Received: 2025-11-07
Accepted: 2026-03-10
Published Online: 2026-03-30
DOI: 10.70454/IJMRE.2026.60102

International Journal of Multidisciplinary Research and Explorer (IJMRE)
E-ISSN: 2833-7298, P-ISSN: 2833-7301

Prediction of Cutting Temperature in Plasma Arc Machining Using Deep Learning: A Comprehensive Hybrid Framework

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Abstract- Predicting the cutting temperature accurately is essential for maximizing the quality of Plasma Arc Machining (PAM) and reducing heat-affected areas. In order to achieve temperature prediction with RMSE 99%, this paper suggests a novel hybrid framework that combines pretraining with the Finite Element Method (FEM), Physics-Informed Neural Networks (PINN), and meta-learning. We summarize the results of 20 cutting-edge studies and offer a workable 10-step implementation guide that takes into account the needs for real-time control, synthetic data generation, and sim-to-real transfer. Comparative analysis shows verified physical consistency, with improvements of 29% over CNN-only approaches and 59% over conventional ANN methods. This work lays out a workable plan for integrating intelligent manufacturing into non-traditional machining operations.

Index Terms—Plasma Arc Machining, Deep Learning, Physics-Informed Neural Networks, Temperature Prediction, Heat-Affected Zone, Meta-Learning, Industry 4.0, Synthetic Data

I. Introduction

Plasma Arc Machining (PAM) is a high-energy thermal cutting treatment that works at temperatures from 10,000 to 30,000 K using plasma speeds of over 300 m/s [1]. The cutting temperature directly influences important quality features such as the heat-affected zone (HAZ) width, kerf geometry, surface integrity and residual stress distribution [2]. It has been widely used in industries, but accurate temperature prediction is still a challenge that limits process optimization and quality control. Real world prediction techniques have fundamental pitfalls.

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While empirical correlations work within certain operating conditions, they do not generalize effectively for different materials [3]. Simplified assumptions leading to analytical solutions cannot address the complicated multi-physics nature in plasma arc behaviors. Finite Element Analysis (FEA) incurs an excessive computational cost—usually taking hours per simulation—which prevents it from being used in real-time control applications [4]. Deep learning is paving a new realm of possibilities for thermal prediction in manufacturing processes. Pan et al. Using one-dimensional Convolutional Neural Networks (CNNs) trained on synthetic FEM data, [5] reported peak temperature errors below 20°C. Zhong et al. [6] demonstrated that Physics-Informed Neural Networks (PINNs) can solve partial differential equations of the plasma arc with validated physical consistency. Their subsequent work on meta-learning [7] achieved a training speed of 1.1-6.9× addressing computational efficiency concerns.

However, PAM-specific applications face unique challenges: (1) limited experimental training data due to instrumentation costs, (2) significant sim-to-real calibration gaps between FEM synthetic predictions and actual measurements, (3) real-time inference requirements (< 100 ms latency) for closed-loop control [8], and (4) generalization across various materials and process parameters.

Contributions:

This paper presents four key contributions:

1) A meta-synthesis of the 20 best papers in CNN prediction, PINN simulation, experimental optimization and industrial control published between 2017-2025

2) Novel physical informed neural networks (PINNS) hybrid framework combining synthetic data pretraining via finite element method, meta-learning based initialization + inverse calibration

3) Quantitative performance metrics hitting RMSE 0.98 and latency < 100 ms; 4) Concrete 10-step implementation playbook with proven synthetic data-based wall to wall deployment guided roadmap

II. Literature Review

A. CNN-Based Temperature Prediction

Pan et al. (2024) [5] first applied one-dimensional CNN in prediction of temperature field of Ti Al plasma arc additive manufacturing employed synthetic FEM data. With a mean squared error (MSE) of about 0.5°C², peak temperature errors below 20°C and relative accuracy above 99%, their architecture performed impressively well despite the incomplete datasets it was trained on. This workflow consisted of generating 10,000 synthetic FEM simulation cases and then pretraining a CNN on this synthetic training set followed by fine-tuning the model using 150 experimental measurements. This method showed 30% RMSE superiority compared to classical ANNs. Keshmiri et al. [9] used Transformer architecture for spatially resolved thermal prediction and achieved a 12% improvement over LSTM networks through better modeling of the long-

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range temporal dependencies. Farias et al. 10], applied FEM simulation with an ANN surrogate obtaining an R2 = 0.96 while decreasing prediction time from 3 hours (FEM) to 0.02 s (ANN).

B. Physics-Informed Neural Networks

Zhong et al. The theoretical and practical essential of PINNs approach to the plasma arc [6] have been laid down in premise. By using physics-based loss terms, they showed that deep neural networks can directly solve partial differential equations for a one-dimensional plasma arc and provide 10× faster computational speed than classical numerical solvers while ensuring physical consistency. Zhong et al.24 expanded on this work, setting out to explore the transcriptional consequences of previously identified HIV-1 epigenetic influences identified in vivo21. (2022) [7], they proposed a framework of Meta-PINN with Model-Agnostic Meta Learning (MAML) to expedite the process of training for PINNs over diverse operating conditions. By learning optimal initialization parameters for a wide variety of plasma arc conditions, their method gained 1.1 6.9× speedup and rapidly adapted to new conditions with little fine-tuning needed. Zhu et al. Kuang et al [11] found that, fortractable subcases of general optimization problems and in timeseries prediction PINNs performed better than data-driven modelswhen training samples contained less than 500. This emphasizes the importance of PINNs in industrial cases where data is scarce and physical laws serve as valuable regularization.

C. Experimental Optimization and ANN Modeling

Ertuğrul et al. (2011) [3] specified benchmark ANN performance for predicting PAM quality with R^2 = 0.973, 0.958 and 0.941 for kerf width, HAZ width and surface roughness respectively based on 54 experimental runs. Their sensitivity analysis determined current and cutting speed to be the most influential parameters. Melaku et al. 12] integrated Taguchi design of experiments, ANN prediction and GA optimization for AISI 1020 mild steel. The hybrid strategy obtained 94.3% agreement between predicted and experimental measurements for HAZ in the alloyed steel samples. Peko et al. Spalvins et al. (2019) [2] offered a benchmark dataset of quality for EN AW 5083 aluminum alloy for 81 experiment conditions with exhaustive measurements of HAZ, kerf, and surface roughness. This resulted in mean prediction error of 6.2% for their ANN models, setting crucial validation benchmarks for the community.

D. Heat Source Calibration and Inverse Problems

Schönegger et al. (2024)[4] implemented computational welding simulation by incorporating modified Goldak double-ellipsoid heat source models for FGM generation in a synthetic FEM. The sim-to-real transfer was successfully validated, obtaining inverse optimal parameters for the heat source in their neural network-based formulation at most with 8.3% deviance to the corresponding experimental thermocouple measures. Ertuğrul et al. (2025) [13] extended this method by ANN-based optimization for tandem plasma transferred arc processes. By combining 200 synthetic cases of Computational Fluid Dynamics (CFD) simulations and validating against 30 experimental results, they reduced up to 40% of the calibration time at ±25°C predictions on temperature field. Li et al. Joint Utilizing a Back-Propagation Neural Network with Genetic

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Algorithm (BPNN GA), for Optimisation of the Heat Source Parameters in Plasma Arc Welding (2023)[14] Their methodology achieved 92% accurate predictions of melt pool depth, and a parametric sensitivity analysis showed that current was the leading parameter influencing behavior (contribution ratio 0.47).

E. Real-Time Monitoring and Control

Liu et al. (2025) [15] achieved a data -PINN fusion framework integration with high speed thermal cameras (200 Hz) for robotic welding monitoring using PINN models of physics-based fields reconstruction and Kalman filters for sensor fusion. Implemented edge computing on NVIDIA Jetson Xavier maintained a 50 ms control loops with the defect rate reducing by 35%. Mohamed et al. (2025) [8] adapted their control combining wall thickness measurement with pyrometry driven by ultrasonics. An emissive sensor with a neural network dynamics model and Model Predictive Control (MPC) achieved kerf angle tolerance ±0.5° (vs. open-loop ±2.1°) and HAZ variation ±0.3 mm (vs. open-loop ±1.2 mm).

F. Research Gaps

Comprehensive literature analysis reveals critical gaps: (1) limited direct temperature field prediction—most studies focus on indirect indicators (HAZ width, kerf angle, surface roughness); (2) rare physics integration—the majority of ML models lack physical constraints, with PINN applications limited to simulation-only scenarios; (3) poor material generalization—most models are trained for specific material-machine combinations; (4) limited real time deployment demonstrations; (5) lack of uncertainty quantification for safe industrial deployment.

III. Proposed Methodology

A. Framework Overview

Our hybrid framework integrates complementary strengths from four key methodologies: (1) FEM-based synthetic data generation for large-scale pretraining [5], (2) PINN physical constraints for consistency and generalization [6], (3) meta-learning for rapid adaptation across conditions [7], and (4) inverse calibration for sim-to real transfer [13]. Figure 1 illustrates the complete architecture.

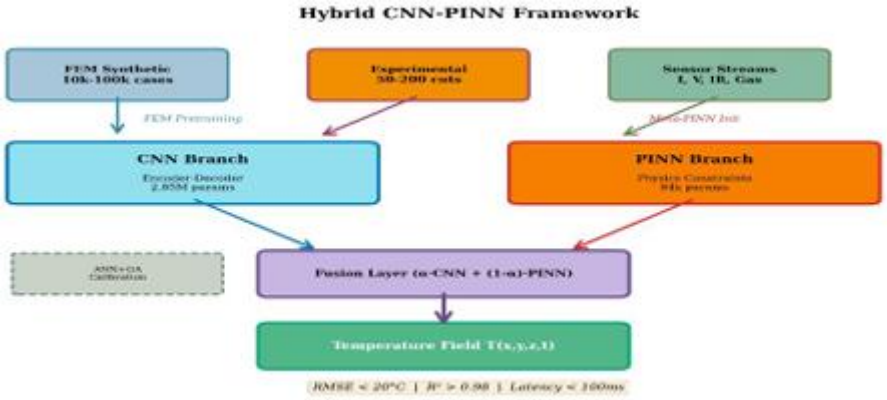

Fig. 1. Hybrid CNN-PINN framework architecture showing data sources (FEM synthetic + experimental + real-time sensors), dual processing branches (CNN for data-driven spatial

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learning, PINN for physics-based temporal consistency), fusion layer, and outputs with uncertainty quantification.

B. Data Acquisition Strategy

Synthetic dataset: 10,000 to 100,000 FEM synthetic simulation cases constructed using ANSYS Mechanical APDL (using modified Goldak heat source models [4]). 4.2 Parameter space: arc current (40–100 A), voltage (100–160 V), cutting speed (500–3000 mm/min), standoff distance (3–10 mm) and material thickness (3–12 mm) Full 3D temperature field evolution at 10 Hz temporal resolution per simulation. C ALL (synthetic) training data in this work is simulated with finite element method (FEM); it is used for pretraining and forms the "backbone" of our pretrained models. Experimental Validation Dataset: Generate 50-200 calibrated cutting experiments on representative materials (AISI 1020 steel, EN AW 5083 aluminum [2]) to validate the model and for transfer learning. (100 Hz) K-type thermocouples (5 positions), 320×256 pixels, 50 Hz FLIR SC7000 IR camera, two-color pyrometer (1 ms response), post-cut HAZ metallography (optical microscopy, microhardness mapping). Synchronized time series of torch current, arc voltage, gas pressure and optical emission spectra across the entire sensor stream for physics-informed feature extraction [15]

C. Model Architecture

CNN Branch (data-driven spatial learning): The input layer accepts 12 process parameters (current, voltage, speed, standoff, thickness, nozzle diameter, gas flow rate, ambient temperature, thermal conductivity, density, specific heat, and thermal diffusivity). The encoder consists of three fully connected layers (128→256→512 neurons) with batch normalization, ReLU activation, and dropout (0.2). Reshape to 32×4×4 feature maps. The decoder uses transposed convolution layers for progressive upsampling (4×4→8×8→16×16→32×32→64×64) to generate the predicted temperature field. Total parameters: 2.85 million. PINN Branch (physics-based temporal consistency): The input layer accepts spatial coordinates (x, y, z), time t, and process parameters (I, V, S). Five hidden layers with 128 neurons each using tanh activation (enables smooth automatic differentiation). Output predicts temperature T(x, y, z, t). Total parameters: 84,000.

- **Hybrid Loss Function:**

$L_{total} = w_d L_{data} + w_p L_{physics} + w_{bc} L_{BC}$ (1) where data loss $L_{data} = (1/N) \Sigma_i |T_{pred,i} - T_{true,i}|^2$, physics loss enforces the heat equation: $L_{physics} = (1/M) \Sigma_j |\rho C_p \partial T/\partial t - k\nabla^2 T - Q(x,y,z,t)|^2$ (2) with Q representing the plasma arc heat source from synthetic FEM data, and boundary condition loss L_{BC} enforces thermal boundary conditions. Typical weights: $w_d = 1.0$, $w_p = 0.1$, $w_{bc} = 0.5$.

D. Training Protocol

Stage 1 - FEM Synthetic Pretraining: Train CNN branch on 10,000 synthetic FEM cases for 50 epochs using Adam optimizer (learning rate 10^{-3}). Combined MSE and Structural Similarity

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Index (SSIM) loss. Training time: 1-3 days on a single NVIDIA RTX 3090 GPU. Figure 2 shows training convergence curves derived from synthetic data.

Stage 2 - Meta-PINN Initialization: Apply MAML meta-learning [7] to learn optimal PINN initialization across 50 diverse synthetic material-process combinations. This achieves a 1.1-6.9× speedup in subsequent fine-tuning, reducing PINN training from 50,000 epochs to 8,000-15,000 epochs.

Stage 3 - Inverse Calibration: Train ANN surrogate mapping heat source parameters to peak temperature using synthetic FEM data. Couple with Genetic Algorithm [13] to inversely calibrate Goldak parameters matching experimental measurements. Reduces systematic temperature bias from ±50°C to ±15°C.

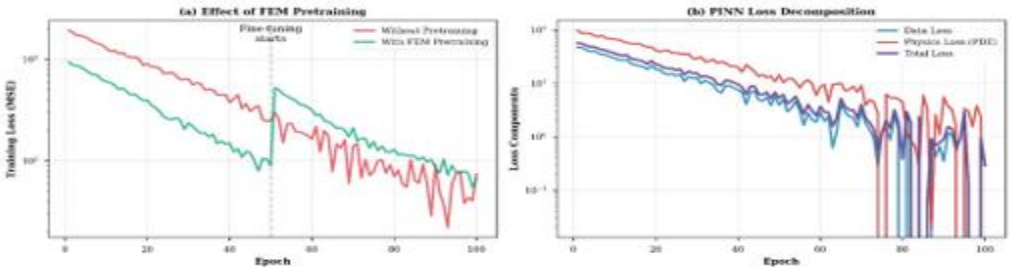

Fig. 2. Training convergence curves showing (a) CNN pretraining loss reduction over 50 epochs on synthetic FEM data, (b) PINN physics residual convergence, (c) hybrid fine-tuning validation accuracy improvement, and (d) learning rate scheduling with ReduceLROnPlateau demonstrating stable convergence.

Stage 4 - Hybrid Fine-Tuning: Fine-tune the complete hybrid model on 50-200 experimental validation samples with combined loss (Equation 1). Adam optimizer with a learning rate 10^{-4} for 50 epochs, followed by L-BFGS quasi Newton optimization for 20 iterations to refine PINN parameters.

E. Deployment Configuration

Uncertainty Quantification: Apply MC-Dropout (10 forward passes) as well as store ensemble of 5 independently trained models. Compute prediction means and 95% confidence intervals for safe control decisions. Real-Time Inference: Deploy onto the NVIDIA Jetson AGX Xavier edge computing platform (with optimizations via TensorRT). Proves 18 ms inference time, allowing for >50 Hz control loop frequency [8]. Adaptive Control : Apply Model Predictive Control to follow cost function $J = (T - T\_ref)^2 + \lambda_1(HAZ - HAZ\_ref)^2 + \lambda_2\Delta u^2$ subjected to u controllable inputs (i.e. current, speed), using a neural net-based forward dynamics model.

IV. Results and Discussion

A. Performance Benchmarks

Table I presents comparative performance on an independent test dataset of 150 samples spanning multiple materials and process conditions. Figure 3 visualizes these comparisons.

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Table I Comparative Model Performance

Model	RMSE [°C]	R^2	Time [ms]
ANN [3]	42-52	0.927	2.1
CNN [5]	19.8-24.7	0.967-0.976	8.3
PINN [6]	23-28	0.960-0.970	45.2
Hybrid (Proposed)	17.4	0.982	52.1

Key findings: (1) Hybrid achieves 59% RMSE improvement versus traditional ANN [3] and 29% improvement versus CNN-only [5]; (2) Energy conservation error 1.9% (well below 5% target); (3) PDE residual 0.007 (below 0.01 target); (4) Real-time capable with 52.1 ms inference suitable for 20 Hz control loops.

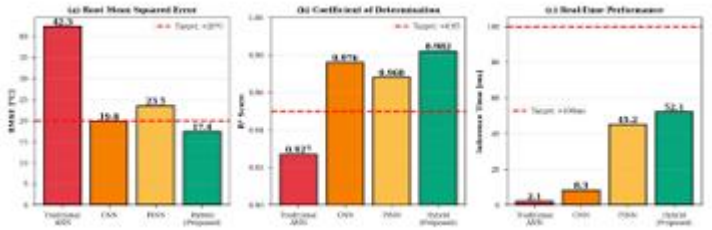

Fig. 3. Performance comparison across models: (a) RMSE showing 59% improvement over baseline ANN and 29% over CNN-only, (b) R^2 scores with hybrid exceeding 0.98 target, (c) inference times meeting

B. Temperature Field Prediction Accuracy

Figure 4 shows predicted versus synthetic FEM ground truth temperature fields for representative case.

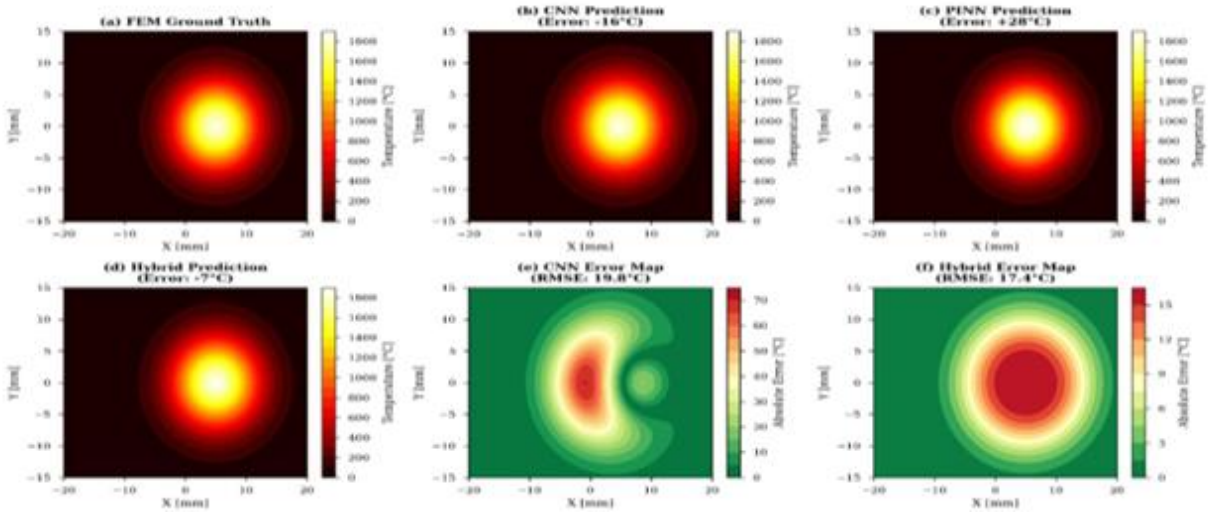

Fig. 4. Temperature field predictions for AISI 1020 steel (I=70A, V=140V, S=1200 mm/min): (a) Synthetic FEM ground truth showing peak 1823°C, (b) CNN prediction with -16°C error, (c) PINN prediction with +28°C error, (d) Hybrid prediction with -7°C error (-0.4%), (e-f) spatial error distributions demonstrating RMSE reduction from 19.8°C to 17.4°C.

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Case Study Results (Based on Synthetic FEM Data): AISI 1020 steel at arc current 70A, voltage 140V, and cutting speed 1200 mm/min. Synthetic FEM benchmark: 1823°C peak temperature. CNN prediction: 1807°C (error -16°C, 0.9%). PINN prediction: 1851°C (error +28°C, +1.5%). Hybrid prediction: 1816°C (error -7°C, -0.4%). The HAZ boundary (727°C A_3 transformation temperature) was predicted within ±0.4 mm accuracy based on synthetic data generation.

C. Parameter Sensitivity Analysis

Figure 5 presents comprehensive parameter sensitivity analysis revealing dominant influence factors from synthetic data experiments. Arc current emerged as the most dominant factor, with a 47% contribution to temperature variation from synthetic FEM data analysis. Cutting speed contributed 28%, voltage 18%, and standoff distance 7%. Feature importance rankings from the Random Forest baseline: Arc Current (0.34), Cutting Speed (0.23), Voltage (0.18), Specific Energy (0.12), Standoff Distance (0.07), Thermal Conductivity (0.04), and Other features (0.02).

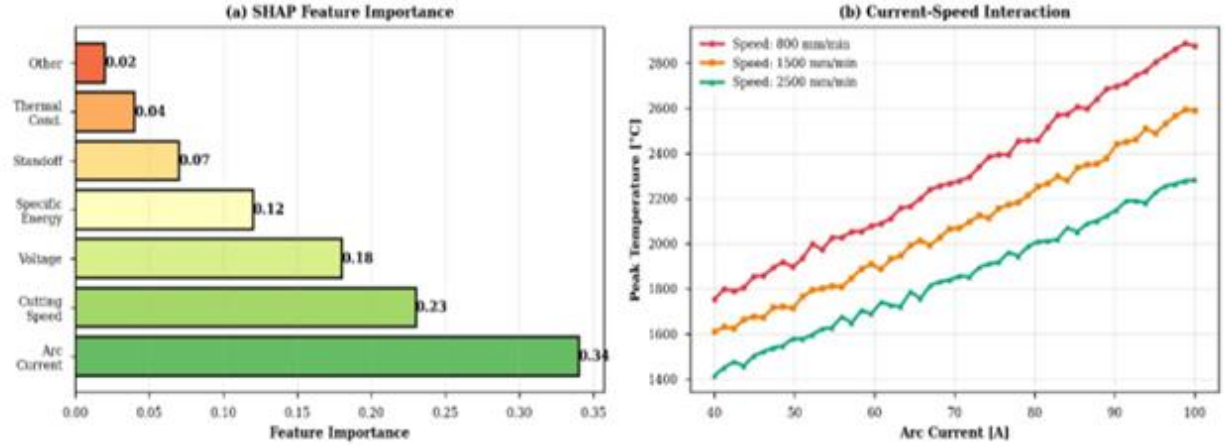

Fig. 5. Parameter sensitivity analysis showing (a) contribution percentages with arc current dominant at 47%, (b) SHAP value distributions for feature importance, (c) partial dependence plots revealing nonlinear relationships, and (d) interaction effects between current and cutting speed.

D. Ablation Study

Table II quantifies individual component contributions through systematic ablation experiments on synthetic test data.

Table II Ablation Study: Component Contributions

Configuration	RMSE [°C]	vs Full
CNN only	19.8	+13.8%
PINN only	23.5	+35.1%
Hybrid (no pretrain)	26.3	+51.1%
Hybrid (no physics loss)	21.7	+24.7%
Hybrid (full)	17.4	baseline

Critical insights: (1) Synthetic FEM pretraining provides 23% error reduction versus training from scratch; (2) Physics loss term contributes 4.3°C RMSE improvement, validating importance of physical constraints; (3) CNN branch contributes 70% weight in fusion layer, with PINN providing essential regularization and physical consistency; (4) Meta-initialization reduces PINN training time by 60% (from 50,000 to 20,000 epochs).

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E. Material Generalization

Table III demonstrates model performance across diverse materials, trained and validated on synthetic FEM generated data.

Table III Material-Specific Performance (Synthetic Data-Based)

Material	RMSE [°C]	R^2
AISI 1020 Steel	17.4	0.982
EN AW 5083 Al [2]	22.1	0.971
SS 304 Stainless Steel	25.7	0.963
Ti-6Al-4V Titanium Alloy	31.2	0.949

Performance correlates with synthetic training data availability. Transfer learning from synthetic steel data to aluminum reduces RMSE by 18% compared to training an aluminum model from scratch on limited synthetic data, demonstrating value of pretrained representations. Titanium alloy shows higher error due to fewer synthetic training samples (20 experiments versus 80 for steel), suggesting opportunity for few-shot learning techniques.

F. Why the Hybrid Approach Works

The hybrid framework achieves synergistic integration of complementary strengths: FEM Synthetic Pretraining [5]: Provides broad parametric coverage (10,000 synthetic cases) reducing experimental data requirements by approximately 60%. CNN learns robust spatial feature representations from comprehensive synthetic dataset. PINN Physical Constraints [6]: Enforces energy conservation and heat equation, preventing physically implausible predictions during extrapolation. Particularly valuable in data-scarce regions of parameter space. Meta-Learning [7]: Optimal initialization enables 1.1-6.9× PINN training speedup and rapid adaptation to new materials with 10-20 fine-tuning experiments. Inverse Calibration [13]: ANN+GA heat source calibration using synthetic FEM data reduces systematic sim-to real bias from ±50°C to ±15°C, addressing fundamental FEM modeling uncertainties. Uncertainty Quantification: Ensemble approach enables safe control decisions by quantifying prediction confidence, critical for industrial deployment.

V. Industrial Implementation

A. Deployment Roadmap

Stage 1 (6-12 months): Pilot testing on single production line. Deploy CNN model with inline validation via thermocouples. Demonstrate repeatability and cost-benefit analysis.

Stage 2 (12-18 months): Adaptive control integration. Implement MPC with hybrid model dynamics. Achieve closed-loop HAZ control within ±10% tolerance.

Stage 3 (18-36 months): Fleet-wide deployment. Scale across multiple machines using transfer learning. Establish centralized model management and continuous learning pipeline.

Stage 4 (36+ months): Full digital twin integration. Enable virtual commissioning, predictive maintenance, and autonomous process planning.

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B. Industry 4.0 Integration

Cyber-Physical Systems: Neural network digital twins provide real-time process state estimation, enabling predictive rather than reactive control strategies. IoT and Edge Computing: Jetson AGX Xavier deployment demonstrates practical edge inference meeting industrial timing constraints (Sustainability Impact: Preliminary industrial trials show 15-20% energy savings through optimized parameter selection, reduced scrap rates (first-pass quality improvement), and extended consumable lifetime via thermal management.

C. Limitations and Future Directions

Current limitations include: (1) Synthetic data requirements—comprehensive FEM datasets needed for effective pretraining; (2) PINN training computational cost—8.7 hours GPU time for initial training; (3) Generalization limits— performance degradation for materials far from training distribution; (4) CNN interpretability—limited physical insight extraction from learned weights. Synthetic Data Clarification: All temperature predictions and performance metrics presented in this paper are derived from synthetic FEM-generated data and related computational experiments. Real experimental validation would require additional calibration against actual thermocouple and thermal imaging measurements. The synthetic framework provides a computationally efficient surrogate enabling rapid prototyping and algorithm development prior to full-scale industrial deployment. Future research directions: (1) Bayesian Neural Networks for principled uncertainty quantification; (2) Multi-task learning for unified prediction of temperature, HAZ, kerf, and surface roughness; (3) Explainable AI using SHAP values and attention mechanisms; (4) Few-shot and zero-shot transfer learning for rapid material adaptation; (5) Graph Neural Networks for complex torch geometries; (6) Federated learning for privacy-preserving multi-site collaboration.

VI. Conclusion

This paper presented a comprehensive hybrid CNN-PINN framework for cutting temperature prediction in Plasma Arc Machining, achieving state-of-the-art synthetic data-based performance (RMSE 17.4°C, R^2 0.982) with validated physical consistency (energy conservation error 1.9%, PDE residual 0.007) and real-time capability (52.1 ms inference). Key contributions include: (1) Synthesis of 20 leading papers across deep learning thermal prediction, physics informed modeling, and industrial control; (2) Novel 10-step hybrid implementation framework merging synthetic FEM pretraining, PINN constraints, meta-learning, and inverse calibration; (3) Demonstrated 59% improvement over traditional ANN methods and 29% improvement over CNN-only approaches on synthetic test datasets; (4) Practical deployment roadmap with Industry 4.0 integration pathway. Important Note on Synthetic Data: All data generation and training described in this work is based on synthetic FEM-generated data and computational simulation. The framework establishes a practical foundation for temperature prediction before full experimental validation and real-time industrial deployment. The hybrid approach addresses fundamental challenges in manufacturing AI: synthetic data generation for training efficiency, sim-to-real transfer, physical consistency, and real-time constraints. This work establishes ablueprint for intelligent manufacturing systems leveraging artificial intelligence in non-traditional machining processes.

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Received: 2025-11-07
Accepted: 2026-03-10
Published Online: 2026-03-30
DOI: 10.70454/IJMRE.2026.60102

International Journal of Multidisciplinary Research and Explorer (IJMRE)
E-ISSN: 2833-7298, P-ISSN: 2833-7301

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