

Multi-Criteria Optimization of Friction Stir Welding Process Parameters: A Comparative Research and Review Analysis

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ABSTRACT

Friction stir welding (FSW) is a solid-state joining technology whose performance depends strongly on the coordinated selection of process parameters. Tool rotational speed, traverse speed, material combination, and other controllable variables influence mechanical performance, corrosion behavior, joint quality, and process stability. Because these responses can conflict with one another, conventional single-response optimization is insufficient for many practical FSW applications. This research and review paper develops a comparative analytical framework for understanding how response surface methodology (RSM), regression analysis, multi-criteria decision-making (MCDM), TOPSIS, WASPAS, MORSM, grey relational analysis, and intelligent multi-objective optimization approaches have been applied to FSW parameter selection. Only the ten supplied references are synthesized. The analysis indicates that MCDM-oriented approaches provide a systematic mechanism for converting multiple performance criteria into an integrated decision, while RSM and regression-based methods provide stronger process-response modeling capabilities. TOPSIS and grey relational analysis are particularly useful when several competing quality characteristics must be considered simultaneously, whereas WASPAS and hybrid MCDM approaches extend the decision space through alternative weighting and aggregation mechanisms. The reviewed evidence also indicates a research gap concerning unified optimization architectures capable of connecting process-level FSW optimization with broader lean production and digital manufacturing objectives. The paper therefore positions multi-objective FSW optimization as a decision layer that can potentially support digitally integrated manufacturing environments.

KEYWORDS: Friction Stir Welding; Process Optimization; Multi-Criteria Decision Making; TOPSIS; WASPAS; Response Surface Methodology; Grey Relational Analysis; Aluminium Alloys; Multi-Objective Optimization; Lean Manufacturing.

INTRODUCTION

1.1 Background

Friction stir welding is a solid-state joining process in which a rotating tool generates frictional heat and severe plastic deformation to consolidate adjoining materials. Unlike fusion welding, the process does not require complete melting of the workpieces, making parameter control particularly important for obtaining consistent weld quality. The process becomes substantially more challenging when dissimilar materials are joined because differences in thermal conductivity, mechanical properties, plastic flow behavior, and corrosion characteristics can produce competing performance outcomes. Simar and Avettand-Fènoël (2017) demonstrate the technological importance of understanding dissimilar-metal FSW,

establishing the broader process context for subsequent optimization studies.

FSW optimization is fundamentally a multi-variable decision problem. A parameter combination that improves one response may deteriorate another. For example, a setting favorable to joint strength may not necessarily minimize corrosion susceptibility or maximize process stability. Consequently, optimization based on only one response can produce technically incomplete solutions. This has encouraged the use of statistical modeling, regression analysis, and MCDM approaches to identify parameter combinations that offer balanced performance.

Several supplied studies demonstrate this progression. RSM and regression analysis have been used to investigate

relationships between FSW parameters and quality characteristics (Suhin et al., 2022). MCDM techniques have subsequently been applied to select preferred parameter combinations under multiple performance criteria (Marichamy and Babu, 2021; Singaravel et al., 2023). More advanced approaches integrate multiple optimization principles, including MORSM, TOPSIS, WASPAS, grey relational analysis, and intelligent multi-objective frameworks (Medhi et al., 2020; Sameer and Birru, 2019; Rajesh et al., 2022; Medhi et al., 2021).

1.2 Problem Statement

The central problem is not merely determining whether an FSW parameter is beneficial, but determining which combination of parameters provides the most balanced overall performance. The problem becomes more complex for dissimilar Al-Cu, aluminium-steel, and related material combinations because process responses can vary significantly according to material pairing.

A second challenge concerns the methodological separation between prediction and decision-making. Regression and RSM can characterize process-response relationships, but a predictive model does not automatically identify the best compromise among competing objectives. Conversely, MCDM can rank alternatives effectively, but its reliability depends on the quality of the underlying experimental or modeled data.

1.3 Research Relevance and Objectives

The objective of this paper is to critically synthesize the supplied research on FSW process optimization and establish a comparative framework for selecting appropriate optimization methodologies. Particular attention is given to the relationship between statistical modeling, MCDM, hybrid optimization, and multi-objective decision-making.

The paper also examines how FSW optimization can be conceptually positioned within broader digital and lean manufacturing environments. The supplied conceptual reference, Lean Production Optimization Through SAP PP and SAP Digital Manufacturing Integration, indicates a broader production-optimization perspective; however, no author name or publication year was supplied for this item. Therefore, an author-year citation for that source cannot be fabricated. The analysis below uses the ten bibliographic references supplied for evidence and treats digital manufacturing integration as a conceptual extension rather than an externally sourced empirical claim.

1.4 Scope and Significance

The study is limited to the ten supplied references. It focuses on FSW parameter optimization, especially applications

involving aluminium and dissimilar-material joints. The significance lies in identifying methodological complementarities rather than treating individual optimization methods as interchangeable. Such differentiation is important because the choice of method should depend on whether the research objective is prediction, ranking, compromise optimization, or simultaneous optimization of multiple responses.

LITERATURE REVIEW

2.1 Development from Process Understanding to Optimization

Simar and Avettand-Fènoël (2017) provide a foundational perspective on dissimilar-metal FSW. Their work establishes why joining dissimilar materials requires careful consideration of process conditions. This foundation is important because optimization cannot be separated from the physical complexity of material interaction.

Suhin et al. (2022) represent a more quantitatively oriented stage through the use of RSM and regression analysis for similar and dissimilar aluminium materials. The methodological advantage of this approach is its ability to represent relationships between process variables and measured responses. Regression provides predictive insight, while RSM supports systematic exploration of parameter spaces.

However, predictive modeling alone does not completely solve a multi-response optimization problem. When several responses must be considered simultaneously, the researcher must determine how individual criteria should be compared or aggregated. This creates the methodological space occupied by MCDM.

2.2 MCDM-Based FSW Optimization

Marichamy and Babu (2021) investigate the selection of optimum parameters for A319 aluminium alloy using an MCDM method. Their contribution illustrates the shift from isolated response optimization toward structured decision-making.

Singaravel et al. (2023) further demonstrate the use of MCDM for FSW parameter optimization. Their work reinforces the relevance of decision-based methodologies where several process-performance criteria influence the final selection.

Sabry et al. (2023) provide a particularly important comparative perspective by examining multiple MCDM methods for selecting FSW parameters for Al 6061 alloy. The significance of comparative MCDM research is that the resulting ranking may depend on methodological assumptions, weighting procedures, and aggregation mechanisms. Therefore, selecting a parameter combination

is not purely a physical problem; it is also a methodological decision problem.

2.3 TOPSIS, Grey Relational Analysis, and WASPAS

Sameer and Birru (2019) combine TOPSIS and grey relational analysis for optimization and characterization of dissimilar DP600 steel and AA6082-T6 aluminium alloy sheets. This combination is important because it demonstrates how complementary analytical mechanisms can be used to transform multiple quality indicators into a consolidated decision.

TOPSIS evaluates alternatives according to their relative proximity to an ideal and anti-ideal solution. Its conceptual advantage is that optimization is framed as a compromise-selection problem rather than simply maximizing or minimizing an isolated response. Grey relational analysis, meanwhile, can assist in integrating multiple response characteristics into a common comparative framework.

Rajesh et al. (2022) apply WASPAS to dissimilar aluminium alloy FSW. WASPAS is relevant because it combines additive and multiplicative aggregation concepts, providing an alternative mechanism for ranking competing process alternatives. The inclusion of WASPAS broadens the methodological landscape beyond conventional MCDM techniques.

2.4 Hybrid and Intelligent Optimization

Medhi et al. (2020) introduce a novel MCDM-amalgamated MORSM approach for dissimilar Al-Cu alloy FSW. The methodological significance is the integration of response-surface modeling with decision-making. This addresses a central weakness of using either modeling or ranking independently: modeling explains process behavior, while MCDM identifies a preferred compromise.

Medhi et al. (2021) subsequently develop an intelligent multi-objective framework for optimizing FSW parameters. This progression suggests movement toward optimization architectures that are less dependent on a single decision criterion. Such frameworks are particularly relevant when process quality is multidimensional and when competing objectives must be evaluated simultaneously.

Montes-González et al. (2021) examine the effects of FSW parameters on the corrosion rate of Al 6061-T6-Cu C11000 joints through experimental analysis and mathematical modeling. Their work expands the optimization problem beyond conventional mechanical quality indicators by demonstrating that corrosion performance can also be treated as a process-dependent response.

2.5 Research Gap

The literature demonstrates substantial methodological diversity, but three gaps remain evident. First, there is limited methodological unification between predictive modeling and final decision selection. Second, the studies employ different materials, responses, and optimization frameworks, making direct comparison of optimal parameters difficult. Third, the reviewed studies primarily address process-level optimization rather than integration of FSW optimization with enterprise-level production planning or real-time digital manufacturing systems.

Thus, the next research opportunity is not necessarily another isolated optimization algorithm. Rather, it is a hierarchical framework in which experimental data, predictive models, MCDM, and production-level decision systems interact. Such integration could enable optimized process parameters to become actionable manufacturing decisions instead of remaining isolated experimental results.

METHODOLOGY

3.1 Research Design

This study adopts a structured research-and-review methodology. The ten supplied references constitute the complete evidence base. The analysis is organized around four methodological dimensions: process modeling, response optimization, multi-criteria ranking, and integrated decision support.

The first dimension concerns process-response modeling. RSM and regression approaches are treated as methods for estimating how changes in FSW parameters affect measurable outcomes. The second dimension concerns single- or multi-response optimization, where objective functions are established around characteristics such as mechanical or corrosion performance. The third dimension concerns MCDM ranking, in which alternative parameter combinations are evaluated according to multiple criteria. The fourth dimension concerns hybrid decision architecture, in which modeling and ranking are combined.

3.2 Conceptual Optimization Framework

A generalized FSW optimization system can be represented as:

Process Parameters → Experimental/Predicted Responses → Normalization → Weighting → MCDM Evaluation → Optimal Parameter Combination → Validation

The process-parameter layer contains controllable variables such as rotational speed and traverse speed. The response layer contains quality indicators measured experimentally or estimated through mathematical models. Normalization converts different response scales into comparable values. Weighting establishes the relative

importance of the criteria. MCDM then ranks the available alternatives.

This framework addresses a fundamental problem in FSW optimization: the parameter combination that is optimal for one response may not be optimal for another. A multi-criteria framework therefore produces a compromise solution rather than assuming that one quality indicator represents total weld performance.

3.3 Statistical Modeling Layer

RSM and regression analysis provide the modeling foundation. Suhin et al. (2022) demonstrate the relevance of these techniques for similar and dissimilar aluminium materials. In a generalized form, a response can be expressed as:

$$Y = \beta_0 + \sum_{i=1}^n \beta_i X_i + \sum_{i=1}^n \beta_{ii} X_i^2 + \sum_{i < j} \beta_{ij} X_i X_j + \epsilon$$

where (Y) represents a weld-quality response, (X_i) represents a process parameter, (β) values represent model coefficients, and (ϵ) represents residual error.

The importance of this layer is explanatory as well as predictive. A model can identify parameter-response relationships and interactions, which can then provide input to an optimization algorithm.

3.4 MCDM Layer

Once alternatives and response values are available, MCDM methods can rank candidate solutions. TOPSIS, WASPAS, and related techniques provide different mechanisms for evaluating alternatives.

A conceptual TOPSIS score can be represented by the relative distance from the positive and negative ideal solutions:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-}$$

where (D_i^+) is the distance from the positive ideal solution and (D_i^-) is the distance from the negative ideal solution. Higher (C_i) values indicate greater relative desirability.

WASPAS offers another aggregation structure, allowing alternatives to be evaluated through additive and multiplicative perspectives (Rajesh et al., 2022). The

methodological implication is that no single ranking mechanism should automatically be considered universally superior.

3.5 Hybrid Optimization

The strongest methodological direction in the supplied literature is hybridization. Medhi et al. (2020) combine MORSM and MCDM, while Sameer and Birru (2019) combine TOPSIS with grey relational analysis. These approaches address the distinction between estimating the process and selecting the preferred solution.

A generalized hybrid architecture can therefore be defined as:

Experimental Design → Mathematical Modeling → Response Prediction → Multi-Criteria Transformation → Alternative Ranking → Experimental Validation

Such a structure is preferable when the number of possible parameter combinations is large and experimental testing of every combination is impractical.

3.6 Validation Strategy

Validation should involve comparison between predicted and experimentally obtained responses. A selected optimum should not be accepted solely because it receives the highest computational ranking. Instead, the selected parameter combination should be experimentally tested and compared with predicted performance.

For dissimilar-material welding, validation should additionally consider material-specific responses. Montes-González et al. (2021) demonstrate the relevance of corrosion rate as an optimization response, while Sameer and Birru (2019) demonstrate the importance of evaluating dissimilar steel-aluminium joints through multiple performance criteria.

3.7 Integration with Digital Production Optimization

A future implementation can place the FSW optimization layer within a broader production-management architecture. In such a system, process data could be converted into optimized manufacturing parameters, while production-planning information could determine when and where a parameter combination should be deployed.

The conceptual objective of Lean Production Optimization Through SAP PP and SAP Digital Manufacturing Integration is relevant to this architectural extension, but because no author and publication year were supplied, it cannot be cited in the required author-year format without inventing bibliographic information. Accordingly, the present methodology does not attribute empirical findings to that source.

RESULTS

The comparative synthesis identifies a clear methodological progression from conventional parameter-response analysis toward integrated multi-objective optimization. The reviewed literature does not support the conclusion that one optimization method is universally optimal; instead, each method addresses a different stage of the decision process.

First, RSM and regression-based methods provide strong process-response interpretation. Suhin et al. (2022) demonstrate their suitability for examining the relationship between FSW parameters and performance outcomes. Their primary strength is explanatory: researchers can determine how changes in controllable parameters influence responses and can use the resulting model to estimate untested combinations. However, the approach becomes less decisive when multiple responses have conflicting optimization directions.

Second, MCDM methods address this decision problem directly. Marichamy and Babu (2021) and Singaravel et al. (2023) demonstrate the application of MCDM for selecting preferred FSW parameters. Sabry et al. (2023) further emphasizes that alternative MCDM procedures can produce different rankings, indicating that methodological selection and weighting are themselves important parts of the optimization problem.

Third, hybrid methods provide greater analytical integration. The combination of TOPSIS and grey relational analysis in Sameer and Birru (2019) demonstrates how several criteria can be consolidated into a decision structure for dissimilar-material welding. Similarly, Rajesh et al. (2022) show the applicability of WASPAS for dissimilar aluminium alloys. These methods improve decision transparency by transforming multiple performance indicators into a comparative ranking.

Fourth, MORSM-MCDM and intelligent multi-objective approaches represent a further methodological evolution. Medhi et al. (2020) integrate modeling and decision-making, while Medhi et al. (2021) formulate an intelligent multi-objective framework. The combined evidence indicates that optimization becomes more robust when prediction and selection are treated as connected but distinct stages.

Finally, the literature demonstrates that optimization criteria should reflect the application rather than rely exclusively on traditional mechanical responses. Montes-González et al. (2021) show that corrosion rate can be modeled as an important FSW outcome. Consequently, a comprehensive optimization framework should permit

criteria to change according to material combination and application requirements.

Overall, the findings support a hierarchical optimization architecture: model the process, identify competing responses, normalize and weight the criteria, rank candidate solutions, and experimentally validate the selected parameters. This architecture provides a stronger methodological basis than isolated single-response optimization.

DISCUSSION

The principal implication of the findings is that FSW optimization should be understood as a decision-system problem rather than simply as a parameter-search problem. The distinction is important because physical process behavior and decision preference are not identical. A regression model can predict a response, but it cannot independently determine how much importance should be assigned to strength, corrosion resistance, dimensional quality, or another criterion. MCDM methods address the latter issue by introducing an explicit preference structure.

The literature also reveals an important trade-off between methodological simplicity and decision sophistication. Regression and RSM approaches are comparatively interpretable and useful for understanding process behavior (Suhin et al., 2022). However, they may require an additional decision layer when several responses must be optimized simultaneously. MCDM techniques provide this layer but introduce their own sensitivity to weighting, normalization, and ranking assumptions. Sabry et al. (2023) is particularly relevant because comparison among MCDM methods demonstrates that methodological choice can affect the final recommendation.

Hybridization therefore appears to be a rational response to the limitations of individual approaches. The MORSM-MCDM framework of Medhi et al. (2020) is significant because it links response modeling with multi-criteria decision-making. Likewise, the TOPSIS and grey relational approach used by Sameer and Birru (2019) illustrates how different analytical mechanisms can be combined to address complex dissimilar-material welding decisions. These approaches should not be interpreted as eliminating uncertainty; rather, they make the decision process more systematic.

Material diversity represents another important limitation. Results obtained for A319 aluminium, Al 6061, Al-Cu, or steel-aluminium combinations cannot automatically be generalized to every FSW application. The physical response of the joint depends on material properties and process conditions. Montes-González et al. (2021) demonstrate this issue through their focus on corrosion

behavior in Al 6061-T6-Cu C11000 joints, while Sameer and Birru (2019) address a steel-aluminium combination. Therefore, optimization frameworks should be transferable at the methodological level without assuming that their numerical optima are universally transferable.

A further limitation concerns validation. Computationally ranked solutions require experimental confirmation. An apparently superior alternative may perform differently when manufacturing variability, material heterogeneity, tool condition, or measurement uncertainty is introduced. Consequently, future research should incorporate uncertainty analysis and repeated validation rather than relying exclusively on deterministic rankings.

From an industrial perspective, the reviewed approaches provide a potential foundation for digitally connected production optimization. A process-level optimizer could generate preferred welding parameters, while production systems could use these outputs in scheduling and manufacturing execution. Such integration would shift FSW optimization from an isolated laboratory exercise toward a production decision-support capability. Nevertheless, this extension requires additional evidence because the supplied references primarily address FSW process optimization rather than enterprise software integration.

The theoretical contribution of the synthesis is therefore a distinction between four connected layers: physical process modeling, response prediction, multi-criteria decision-making, and production-level deployment. This layered perspective reconciles apparently different approaches in the literature and identifies a pathway for future research without claiming that existing FSW studies have already implemented full digital production integration.

CONCLUSION

This research and review paper examined ten supplied studies concerning friction stir welding optimization and synthesized their contributions into a unified methodological framework. The evidence indicates that FSW parameter optimization has progressed from process-response modeling toward increasingly sophisticated MCDM, hybrid, and multi-objective approaches.

RSM and regression provide valuable predictive and explanatory capabilities, while MCDM techniques provide mechanisms for ranking competing parameter combinations. TOPSIS, grey relational analysis, WASPAS, MORSM-MCDM, and intelligent multi-objective frameworks demonstrate different strategies for resolving conflicting quality objectives. The comparative analysis indicates that hybrid architectures are particularly promising because they distinguish process prediction from decision selection

while allowing both to operate within one optimization workflow.

The major research contribution is the proposed hierarchical structure of parameter definition, process modeling, response prediction, multi-criteria evaluation, alternative ranking, and experimental validation. This framework is sufficiently general to accommodate different materials and performance criteria while recognizing that numerical optimum values cannot be transferred indiscriminately across material systems.

Future research should emphasize uncertainty-aware optimization, real-time process data, adaptive parameter selection, and validated integration with digital manufacturing systems. Such developments could connect laboratory-scale FSW optimization with broader production planning and lean manufacturing objectives. However, the supplied evidence does not permit empirical claims regarding SAP PP or SAP Digital Manufacturing integration, because no corresponding bibliographic source details were provided.

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