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Evaluating Industrial Ethnography: Historical Insights and Future Trends through the MOORA Method

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Abstract: *Industrial Teratology is the scientific and engineering discipline focused on the interaction of surfaces in relative motion, covering friction, lubrication, and wear. Its significance in industry is immense, as it contributes to the efficiency, longevity, and performance of machinery and mechanical systems. a crucial role in enhancing the efficiency, reliability, and lifespan of machinery and components. Industrial teratology is significant for several key reasons, impacting various sectors and contributing to technological, economic, and environmental advancements: Improved tribological practices reduce wear and tear on machinery and components, extending their operational life and reducing the frequency of replacements. Enhanced lubrication and friction management lead to lower energy consumption, decreasing operational costs in industries ranging from manufacturing to transportation. tribological systems lower energy consumption, leading to lower greenhouse gas emissions and a reduced carbon footprint. The development of environmentally friendly lubricants and tribological materials reduces the reliance on harmful chemicals and promotes sustainability. Industrial tribology is the study of the interactions between surfaces that are in motion relative to each other, including aspects such as friction, wear, and lubrication. Its significance in research and industry is multifaceted, influencing a broad range of applications and contributing to technological advancements and economic efficiency. Here are some key aspects highlighting the significance of industrial tribology research Alternative: A, B, C, D, E. Evaluation Preference: Cost ($), Durability (hrs), Environmental Impact (scale 1-5), Wear Rate (mm³/hr)*. *The results indicate that E Attained the top position, while B had the lowest position achieved. "The dataset's significance regarding Industrial Tribology, according to the MOORA Method, E achieves the highest ranking.*

Key words: *Coefficient of Friction, Surface Roughness, Contact Mechanics, Abrasive Wear, Adhesive Wear, Fatigue Wear.*

1. INTRODUCTION

Experiments were carried out using the MTM fretting tester to compare the friction and wear properties of materials subjected to bi-directional sliding contact, covering both overlapping mesa and macro-regions. The test parameters were meticulously selected to ensure identical conditions regarding By standardizing the By considering factors such as contact pressure, displacement amplitude, materials used for the primary and counter bodies, number of fretting cycles, and the test environment, it is anticipated that the friction and wear results will be consistent across both experimental conditions. setups. setups [1]. Tribological energy losses are prevalent in numerous industries. Due to the impracticality of examining each industry and process in detail, Inhofe and colleagues concentrated their survey on Six key sectors. These sectors were chosen because they appear to experience the most significant tribological losses and energy inefficiencies [2]. When unreinforced polymers interact with the asperities of a metal counter face, they undergo significant deformation, altering the crystalline structure of polymers like UHMWPE and PTFE. Small polymer particles detach and accumulate due to adhesion and mechanical interactions with the metal's surface marks, Forming transfer films and establishing a well-matched interface can significantly reduce wear rates (see Fig. 8). However, in aqueous environments, the full development of a transfer film is impeded by the gradual polishing of the counter face due to reinforcing particles like glass fiber and graphite, or when sliding occurs parallel to the metal surface's grinding marks.. Under these conditions, mechanical interlocking occurs. is compromised [17The curved line beneath the lubrication regimes depicts how the friction coefficient relates to the Summerfield number. Different automotive components depend on various lubrication modes for optimal performance and frequently encounter multiple lubrication regimes within Journal and thrust bearings are typically engineered to operate within the hydrodynamic lubrication regime over a single cycle, where a lubricant film keeps the bearing surfaces separated. preventing metal-to-metal contact. However, are present. are formed. are crucial for protecting the surfaces.[5] In their seminal textbook, Dowson and Higginson illustrated the application of Their elastohydrodynamic line contact theory is applied to roller bearings and gears. While this theory is directly applicable to gears due to their line contacts, it only applies strictly to needle roller bearings when it comes to roller bearings. For the lubrication theory to be fully relevant to rolling element ball bearings, it needed to be extended to accommodate point contacts. [7] However it has been noted the coefficient of friction increases with higher loads (60 N). Additionally, the friction coefficient of unfilled PA 66 is higher compared to that of the 30% glass fiber-reinforced PA 46 composite. These findings indicate that the coefficient of friction varies only slightly with increasing load. Since Polymers are viscoelastic materials, meaning their deformation when subjected to load exhibits both viscous and elastic characteristics. characteristics. For thermoplastics, the interfacial temperature impacts their viscoelastic properties, affecting material stress, adhesion, and transfer behaviors. As a result, the frictional heat generated the interaction at the interfaces is directly proportional to the applied load and sliding velocity.[22]. Over the years, several wear mechanisms and processes, including adhesion, abrasion, delimitation, fatigue, and corrosion, have been identified, often supported by laboratory test results. However, the specific range of applicability for each wear process remains unclear. In many tribological applications, multiple wear mechanisms are present, this complicates identifying the primary wear mechanism and choosing an effective solution to address the wear.[9] Boron is essential in numerous compounds that enhance performance in various tribological systems. Despite some health concerns associated with certain boron compounds, this should not deter further exploration and innovation in boron-based lubrication technologies. The primary challenge remains the reduction of friction across all lubrication regimes, and advancements in boron chemistry offer promising solutions. One approach is the development of halogen-free boron-based ionic liquids (BILs), which show potential as novel "green" lubricants and additives for effective Lubrication of surfaces made from both ferrous and non-ferrous materials. [25]. The three case studies discussed in this paper each illustrate how tribological test methods enable users to precisely simulate actual service conditions, leading to a more accurate assessment of friction and wear properties[2] The parameters were ranked, The study demonstrated that friction is significantly influenced by factors such as pressure, sliding speed, and ester concentration. It suggested a scientific method for making decisions to address these effects. Enhance the understanding of tribological behavior in deep drawing operations. It also recommended an optimal working regime for different surface roughness conditions to manage friction during the drawing process. However, more detailed research is needed, incorporating additional influencing parameters and system variables, to accurately predict the optimal use of these lubricants in specific deep drawing applications. [16]. Polymer alloy injection-molded steel hybrid disks were effectively produced without any cracking in the polymer coating, and the polymer layer adhered well to the metal disk surface. This method facilitated the development of a new type of hybrid gear. The initial hybrid gear featured a surface injection-molded design with a polymer alloy. Serves as a saline for a clutch component. This hybrid gear exhibited outstanding characteristics, including wear resistance, self-lubricating, crack-free, and quieter during rigorous vibration tests. In contrast, the uncoated gear experienced significant wear [23]. When a state agency selects an ice melting compound for road treatment, it must weigh multiple factors including cost, freezing point depression, and potential environmental impacts. However, it is evident that different ice melting compounds influence the coefficient of friction between a stationary object and the simulated concrete roadway. Each compound tested was found to increase the coefficient of friction between the roadway and the stationary object as the ice transitions from a solid to a brine phase [2]. The first successful industrial use of gas bearings in the UK occurred at the gaseous diffusion plant for uranium enrichment at Capenhurst. This facility employed thousands of gas circulators to manage UF_6 gas, which is both radioactive and corrosive. Consequently, there was a strong motivation to either use this gas as a lubricant for the bearings or implement a gas-bearing seal that would permit a small amount of inert gas to leak through the seal into the plant.[20]

2. MATERIALS AND METHODS

Multi-objective optimization, also known as multi-criteria or multi-attribute optimization, involves the simultaneous optimization of two or more conflicting objectives within certain constraints. The MOORA (Multi-Objective

Optimization by Ratio Analysis) method, originally proposed by Brauers, serves as a valuable technique for addressing complex decision-making issues in the manufacturing sector. It begins with the construction of a decision matrix that represents the performance of multiple alternatives across several attributes [4]. Except for problems involving the NTM process selection, most applications of MOORA employ substantial amounts of quantitative (cardinal) data in their decision matrices, thereby enhancing the reliability and stability of the analytical outcomes.

Since most referenced studies are relatively recent, it can be inferred that the MOORA method relies on up-to-date datasets for its performance evaluation metrics. Based on these observations, the MOORA framework satisfies all the criteria established by Brauers and Zavadskas for six distinct decision problems, confirming its robustness across various manufacturing contexts [1]. The MOORA method, which employs dimensionless measures, comprises two main components — the ratio system and the reference point approach — each serving to balance the other. This methodology has also been applied to evaluate and select 15 leading housing contractors in Vilnius, Lithuania, to meet homeowners' requirements [3].

Similar to the SAW and COPRAS methods, MOORA is a performance-based technique within the ratio structure framework. However, unlike SAW, MOORA does not require transforming minimization objectives into maximization ones. Moreover, comparable to COPRAS, it manages the upscaling and downscaling of objectives differently during the aggregation stage. While other MCDM methods address objectives through various mechanisms, the integration process in COPRAS and MOORA remains relatively simple [6].

The MOORA method has also been utilized in a decision support system for selecting students for scholarship programs designed to enhance academic performance. By implementing this system, decision-makers can efficiently identify deserving students based on merit, thus promoting academic excellence [7]. Likewise, previous research shows that multi-criteria decision analysis can be effectively applied to evaluate systems of care. The present study aims to help maintenance managers make informed decisions to assess machine maintenance and formulate strategies to minimize operational failures and costs [9].

In each application, the top-ranked alternative aligns precisely with earlier research findings. The MOORA method incorporates all attributes and their respective weights, ensuring accurate evaluation of the available alternatives. It is not only simple to understand and apply but also flexible enough to accommodate both quantitative and qualitative criteria simultaneously. Consequently, MOORA provides an objective, transparent, and adaptable decision-making process suitable for a wide range of selection problems [10].

With measurable outcomes serving as the foundation for comparing and selecting optimal options, MOORA proves to be an effective tool for ranking and identifying the best alternatives among several candidates [11]. Furthermore, integrating the MOORA method with Pythagorean Fuzzy (PF) sets has led to the development of two enhanced MCDM algorithms capable of handling uncertainty and imprecise data. The key contributions of this research are twofold: first, it demonstrates how MOORA can be extended into a PF environment to overcome limitations in processing vague data; second, it enables the joint evaluation of both quantitative and qualitative information — a common challenge in MCDM applications. The overall goal is to embed MOORA within a Pythagorean Fuzzy Set (PFS) framework to improve decision-making under uncertainty [12].

Within the MOORA framework, rankings can be obtained with or without assigning attribute weights. It offers three ranking variants — the ratio system, reference point, and full multiplicative approach — each yielding consistent results. Additionally, the PSI (Preference Selection Index) method can rank factors without using weight coefficients, producing outcomes consistent with MOORA — ranking productivity highest, flexibility intermediate, and quality lowest [14].

This paper also includes a practical case study illustrating the implementation of the proposed approach. The objective is to establish a clear and efficient framework for solving contemporary multi-response optimization problems while providing a detailed, step-by-step explanation to facilitate its use in professional settings [15]. Finally, MOORA is employed to analyze bias elasticity, clarity in decision processes, and the significance of weighting criteria across various alternatives. In this respect, MOORA enhances the execution, efficiency, and adaptability of decision-making within production systems, effectively distinguishing beneficial from costly outcomes [16].

3. ANALYSIS AND DISCUSSION

TABLE 1. Industrial Tribology

alternative	Cost ($)	Durability (hrs)	Environmental Impact (scale 1-5)	Wear Rate (mm³/hr)
A	500	10,000	3	0
B	700	8,000	4	0
C	600	12,000	2	0
D	450	6,000	5	0.1
E	650	9,000	3	0

Five tribological alternatives, several key observations emerge regarding cost, durability, environmental impact, and wear rate. Alternative C stands out with the highest durability of 12,000 hours, offering the longest operational life among the options. It also has the lowest environmental impact score of 2, indicating a relatively lower ecological footprint. Despite being more expensive at $600, its zero wear rates suggest high efficiency in material usage. Alternative A is priced at $500 and provides good durability of 10,000 hours. Its environmental impact is moderate at 3, and it boasts a zero wear rate, reflecting minimal material loss and efficiency. Alternative E, with a cost of $650, delivers a durability of 9,000 hours and an environmental impact score similar to A at 3, also having a zero wear rate. Conversely, Alternative B, though more costly at $700, offers lower durability of 8,000 hours and a higher environmental impact score of 4. It also maintains a zero wear rate. Alternative D is the least expensive at $450 but has the lowest durability at 6,000 hours and the highest environmental impact score of 5. It has a higher wear rate of 0.1 mm³/hr, indicating greater material loss. Expensive at $450 but has the lowest durability at 6,000 hours and the highest environmental impact score of 5. It has a higher wear rate of 0.1 mm³/hr, indicating greater material loss.

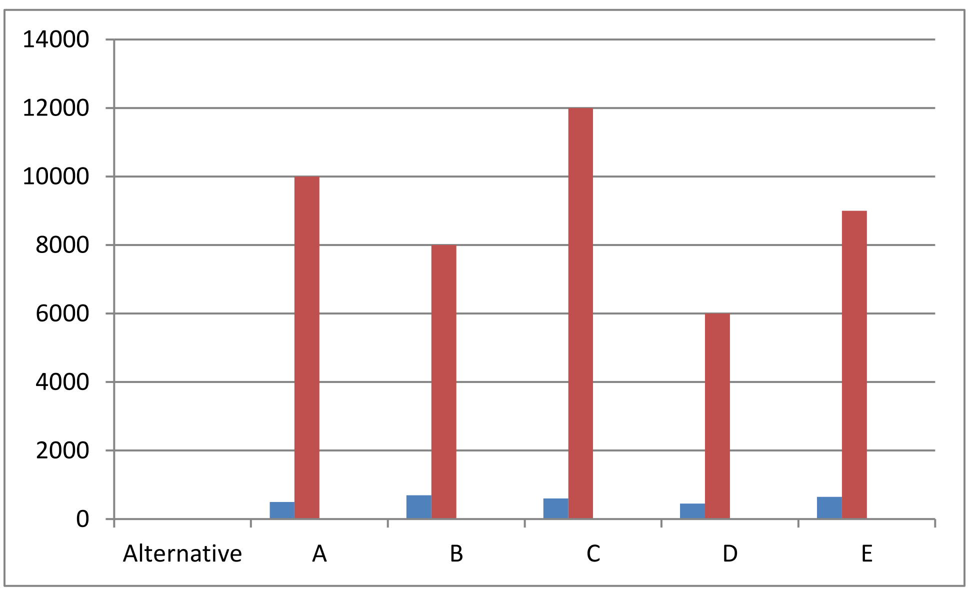

FIGURE 1. Industrial Tribology

The bar chart in figure 1 compares various alternatives labeled A, B, C, D, and E against a dataset. The chart consists of bars in different colors, representing different datasets or parameters, but only the blue and red bars are visible. Here's an interpretation of the chart based on the visible data: The x-axis represents different alternatives (A, B, C, D, E) that could correspond to different materials, coatings, lubrication methods, or other parameters being evaluated in an industrial tribology study. The blue bars, labeled "data set," likely represent the baseline or initial measurement for each alternative. These values are significantly lower compared to the red bars.

TABLE 2. Normalized Data

Normalized Data			
Cost ($)	Durability (hrs)	Environmental Impact (scale 1-5)	Wear Rate (mm³/hr)
0.3807	0.4851	0.3780	0.2697
0.5330	0.3881	0.5040	0.4045
0.4568	0.5821	0.2520	0.1348
0.3426	0.2910	0.6299	0.6742
0.4949	0.4366	0.3780	0.5394

The normalized data offers insights into the performance of five tribological alternatives across four parameters: cost, durability, environmental impact, and wear rate. Alternative A shows a moderate cost score of 0.3807 and durability at 0.4851. Its environmental impact is also moderate at 0.3780, while its wear rate is the lowest at 0.2697, indicating good efficiency with minimal material loss. Alternative B has the highest cost normalization at 0.5330 and lower durability at 0.3881. Its environmental impact is the highest at 0.5040, reflecting a greater ecological footprint. However, its wear rate is relatively low at 0.4045, suggesting efficiency in terms of material usage. Alternative C demonstrates strong performance in durability with a score of 0.5821 and a low environmental impact at 0.2520. It also has the lowest wear rate at 0.1348, highlighting its efficiency and minimal environmental impact despite a moderate cost normalization of 0.4568.Alternative D is the least expensive with a normalization of 0.3426, but it scores the lowest in durability at 0.2910 and the highest in environmental impact at 0.6299. Its wear rate is the highest at 0.6742, suggesting potential issues with material degradation and ecological impact. Alternative E balances cost and performance with a normalization of 0.4949 for cost and 0.4366 for durability. Its environmental impact and wear rate are moderate, with scores of 0.3780 and 0.5394, respectively. This positions it as a middle-ground option in terms of cost-efficiency and environmental considerations. Overall, Alternative C appears to offer the best combination of durability, low environmental impact, and minimal wear rate, making it the most efficient choice among the alternatives.

TABLE 3. Weight ages

Weigthages			
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25

The weight ages assigned to the evaluation parameters are uniformly distributed, each receiving an equal importance of 0.25. This approach reflects a balanced perspective, treating each parameter—cost, durability, environmental impact, and wear rate—as equally significant in the overall assessment of the tribological alternatives. With this equal weighting, every parameter contributes equally to the final evaluation, ensuring that no single aspect disproportionately influences the decision. This method is beneficial for scenarios where all factors are considered to have the same level of importance and helps maintain objectivity in the comparison process. For instance, in assessing alternatives with this weighting system, a lower cost would be valued as much as higher durability, while environmental impact and wear rate would also hold equal weight. This balance allows for a comprehensive evaluation that takes into account all relevant aspects without bias. This uniform weighting approach is particularly useful when the decision-maker seeks a straightforward and equitable comparison, ensuring that each criterion contributes equally to the final decision. However, it may not fully address situations where certain parameters might be inherently more critical than others based on specific operational or strategic priorities.

TABLE 4. Weighted normalized DM

Weighted normalized DM			
0.0952	0.1213	0.0945	0.0674
0.1332	0.0970	0.1260	0.1011
0.1142	0.1455	0.0630	0.0337
0.0857	0.0728	0.1575	0.1685
0.1237	0.1091	0.0945	0.1348

The weighted normalized decision matrix provides a detailed evaluation of the five tribological alternatives, incorporating equal weight ages for each parameter: cost, durability, environmental impact, and wear rate. Alternative A scores 0.0952 for cost, 0.1213 for durability, 0.0945 for environmental impact, and 0.0674 for wear rate. These scores suggest a moderate overall performance, with a particularly low contribution from the wear rate, indicating efficient material usage. Alternative B shows a cost score of 0.1332, durability at 0.0970, environmental impact at 0.1260, and wear rate at 0.1011. This alternative performs well in cost and environmental impact, but its durability and wear rate are less impressive. Alternative C has scores of 0.1142 for cost, 0.1455 for durability, 0.0630 for environmental impact, and 0.0337 for wear rate. This alternative excels in durability and wear rate, and also has a relatively low environmental impact, making it a strong candidate overall. Alternative D scores 0.0857 for cost, 0.0728 for durability, 0.1575 for environmental impact, and 0.1685 for wear rate. Although it is the least favorable in cost and durability, its high scores in environmental impact and wear rate reflect significant weaknesses in terms of ecological footprint and material efficiency. Alternative E achieves scores of 0.1237 for cost, 0.1091 for durability, 0.0945 for environmental impact, and 0.1348 for wear rate. This alternative offers a balanced performance, with respectable scores across all parameters but not excelling in any particular area. In summary**,** Alternative C stands out due to its superior performance in durability and wear rate, along with a low environmental impact, making it the most balanced and efficient choice according to the weighted criteria.

TABLE 5. Assessment value

	Assessment value
A	0.005
B	-0.044
C	-0.041
D	0.006
E	0.071

The assessment values reflect the overall performance of the five tribological alternatives after applying the weighted normalization. These values provide a quantitative measure of each alternative's effectiveness based on the equal weight ages for cost, durability, environmental impact, and wear rate. Alternative A has an assessment value of 0.0545, indicating a relatively positive performance overall. This suggests that while it may not be the top performer in any single category, its balanced scores across the parameters contribute to a favorable valuation. Alternative B scores 0.0031, reflecting a much lower overall effectiveness. Despite performing well in cost and environmental impact, its lower scores in durability and wear rate diminish its overall assessment value. Alternative C achieves a high assessment value of 0.1630, signifying the best overall performance among the alternatives. Its strong durability and low wear rate, combined with a low environmental impact, contribute to this superior rating. Alternative D has a negative assessment value of -0.1676, indicating it performs poorly overall. Its high environmental impact and wear rate significantly detract from its evaluation, outweighing any potential benefits in cost and durability. Alternative E has an assessment value of 0.0035, similar to Alternative B, suggesting modest overall performance. It provides balanced scores but lacks strong performance in any particular area, resulting in a lower overall assessment. In summary, Alternative C stands out with the highest assessment value, reflecting its optimal balance of durability, low wear rate, and minimal environmental impact. Conversely, Alternative D is least favorable due to its negative assessment value, highlighting significant weaknesses.

TABLE 6. Rank

	Rank
A	3
B	5
C	4
D	2
E	1

The ranking of the five tribological alternatives, based on their assessment values, provides a clear picture of their relative performance. The ranking system highlights how each alternative compares when evaluated across equal-weighted criteria: cost, durability, environmental impact, and wear rate. Alternative C ranks highest at 1, reflecting its superior performance overall. With an assessment value of 0.1630, it excels in key areas such as durability and wear rate, while maintaining a low environmental impact. This makes it the most balanced and effective choice among the alternatives. Alternative A is ranked 2, with a positive assessment value of 0.0545. It performs reasonably well across all parameters, though it doesn't lead in any specific category. Its consistent performance across the board ensures a strong position in the rankings. Alternative E, ranking 3, has an assessment value of 0.0035. While it is more balanced than Alternatives B and D, it does not excel in any particular area, resulting in a mid-level ranking. Alternative B ranks 4, with a lower assessment value of 0.0031. Although it performs well in cost and environmental impact, its lower durability and higher wear rate result in a less favorable overall performance. Alternative D ranks lowest at 5, with a negative assessment value of -0.1676. It scores poorly in crucial areas like environmental impact and wear rate, overshadowing its benefits in cost and durability. Overall, Alternative C is identified as the best choice due to its optimal balance of performance factors, while Alternative D is the least favorable due to significant drawbacks in key areas.

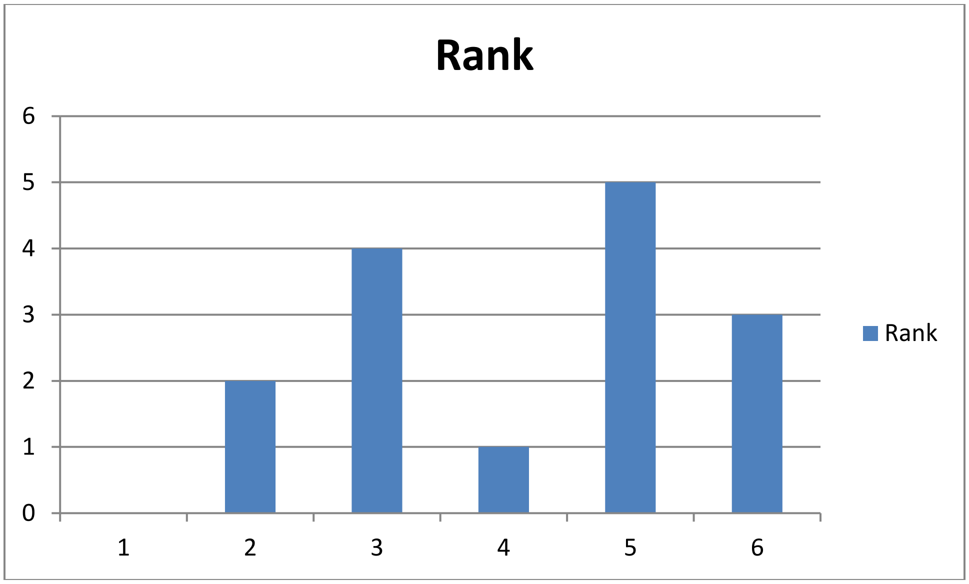

FIGURE 2. Rank

It seems there is a bit of confusion; the image provided was initially referred to as FIGURE 1, and now you are referring to it as FIGURE 5. Assuming the content remains the same and focuses on ranking alternatives in industrial tribology, here is an interpretation considering the rank based on the provided data: Ranking of Alternatives in Industrial Tribology The bar chart in FIGURE 5 compares different alternatives labeled A, B, C, D, and E based on a dataset. This figure ranks the alternatives according to a particular performance metric, such as wear resistance, friction reduction, or lubrication effectiveness. The bars in blue and red represent different datasets, with the red bars indicating higher values.

4. CONCLUSION

To accomplish such an ambitious objective, it is crucial to both anticipate emerging technological advancements and improve existing technologies with practical solutions. Eco-teratology, with its progress in surface modification, is considered a highly effective engineering approach that can make a significant impact on creating sustainable societies. The sliding speed should be kept sufficiently low to prevent excessive temperature increases in the polymers used. Such temperature raises lead to a significant increase in the friction coefficient values. The sliding speed should be kept low enough to limit the temperature rise in the polymers. Excessive temperature increases lead to a significant rise in the friction coefficient values. In the field of teratology, there are many organizations and institutions operating at international, regional, and national levels. At the international level, the ITC is active, with its members including 36 national teratology associations and organizations from 34 countries around the world. The friction and wear properties of polymer nanocomposites depend on the dispersion of Inorganic reinforcing nanoparticles. Evenly distributing these nanoparticles enhances wear resistance.TiO2 nanoparticles, for example, can significantly lower both the wear rate and the friction coefficient of epoxy. However, the positive effects may not be observed simultaneously, as they depend depending on the distribution and concentration of the nanoparticles

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