Optimization of Weld Qualities in Various Welding Operations Using Advanced Computational Techniques: A Comprehensive Review

B. Ellaswamy

Senior Lecturer in Mechanical Engineering

Department of Mechanical Engineering, Government Polytechnic Kataram

Abstract

This study explores various computational methodologies for optimizing the weld-bead geometry and parameters in different welding processes. It encompasses a range of techniques, including linear progression, response surface methodology, artificial neural networks, Taguchi techniques, and genetic algorithms. The optimization of process parameters significantly impacts productivity, quality, and production costs. This review highlights the profound effects of these optimization methodologies on manufacturing processes and demonstrates their integral role in welding. Detailed insights into each method are provided, forming a robust foundation for further research and development in welding procedure optimization.

Keywords: Weld Bead Geometry, Optimization Techniques, Computational Methods, Welding Processes, Neural Networks

1. Introduction

The welding input parameters shape the weld joint's quality, making welding a sophisticated process with multiple inputs and outputs[1]. The weld bead's geometry is paramount because it governs the weld's mechanical characteristics. To produce high-quality welds, one must develop mathematical models capable of anticipating the bead geometry and shape[2]. This method ensures the achievement of the mechanical traits desired for the weldment. Earlier efforts to build mathematical models for optimal outcomes have been explored in this study, emphasizing the selection of process parameters and the prediction of bead geometry. Consequently, mathematical formulas that can anticipate the weld bead geometry can best balance bead parameters and dilution to fulfill the desired economy and mechanical features. The general process of welding operation is shown in Fig. 1.

Fig. 1 Process of welding operation[3]

The development of weld input parameters for every novel welded product traditionally requires a laborious testing process that leans heavily on the expertise of a technician or machine machinist[4]. Technological solutions to this include optimization procedures that leverage mathematical models to conceptualize the bond between input parameters and output elements. Techniques such as Design of Experiment (DoE), evolutionary algorithms, and computation networks have seen increasing adoption for optimization in the past 20 years [5]. Today's discussion seeks to present an exhaustive literature review related to these techniques, underscoring the connection between input parameters and output elements. The literature surveyed is categorized by welding joint characteristics and features and the optimization of various welding procedures via mathematical models.

1.1 Weld quality measures

Weld quality is defined by bead geometry, influenced by a myriad of intertwined process parameters[6] as shown in Fig. 1. Identifying their separate influences on the desired outcome proves to be complicated. Experienced welders often resort to a trial-and-error method when selecting parameters, but this approach might not always provide the best results. Developing an appropriate mathematical model could prevent this hit-or-miss approach by accurately predicting the outcome from a specified set of parameters[7]. This could be achieved by using differential equations that represent physical phenomena. Given the intricate natural phenomena involved in welding, models grounded in experimental results and regression methods can efficiently predict the required results for a given weld.

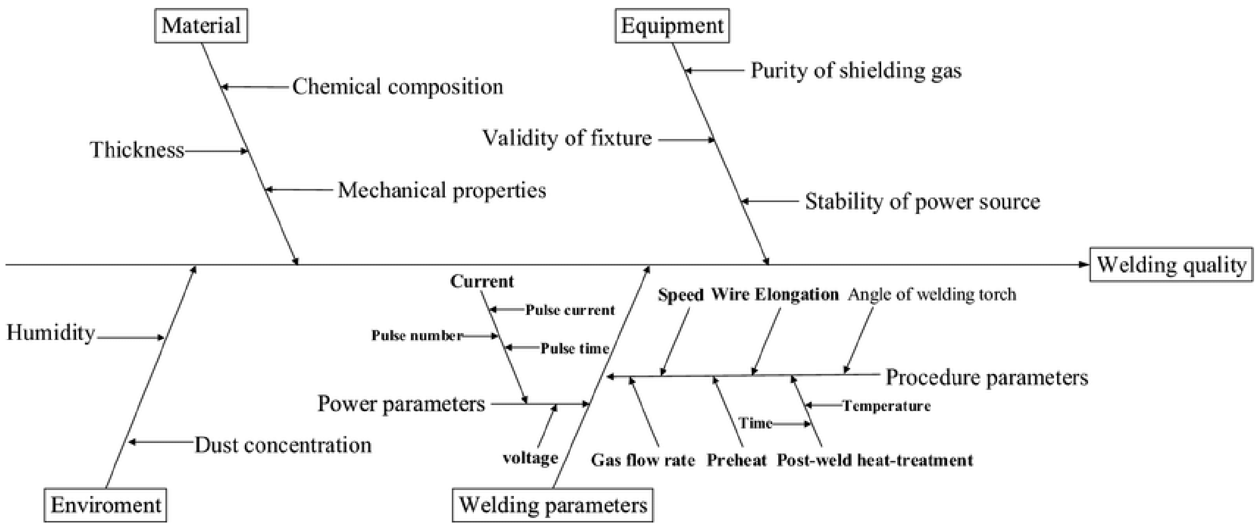

Fig. 1. Fishbone diagram for quality of weldment [8]

2. Literature survey

A variety of studies have delved into optimizing weld bead geometry using advanced computational methods:

Andersen et al. [9] reported work on employing neural networks for modeling weld-bead geometry based on the equipment parameters. Their research findings highlighted that the accuracy level obtained from neural network modeling techniques was in line with that of conventional modeling strategies. The study provides compelling evidence that this method can serve as a sturdy alternative to traditional efforts since it delivers exact predictions of weld-bead characteristics. Thus, this illustrates the potential of neural network-based predictive modeling for improving accuracy in the weld industry. In a study conducted by Yang and Chandel[10], they utilized linear and non-linear regression analysis to model the submerged arc welding process. The study identified that linear regression equations can successfully model welding phenomena traditionally modeled using non-linear regression. This outcome implies that simpler linear models are sometimes just as efficient and accurate as the more complex and intricate non-linear ones in representing different phenomena. Thus, the complexity of a model does not always determine its success in illustrating real-world processes.

Park and Rhee[11] pioneered a novel system geared towards accurately estimating the size of beads by applying regression and methods intrinsic to neural networks. The outcome of their intensive research underscored the superior accuracy of neural networks when tasked with bead size estimation. As a result, this lent significant credence to the potential of utilizing neural networks as an innovative means to enhance the precision associated with weld quality predictions. Gunaraj and Murugan [12] conducted a series of tests involving the submerged arc welding of stainless steel piping. By employing regression equations, they successfully predicted several bead geometric parameters. These successful predictions yielded satisfactory results and clearly illustrated the credible functionality of regression models. Their work demonstrated how these models could effectively forecast welding results by considering the role of input variables.

In their study, Raveendra and Parmar [13]delved into the complexities of flux-cored arc welding by developing mathematical models for predicting weld-bead geometry. They accounted for several factors, including arc voltage, welding current, and welding speed. By incorporating these parameters, their model showed an impressive ability to estimate the bead geometry's dimensions accurately. This type of modeling could potentially revolutionize the practice of arc welding, enhancing both efficiency and precision. In a study conducted by Kim et al. [14]an in-depth analysis was carried out to determine the link between process variables and bead penetration observed in robotic CO2 arc welding. They devised mathematical formulations that tied these variables to the geometry of the weld bead. This offered an unambiguous comprehension of how alterations in the process can lead to variations in the quality of the weld.

In their research, Tarng, et al. [15]employed grey-based Taguchi methods to pinpoint the precise settings for optimal results in submerged arc welding. The researchers discovered that augmenting the deposition rate and the hardness improved welding performance. This highlights the importance of fine-tuning these particular parameters to achieve high-quality welds. Therefore, anyone engaged in this type of welding could greatly benefit from adjusting these factors to optimize performance and outcomes. Koleva [16] developed various innovative models to enhance the parameters associated with electron beam welding. Through the application of the desirability approach, they were able to pinpoint the most effective welding conditions. These optimal situations can profoundly impact the welding process, potentially significantly boosting efficiency levels and enriching the overall quality of the welding outcomes. This groundbreaking discovery provides valuable insight into how these processes can be refined and improved.

In the profound study conducted by Paola Bassani et al. [17], the emphasis was on elevating the efficiency of beam power and laser travel pace for laser welding of A359/SiC metal matrix composites. Their experimentation underscored the indispensability of exact supervision of laser parameters to accomplish the best weld bead properties. Their findings concluded that delicately tuning these parameters could improve the quality of the welded joints, thereby pushing the boundaries of what can be achieved using laser welding techniques. Palani and Murugan [18] reported work to enhance weld bead geometry in stainless steel claddings. They constructed regression models to aid in their cause. These models were pivotal in anticipating multiple parameters, which improved control and forecast of the results in weld processes. Their work allegorically uncovered the art hidden behind traditional welding methods by equating it to the accuracy of mathematical regressions. Their tireless efforts and groundbreaking methods successfully achieved efficiency and predictability, which are critical in any construction process.

In MIG welding processes, Ganjigatti [19] has pioneered an innovative regression analysis technique that evaluates bead geometry predictions on a cluster basis. This method improves the precision of these forecasts by considering the intermediate data set points. Thereby allowing for more accurate results and streamlining the overall process. Vidyut et al. [20] have presented a unique and innovative proposal - a model based on genetic algorithms specifically designed to optimize bead geometry during electron beam welding. This groundbreaking model provides a complex yet precise tool. It aids in attaining the ideal weld bead dimensions by manipulating varied welding parameters such as voltage, the intensity of current, and speed. This algorithm-based model shows promise for increasing the efficiency and quality of electron beam welding techniques. The utilization of a genetic algorithm for the optimization of weld bead geometry in plasma-transferred arc hard-faced stainless-steel plates was pioneered by Siva Murugan and Logesh[21]. This marked an innovative approach to managing welding operations. The foundations of their experimental investigations were rooted in a central composite rotatable design matrix. Findings from their extensive research ultimately resulted in the inception of a robust and efficient optimization algorithm, dramatically redefining the knowledge base of this aspect of engineering. Babu and Balasubramanian [22] effectively fine-tuned the parameters of pulsed current gas tungsten arc welding by utilizing the Hooke and Jeeves algorithm. They performed extensive experiments, plotting diverse graphs and contours to visualize the results. These plots served as a comprehensive map that demonstrated the impact of parameter adjustments on the overall quality of the weld. Their work essentially offers a systematic approach to coaxing the highest possible quality out of this welding method.

3. Discussion on results

The studies reviewed indicate that various computational and experimental techniques can effectively optimize weld bead geometry across different welding processes. Neural networks and regression models have shown significant promise in accurately predicting weld outcomes based on input parameters. Applying genetic algorithms and grey-based Taguchi methods highlights the potential of advanced optimization techniques in refining welding processes. The integration of these methods can lead to enhanced precision, efficiency, and quality in welding operations. Moreover, exploring cluster-wise regression and hybrid approaches combining multiple optimization techniques offers new avenues for achieving optimal welding conditions. These advancements underscore the importance of continuous research and innovation in welding technology.

4. Conclusion

The review of optimization methods has effectively demonstrated their applicability in modeling, control, and enhancement of various welding procedures. There has been an evident surge in the utilization of response surface methodology (RSM) and artificial neural networks (ANNs) to forecast responses and fine-tune welding procedures. Additionally, to establish the most productive approach for specific optimization problems, studies need to compare the efficacy of different optimization methods. Interestingly, the combination of genetic algorithms and RSM might lead to the derivation of ideal welding conditions. Looking toward the future, it would be highly beneficial if these modeling and optimization techniques were used to ascertain welding procedure combinations that are safe, friendly to the environment, and economically viable.

5. Future Scope of Work

The future scope of work in optimizing weld bead geometry and parameters using advanced computational techniques is vast and promising. Several areas warrant further exploration and development:

1. **Integration of Hybrid Optimization Techniques**: Combining different optimization methods, such as genetic algorithms with response surface methodology (RSM) or neural networks with Taguchi techniques, can yield more robust and efficient solutions. Exploring these hybrid approaches can lead to more precise control over welding parameters and improved weld quality.
2. **Real-time Optimization and Control**: Developing real-time optimization systems that adjust welding parameters dynamically during the welding process based on continuous feedback can significantly enhance weld quality and efficiency. Incorporating machine learning and artificial intelligence to create adaptive control systems is critical for future research.
3. **Application to Emerging Welding Technologies**: As new welding technologies such as laser welding, friction stir welding, and additive manufacturing continue to evolve, there is a need to adapt and refine optimization techniques to suit these processes. Investigating these technologies' unique challenges and opportunities will be essential for advancing welding science.
4. **Artificial Intelligence and Machine Learning**: The application of artificial intelligence (AI) and machine learning (ML) in welding optimization is a promising area. Future studies should explore the development of sophisticated AI and ML models that can predict weld outcomes with high accuracy and adapt to varying conditions[23].
5. **Environmental and Economic Considerations**: Research should address welding processes' environmental impact and cost-effectiveness. Developing optimization techniques that minimize energy consumption and material waste while maximizing productivity and quality will be crucial for sustainable manufacturing.

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