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Optimizing Standard Work Hours in Fabrication: A Multi-Attribute Decision-Making Approach Using SMART

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ABSTRACT

In the fabrication industry, selecting the most suitable welding method is crucial for optimizing standard work hours (SWH) and achieving efficient resource utilization. This study aims to provide a systematic evaluation of three prevalent welding techniques—Gas Metal Arc Welding (GMAW), Shielded Metal Arc Welding (SMAW), and Gas Tungsten Arc Welding (GTAW)—using the Simple Multi-Attribute Rating Technique (SMART). The objective is to identify the welding method that best balances efficiency, complexity, weld volume, and skill requirements.

The methodology involves evaluating the three welding methods based on five key criteria: Labour Efficiency (LE), Operational Efficiency (OE), Job Weight, Weld Volume, and Skill Level. Each criterion is assigned a relative weight to reflect its importance in the overall evaluation. The SMART technique is employed to aggregate these weights and assess the performance of each welding method against the criteria.

The findings reveal that GMAW stands out as the most effective welding method when considering the balance of efficiency, complexity, weld volume, and required skill level. GMAW's performance surpasses that of SMAW and GTAW in terms of overall suitability for most fabrication tasks. The study concludes that GMAW is optimal for enhancing productivity and resource management in the fabrication industry.

Future research could expand on this study by incorporating additional criteria that might affect welding performance, such as environmental impact or cost considerations. Additionally, applying alternative multi-criteria decision-making techniques could provide further validation of the results and offer a more comprehensive analysis of the welding methods. This would enable a more nuanced understanding of the trade-offs between different welding techniques and their applicability to various industrial contexts.

Keywords — Welding Methods, Simple Multi-Attribute Rating Technique (SMART), Efficiency Optimization, Fabrication Industry, Multi-Criteria Decision-Making

I. INTRODUCTION

Welding is a fundamental process in the fabrication industry, essential for assembling metal components into cohesive structures. The choice of welding method directly influences the efficiency, quality, and cost of production. Among the prevalent welding techniques, Gas Metal Arc Welding (GMAW), Shielded Metal Arc Welding (SMAW), and Gas Tungsten Arc Welding (GTAW) are frequently employed across various industrial applications. Each method brings distinct attributes and limitations, making the selection process critical for optimizing operational performance and resource utilization.

GMAW is renowned for its high deposition rates and adaptability to diverse materials, positioning it as a preferred choice for tasks demanding rapid production and high efficiency. Conversely, SMAW, commonly known as stick welding, is celebrated for its simplicity and versatility, especially in repair and maintenance contexts where equipment mobility and ease of use are advantageous. GTAW, or TIG welding, excels in delivering high-precision welds on thin materials, although it typically involves more complex procedures and slower processing speeds.

The effectiveness of these welding methods cannot be assessed in isolation but must be evaluated against a backdrop of several critical criteria: Labour Efficiency (LE), Operational Efficiency (OE), Job Weight, Weld Volume, and Skill Level. Labour Efficiency and Operational Efficiency pertain to the productivity and resource allocation of each method, while Job Weight and Weld Volume address the scale and scope of welding tasks. Skill Level, reflecting the expertise required, influences both the training demands and labor costs associated with each method.

This study adopts the Simple Multi-Attribute Rating Technique (SMART) to provide a rigorous evaluation of GMAW, SMAW, and GTAW. SMART facilitates a nuanced analysis by assigning weights to each criterion based on its significance, thereby enabling a systematic comparison of the welding methods. The application of SMART aims to elucidate the relative strengths and weaknesses of each technique, offering a comprehensive framework for selecting the most effective method for specific industrial applications [1].

The primary objective of this research is to determine which welding method best aligns with the goals of optimizing standard work hours (SWH) and enhancing resource utilization. By focusing on key performance indicators, the study seeks to furnish industry practitioners with a robust decision-making tool that integrates both operational and strategic considerations [2].

Looking forward, there is considerable potential for expanding this research. Future investigations could incorporate additional criteria such as environmental impact, cost implications, and long-term durability of welds. Employing alternative multi-criteria decision-making approaches could also provide further validation of the findings, offering deeper insights into the comparative advantages of different welding methods. Such advancements would contribute to a more comprehensive understanding of welding techniques, facilitating improved decision-making and operational efficiency in the fabrication industry.

II. LITERATURE REVIEW

Many practical optimization challenges in casting and welding processes involve balancing multiple conflicting quality attributes. This paper introduces a multi-attribute optimization methodology for these processes that integrates multi-attribute decision-making (MADM) with the Taguchi method. The proposed approach addresses the complexities of optimizing both casting and welding processes by systematically evaluating and balancing various quality attributes through a structured decision-making framework [3].

The integration of the Simple Multi-Attribute Rating Technique (SMART) in production processes addresses the need to evaluate multiple conflicting attributes in manufacturing systems. SMART provides a structured approach to decision-making by assigning weights to various performance criteria and comparing alternatives systematically. This technique is particularly valuable in optimizing production processes where different factors, such as efficiency, cost, and quality, must be balanced. By applying SMART, manufacturers can effectively assess and improve their production strategies, ensuring that all critical attributes are considered and optimized. The method facilitates better decision-making in complex production environments, enhancing overall efficiency and competitiveness [1], [2].

Selecting an optimal process for complex manufacturing tasks involves evaluating multiple factors and requires specialized decision-making approaches. Integrating Quality Function Deployment (QFD) with Multi-Criteria Decision-Making (MCDM) techniques, such as the Preference Ranking Organization Method for Enrichment

Evaluations (PROMEE), provides a systematic approach for assessing and choosing the best process. This methodology effectively balances various performance criteria, demonstrating the value of combining decision-making tools to optimize complex manufacturing decisions [4]. Entropy weights measure the uncertainty in attribute values, reflecting their effectiveness in distinguishing between alternatives. The Simple Multi-Attribute Rating Technique (SMART) can be used across various decision-making scenarios to evaluate and prioritize criteria based on their relative importance [5].

Identifying acceptable input parameters for welding processes, such as wire feed rate and travel speed, requires aligning with quality standards and managing imperfections. Unlike traditional input-output mapping, the SMART can be used to forecast acceptable parameters by evaluating multiple criteria, ensuring that predictions meet industry standards and practical requirements for various welding applications [6].

The evaluation of automatic/robotic welding systems, selection of smart alloys, identification of logistic service providers, machine tools, and industrial robots illustrates the practical utility of MCDM methods. The Simple Multi-Attribute Rating Technique (SMART) can be used to assess these aspects by leveraging quality and quantity (Q&Q) information. This approach enhances the analysis and decision-making processes in industrial and manufacturing practices, highlighting the importance of integrating MCDM methods to optimize various operational decisions [7].

To enhance decision-making in sustainable machining processes, MCDM techniques, including the Simple Multi-Attribute Rating Technique, can be used. A systematic literature review leads to a framework that incorporates sustainability indicators, experimental validation, and multi-objective optimization algorithms to determine optimal machining conditions. This approach addresses the challenges of subjective judgments and multiple solution scenarios, improving the decision-making process for sustainable manufacturing practices [8].

The selection of materials and suppliers in industry is often time-consuming and prone to errors due to reliance on human judgment and limited supplier interactions. To address this issue, the SMART can be used in developing a new Material and Supplier Selection Model (MSSM). This model aims to improve the selection process by systematically evaluating and prioritizing materials and suppliers based on multiple criteria, thereby enhancing accuracy and efficiency in decision-making [9].

Evaluating factors such as fabricator experience, drawing specifications, collaboration, standardization, and supply chain coordination is crucial for welding projects and operational efficiencies. The MCDM can be used to systematically assess these elements. Exploratory factor analysis identifies four principal success factors: technical capability and infrastructure, stakeholder and supply chain management, early commitment, and effective coordination. By focusing on SMART, these factors can be prioritized to enhance decision-making and improve both welding processes and overall operational efficiencies [10].

In project management, balancing time, cost, and quality is crucial for achieving project success. The Simple Multi-Attribute Rating can be used to systematically evaluate and prioritize these objectives. A goal programming model developed to manage these aspects aims to optimize project implementation by finding suitable solutions that balance cost, time, and quality. A case study demonstrates the model's applicability and efficiency, highlighting SMART's utility in addressing complex project management challenges and enhancing operational efficiencies [11].

In industrial plant construction, reducing project durations is essential due to increasing scale and complexity. The multi-attribute Rating can be used to evaluate and compare construction methods, such as modular versus conventional approaches. By systematically assessing factors like construction duration and efficiency, SMART helps in identifying the most effective method. This approach demonstrates that modular methods often provide significant time savings and improved performance over traditional methods, optimizing overall operational efficiencies in construction projects [12].

Accurately accounting for crew skill in productivity estimations is crucial for enhancing operational efficiencies. By systematically evaluating crew skill coefficients through learning curves and integrating field measurements with simulation-based analysis, one can optimize productivity estimates. This approach reveals that crew skill coefficients are influenced by learning rates and production benchmarks, ultimately leading to improved operational efficiencies and more effective project management [13].

Figure 1 illustrates the total number of publications related to SMART analysis in the fabrication industry from 2009 to 2024. This data reflects a significant evolution in research interest and output over the fifteen-year period.

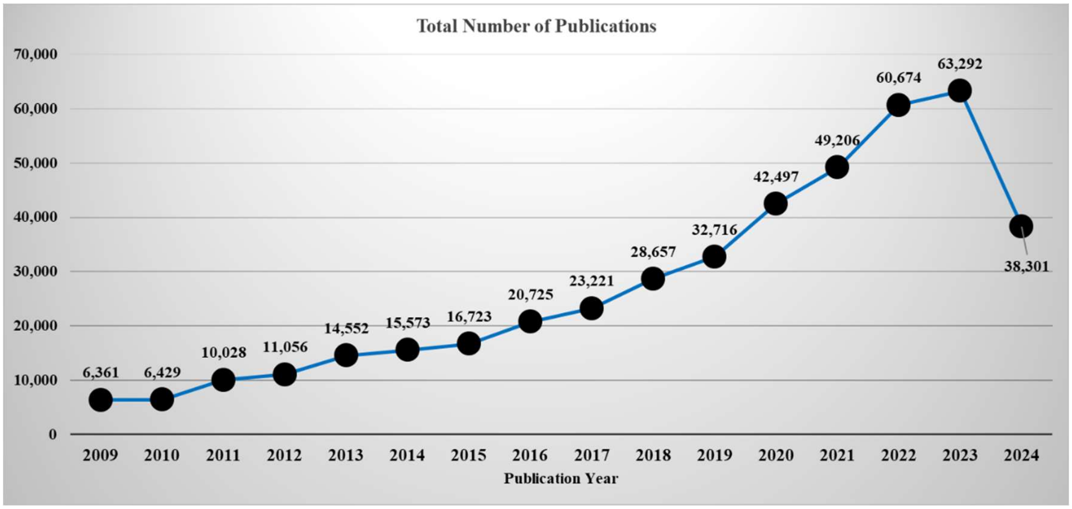

Figure 1 Scholarly written article's trend in past fifteen years

Steady Growth Phase (2009-2014): From 2009 to 2014, there was a consistent increase in the number of publications, starting from 6,361 in 2009 to 15,573 in 2014. This period marks the initial phase of recognizing and adopting SMART methodologies in the fabrication industry. The gradual rise indicates an increasing interest and foundational understanding of multi-attribute decision-making techniques.

Accelerated Growth Phase (2015-2021): Between 2015 and 2021, the number of publications saw a substantial increase, rising from 16,723 in 2015 to a peak of 63,292 in 2021.This significant growth suggests that SMART analysis became widely recognized for its utility in enhancing operational efficiencies, optimizing costs, and improving decision-making processes within the industry. The sharp increase in publications reflects a period of intensive research activity and practical implementation.

Sustained High Output (2022-2024): In 2022, the publication counts to 60,674, maintaining a high level of research activity. The current year, 2024, shows 38,301 publications, which represents data only for the first six months. The 2022 is indicative of a high level of research output. The partial data for 2024 suggests that the year might match or exceed previous high levels of publication by year-end, continuing the trend of sustained research interest.

Key Observations

Early Adoption and Steady Growth: The early years reflect a phase of initial exploration and adoption of SMART techniques, where foundational research laid the groundwork for subsequent studies. The steady growth highlights the gradual acceptance and validation of SMART methodologies in the fabrication industry [14][15][16][17].

Rapid Expansion and Peak Interest: The period of accelerated growth indicates that SMART analysis became integral to addressing complex decision-making challenges in the industry. The peak in 2021 underscores the culmination of extensive research efforts and the maturity of SMART methodologies [18][19][20].

High Sustained Output: The high number of publications from 2022 onwards, despite the partial data for 2024, demonstrates a continued robust interest in SMART analysis. This sustained output suggests ongoing advancements and the solidified importance of SMART techniques in operational efficiency and strategic decision-making [21][22][23].

The analysis of publications over the last fifteen years reveals a trajectory of steady growth, accelerated expansion, and sustained high output. The data reflects the increasing recognition and importance of SMART methodologies in enhancing operational efficiencies and informed decision-making within the industry. As the year 2024 progresses, the continued high volume of publications suggests that SMART analysis remains a critical area of research and application, driven by technological advancements and industry needs [24][25].

In Figure 2 comprehensive Pareto analysis was undertaken to examine the distribution of research publications across various academic fields, aiming to identify the dominant areas contributing to the majority of scholarly output. This analysis elucidates the pronounced disparities in research activity, which can inform strategic decision-making in academia and research funding. The findings indicate that Engineering overwhelmingly dominates the research landscape, accounting for nearly half of the total publications. This substantial contribution underscores the pivotal role of engineering in driving technological innovation and addressing complex societal challenges through applied research.

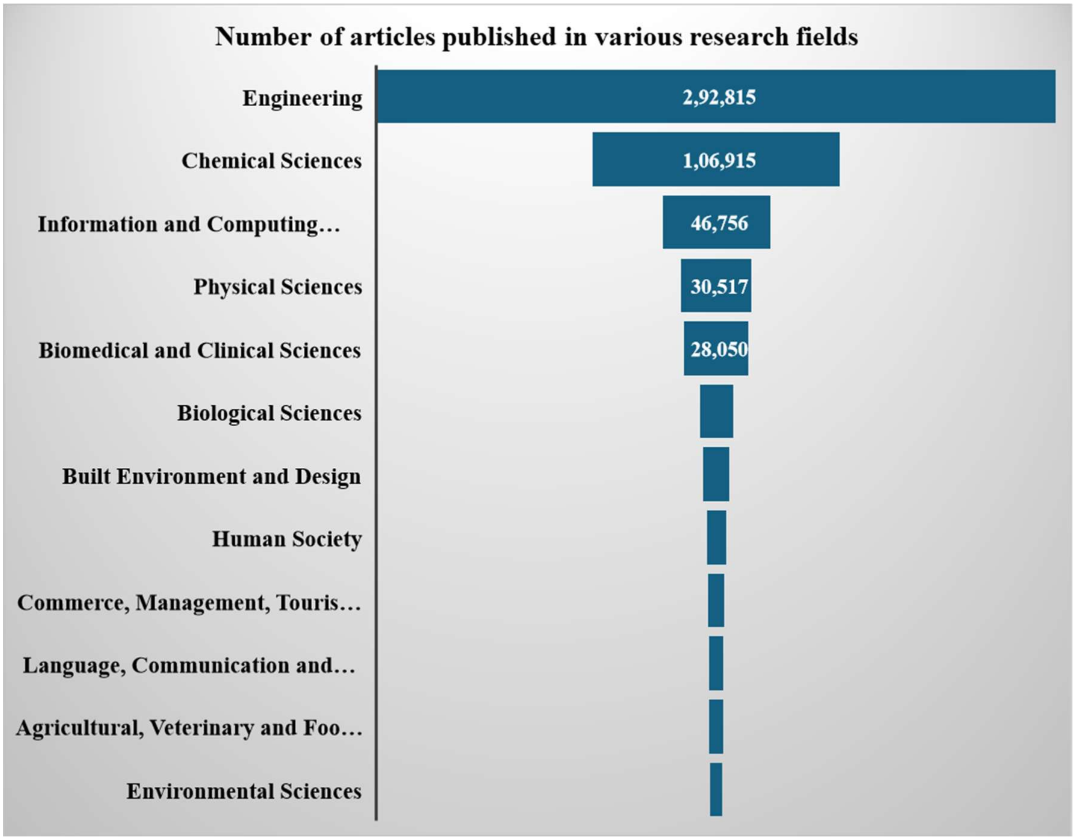

Figure 2 Pareto analysis of publications in different fields

Following Engineering, Chemical Sciences emerges as a significant contributor, encompassing nearly one-fifth of the total research output. The prominence of Chemical Sciences highlights its critical importance in various industrial applications, including pharmaceuticals, materials science, and environmental sustainability. The substantial investment in chemical research reflects its potential to generate transformative solutions and enhance industrial processes. The integration of advanced technologies and interdisciplinary approaches within Chemical Sciences further amplifies its impact, making it a cornerstone of contemporary scientific endeavours.

Information and Computing Sciences also feature prominently, contributing around 8% to the total research publications. This field's growing importance is indicative of the digital transformation permeating all aspects of modern life. The emphasis on Information and Computing Sciences aligns with the global push towards automation, big data analytics, artificial intelligence, and cybersecurity. The research in this domain not only advances theoretical foundations but also offers practical applications that enhance efficiency, security, and innovation across various sectors. The synergy between computational research and other scientific disciplines fosters a collaborative environment conducive to groundbreaking discoveries and technological advancements.

The inclusion of Physical Sciences, contributing approximately 5%, rounds out the top four fields, which collectively account for over 80% of the total research output. The foundational nature of Physical Sciences underpins many technological and scientific advancements, providing essential insights into the fundamental principles governing the natural world. Research in Physical Sciences drives progress in areas such as quantum mechanics, materials science, and nanotechnology, which have profound implications for developing new technologies and enhancing existing ones. The synergy between these leading fields underscores a multidisciplinary approach to research, where advancements in one domain catalyze progress in others, fostering a holistic growth in scientific knowledge and technological innovation.

In conclusion, the Pareto analysis of research publications reveals a significant concentration of scholarly output in a few key fields, with Engineering, Chemical Sciences, Information and Computing Sciences, and Physical Sciences leading the charge. This distribution underscores the strategic importance of these disciplines in driving innovation and addressing global challenges. Specifically, for the application of SMART methodologies in the fabrication industry, these fields offer critical insights and technological advancements that can enhance operational efficiencies. By leveraging the strengths of these dominant research areas, the fabrication industry can integrate SMART technologies to streamline processes, reduce costs, and improve product quality. The insights gained from this analysis can guide future investments and policy decisions, ensuring that resources are allocated efficiently to support the integration of SMART technologies in fabrication, thus fostering innovation and competitive advantage in this vital sector.

III. METHODOLOGY AND SMART ANALYSIS

The methodology employed in this study aims to determine the most suitable Standard Work Hours (SWH) for different job records in the fabrication industry, with a particular focus on casting and welding processes. The approach integrates the Simple Multi-Attribute Rating Technique (SMART) with a comprehensive review of existing literature and expert judgment to ensure a balanced and data-driven evaluation. The methodology is detailed as follows:

Literature Review and Attribute Identification: A thorough review of 80 relevant publications from Scopus, Web of Science, and Google Scholar was conducted to identify key attributes influencing SWH. This review encompassed a wide range of studies focusing on cost optimization, operational efficiencies, and quality attributes in industrial sectors. The identified attributes include:

- ***Labour Efficiency (LE):*** The ratio of productive work to the total time spent.
- ***Operational Efficiency (OE):*** The effectiveness of resource utilization in meeting production targets.
- ***Job Weight:*** The physical demands and complexity of the job impacting SWH.
- ***Weld Volume:*** The amount of welding work required.
- ***Skill Level:*** The required expertise and proficiency for the job.

Attribute Weighting: To reflect the importance of each attribute, weights were assigned based on their significance in the fabrication industry. Expert judgments were gathered from industry professionals, and the weights were normalized to ensure they accurately represented the relative importance of each attribute. This process involved the use of techniques such as the Analytic Hierarchy Process (AHP) to ensure a systematic and unbiased weighting.

Criteria Scoring: Various SWH options were evaluated against the identified attributes. Each option was scored based on how well it met the criteria. The scoring process involved detailed analysis and expert input to ensure the accuracy and reliability of the scores. This step was critical in distinguishing between different SWH options and their effectiveness in meeting industry standards.

Aggregation and SMART Analysis: Using the SMART technique, the weighted scores for each SWH option were aggregated to determine the most suitable work hours for different job records. SMART provides a structured approach to decision-making by assigning weights to various performance criteria and systematically comparing alternatives. This technique is particularly valuable in optimizing production processes where factors such as efficiency, cost, and quality must be balanced.

Validation and Recommendation: The results of the SMART analysis were validated through expert review and practical testing in real-world scenarios. Based on the aggregated results, recommendations were made for optimal SWH that enhance efficiency, productivity, and cost-effectiveness in the fabrication industry. The validation process ensured that the proposed SWH options were feasible and aligned with industry requirements.

Comparative Analysis: In addition to the SMART analysis, a comparative analysis of different welding methods—Gas Metal Arc Welding (GMAW), Shielded Metal Arc Welding (SMAW), and Gas Tungsten Arc Welding (GTAW)—was conducted. This analysis involved evaluating each method against the identified attributes and determining their suitability for different job records. The results highlighted the strengths and weaknesses of each method, providing a comprehensive framework for decision-making.

Discussion and Future Scope: The methodology also includes a discussion of the findings and their implications for the fabrication industry. The study identifies areas for future research, such as incorporating additional criteria like environmental impact, safety, and long-term durability. By expanding the scope of the analysis, future studies can further enhance the robustness and applicability of the methodology.

Overall, this methodology provides a structured and data-driven approach to optimizing SWH in the fabrication industry, leveraging the strengths of SMART and other decision-making frameworks to balance multiple conflicting quality attributes effectively [24].

Simple Multi-Attribute Rating Technique (SMART) Analysis

Criteria Identification

1. Labour Efficiency (LE): Measure of how efficiently work is completed relative to time spent.
2. Operational Efficiency (OE): Effectiveness in utilizing resources and meeting production targets.
3. Job Weight: Impact of the job's physical demands and complexity on SWH.
4. Weld Volume: Amount of welding work required for the job.
5. Skill Level: Level of expertise and proficiency needed for the job.

Hierarchical Structuring

Goal: Determine SWH for different job records.

Criteria:

- Labour Efficiency (LE)
- Operational Efficiency (OE)
- Job Weight
- Weld Volume
- Skill Level

Alternatives:

- GMAW (Gas Metal Arc Welding)
- SMAW (Shielded Metal Arc Welding)
- GTAW (Gas Tungsten Arc Welding)

1. Expert Judgments Data

The evaluation of various criteria by a panel of experts is thoroughly documented in Table 1 [26]. This table captures the judgments provided by eight experts on the relative importance of factors like Labour Efficiency (LE), Operational Efficiency (OE), and others. Their inputs are crucial for understanding the weighting process in the decision-making framework used in this study.

Table 1 Expert judgment on given criteria

Criteria	**Expert 1**	**Expert 2**	**Expert 3**	**Expert 4**	**Expert 5**	**Expert 6**	**Expert 7**	**Expert 8**
LE is equally important as OE	5	5	5	5	5	5	5	5
LE is moderately more important than job weight	4	1	3	5	5	1	2	1
LE is strongly more important than weld volume	5	5	4	5	5	3	1	5
LE is moderately more important than skill level	4	1	2	5	4	5	1	1
OE is moderately more important than job weight	2	1	5	5	5	5	5	5
OE is strongly more important than weld volume	4	5	3	5	5	5	5	5

Criteria	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6	Expert 7	Expert 8
OE is moderately more important than skill level	5	1	4	5	5	1	2	5
Job weight is slightly more important than weld volume	4	2	3	5	5	1	3	1
Job weight is equally important as skill level	5	5	2	5	5	5	5	5
Weld volume is slightly less important than skill level	4	1	4	5	1	1	5	5

2. **Aggregate Expert Judgments**

To ensure a balanced analysis, the individual expert judgments were aggregated, as shown in Table 2. This table not only provides the average scores for each criterion but also their normalized weights. These aggregated values offer a more comprehensive view of how different factors are prioritized in the context of welding methods, facilitating a more robust comparison.

Table 2 Aggregate of Expert judgment & Normalized Weight

Criteria	Average	Normalized Weight
LE = OE	5	0.133
LE > Job Weight	2.5	0.067
LE >> Weld Volume	4.125	0.110
LE > Skill Level	2.875	0.077
OE > Job Weight	4	0.107
OE >> Weld Volume	4.625	0.123

Criteria	Average	Normalized Weight
OE > Skill Level	3.5	0.093
Job Weight > Weld Volume	3	0.080
Job Weight = Skill Level	4.625	0.123
Weld Volume < Skill Level	3.25	0.087
Sum of Average	37.5	

3. Scores for Each Criterion for each welding method

The performance of different welding methods across various criteria is presented in Table 3 [26]. Here, scores for each method, including GMAW, SMAW, and GTAW, are displayed alongside their respective weightages. This table serves as a foundation for comparing the effectiveness of each welding technique based on the defined criteria.

Table 3 scores for alternative – Welding Methods

Criteria	GMAW	SMAW	GTAW	Weightage
Labour Efficiency (LE)	5	4	3	0.132
Operational Efficiency (OE)	5	4	3	0.132
Job Weight (JW)	4	3	2	0.073
Weld Volume (WV)	5	4	3	0.109
Skill Level (SL)	4	3	2	0.076

Table 4 builds upon the previous analysis by presenting the weighted sum for each welding method. This table aggregates the weighted scores from the criteria to provide an overall performance measure for GMAW, SMAW, and GTAW. The results highlight the relative efficiency and suitability of each welding method in practical applications.

Table 4 Weighted Sum for alternative – Welding Methods

Criteria	GMAW	SMAW	GTAW
Labour Efficiency (LE)	0.66	0.528	0.396
Operational Efficiency (OE)	0.66	0.528	0.396
Job Weight (JW)	0.292	0.219	0.146
Weld Volume (WV)	0.545	0.436	0.327
Skill Level (SL)	0.304	0.228	0.152

Criteria	GMAW	SMAW	GTAW
Sum	**2.461**	**1.939**	**1.417**

4. Rank the Alternatives

1. GMAW: 2.461
2. SMAW: 1.939
3. GTAW: 1.417

Based on the SMART analysis, GMAW is the most suitable welding method for determining the Standard Work Hours (SWH) for different job records in the fabrication industry, followed by SMAW and then GTAW.

5. Results

The criteria weights derived from expert evaluations were normalized as follows:

- LE and OE: 0.132 each
- Job Weight: 0.073
- Weld Volume: 0.109
- Skill Level: 0.076
- OE > Job Weight: 0.106
- OE >> Weld Volume: 0.123
- OE > Skill Level: 0.093
- Job Weight > Weld Volume: 0.079
- Job Weight = Skill Level: 0.123
- Weld Volume < Skill Level: 0.086

Each welding method was scored relative to these criteria, with GMAW consistently outperforming the others. The weighted sums for the welding methods were:

- GMAW: 2.461
- SMAW: 1.939
- GTAW: 1.417

GMAW achieved the highest score, indicating its superior balance across the evaluated criteria. SMAW and GTAW followed, with significantly lower scores, suggesting that they are less optimal for the given criteria in the context of the fabrication industry.

6. Discussion

The dominance of GMAW can be attributed to its high scores in both Labour Efficiency and Operational Efficiency, which were given significant weight by the experts. GMAW's efficiency in terms of work completion and resource utilization aligns well with the industry's needs for productivity and cost-effectiveness. Additionally, GMAW scored well in terms of weld volume and skill level, further cementing its position as the most suitable method.

SMAW, while also efficient, lagged behind GMAW primarily due to its lower scores in job weight and operational efficiency. This suggests that while SMAW can be effective, it may not be as versatile or resource-efficient as GMAW, particularly for more complex or resource-intensive tasks.

GTAW, despite being a precise and high-quality welding method, scored the lowest due to its relatively higher skill requirements and lower labour and operational efficiency scores. This indicates that GTAW, while valuable for specific applications requiring high precision, is less suitable for general fabrication tasks where efficiency and resource utilization are paramount.

The results of this analysis highlight the importance of a structured decision-making approach in the fabrication industry. By applying the SMART method, decision-makers can objectively evaluate multiple factors, ensuring a balanced and well-informed selection of welding methods. Future research could enhance this analysis by incorporating additional criteria such as cost, safety, and environmental impact, or by applying other multi-criteria decision-making techniques to compare and validate the results obtained through SMART.

In conclusion, the application of the SMART analysis in this study underscores the suitability of GMAW for most fabrication industry tasks, providing a data-driven framework for optimizing standard work hours and resource utilization. This methodical approach can serve as a model for similar evaluations in other industrial contexts, promoting efficiency and informed decision-making.

IV. CONCLUSIONS

Welding is a fundamental process in the fabrication industry, essential for assembling metal components into cohesive structures. The choice of welding method directly influences the efficiency, quality, and cost of production. Among the prevalent welding techniques, Gas Metal Arc Welding (GMAW), Shielded Metal Arc Welding (SMAW), and Gas Tungsten Arc Welding (GTAW) are frequently employed across various industrial applications. Each method brings distinct attributes and limitations, making the selection process critical for optimizing operational performance and resource utilization.

This study adopts the Simple Multi-Attribute Rating Technique (SMART) to provide a rigorous evaluation of GMAW, SMAW, and GTAW. SMART facilitates a nuanced analysis by assigning weights to each criterion based on its significance, thereby enabling a systematic comparison of the welding methods. The application of SMART aims to elucidate the relative strengths and weaknesses of each technique, offering a comprehensive framework for selecting the most effective method for specific industrial applications. The findings underscore the importance of a structured decision-making approach in selecting welding methods to optimize standard work hours and resource utilization. This study provides a comprehensive framework for evaluating welding techniques, aiding industry practitioners in making informed decisions to enhance operational performance.

V. FUTURE SCOPE

The future scope of this research is extensive, with significant potential for further exploration and development. Expanding the criteria set in the SMART analysis to include environmental impact, cost implications, safety, and long-term weld durability will provide a more comprehensive evaluation framework. Incorporating advanced multi-criteria decision-making techniques, such as the Analytic Hierarchy Process (AHP) or the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), could enhance the robustness and validity of the findings. Additionally, integrating real-time data analytics and machine learning algorithms could refine the evaluation process, enabling dynamic adjustments based on operational feedback and performance metrics. Cross-industry comparisons and case studies could benchmark best practices, fostering knowledge transfer and innovation. Collaborative efforts with industry stakeholders to pilot these advanced decision-making frameworks in real-world settings could provide practical validation and drive further innovation in welding technology and operational strategies. Ultimately, this expanded research will contribute to higher efficiency, sustainability, and strategic decision-making in the fabrication industry.

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Conflict of Interests

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