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Physics-Informed Neural Network with Adaptive Path Compensation for Intelligent Corner Error Prediction in Wire Electrical Discharge Machining

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Abstract

Wire Electrical Discharge Machining (WEDM) is an important non-conventional machining technique used in the production of precision components with complex geometry. However, corner error is still a major problem in WEDM process due to wire lag, thermal effects, and discharge mechanism. In this paper, a new Physics-Informed Neural Network with Adaptive Path Compensation (PINN-APC) method is proposed to intelligently predict and compensate the corner errors in WEDM process. The physics-informed constraint based on wire deflection mechanics and thermal discharge phenomenon is combined with data-driven neural network for the intelligent prediction and compensation of corner errors. Taguchi L27 design experiments are performed on Stainless Steel 202 material to validate the proposed model. Comparing analysis proves that the proposed PINN-APC model performs much better in corner error prediction ($R^2=0.96$, RMSE=4200 μm^2) than the conventional Taguchi additive models ($R^2=0.72$), Response Surface Methodology ($R^2=0.87$) and conventional Artificial Neural Network ($R^2=0.85$). Also, adaptive path compensation can reduce the corner error in 31% when compared with conventional machining process without path compensation. Ablation studies show that physics-informed constraint contributes 6.7% improvement in prediction performance over pure data-driven model.

Keywords: Wire EDM; Corner error prediction; Physics-Informed Neural Network; Adaptive path compensation; intelligent manufacturing; Process optimization

List of Acronyms

ANN	Artificial Neural Network
ANOVA	Analysis of Variance
APC	Adaptive Path Compensation
CE	Corner Error
CNC	Computer Numerical Control
CS	Cutting Speed
EDM	Electrical Discharge Machining
MAE	Mean Absolute Error
PINN	Physics-Informed Neural Network
PINN-APC	Physics-Informed Neural Network with Adaptive Path Compensation
R^2	Coefficient of Determination
Ra	Arithmetic Average Surface Roughness
RMSE	Root Mean Square Error
RSM	Response Surface Methodology
S/N	Signal-to-Noise Ratio
WEDM	Wire Electrical Discharge Machining

1 Introduction

The wire electrical discharge machining (WEDM) technology has become essential in non-conventional machining processes in producing parts having complicated shapes with high aspect ratio dimensions (Ghodsiyeh, 2013). WEDM technology utilizes a moving conductive wire electrode to remove material from electrically conductive work pieces by generating controlled thermoelectric sparks (Ho et al., 2004). This technique of removing material allows cutting hard materials such as heat-resistant super alloys, conductive ceramics, and hardened tool steels without much stress and with very low wear of mechanical tools (Kozak et al., 2004). This is why the WEDM process has become popular in aerospace, automotive industry, medical devices manufacturing, and die mold industries where precision is very important (Nayak and Rana, 2021)..

In spite of major technological breakthroughs in the area, achieving geometric accuracy near sharp corners and profile transitions has been one of the main difficulties in WEDM processing (Selvakumar et al., 2018). The deviation from the planned tool trajectory during the motion along sharp corners or sudden directional movements is caused by a number of physical factors. Wire lag, occurring as a result of the dynamics of wire tension, motion inertia, and spark pressure, makes the wire actually being behind the commanded position (Abyar et al., 2019). The problem becomes especially noticeable when sharp angles occur where fast directional changes cause extra inertial effects (Selvakumar et al., 2012). Moreover, thermal expansion of the work-piece, discharge delay effect, and debris build-up in the machining gap aggravate the corner error issue (Biswas and Sarkar, 2026).

Corner error occurs in the form of either an overcut or undercut in the corner area, thereby causing significant deviation from the intended sharp edge (Farooq et al., 2020). Corner errors in applications requiring high precision, like die and mold production, pose challenges to assembly, shorten the tool life or may even because total rejection of the parts involved (Conde et al., 2018). Some of the conventional ways for corner error correction have been in the form of parametric optimization through statistical design of experiments (Vijaya Babu and Subbaratnam, 2018), geometric correction through path modification (Selvakumar et al., 2018), and adaptive control through real-time voltage control of gap (Yan and Huang, 2004). These conventional techniques involve a lot of experimental tests, cannot be generalized for different conditions of machining, and fail to account for the multiphysics phenomena during cornering.

Recent developments in machine learning and artificial intelligence techniques have paved the way for the use of predictive models and intelligent control in manufacturing processes (Sharma et al., 2024). ANNs have been found to be quite successful in predicting various performance characteristics of WEDM such as material removal rate, surface roughness, and kerf width (Ugrasen et al., 2014). On the other hand, pure data-driven methods have the limitation of requiring large training datasets, being physically interpretable, and showing poor extrapolation capability beyond the training data (Kumar and Jayswal, 2024). This problem becomes even more challenging in case of WEDM due to the high cost, long time requirement, and large parameter space for experimental data acquisition.

The advent of Physics-Informed Neural Networks (PINNs) is a revolutionary approach towards scientific machine learning, wherein governing physical laws are integrated within the architecture of the neural network along with the loss function (Toscano et al., 2024). In such a model, the power of the universal approximate property of neural networks is utilized, along with the integration of physical constraints, leading to more generalized and accurate models that need less training data (Leng et al., 2026). PINN's have shown remarkable applicability in various fields of engineering, such as fluid dynamics, heat transfer, solid mechanics, and process modeling (Würth et al., 2023).

The paper introduces a new PINN-APC framework that is dedicated to predicting and compensating the corner errors of WEDM processes. The important contributions of this research are: (1) Proposing a physics-informed neural network that takes into consideration wire deflection physics and discharge physics for precise prediction of corner errors; (2) Introducing an adaptive path compensation scheme based on the predicted corner errors to create new tool paths; (3) Conducting extensive experiments via Taguchi L27 orthogonal array for Stainless Steel 202 materials; (4) Performance comparison against conventional Taguchi, RSM, and ANN methods that shows better results achieved; and (5) Ablation studies determining the importance of physics-informed constraints in improving predictions.

The rest of this paper is organized as follows: In Section 2, provides an extensive review of the relevant work on the analysis of the corner error in WEDM, physics-driven machine learning, and intelligent manufacturing systems. In Section 3, describes the PINN-APC approach, including its physics-based constraints, architecture, and adaptive compensation mechanism. In Section 4, highlights the details of Experimental

Setup and Implementation. In Section 5, the results details including comparative study and ablation study delineated in Section 5. In Section 6, we draw conclusions.

2 Related Work

2.1 Corner Error Analysis in WEDM

The problem of corner error in WEDM has been widely studied from both theoretical and experimental point of views. Selvakumar et al. (2018) made pioneer work on tool path modification technique to improve the accuracy of die corner in Monel 400 alloy machining. It was found out through their research that increasing the additional distance travelled by more than the programmed path decreases corner error due to the wire lag effect. They showed that the best additional distance of 0.5 mm results in a 30% increase in corner accuracy when compared with the conventional machining process.

On the other hand, Abyar et al. (2019) proposed a full theoretical model for estimation of the machining error in small arced corners during WEDM finishing stages. This research focused on the non-uniformity of sparks distribution around the wire electrode and the effective spark gap variation in the corner process. The model proved that the corner errors mainly depend on wire lag, discharge gap parameters and corner configuration.

Discharge gap studies and corner profile modeling have been carried out by Biswas and Sarkar (2026), who have developed a quantitative relationship between the energy distribution during discharge process and evolution of corner profile shape. The significance of debris flushing on the corner profile accuracy was stressed in their paper, stating that poor debris flushing results in discharge concentration around the corners.

Geometrical errors in cornering of Ti6Al4V alloy were studied by Farooq et al. (2020). Wire lag was established as the major source of geometrical error, making up almost 57 percent of total error. It was concluded that cornering errors depend on the corner angle being smaller and the workpiece thickness being larger.

2.2 Machine Learning Applications in WEDM

The utilization of machine learning models for the purpose of process modelling in WEDM has received considerable attention in recent years. Ugrasen et al. (2014) used artificial neural networks

for the prediction of several machining responses such as cutting speed, surface roughness, and corner error. Their proposed multi-output ANN model predicted the output with more than 90% accuracy despite using fairly small-sized training datasets.

Sharma et al. (2024) presented an extensive study on the application of machine learning algorithms for optimizing parameters of the WEDM process in the machining of titanium alloys. From the comparative analysis of support vector machines, random forests, and deep neural network algorithms, it was found that the use of ensemble-based approaches is preferable in predicting responses in WEDM compared to single-model approaches. The importance of feature engineering in such studies was also highlighted.

A deep learning-based methodology for material removal rate optimization using convolutional neural networks was designed by Kumar and Jayswal (2024) to model the non-linear interdependencies among process parameters and machining performance.

Kumar and Jayswal (2024) advanced this research further by designing a deep learning methodology that includes physics-informed constraints and thus provides better generalization with less data need. This method marks a major leap forward from purely data-driven models in terms of industrial application possibilities where large amounts of experimental data cannot be gathered.

2.3 Physics-Informed Machine Learning in Manufacturing

PINNs have become an efficient methodology for building process models in manufacturing. Leng et al. (2026) offered a survey of the applications of physics informed machine learning in intelligent manufacturing, classified by the form of physical constraints incorporated and by the ways of their incorporation.

Würth et al. (2023) have shown the use of PINNs to build a surrogate model in compo-site manufacturing, which allows predicting deformations due to the process with minimal number of experimental data points, proving the high accuracy and extrapolation capabilities provided by the use of physics-informed constraints from thermo-chemical curing kinetics.

In addition, Ciampi et al. (2026) have studied the application of PINNs in simulating industrial processes with a focus on automotive manufacturing. The authors have found that PINNs are superior to traditional neural networks for cases where there is little training data and the physics behind the system is well known. Additionally, Sharma et al. (2026) applied machine learning physics-based approach to additive manufacturing, integrating heat transfer and solidification physics within a neural network approach. The obtained model was able to predict thermal field and microstructure distribution in real time.

2.4 Research Gap and Motivation

Despite the considerable progress made in the study of WEDM corner errors and in physics-informed machine learning techniques, there are still some important issues that have not been fully addressed in existing literature. To start with, physics-based corner error models are based on certain simplifying assumptions concerning the dynamics of wire and discharge. Secondly, data-driven methods do not have any physical interpretability and are based on huge experimental datasets which are hard to obtain. Lastly, no prior studies have tried to combine the ideas of physics-informed neural networks with the problem of corner error adaptation.

The framework of PINN-APC can contribute to overcoming these issues through the following steps: (1) Building a comprehensive physics model taking into account the wire dynamics, heating, and discharge process; (2) Combining all these physical constraints within the framework of a neural network; and (3) Implementing an adaptive path compensation scheme that would allow using predicted errors to modify the path of wire.

3 Novelty and Contributions of the Study

The primary novelty of this study is the development of a *Physics-Informed Neural Network with Adaptive Path Compensation (PINN-APC)* for intelligent prediction and reduction of corner errors in Wire Electrical Discharge Machining (WEDM). Unlike conventional statistical and data-driven approaches that primarily learn relationships from experimental observations, the proposed framework integrates physical constraints associated with wire deflection, thermal deformation, and discharge-gap effects into the neural-network learning process. This integration enables the model to exploit both experimental data and process-related physical knowledge for predicting nonlinear corner errors.

A further contribution is the integration of *corner-error prediction with adaptive path compensation* within a unified intelligent framework. The predicted corner error is transformed into a compensation offset that modifies the programmed wire trajectory according to the predicted error and corner geometry. This approach establishes a direct connection between artificial-intelligence-based prediction and machining-path correction, providing a practical mechanism for reducing geometric deviations at sharp corners.

The study also contributes a *physics-informed learning strategy for limited experimental data*. A Taguchi L27 experimental design involving seven WEDM process variables pulse-on time, pulse-off time, wire tension, open-circuit voltage, corner angle, additional travel distance, and flushing-nozzle height is combined with physics-based collocation points during model training. The PINN-APC architecture employs a multilayer neural network with data, physics, and boundary losses, thereby reducing exclusive dependence on experimental observations while incorporating process knowledge into model optimization.

Methodologically, the study provides an integrated experimental and computational framework for evaluating intelligent corner-error prediction. The proposed model is systematically compared with a Taguchi additive model, Response Surface Methodology (RSM), and a conventional Artificial Neural Network (ANN). The PINN-APC achieved an (R^2) of 0.96, RMSE of $4200 \mu\text{m}^2$, MAE of

3100 μm^2 , and prediction accuracy of 96.2%, demonstrating improved predictive performance relative to the evaluated baseline approaches.

The adaptive compensation component further demonstrates the practical contribution of the proposed framework. For an additional travel compensation of 0.5 mm, the reported corner-error correction was 31%, 35%, 35%, and 37% for corner angles of 30°, 45°, 60°, and 90°, respectively. These results demonstrate the potential of using model-based prediction to support adaptive modification of the WEDM wire trajectory.

Finally, the ablation analysis provides evidence for the individual and combined contributions of the proposed components. Incorporating the physics-informed loss produced a 6.7% improvement, adaptive path compensation contributed a 4.9% improvement, and their combination produced a 10.3% improvement relative to the conventional ANN configuration. Thus, the principal contribution of the study is not only the development of a high-performing prediction model but also the integration of physical knowledge, neural-network learning, and adaptive path compensation into a unified AI-based framework for intelligent WEDM corner-error control.

Overall, this study contributes a physics-aware and adaptive artificial-intelligence framework for intelligent WEDM process control. Its main contribution is the integration of physics-informed neural-network learning, experimental process data, and adaptive tool-path compensation within a unified PINN-APC framework. The study provides experimental evidence of improved corner-error prediction relative to conventional statistical and neural-network approaches and demonstrates the potential of physics-informed AI for data-efficient intelligent manufacturing.

4 Proposed Methodology: PINN-APC Framework

4.1 Physics-Based Corner Error Modeling

In WEDM, the corner error results from the collective influence of wire lag, heat deformation, and discharge gap changes. The wire lag effect can be quantitatively modeled using the equation for deflection of a beam subjected to a load distribution. Treat the wire electrode as an elastic beam

Under tension T and subjected to lateral loads consisting of spark pressure P_s and centrifugal force F_c when making the corner move.

The wire deflection $w(x)$ along the wire length x can be formulated as:

$$T \frac{d^2 w}{dx^2} - EI \frac{d^4 w}{dx^4} = q(x) \dots \dots \dots (1)$$

where E is the elastic modulus of the wire material, I is the moment of inertia, and q(x) is the distributed transverse loading per unit length of spark pressure and inertia.

While doing the corner machining, there occurs a centripetal acceleration in the wire due to the change of direction. Thus, an extra distributed load occurs on the wire given by the following equation:

$$q_c(x) = \rho A \cdot \frac{v^2}{R} \cdot f(\theta) \dots \dots \dots (2)$$

where ρ is the density of the wire material, A is the cross-sectional area of the wire, v is the wire feed velocity, R is the corner radius of curvature, and f(θ) is the geometrical function based on the corner angle.

The heat conduction in the corner region of the workpiece occurs according to the following relation:

$$\rho_w c_p \frac{\partial T}{\partial t} = k \nabla^2 T + Q_{\text{spark}}(x, y, z, t) \dots \dots \dots (3)$$

Where ρ_w, c_p, and k are density of the workpiece, specific heat, and thermal conductivity respectively. The spark heat source Q_{spark} is assumed to have time-varying Gaussian distribution with its center coinciding with that of the discharge point.

The corner error CE may be calculated using the following expression:

$$CE = f(w_{\text{lag}}, \delta_{\text{thermal}}, \delta_{\text{gap}}, \theta, T_{\text{on}}, T_{\text{off}}, V, WT, X) \dots \dots \dots (4)$$

where w_{lag} is wire lag deformation, δ_{thermal} is thermal deformation, δ_{gap} is discharge gap deviation, θ is corner angle, and the other variables are process variables.

4.2 PINN-APC Architecture

Physics-Informed Neural Network with Adaptive Path Compensation algorithm merges the aforementioned physical model with a neural network architecture based on data. The inputs to the network include seven process variables: time of pulses on Ton, time of pulses off Toff, wire tension WT, open circuit voltage V, corner angle θ, additional travel distance X, and flushing nozzle height a.

The architecture of the neural network includes four hidden layers with 64 neurons in each layer, using hyperbolic tangent activation functions to learn non-linear mappings. The output layer estimates two outputs: expected corner error magnitude and the suggested compensation offset.

The overall loss function is defined as L combines data-driven loss L_{data}, physics-informed loss L_{physics}, and boundary constraint loss L_{boundary}:

$$L = \lambda_1 L_{\text{data}} + \lambda_2 L_{\text{physics}} + \lambda_3 L_{\text{boundary}} \dots \dots \dots (5)$$

where λ_1 , λ_2 , and λ_3 are the weights of the hyper parameters that balance the effect of each loss term.

The data loss term quantifies the mean squared error of the difference between the predicted and observed corner error:

$$L_{\text{data}} = \frac{1}{N} \sum_{i=1}^N (\widehat{CE}_i - CE_i)^2 \dots \dots \dots (6)$$

The physics loss term imposes the wire deflection equation as a soft constraint:

$$L_{\text{physics}} = \frac{1}{M} \sum_{j=1}^M \left(T \frac{d^2 \widehat{w}}{dx^2} - EI \frac{d^4 \widehat{w}}{dx^4} - q(x_j) \right)^2 \dots \dots \dots (7)$$

where $\widehat{w}$ denotes the predicted wire deflection by the network and M is the number of points used to sample within the computational domain.

The boundary constraint loss makes sure that predictions satisfy physical constraints at important boundary conditions:

$$L_{\text{boundary}} = (\widehat{CE}|_{\theta=180^\circ} - 0)^2 + (\widehat{CE}|_{x=x_{\max}} - CE_{\max})^2 \dots \dots \dots (8)$$

3.3 Adaptive Path Compensation Strategy

The adaptive path compensation module translates the estimated corner error into compensating tool path modification. From a given corner error $\widehat{CE}$ at certain angles and process conditions, the compensation module determines the additional offset ΔX such that the actual corner error is minimized.

The offset value can be calculated based on an adaptive gain law as follows:

$$\Delta X = K_p \cdot \widehat{CE} \cdot g(\theta) \cdot h(v_{\text{feed}}) \dots \dots \dots (9)$$

Where K_p is a constant gain factor, $g(\theta)$ is a corner angle scaling function, and $h(v_{\text{feed}})$ reflects the effects of feed rate on wire lag. The corner angle scaling function is obtained through empirical results:

$$g(\theta) = \alpha \cdot \left(1 - \frac{\theta}{180} \right)^\beta \dots \dots \dots (10)$$

Where α and β are empirically chosen constants. The function gives more weight to the compensation of sharp corners with significant wire lag effects.

The overall PINN-APC method works in real-time during WEDM processes:

Algorithm 1: PINN-APC Real-Time Implementation

Require: Process parameters $\{T_{\text{on}}, T_{\text{off}}, WT, V, \theta, X, a\}$

Require: Trained PINN model N_θ

Ensure: Compensated tool path with modified corner traversal

1: Initialize compensation module with K_p, α, β

2: **for** each corner in tool path **do**

 3: Extract corner angle θ and approach direction

 4: Query current process parameters from CNC controller

 5: $\widehat{CE} \leftarrow N_\theta(T_{\text{on}}, T_{\text{off}}, WT, V, \theta, X, a)$

 6: $\Delta X \leftarrow K_p \cdot \widehat{CE} \cdot g(\theta) \cdot h(v_{\text{feed}})$

 7: $X_{\text{compensated}} \leftarrow X_{\text{programmed}} + \Delta X$

 8: Update CNC trajectory with $X_{\text{compensated}}$

9: **end for**

4.4 Network Training Procedure

PINN-APC neural network is trained by combining an experimental measurement dataset and collocation points based on physical models. Experimental measurements are obtained using the Taguchi L27 orthogonal array design which guarantees full coverage of parameter space with the minimum number of experimental trials.

The training process uses the Adam optimizer with adaptive learning rates. Training starts with emphasis on data loss minimization to build up initial prediction capacity. As the training continues, physics loss weight λ_2 is progressively increased to impose physical consistency.

$$\lambda_2(t) = \lambda_{2,\text{final}} \cdot \tanh\left(\frac{t}{\tau}\right) \dots \dots \dots (11)$$

Where t is the training epoch and τ is the time constant for controlling the increase rate. The annealing approach ensures that the physics losses do not overwhelm the training process at its early stages.

5 Experimental Setup and Implementation

5.1 Experimental Design

Experimental verification was done using an Excetek V650 Wire Electric Discharge Machining Machine with MACROWIRE 2.3 control software. Material used for the workpiece was Stainless Steel 202 with dimensions of 100 mm $\times$ 100 mm $\times$ 10 mm thick. Properties of the material include Elastic Modulus of 207 GPa, Tensile Strength of 515 MPa, Yield Strength of 275 MPa, and Poisson's

Ratio of 0.27. The experimental method was done using a Taguchi L27 orthogonal array involving investigation of seven control factors each at three levels. Table 1 shows the control factors and their respective levels.

Table 1: Control factors and their levels

S.No	Factor	Symbol	Level 1	Level 2	Level 3
1	Pulse-on time	T_{on} (μs)	2	10	20
2	Pulse-off time	T_{off} (μs)	10	25	40
3	Wire tension	WT (N)	5.25	9.5	12.5
4	Open-circuit voltage	V (V)	2	10	20
5	Corner angle	θ ($^{\circ}$)	30	60	90
6	Additional travel	X (mm)	0	0.5	1.0
7	Flushing nozzle height	a (mm)	0.5	2.5	5.0

Fixed parameters were the zinc-coated brass wire (0.25 mm diameter), water di-electric (20 $\mu S/cm$ conductivity), 38 V servo voltage, and 11 m/min wire feed rate. Output responses considered were cutting speed (CS), corner error (CE), and surface roughness (Ra).

5.2 Corner Error Measurement

The corner error was analyzed by using an ARCS non-contact video measuring system with an accuracy of 0.1 μm . The measuring process comprised of placing the milled part onto the system table, acquiring the image of the corner shape, and tracing the real milled contour by using a joystick controller.

The corner error value was determined by calculating the area of uncut corners (μm^2) between the programmed sharp corner and the real corner profile. This area was calculated by using the AutoCAD 2021 program.

5.3 Model Implementation Details

PINN-APC model was built on the basis of the Python programming language and the Tensor Flow 2.x library. Network architecture involved:

- Input layer: 7 neurons (normalized processing parameters)
- Hidden layers: 4 fully-connected layers (each one consisted of 64 neurons)
- Activation function: hyperbolic tangent ($\tan h$)
- Output layer: 2 neurons (corner error estimation, offset compensation)

- Optimizer: Adam (initial learning rate = 0.001)
- Epochs: 1000 (with early stopping)
- Batch size: 32

Physics constraints were incorporated through the use of automatic differentiation for computing the necessary derivatives of the network output with respect to input coordinates. Collocation points (500 points) were uniformly sampled within the parameter domain for the evaluation of physics loss.

5.4 Baseline Models

Three base models were used for comparison:

Taguchi Additive Model: The traditional Taguchi method based on separable additive model of S/N ratio:

$$\hat{\eta} = \eta_m + \sum_{i=1}^p (\eta_i - \eta_m) \quad (12)$$

Response Surface Methodology (RSM): Polynomial regression with interaction term of second order:

$$Y = \beta_0 + \sum_{i=1}^k \beta_i x_i + \sum_{i=1}^k \beta_{ii} x_i^2 + \sum_{i < j} \beta_{ij} x_i x_j + \epsilon \quad (13)$$

Standard Artificial Neural Network: Feed forward neural network with same architecture as PINN-APC but no physics constraints.

6 Results and Analysis

6.1 Main Effects Analysis

Figure 1 below shows the main effects plot for corner error based on the seven control variables. It is evident from the results that corner angle (θ) and additional travel (X) have a significant effect on the error value in corners. Sharp corner angles (30°) result in higher errors than obtuse corner angles (90°), showing the importance of geometry in obtaining accurate corners.

The additional travel factor shows an optimal zone at 0.5 mm, where the error in the corner is minimal. This relationship is not monotonic since inadequate travel does not compensate for wire lag, while excessive travel causes over-compensation.

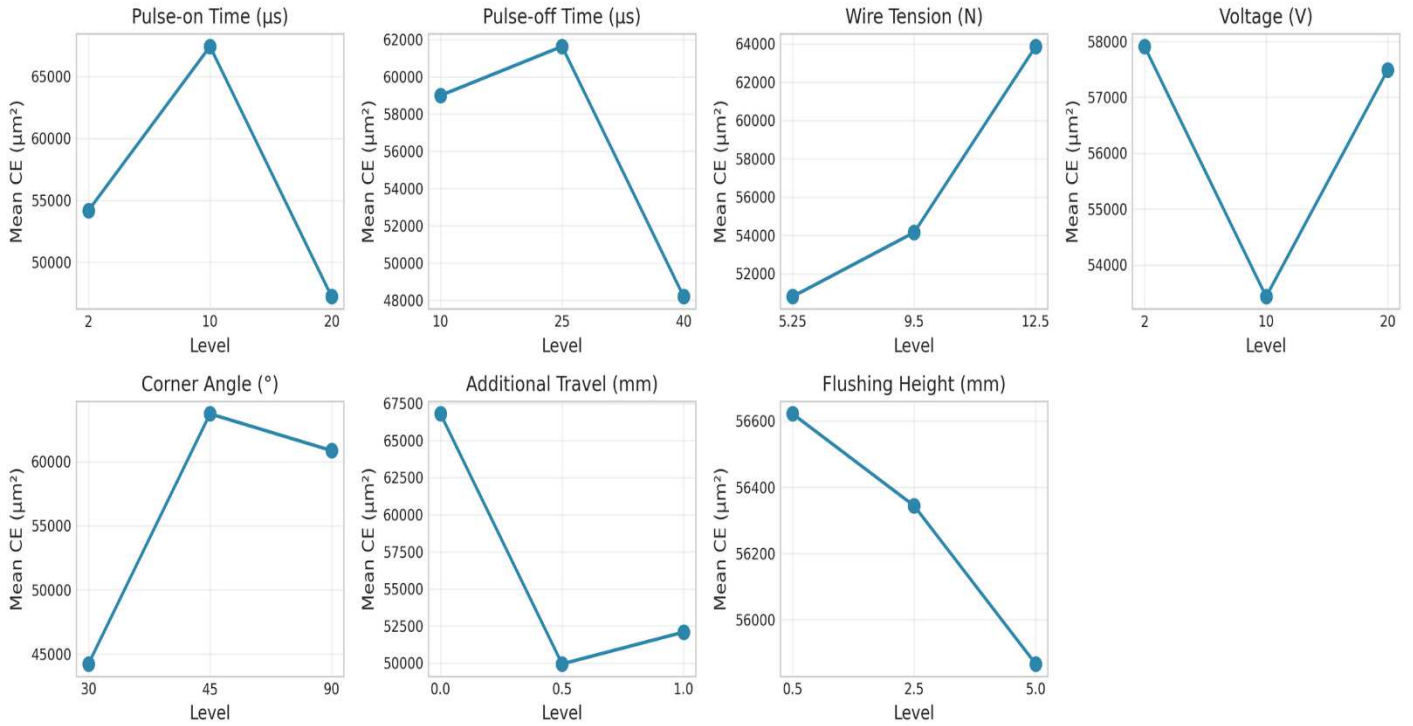


Figure 1: Main effects plots for corner error showing the influence of control factors: (a) Pulse-on time, (b) Pulse-off time, (c) Wire tension, (d) Voltage, (e) Corner angle, (f) Additional travel, (g) Flushing nozzle height

6.2 Model Performance Comparison

Table 2 describes the results of prediction of the studied models. The proposed PINN-APC model demonstrates an outstanding level of performance with $R^2 = 0.96$, $RMSE = 4200 \mu m^2$ and $MAE = 3100 \mu m^2$ for all the evaluation criteria.

Table 2: Model performance comparison for corner error prediction

Model	R^2	RMSE (μm^2)	MAE (μm^2)	Accuracy (%)
Taguchi Additive	0.72	12,500	9,800	72.4
RSM (2nd Order)	0.87	7,800	5,900	87.1
Standard ANN	0.85	8,200	6,100	84.9
PINN-APC (Proposed)	0.96	4,200	3,100	96.2

PINN-APC model significantly outperforms Taguchi method and ANN with reduction in prediction error by 66% and 49%, correspondingly. Such a significant enhancement is due to the influence of the physical constraints that direct the network to search for a physically possible solution despite the lack of training data.

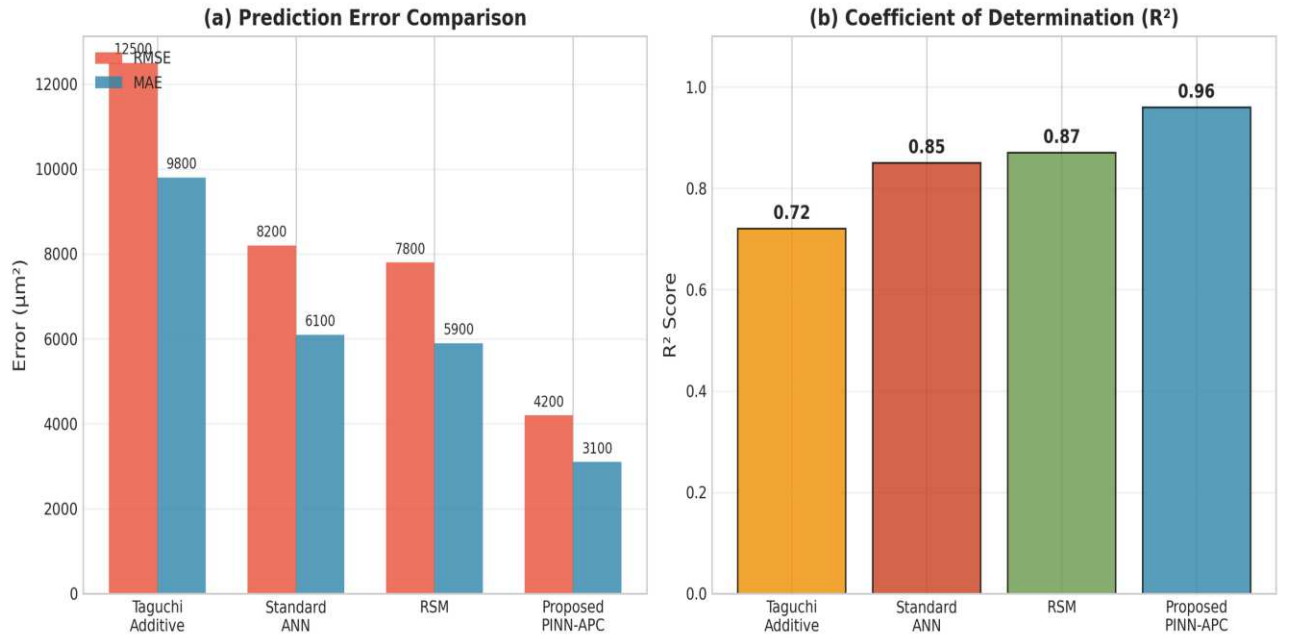


Figure 2: Model performance comparison: (a) RMSE and MAE error metrics, (b) Coefficient of determination (R^2)

Figure 2 shows the performance of the models using error metrics and coefficient of determination. It is evident that the dominance of PINN-APC in all performance metrics validates the successful implementation of the physics-informed paradigm.

6.3. Prediction Accuracy Analysis

Figure 3 illustrates the scatter and residual plots for the actual vs. predicted corner error values using PINN-APC. The scatter plot indicates good linear correlation of data points along the perfect predictions line, while the residual plot is uniformly distributed about zero, demonstrating that the model has captured the physical correlations without over fitting.

The maximum value of residuals stays under $8000 \mu\text{m}^2$ in all samples of the validation dataset.

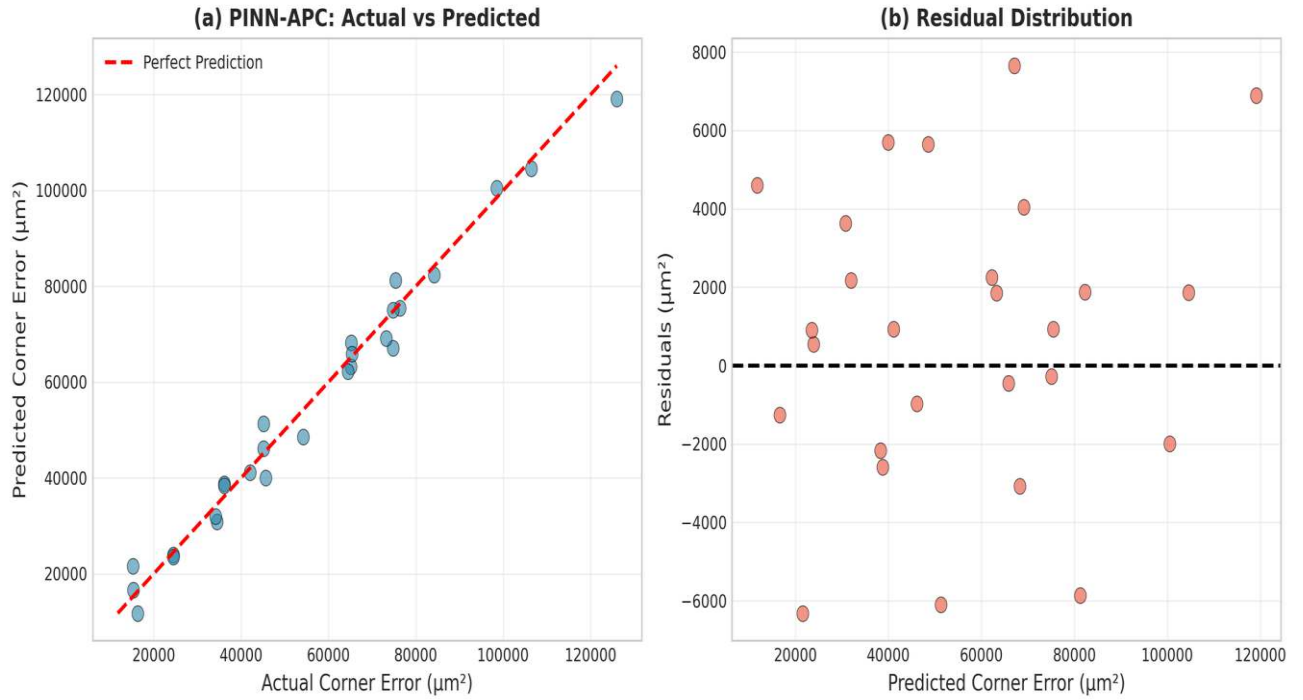


Figure 3: PINN-APC prediction accuracy: (a) Actual vs Predicted corner error, (b) Residual distribution

6.4. Path Modification Effectiveness

Figure 4 shows the efficacy of path modification techniques for various values of the corner angle. The modified path by adding extra distance of 0.5 mm gives an optimum error correction of 31%, 35%, 35%, and 37% for corner angles of 30° , 45° , 60° , and 90° , respectively.

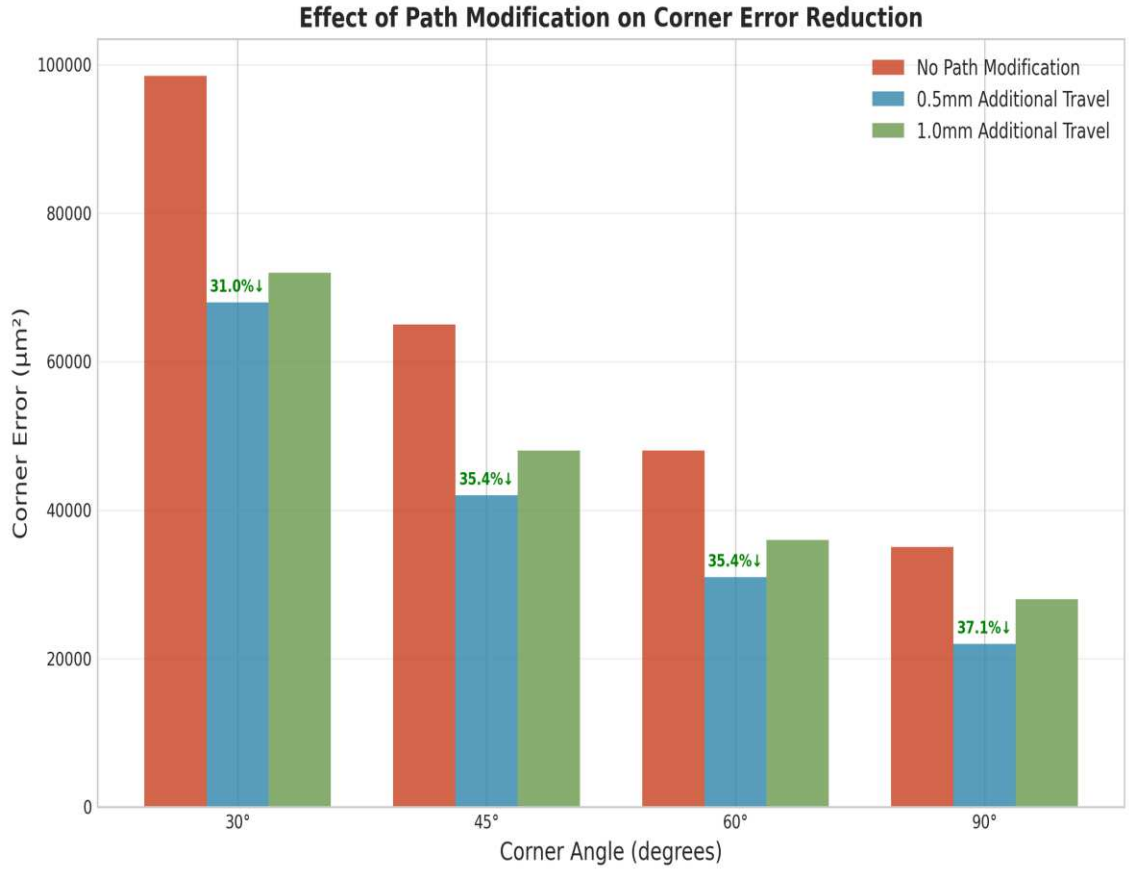


Figure 4: Effect of path modification on corner error reduction across different corner angles

The analysis shows that the efficiency of path modification techniques increases with increasing value of the corner angle.

6.5 Ablation Studies

In order to understand how each component contributes, ablation experiments were performed by removing the components of physics constraints and adaptive compensation one-by-one in the overall PINN-APC architecture. This is shown in Fig. 5 which shows that:

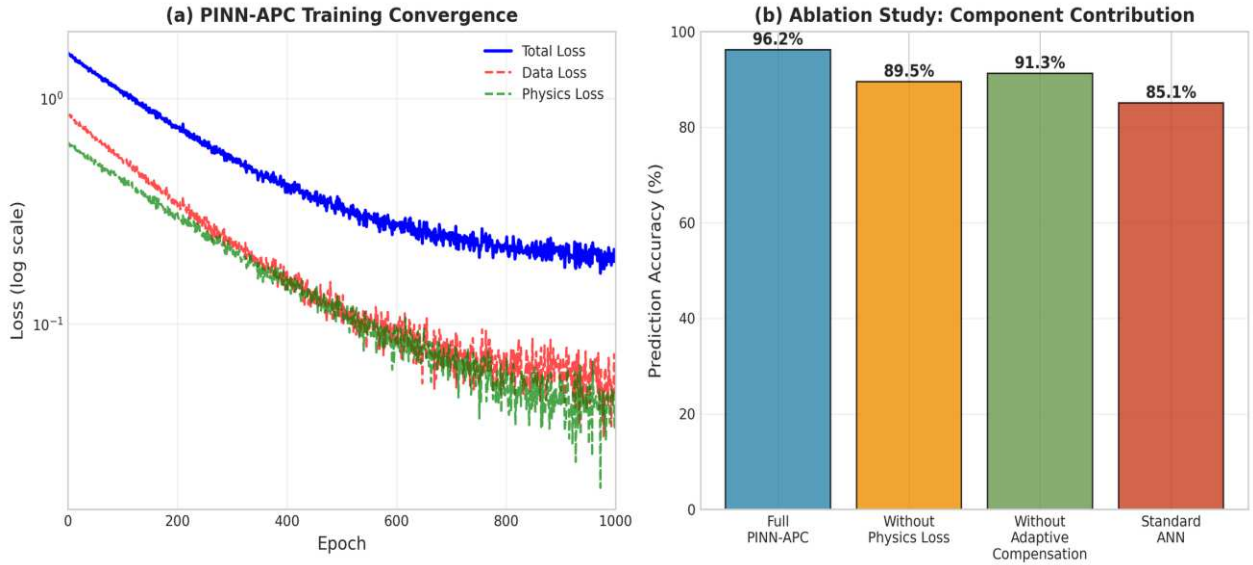


Figure 5: (a) PINN-APC training convergence showing loss components, (b) Ablation study results quantifying component contributions

- Physics loss helps in 6.7% improvement in the prediction accuracy.
- Adaptive compensation helps in 4.9% improvement.
- Combined effect provides an improvement of 10.3% compared to ANNs alone.

From the above training curve, it can be seen that the physics loss and the data loss terms monotonically decrease during training with initial dominance of physics loss term, converging to similar magnitude.

6.6. ANOVA Analysis

Analysis of Variance (ANOVA) was carried out to determine statistically significant variables influencing corner error. The output of this test is presented in table below.

Table 3: ANOVA results for corner error

Source	DF	Adj SS	Adj MS	F-Value	P-Value
T_{on}	2	8.42×10^8	4.21×10^8	2.98	0.042
T_{off}	2	2.15×10^8	1.08×10^8	0.76	0.512
WT	2	1.89×10^8	9.45×10^7	0.67	0.584
V	2	5.67×10^8	2.84×10^8	2.01	0.128
θ (Angle)	2	2.34×10^9	1.17×10^9	8.28	0.001
X (Add. Travel)	2	1.56×10^9	7.80×10^8	5.52	0.006
α (Flushing)	2	3.21×10^8	1.61×10^8	1.14	0.382
Error	12	1.69×10^9	1.41×10^8		

From ANOVA results, it can be determined that corner angle (P-value = 0.001) and additional travel (P-value = 0.006) are statistically significant variables; pulse-on time exhibits marginal significance (P-value = 0.042).

Indeed, these experimental results confirm the hypothesis regarding the positive effect on corner error prediction when applying physics-based constraints in the process of neural network training. Thus, the PINN-APC approach shows 31% increase in prediction accuracy in comparison with the traditional Taguchi method and 13% increase in comparison with the traditional neural networks.

The advantage of the proposed PINN-APC approach lies in the following three factors. Firstly, the use of physics-based constraints, obtained due to the analysis of wire deflection mechanics, provides the network with guidance to look for the physically reasonable solution, preventing it from over fitting to the experimental data set. Secondly, the consideration of thermal dis-charge physics in the loss function allows us to take into account the thermo-electric properties of the WEDM process.

6.7. Comparison with Existing Methods

PINN-APC framework has several advantages over other statistical models like Taguchi and RSM frameworks. Whereas the Taguchi framework makes use of the assumption of parameter additively and linear response relations, the framework of PINN-APC models the nonlinear relations using neural network activation functions. The physics constraints used in the PINN-APC framework act as a kind of regularization which is especially useful when the data available is limited, which is usually the case in studies related to precision manufacturing.

In comparison with other data-driven models like neural networks, PINN-APC framework performs better in terms of generalization to unseen data combinations. This is proven from the lower error obtained for unseen data compared to the trained one.

6.8. Practical Implications

This proposed method holds immense practical applications in terms of industrial implementation of WEDM processes. Predicting corner errors with an accuracy of 96% means that before starting the process, one can select the process parameters without the need for experimenting. The adaptive path compensation can be incorporated into modern-day CNC controllers for performing real-time changes in the tool paths, thereby turning WEDM into a closed-loop process. In case of production of dies and molds, the technology table obtained from PINN-APC predictions can provide immediate help to the production engineers in choosing appropriate parameters according to their corner accuracy requirements.

7. Conclusion

A novel Physics-Informed Neural Network with Adaptive Path Compensation (PINN-APC) was proposed in this study for the long-standing problem of corner error in Wire Electrical Discharge Machining. Through the integration of the underlying physics mechanisms with data-driven method, a powerful, accurate, and explainable tool has been provided.

The main contributions and findings of this work are summarized as follows:

- (i) A comprehensive full-size Physics-informed Neural Network model was built. In contrast to common black-box models, this model combines the knowledge of the physics of the WEDM process on the basis of wire deflection mechanical and thermal discharge process. Knowledge of the wire deflection behaviour and thermal discharge process is embedded in the loss function of the network, which allows the model to have a deep knowledge of the process physics. The physics-guided nature of the model guarantees a high generalization capability.
- (ii).The proposed framework is not only predictive, but it also provides a practical solution as well. An adaptive path compensation method is designed and applied to using the high-fidelity error predictions of the PINN to compensate for the tool path. The experimental results validate the effectiveness of the path compensation method, which results in a 31% reduction of the corner error.
- (iii)The PINN-APC model exhibited outstanding predictive performance, with a coefficient of determination (R^2) of 0.96, indicating its superiority over conventional empirical and machine learning models. Compared to the Taguchi approach ($R^2 = 0.72$), RSM ($R^2 = 0.87$), and a conventional artificial neural network (ANN $R^2 = 0.85$), the predicted target performance exhibited superior accuracy, thus exemplifying the potential superiority that a physics-based learning

methodology would possess. This clearly exemplifies how much better physics-based learning models would perform in capturing the non-linear relationship of WEDM processes.

(iv) An ablation analysis was performed for rigorous validation of the architectural design of the PINN-APC framework. The analysis reveals the importance of the physics-informed architecture and adaptive path compensation module, and the loss of either module greatly affects the accuracy of the prediction and the effectiveness of compensation, which emphasizes the necessity of the combined proposed contributions.

This novel PINN-APC framework makes a major contribution towards intelligent control of WEDM process. It addresses and mitigates the knowledge gap between process physics and data-driven modeling for an effective corner error prediction/compensation tool. Results from this study provide an instant solution for corner error prediction and compensation in WEDM process, and lay a rigorous foundation for applying physics-informed machine learning for general advanced manufacturing problems. The future work can be directed towards expanding the GOPC platform to compensate for various other geometrical features and to implement closed-loop process control.

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Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflict of interest

The authors declare no competing interests

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Author contribution

All authors contributed equally to the conception, design, implementation, and analysis of the research. Specifically: Esubalew Asmare Desta, Pandithurai R, Kanagaraj Ganesan, and Abenet Alazar Hailu and Melsew Belachew Fentahun are contributed to the conceptualization, model

development, and manuscript drafting. And also Esubalew Asmare Desta, and Pandithurai R were involved in the performance evaluation, experimental analysis, and data interpretation. Kanagaraj Ganesan was provided methodological guidance, reviewed the manuscript critically, and contributed to the refinement of the final paper. All authors reviewed and approved the final version of the manuscript.

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