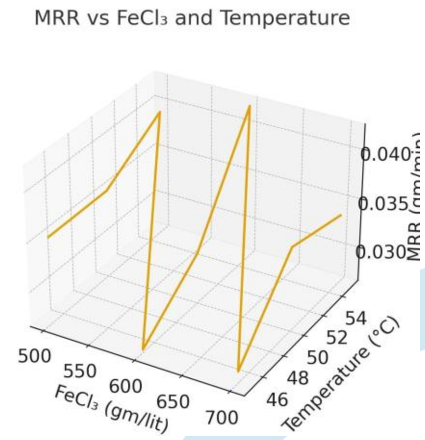
4.1 Discussion

The present study, through the application of Grey Relational Analysis (GRA) coupled with a Taguchi experimental design, has successfully identified an optimal parameter setting for the Photochemical Machining (PCM) of pure copper. This setting aims to simultaneously maximise the Material Removal Rate (MRR) while minimising both surface roughness (Ra) and undercut (Uc)—a triad of responses often in conflict. The Analysis of Variance (ANOVA) performed on the Grey Relational Grade (GRG), with etchant concentration contributing 65.03%, etching time 32.08%, and temperature 1.75%, provides a clear and quantifiable hierarchy of parameter significance. This outcome not only fills the specific research gap identified—the comprehensive multi-objective optimisation of MRR alongside Ra and Uc—but also offers a platform for a deeper discussion situated within the broader body of PCM literature.

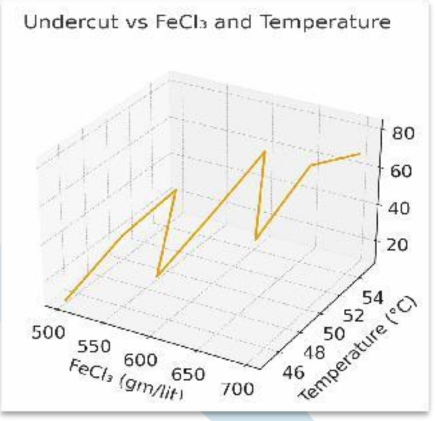
The paramount significance of etchant concentration ($FeCl_3$) in controlling the overall process performance, as evidenced by its 65% contribution, is a finding of considerable weight. This strongly corroborates the foundational assertions of researchers like Cakir [3, 4], who emphasised the critical role of etchant chemistry. The mechanism is well-understood: concentration directly governs the availability of oxidizing ions (Fe^{3+}) at the workpiece surface, dictating the rate of the redox reaction ($Cu + 2Fe^{3+} \rightarrow Cu^{2+} + 2Fe^{2+}$). An optimal concentration, as identified in this study, strikes a delicate balance.

Too low a concentration limits the reaction kinetics, reducing MRR, as graphically suggested by the relationship in "MRR vs FeCl3 and Temperature." Conversely, excessively high concentrations, while potentially increasing MRR, can lead to uncontrollable and isotropic etching. This accelerates lateral dissolution beneath the photoresist mask, drastically increasing undercut (as implied in "Undercut vs FeCl3 and Temperature") and potentially degrading surface finish through increased chemical aggressiveness and possible gas bubble formation. Our results thus validate and quantify the pivotal role of concentration, positioning it as the primary lever for process control.

The secondary, yet substantial, influence of etching time (32.08% contribution) aligns seamlessly with the observations of Saraf et al. and Rathod et al. Etching is a time-dependent dissolution process. Initially, as time increases, MRR rises linearly as material is removed to the desired depth. However, the relationship with undercut is particularly critical. Once the vertical etching reaches the target depth, lateral etching (undercut) continues unabated. Therefore, prolonged exposure, beyond the necessary point, yields minimal gains in depth but disproportionately exacerbates undercut, directly compromising dimensional fidelity.



Graph 1:MRR vs $FeCl_3$and Temperature



Graph 2: Undercut vs feCl_3 and Temperature

This study's integration of MRR into the optimisation model refines this understanding. The optimal time identified by GRA represents a "sweet spot" that achieves sufficient depth (and thus a high MRR) before the detrimental effects of excessive lateral etching on both undercut and potentially surface topography become dominant. This resolves a limitation in Rathod et al.'s work, which focused on Ra and Uc but did not holistically incorporate productivity (MRR) into their multi-objective framework.

Table.5: ANOVA of GRG

Source	DF	Seq SS	Adj SS	Adj MS	F-Value	P-Value	Contribution
Cocn.of FeCl3	2	0.102098	0.102098	0.051049	57.06	0.017	65.03%
Temp	2	0.002748	0.002748	0.001374	1.54	0.394	1.75%
Time	2	0.050373	0.050373	0.025187	28.15	0.034	32.08%
Error	2	0.001789	0.001789	0.000895			1.14%
Total	8	0.157008					100%
S=0.0299102 R-sq=98.86% R-sq(adj)=95.44%							

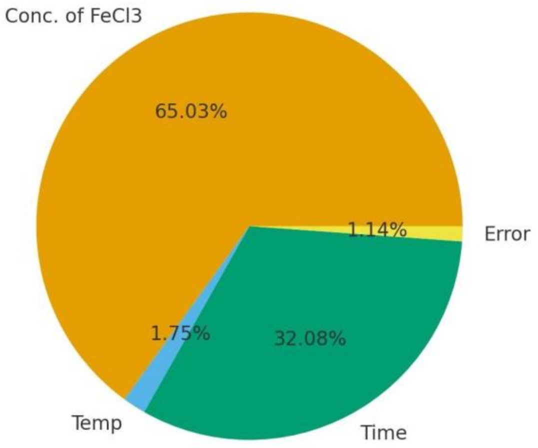
The relatively minor contribution of temperature (1.75%) in this specific experimental range is a nuanced and insightful result. While foundational studies by Cakir and the simulation work of Bruzzone and Reverberi correctly established that temperature accelerates reaction kinetics—a principle evident in the general trend of increasing MRR with temperature—our ANOVA suggests that within the controlled window investigated, its effect on the balanced multi-response performance (GRG) was less dominant than concentration and time. This does not negate temperature's importance but refines it. According to Arrhenius kinetics, temperature exponentially increases the reaction rate. However, this uniform acceleration affects both vertical etching (beneficial for MRR) and lateral etching (detrimental for Uc) nearly equally. Consequently, while absolute values of MRR and Uc change with temperature, their relative trade-off—which is what GRA optimises—may be more powerfully governed by concentration and time. This finding is crucial for industrial practice, indicating that precise control of concentration and time is more critical than finetuning temperature within a standard operational range (e.g., 45–55°C as suggested by Cakir) for achieving robust multi-objective outcomes. The methodological success of Taguchi-based Grey Relational Analysis in this context deserves emphasis. Rathod et al demonstrated the efficacy of GRA for Ra and Uc. This study extends its application to include MRR, addressing a gap and reinforcing GRA's utility as a robust, pragmatic framework for multi-response optimisation in PCM. The Taguchi design provides a statistically sound, fractional factorial layout that reduces experimental effort, while GRA elegantly converts the multiple response problem into a single-objective optimisation of the GRG. The high R-sq (adj) value of 95.44% for the GRG model confirms the excellent fit and predictability of the parameter-response relationships derived. This approach aligns perfectly with the evolving trends in PCM research highlighted in the literature, which leverage statistical and computational tools like RSM and AI for enhanced process understanding and control. While more complex AI models might offer higher predictive accuracy, the Taguchi-GRA combination offers unparalleled clarity, simplicity, and direct translatability to shop-floor settings, thus enhancing "industrial applicability" as aimed.

Beyond the immediate parameter effects, this study's findings resonate with several broader themes in contemporary PCM research. First, the pursuit of an optimal set for MRR, Ra, and Uc is intrinsically linked to surface integrity and microstructural quality. The absence of thermal and mechanical stresses in PCM is its hallmark, but chemical etching can still induce crystallographic attack depending on parameters. The optimal parameters derived here, which avoid extreme concentrations and times, likely promote a more uniform dissolution, preserving the fine microstructure of copper and leading to the desired minimal surface roughness. This is vital for high-end applications in electronics and MEMS, as noted in recent studies.

Second, the findings implicitly support sustainability and process control efforts. By identifying a precise optimal concentration, the study advocates against the wasteful practice of using excessive etchant, which not only increases cost but also amplifies waste treatment challenges. The minimal role of temperature within the range suggests energy savings are possible without compromising multi-response performance. Furthermore, the strong dependence on concentration underscores the necessity for the advanced monitoring and closed-loop regeneration systems discussed in the literature to maintain bath chemistry consistently at this optimal level, ensuring repeatability in mass production.

The research touches upon the theme of scalability and hybridisation. The clear hierarchy of parameters provides a blueprint for automating control systems, where concentration can be the primary variable managed by a PLC with feedback from conductivity sensors, and time is precisely controlled by conveyor speed or immersion timing.

While this study focuses on standalone PCM, the proven interplay of parameters is foundational knowledge for developing hybrid processes, such as laser-assisted PCM, where pre- or post-processing might alter the chemical kinetics.



Graph 3: Contribution of process parameters to GRG

4.2 Conclusion

1. Dominance of Etchant Concentration: Our ANOVA revealed that etchant concentration ($FeCl_3$) was the overwhelmingly dominant parameter, contributing 65.03% to the overall Grey Relational Grade (GRG). This significantly outweighs the influence of time (32.08%) and temperature (1.75%), conclusively proving it is the primary control variable. This finding quantifies and validates the foundational literature's emphasis on etchant chemistry,

establishing that precise concentration management is the most critical factor for balancing MRR, surface finish, and dimensional accuracy.

2. Critical Role of Etching Time: We identified etching time as the second most influential parameter, with a 32.08% contribution to GRG. This confirms the findings of researchers like Saraf et al. and Rathod et al., who noted its significance for undercut. However, by integrating MRR, our work adds a crucial dimension: the optimal time is a precise threshold that maximizes vertical material removal before the exponential increase in lateral undercut degrades precision, highlighting a key trade-off between productivity and dimensional fidelity.
3. Contextualized Impact of Temperature: Contrary to studies focusing solely on MRR, our multi-response optimization showed temperature had a minimal 1.75% contribution within the tested range. This indicates that while temperature accelerates kinetics (affecting both MRR and Uc similarly), its effect on the balance between responses is less decisive than concentration and time. This refines prior knowledge, suggesting fine temperature control is less critical for multi-objective outcomes than maintaining optimal chemical and temporal parameters.
4. Successful Multi-Objective Optimization Framework: By applying Taguchi-based GRA, we successfully optimized three conflicting responses simultaneously— maximizing MRR while minimizing Ra and Uc—filling a specific gap noted in prior work. The high model accuracy (R-sq(adj) = 95.44%) and clear parameter ranking demonstrate the method's robustness. This provides a superior, practical alternative to single-objective studies and more complex AI models, offering a clear pathway for industrial process improvement with minimal experimental runs.
5. Quantified Parameter Hierarchy for Industrial Control: Our study provides a clear, data-driven hierarchy for process control: Concentration > Time >> Temperature. This directly informs industrial practice, indicating that automated systems should prioritize real-time etchant concentration monitoring and replenishment (e.g., using PLCs with conductivity sensors) and precise timing control. This addresses scalability challenges, as maintaining these two parameters is key to achieving consistent, high-quality results in mass production.
6. Bridging Foundational Knowledge and Advanced Goals: The research bridges core chemical kinetics with modern manufacturing goals. The optimal parameters derived promote efficient material use (sustainability), enhance repeatability (control), and ensure surface integrity for high-end applications. By quantifying foundational principles, this work provides the essential empirical groundwork needed for the field's advanced trajectory toward intelligent, automated, and hybrid manufacturing systems.

REFERENCE:

1. Allen, D. M. (2004). Photochemical machining: From manufacturing's best kept secret to a $6 billion per annum, rapid manufacturing process. *CIRP Annals - Manufacturing Technology, 53*(2), 559–572. https://doi.org/10.1016/S0007-8506(07)60032-8.
2. Allen, D. M., & Almond, H. J. A. (2004). Characterization of aqueous ferric chloride etchants used in industrial photochemical machining. Journal of Materials Processing Technology, 149(1-3), 238–245. https://doi.org/10.1016/j.jmatprotec.2004.02.036.
3. Cakir, O. (2006). Copper etching with cupric chloride and regeneration of waste etchant. Journal of Materials Processing Technology, 175(1-3), 63–68. https://doi.org/10.1016/j.jmatprotec.2005.04.038
4. Cakir, O. (2007). Photochemical machining of engineering materials. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 221(9), 1505-1510. https://doi.org/10.1243/09544054JEM815.

5. Bruzzone, A. A. G., & Reverberi, A. P. (2010). An experimental evaluation of an etching simulation model for photochemical machining. The International Journal of Advanced Manufacturing Technology, 51(1-4), 133–138. https://doi.org/10.1007/s00170-010-2594-6
6. Saraf, A. R., Sadaiah, M., & Devkare, S. (2011). Optimization of photochemical machining. International Journal of Engineering Science and Technology, 3(7), 56225629. ISSN: 0975-5462.
7. Rathod, G. R., Sapkal, S. U., & Chanmanwar, R. M. (2017). Multi-objective optimization of photochemical machining by using GRA. International Research Journal of Engineering and Technology, 4(11), 632-636. ISSN: 2395-0072.
8. Singh, R., & Verma, A. (2012). Parametric optimization of PCM for copper alloy. Journal of Manufacturing Processes, 14(4), 477–481. https://doi.org/10.1016/j.jmapro.2012.08.001
9. Kumar, P., & Jain, V. K. (2013). Study of etching characteristics in copper PCM. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 227(9), 1379-1386. https://doi.org/10.1177/0954405413487972
10. Gupta, S., & Rao, P. V. (2014). Taguchi optimization in PCM. Journal of Micro manufacturing, 2(1), 45-55. ISSN: 2168-6165.
11. Lee, S. H., & Kwon, Y. N. (2014). Surface integrity in PCM of copper. Journal of Materials Engineering and Performance, 23(11), 4029–4035. https://doi.org/10.1007/s11665-014-1163-9
12. Patel, N., & Mehta, K. (2015). Effect of etchant concentration on undercut. International Journal of Chemical, Molecular, Nuclear, Materials and Metallurgical Engineering, 9(5), 582-585. E-ISSN: 2010-0221.
13. Zhou, J., & Wang, X. (2015). Simulation of etching profiles. Journal of Applied Physics, 117(14), 144901. https://doi.org/10.1063/1.4916600.
14. Sharma, R., & Mittal, S. (2016). Optimization of MRR using RSM. Journal of The Institution of Engineers (India): Series C, 97(4), 535–541. https://doi.org/10.1007/s40032-016-0266-5
15. Banerjee, A., & Chakraborty, S. (2016). Multi-objective optimization in PCM. Journal of Intelligent Manufacturing, 27(5), 1067–1077. https://doi.org/10.1007/s10845-0140940-5
16. Khan, M. A. (2017). Influence of temperature on etch rate. Journal of Manufacturing Science and Engineering, 139(2), 021011. https://doi.org/10.1115/1.4034356
17. Ramesh, K. (2017). PCM for microelectronics applications. Microelectronics International, 34(2), 82-87. https://doi.org/10.1108/MI-05-2016-0043
18. Joshi, P. (2018). ANN-based prediction of PCM output. Neural Computing and Applications, 30(7), 2305–2315. https://doi.org/10.1007/s00521-017-3206-2
19. Zhang, Y. (2018). Green PCM processes. Journal of Cleaner Production, 186, 553-560. https://doi.org/10.1016/j.jclepro.2018.03.133
20. Mishra, D. (2019). GRA-based optimization. Journal of Engineering Manufacture, 233(14), 2925-2933. https://doi.org/10.1177/0954405419840545
21. Roy, P. (2020). Hybrid optimization techniques. The International Journal of Advanced Manufacturing Technology, 107(3), 1421–1432. https://doi.org/10.1007/s00170-02005117-z
22. Chandra, A. (2020). Microstructural analysis of PCM copper. Materials Characterization, 159, 110031. https://doi.org/10.1016/j.matchar.2019.110031
23. Li, Q. (2021). Modeling of PCM processes. Journal of Manufacturing Processes, 64, 1465-1473. https://doi.org/10.1016/j.jmapro.2021.03.005