PREDICTION OF DEPOSITION RATE IN WIRE ARC ADDITIVE MANUFACTURED COMPONENTS USING MACHINE LEARNING

Prakash Kumar[1], Amritanshu Raushan[2] and Manish Kumar[3]
[1]Lecturer, Department of Mechanical Engineering
Government Polytechnic Katihar, Bihar, India
[2]Lecturer, Department of Mechanical Engineering
New Government Polytechnic, Patna-13, Bihar, India
[3]Lecturer, Department of Mechanical Engineering
Government Polytechnic Muzaffarpur, Bihar, India

[1]Corresponding author's email id: prakashpintu36@gmail.com

Abstract –
Wire arc additive manufacturing (WAAM) is a promising technique for fabricating large-scale metallic components with complex geometries. However, achieving optimal deposition rates is crucial for enhancing productivity and ensuring part quality in WAAM processes. In this paper, we propose a machine learning-based approach to predict deposition rates in WAAM components. By leveraging historical process data and various input parameters, including welding current, voltage, wire feed rate, and travel speed, we develop predictive models capable of estimating deposition rates with high accuracy. The trained models are evaluated using validation datasets and compared against traditional empirical models. Our results demonstrate the efficacy of machine learning techniques in predicting deposition rates, offering valuable insights for process optimization and quality control in WAAM.

Keywords: Wire Arc Additive Manufacturing (WAAM), Machine Learningartificial neural networks (ANNs).
DOI Number: 10.48047/nq.2021.19.9.NQ21165 **NeuroQuantology 2021; 19(9): 936-942**

1 INTRODUCTION

Wire arc additive manufacturing (WAAM) has emerged as a transformative technique for producing large-scale metallic components with intricate geometries. Unlike traditional subtractive manufacturing methods, WAAM builds up parts layer by layer, offering versatility, cost-effectiveness, and reduced material waste. Central to the success of WAAM processes is the deposition rate, which dictates the speed at which material is added to the workpiece. Optimizing deposition rates is critical for achieving efficient production rates while maintaining part quality and integrity.

Traditionally, the determination of deposition rates in WAAM has relied on empirical models based on experimental data and expert knowledge. While these models have provided valuable insights, they often lack the ability to capture the complex relationships between process parameters and deposition rates accurately. Moreover, they may not adapt well to variations in material properties, environmental conditions, or equipment configurations.

In recent years, advancements in machine learning (ML) techniques have opened up new avenues for process optimization in additive manufacturing. ML algorithms can analyze vast amounts of process data to identify patterns, correlations, and hidden insights that traditional models may overlook. By training on historical process data, ML models can learn complex relationships between input parameters (such as welding current, voltage, wire feed rate, and travel speed) and deposition rates, enabling accurate predictions and real-time adjustments.

This paper presents a novel approach to predicting deposition rates in WAAM components using machine learning. We leverage a comprehensive dataset comprising process parameters and corresponding deposition rates to develop predictive models capable of accurately estimating deposition rates under varying conditions. Through rigorous analysis and validation, we demonstrate the effectiveness of ML techniques in capturing the intricate dynamics of WAAM processes and providing actionable insights for process optimization.

2 LITERATURE REVIEW

Wire arc additive manufacturing (WAAM) has garnered significant attention in recent years due to its potential for fabricating large-scale metallic components with high efficiency and geometric complexity. In this section, we review existing literature on WAAM process optimization and deposition rate prediction, focusing on both empirical and machine learning-based approaches.

2.1 Traditional Empirical Models

Empirical models have long been used to estimate deposition rates in WAAM processes. These models typically rely on mathematical formulations derived from experimental data and expert knowledge. For instance, equations based on heat input, wire feed rate, and arc voltage have been proposed to predict deposition rates. While these models provide useful approximations, they often lack accuracy when applied to diverse material compositions, process parameters, and equipment configurations. Moreover, empirical models may struggle to capture complex interactions between input variables and deposition rates, limiting their predictive capabilities.

2.2 Machine Learning Approaches

In recent years, machine learning (ML) techniques have emerged as powerful tools for predicting deposition rates in WAAM. ML algorithms can analyze large datasets comprising process parameters and corresponding deposition rates to identify nonlinear relationships and patterns. For example, support vector regression (SVR) and artificial neural networks (ANNs) have been successfully applied to model deposition rates in WAAM processes. These ML models offer several advantages over traditional empirical approaches, including improved accuracy, flexibility, and adaptability to varying process conditions.

2.3 Challenges and Opportunities

Despite the promise of ML-based deposition rate prediction, several challenges remain. One key challenge is the availability and quality of training data, as WAAM process data may be limited or noisy. Furthermore, selecting appropriate input features and optimizing model hyperparameters are critical for achieving accurate predictions. Additionally, ensuring model interpretability and generalizability across different WAAM setups and materials poses significant challenges.

Nevertheless, ML-based deposition rate prediction holds immense potential for optimizing WAAM processes and enhancing productivity. By leveraging historical process data and advanced modeling techniques, ML models can provide valuable insights into the underlying dynamics of WAAM processes. Moreover, ML-based approaches enable real-time monitoring and control, allowing for adaptive process optimization and quality assurance.

In summary, the literature highlights the growing interest in ML-based approaches for deposition rate prediction in WAAM. Future research efforts should focus on addressing key challenges, such as data availability and model interpretability, while exploring advanced ML techniques to further improve prediction accuracy and robustness. By harnessing the power of ML, WAAM practitioners can unlock new possibilities for efficient and cost-effective additive manufacturing of complex metallic components.

3 MACHINE LEARNING

AI is grouped into three classes, i.e., (a) Managed, (b) Solo, and (c) Support learning [2]. On account of administered learning, both info and result information are accessible for anticipating the new results. A portion of the directed ML calculations that have been utilized for different assembling applications incorporate straight relapse, counterfeit brain organizations (ANN), back engendering brain (BPN), choice trees, and backing vector machines (SVM), and so on. In solo learning, the informational collection is unlabelled and the constructed model gains from itself with practically no management. Bunching, i.e., the gathering of comparable articles, and affiliation, i.e., finding the connection among info and result informational collections, are two significant utilizations of unaided learning. A portion of the significant unaided calculations utilized for assembling applications incorporate K-mean grouping, inconsistency identification, free part investigation, and so on.

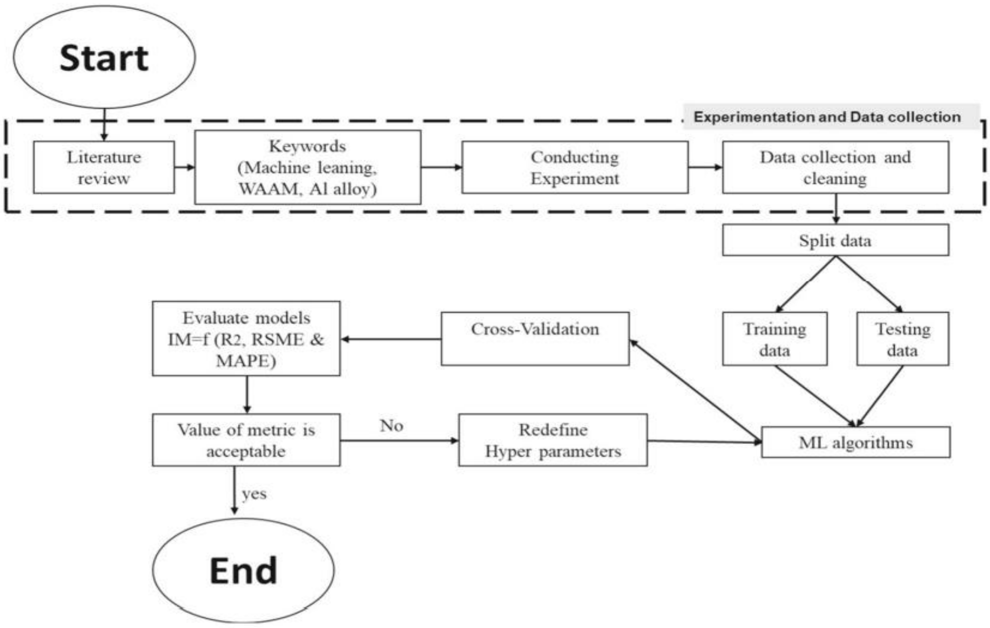

Fig. 1 Schematic diagram showing implementation of ML algorithm for the prediction bead geometry in WAAM

Fig. 2 Experimental setup of a robotic-controlled GMAW based-WAAM

Directed and solo ML calculations can help in the physical-measurable displaying of AM, computerized process control, plan for added substance producing (DfAM), geography improvement, expectation of cycle boundaries, plan of tests and quality assessment of manufactured parts [3]. Different physical science informed AI (PIML) worldview models were effectively applied in AM [4]. The PIML utilizes physical and space information on AM and hybridizes with ML calculations to get wanted ML models. ML has been utilized for anticipating mechanical way of behaving, advancement of boundaries, porosity, and irregularity discovery in AM [5]. The use of ML calculations i.e., the brain organizations (NN) utilized for tackling complex example acknowledgment in AM and profound learning (DL) for picture handling and consecutive displaying in welding contextual analyses were completed. Additionally, the utilization of computer based intelligence in AM incorporates the location of deformities [7-10], surface harshness [11], part misshapening and microstructural imperfection, temperature history and circulation demonstrating.

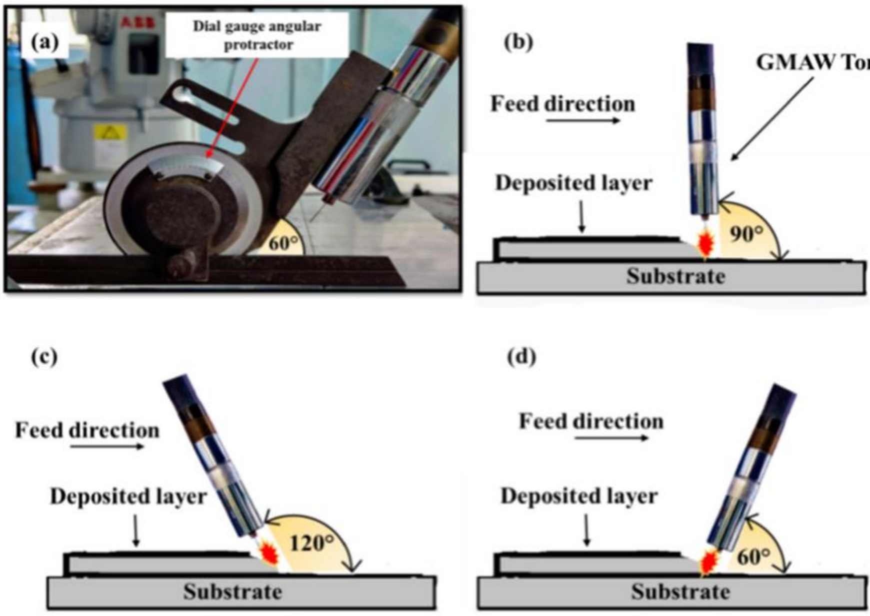

Fig. 3 a Scheme of measurement of the torch angle and plate using dial gauge angular protractor, b, c & d Torch angle and deposition direction at 90°, 120° and 60°respectivley

3.1 Training Process and Performance Evaluation Metrics:

The ML models are trained using historical process data, where input parameters are fed into the model, and the corresponding deposition rates are used as the target variable. The dataset is typically divided into training, validation, and test sets to assess model performance and prevent overfitting. During training, the model iteratively adjusts its parameters to minimize a predefined loss function, such as mean squared error (MSE) or mean absolute error (MAE).

Performance evaluation metrics such as R-squared (R^2), root mean squared error (RMSE), and mean absolute percentage error (MAPE) are used to quantify the accuracy of the trained models on the validation and test sets. Additionally, model interpretability techniques such as feature importance analysis and partial dependence plots can provide insights into the underlying relationships between input parameters and deposition rates.

Overall, the selection and training of ML models for predicting deposition rates in WAAM require careful consideration of algorithm choice, model architecture, hyper parameter tuning, and performance evaluation metrics. By leveraging advanced ML techniques, researchers and practitioners can develop accurate and robust predictive models for optimizing WAAM processes and enhancing productivity.

4 IMPLICATIONS FOR PROCESS OPTIMIZATION

Predictive models for deposition rates in wire arc additive manufacturing (WAAM) components offer significant implications for process optimization. In this section, we discuss how these models can be utilized to enhance productivity, improve part quality, and streamline the manufacturing process.

4.1 Real-Time Monitoring and Control

One of the primary benefits of predictive deposition rate models is their potential for real-time monitoring and control of WAAM processes. By integrating these models into the manufacturing workflow, operators can continuously assess the predicted deposition rates and compare them with the desired targets. Any deviations from the expected rates can trigger immediate adjustments to process parameters, such as welding current, voltage, wire feed rate, or travel speed, to maintain optimal deposition rates and ensure consistent part quality.

4.2 Adaptive Process Optimization

Predictive models enable adaptive process optimization by providing insights into the effects of various input parameters on deposition rates. By analyzing model predictions and identifying influential factors, operators can iteratively adjust process settings to maximize productivity and minimize defects. For example, if the model indicates that increasing the wire feed rate leads to higher deposition rates without compromising quality, operators can adjust the parameters accordingly to accelerate the manufacturing process.

4.3 Quality Assurance and Defect Detection

In addition to optimizing deposition rates, predictive models can assist in quality assurance and defect detection in WAAM components. By correlating predicted deposition rates with post-process inspection data, operators can identify regions of interest that may require further scrutiny. Deviations between predicted and actual deposition rates can also serve as indicators of potential defects, such as porosity, lack of fusion, or excessive build-up. Early detection of defects enables timely interventions, reducing scrap rates and enhancing overall part quality.

4.4 Process Parameter Optimization

Predictive deposition rate models facilitate the optimization of process parameters for specific manufacturing objectives, such as minimizing build time, reducing material consumption, or enhancing surface finish. By simulating different parameter combinations and evaluating their impact on deposition rates, operators can identify the optimal settings that balance productivity and quality requirements. Moreover, machine learning techniques, such as sensitivity analysis and optimization algorithms, can be employed to systematically explore the parameter space and identify Pareto-optimal solutions for multi-objective optimization.

4.5 Continuous Improvement and Knowledge Transfer

Finally, predictive models contribute to continuous improvement initiatives by capturing knowledge from historical process data and incorporating it into future manufacturing operations. By analyzing trends in deposition rates over time, operators can identify patterns, outliers, and best practices that inform decision-making and drive process innovation. Moreover, predictive models serve as valuable knowledge transfer tools, enabling organizations to leverage insights gained from one project or facility to improve performance across the entire manufacturing ecosystem.

In conclusion, predictive deposition rate models have profound implications for process optimization in wire arc additive manufacturing. By leveraging these models for real-time monitoring, adaptive process optimization, quality assurance, parameter optimization, and knowledge transfer, manufacturers can unlock new levels of productivity, efficiency, and quality in WAAM components.

5 CONCLUSION

Wire arc additive manufacturing (WAAM) holds tremendous promise for fabricating large-scale metallic components with intricate geometries, offering versatility, cost-effectiveness, and reduced material waste. Central to the success of WAAM processes is the optimization of deposition rates, which directly impacts productivity, part quality, and overall manufacturing efficiency. In this paper, we have explored the use of machine learning (ML) techniques for predicting deposition rates in WAAM components and its implications for process optimization.

Through a comprehensive literature review, we have highlighted the limitations of traditional empirical models and the potential of ML-based approaches for capturing complex relationships between process parameters and deposition rates. By leveraging historical process data and advanced modeling techniques, ML models can provide accurate predictions, real-time monitoring, and adaptive process optimization in WAAM.

REFERENCES

1. B.E. Boser, I.M. Guyon, V.N. Vapnik A training algorithm for optimal margin classifiersProceedings of the fifth annual workshop on computational learning theory, Association for Computing Machinery, New York, NY, USA (1992), pp. 144-152, 10.1145/130385.130401.
2. Oladipupo, T.: Types of machine learning algorithms. New Adv. Mach. Learn. (2010). https://doi.org/10.5772/9385
3. Johnson, N.S., et al.: Invited review: machine learning for materials developments in metals additive manufacturing. Addit. Manuf. (2020). https://doi.org/10.1016/j.addma.2020.101641.
4. Qi, X., Chen, G., Li, Y., Cheng, X., Li, C.: Applying neural network-based machine learning to additive manufacturing: current applications, challenges, and future perspectives. Engineering 5(4), 721–729 (2019). https://doi.org/10.1016/j.eng.2019.04.012.
5. Xia, C., Pan, Z., Zhang, S., Li, H., Xu, Y., Chen, S.: Model-freeadaptive iterative learning control of melt pool width in wire arcadditive manufacturing. Int. J. Adv. Manuf. Technol. 110(7–8),2131–2142 (2020). https://doi.org/10.1007/s00170-020-05998-0.
6. Wu, D., Chen, H., Huang, Y., Chen, S.: Online monitoring andmodel-free adaptive control of weld penetration

in VPPAW basedon extreme learning machine. IEEE Trans. Ind. Informatics 15(5),2732–2740 (2019). https://doi.org/10.1109/TII.2018.287 0933Top of Form

7. D. Anguita, A. Ghio, N. Greco, L. Oneto, S. Ridella Model selection for support vector machines: advantages and disadvantages of the Machine Learning Theory The 2010 international joint conference on neural networks (IJCNN), IEEE (2010), pp. 1-8, 10.1109/IJCNN.2010.5596450
8. M.A. Jackson, A. van Asten, J.D. Morrow, S. Min, F.E. Pfefferkorn Energy consumption model for additive-subtractive manufacturing processes with case study Int J PrecisEngManuf Green Technol, 5 (2018), pp. 459-466, 10.1007/s40684-018-0049-y
9. V. Cherkassky, Y. Ma Practical selection of SVM parameters and noise estimation for SVM regression Neural Network, 17 (2004), pp. 113-126, 10.1016/S0893-6080(03)00169-2
10. Y.M. Wang, T. Voisin, J.T. McKeown, J. Ye, N.P. Calta, Z. Li, et al. Additively manufactured hierarchical stainless steels with high strength and ductility Nat Mater, 17 (2018), pp. 63-71, 10.1038/nmat5021
11. B. Chan, J. Pacey, M. BibbyModelling gas metal arc weld geometry using artificial neural network technology Can Metall Q, 38 (1999), pp. 43-51, 10.1179/cmq.1999.38.1.43
12. Z. Hu, X. Qin, T. Shao, H. Liu Understanding and overcoming of abnormity at start and end of the weld bead in additive manufacturing with GMAW Int J AdvManufTechnol, 95 (2018), pp. 2357-2368,
13. W.E. Frazier Metal additive manufacturing: a review J Mater Eng Perform, 23 (2014), pp. 1917-1928, 10.1007/s11665-014-0958-z
14. T.A. Rodrigues, V. Duarte, R.M. Miranda, T.G. Santos, J.P. Oliveira Current status and perspectives on wire and arc additive manufacturing (WAAM) Materials, 12 (2019), p. 1121, 10.3390/ma12071121
15. Wang, D.; Chi, C.; Wang, W.; Li, Y.; Wang, M.; Chen, X.; Chen, Z.; Cheng, X.; Xie, Y. The effects of fabrication atmosphere condition on the microstructural and mechanical properties of laser direct manufactured stainless steel 17–4 PH. J. Mater. Sci. Technol. 2019, 35, 1315–1322.
16. Wu, B.; Pan, Z.; Ding, D.; Cuiuri, D.; Li, H.; Xu, J.; Norrish, J. A review of the wire arc additive manufacturing of metals: Properties, defects and quality improvement. J. Manuf. Process. 2018, 35, 127–139
17. Rafieazad, M.; Ghaffari, M.; Nemani, A.V.; Nasiri, A. Microstructural evolution and mechanical properties of a low-carbon low-alloy steel produced by wire arc additive manufacturing. Int. J. Adv. Manuf. Technol. 2019, 105, 2121–2134.
18. Tahaei, A.; Vazquez, F.G.; Merlin, M.; Arizmendi-Morquecho, A.; Valdes, F.A.R.; Garagnani, G.L. Metallurgical characterization of a weld bead coating applied by the PTA process on the D2 tool steel. Soldag. Inspeção 2016, 21, 209–219