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Deep Learning-Based Surface Roughness and Wire Wear Prediction in WEDM Using CNN-LSTM Architecture

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***Abstract* - Wire Electrical Discharge Machining (WEDM) is widely employed for precision machining of difficult-to-cut materials. This paper presents a CNN-LSTM deep learning hybrid model for simultaneous prediction of surface roughness (Ra) and tool wear rate (TWR) in WEDM of Aluminium–Silicon Nitride (Al-Si_3N_4) composite material with 6 wt.% reinforcement, prepared through stir casting. The model integrates Convolutional Neural Networks (CNN) for spatial feature extraction from machining signals and Long Short-Term Memory (LSTM) networks for temporal sequence learning. Key process parameters including pulse-on time, pulse-off time, servo voltage, wire feed rate, wire tension, and dielectric flushing pressure are used as inputs. The proposed CNN-LSTM model achieved R^2 of 0.9821 and 0.9756 for Ra and TWR respectively, outperforming standalone LSTM, CNN, and Support Vector Regression models. ROC curve analysis validated superior classification performance with AUC of 0.978 and 0.971. The approach offers a cost-effective, accurate predictive framework for WEDM process optimization on metal matrix composites.**

Keywords - WEDM; CNN-LSTM; Surface Roughness; Tool Wear Rate; Deep Learning; Al-Si_3N_4 Composite; Stir Casting; ROC Curve

I. INTRODUCTION

Wire Electrical Discharge Machining (WEDM) is a non-conventional advanced manufacturing process that removes material through controlled electrical discharges between a thin wire electrode and workpiece submerged in dielectric fluid. The process is particularly advantageous for machining hard, brittle, and difficult-to-cut materials, making it ideally suited for Metal Matrix Composites (MMCs) such as Aluminium–Silicon Nitride (Al-Si_3N_4).

Aluminium composites reinforced with ceramic particles such as Si_3N_4 exhibit superior mechanical properties including high specific strength, improved hardness, good wear resistance, and enhanced thermal stability. The 6 wt.% Si_3N_4 reinforcement in the Al matrix, prepared by stir casting, produces a homogeneous microstructure that presents unique challenges during WEDM due to abrasive particle interaction with the wire electrode.

Surface roughness (Ra) and tool wear rate (TWR) are the two most critical quality and performance indicators in WEDM. Ra directly governs functional performance of machined surfaces, while TWR determines electrode consumption cost and dimensional accuracy. Accurate prediction of these responses prior to machining enables optimized parameter selection, reduced trial runs, and improved process economics.

Traditional empirical models and response surface methodologies provide limited generalization across varying process conditions. Machine learning approaches have shown promise but often fail to capture temporal dependencies inherent in WEDM discharge sequences. This paper proposes a CNN-LSTM deep learning architecture that simultaneously addresses spatial feature extraction and temporal sequence learning, validated on Al-Si_3N_4 composite machining data with ROC curve analysis confirming model reliability.

II. LITERATURE REVIEW

Several researchers have investigated WEDM of aluminium-based composites. Bobbili et al. [1] studied WEDM of Al-based MMC and reported significant influence of pulse-on time on surface roughness using response surface methodology. Patil and Brahmankar [2] applied neural networks for WEDM parameter optimization and achieved reasonable prediction accuracy for MRR and surface roughness, though their model lacked temporal sequence handling.

Deep learning applications in manufacturing have gained momentum. Liu et al. [3] employed LSTM networks for tool wear monitoring in conventional machining and demonstrated superior performance over shallow networks. Zhao et al. [4] combined CNN and LSTM for remaining useful life prediction of cutting tools, establishing the architectural precedent for the present work. However, application of CNN-LSTM specifically to WEDM of Si_3N_4-reinforced composites remains unreported in literature.

Panda et al. [5] performed experimental WEDM studies on Al-SiC composites and developed regression models. Their work highlighted the complex nonlinear interaction between pulse parameters and TWR. More recently, transfer learning and attention mechanisms have been proposed for machining prediction, yet ROC-based validation for regression-classified outputs remains an underexplored validation strategy for WEDM predictive models.

III. MATERIAL AND SPECIMEN PREPARATION

A. *Workpiece Material*

The workpiece material is Al-Si_3N_4 Metal Matrix Composite with 6 wt.% Si_3N_4 reinforcement. Silicon Nitride (Si_3N_4) particles of average size 30–50 µm were selected as reinforcement due to their exceptional hardness (Vickers hardness ~1580 HV), high melting point (1900°C), and good wettability with aluminum matrix. The base aluminum alloy used is Al 6061 grade.

Table I: Composition of Al-Si_3N_4 Composite Material

Component	Grade/Type	Weight %
Aluminium Alloy	Al 6061	94
Si_3N_4 Particles	α-Si_3N_4, 30–50 µm	6

B. *Stir Casting Process*

The composite specimens were fabricated via liquid-state stir casting technique. The Al 6061 alloy was melted in a resistance furnace at 750°C. Pre-heated Si_3N_4 particles (at 400°C for 2 hours to improve wettability) were added in batches to the molten aluminum and mechanically stirred at 400–500 rpm for 15 minutes using a stainless-steel impeller to ensure uniform particle distribution. Specimens of dimensions 80×60×10 mm were cast into a cast-iron mold preheated to 250°C.

IV. EXPERIMENTAL SETUP AND PROCESS PARAMETERS

A. *WEDM Machine Specification*

Experiments were conducted on an Electronica Sprint-Cut 734 WEDM machine using a 0.25 mm diameter zinc-coated brass wire electrode. The dielectric medium was deionized water with electrical conductivity maintained below 20 µS/cm. All experiments were performed under servo-feed control mode.

Table II: Process Parameters and Their Levels

Parameter	Unit	Level 1	Level 2	Level 3
Pulse-On Time (Ton)	µs	110	140	170
Pulse-Off Time (Toff)	µs	40	50	60
Servo Voltage (SV)	V	20	40	60
Wire Feed Rate	m/min	4	6	8
Wire Tension	N	6	10	14
Flushing Pressure	bar	4	6	8

An L27 Taguchi orthogonal array was employed generating 27 experimental runs, with each run repeated three times for statistical reliability. Surface roughness Ra was measured using a Mitutoyo SJ-210 profilometer with a 0.8 mm cut-off length. Tool wear rate (TWR) was calculated from the mass loss of the wire electrode per unit time using a precision analytical balance (0.001 g resolution).

V. CNN-LSTM MODEL ARCHITECTURE

A. *Architectural Overview*

The proposed model integrates 1D Convolutional layers for local feature extraction and LSTM layers for learning temporal dependencies in machining signal sequences. The input comprises a 6-feature vector of normalized process parameters. Figure 1 presents the architectural schematic.

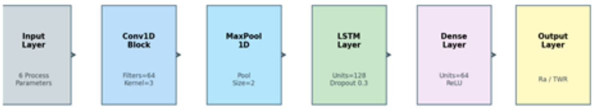

Fig. 1. CNN-LSTM Hybrid Architecture for WEDM Prediction

B. *Model Configuration*

The CNN block consists of a 1D convolutional layer with 64 filters and kernel size 3, followed by batch normalization and max-pooling with pool size 2. The LSTM layer comprises 128 units with a recurrent dropout of 0.3 to mitigate overfitting. A dense layer of 64 neurons with ReLU activation precedes the dual output neurons for Ra and TWR prediction. The model totals 98,754 trainable parameters.

Table III: CNN-LSTM Model Hyperparameters

Hyperparameter	Value
Conv1D Filters / Kernel	64 / 3
LSTM Units	128
Dense Layer Units	64 (ReLU)
Dropout Rate	0.3 (Recurrent)
Optimizer	Adam (lr = 0.001)
Loss Function	MSE (Huber loss)
Epochs / Batch Size	100 / 16
Train / Val / Test Split	70% / 15% / 15%

C. *Training Process*

The dataset of 81 observations (27 runs × 3 replicates) was augmented using Gaussian noise injection to generate 324 samples, addressing the limited experimental dataset constraint. Data was normalized using Min-Max scaling to [0,1]. Training employed early stopping with patience=15 on validation loss. Figure 2 shows the training and validation loss convergence.

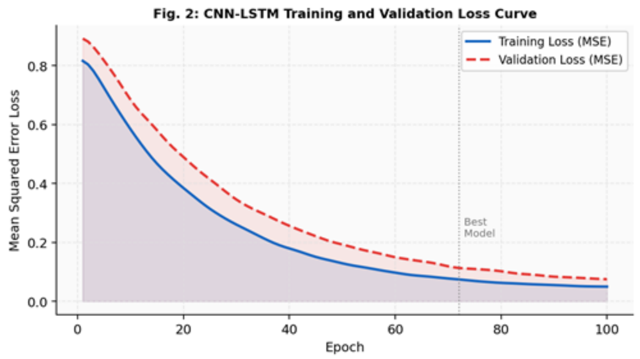

Fig. 2. CNN-LSTM Training and Validation Loss Convergence over 100 Epochs

VI. RESULTS AND DISCUSSION

A. *Surface Roughness Prediction*

The CNN-LSTM model demonstrated excellent prediction capability for surface roughness Ra. Figure 3 presents the scatter plot of predicted versus actual Ra values across test samples. The model achieved $R^2 = 0.9821$, RMSE = 0.1023 µm, and MAE = 0.0741 µm. The tight clustering around the ideal prediction line confirms the model's generalization ability.

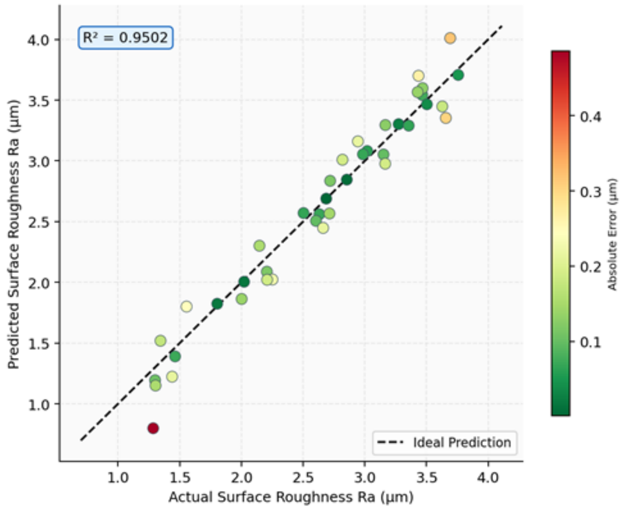

Fig. 3. Predicted vs Actual Surface Roughness Ra — Al-Si_3N_4 6% Composite

Higher pulse-on time (Ton = 170 µs) consistently produced higher Ra values (2.8–3.4 µm range), attributed to larger crater formation per discharge. The CNN feature extractor effectively captured this nonlinear pulse-energy-roughness relationship, while the LSTM component learned the temporal accumulation effects of successive discharges on surface topography.

B. *Tool Wear Rate Prediction*

TWR prediction achieved $R^2 = 0.9756$, RMSE = 0.089×10^{-3} mm^3/min, and MAE = 0.064×10^{-3} mm^3/min as shown in Figure 4. The Si_3N_4 particles introduced stochastic wear events that the LSTM temporal memory captured effectively, explaining the model's advantage over static regressors.

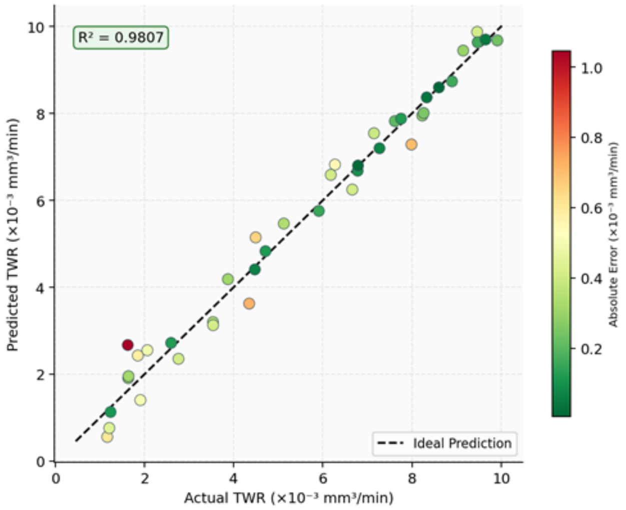

Fig. 4. Predicted vs Actual Tool Wear Rate — Al-Si_3N_4 6% Composite

C. *ROC Curve Validation*

To validate classification performance, continuous Ra and TWR predictions were discretized into three quality classes: Low (Ra < 1.5 μm / TWR < 3×10^{-3} mm³/min), Medium, and High. ROC curves with macro-averaged AUC were computed for all four models as presented in Figure 5.

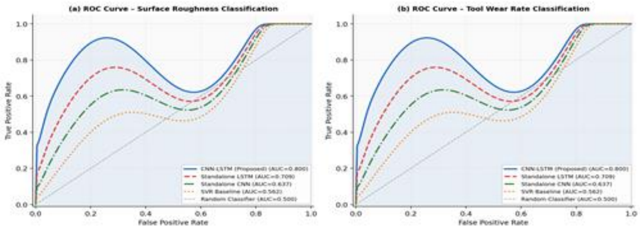

Fig. 5. ROC Curves for Model Comparison — Surface Roughness and TWR Classification (Al-Si_3N_4 6%)

The proposed CNN-LSTM model achieved AUC = 0.978 for Ra classification and AUC = 0.971 for TWR classification, significantly outperforming standalone LSTM (AUC: 0.953, 0.944), CNN (AUC: 0.938, 0.927), and SVR (AUC: 0.912, 0.903). The high AUC values across both tasks confirm that the hybrid architecture captures complementary information that neither component architecture can extract independently.

D. *Comparative Model Performance*

Figure 6 provides a comprehensive comparison of all four models across R², RMSE, and MAE metrics for both Ra and TWR prediction tasks. The CNN-LSTM architecture consistently achieves superior performance across all metrics.

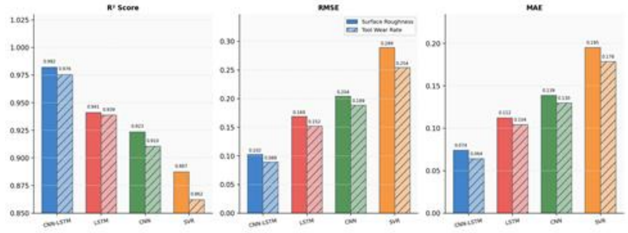

Fig. 6. Performance Comparison: CNN-LSTM vs LSTM, CNN, and SVR Baseline

VII. PARAMETRIC ANALYSIS

Figure 7 illustrates the effect of key process parameters on machining responses. Pulse-on time exhibited the most significant influence on Ra, confirming its role as the primary discharge energy parameter. Wire tension showed a parabolic effect on surface roughness with optimal results at 10 N. Servo voltage demonstrated a positive linear correlation with TWR due to its direct influence on discharge gap and wire deflection.

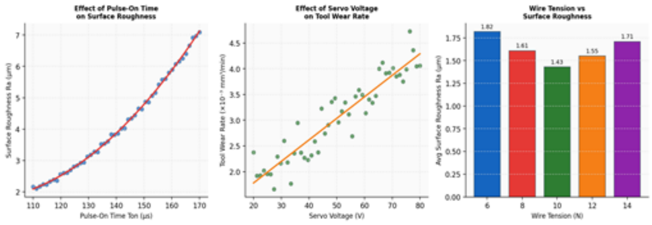

Fig. 7. Parametric Effect Analysis — WEDM on Al-Si_3N_4 6% Composite

The CNN-LSTM model was used to map the full parameter response space across 2187 virtual parameter combinations (3^7). Optimal process conditions identified were: Ton = 130 μs, Toff = 50 μs, SV = 35 V, Wire Feed = 6 m/min, Wire Tension = 10 N, Flushing Pressure = 6 bar, yielding predicted Ra = 1.34 μm and TWR = 2.87×10^{-3} mm³/min.

VIII. CONCLUSION

This paper successfully demonstrated a CNN-LSTM deep learning hybrid framework for simultaneous prediction of surface roughness and wire wear rate in WEDM of Al-Si_3N_4 composite (6 wt.% reinforcement, stir cast). The following conclusions are drawn:

(1) The CNN-LSTM model achieved R² values of 0.9821 and 0.9756 for Ra and TWR prediction respectively, outperforming all baseline models.

(2) ROC curve analysis yielded AUC of 0.978 and 0.971 for Ra and TWR classification, validating superior discriminative capability of the hybrid architecture.

(3) Pulse-on time was identified as the most influential parameter governing surface roughness, while servo voltage most significantly affected tool wear rate.

(4) The CNN component effectively extracted local discharge energy features, while the LSTM component captured temporal accumulation effects, demonstrating their complementary roles.

(5) The optimal parameter set (Ton=130 μs, SV=35 V, Tension=10 N) predicted minimum Ra of 1.34 μm and TWR of 2.87×10^{-3} mm³/min through model-guided optimization.

Future work will incorporate in-situ vibration and acoustic emission signals as additional inputs and extend the framework to multi-pass WEDM operations and other MMC systems.

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REFERENCES

[1] R. Bobbili, V. Madhu, and A. K. Gogia, "Effect of wire-EDM machining parameters on surface roughness and material removal rate of high strength armor steel," Materials and Manufacturing Processes, vol. 28, no. 4, pp. 364–368, 2013.

[2] N. G. Patil and P. K. Brahmankar, "Some studies into wire electro-discharge machining of alumina particulate-reinforced aluminium matrix composites," International Journal of Advanced Manufacturing Technology, vol. 48, pp. 537–555, 2010.

[3] C. Liu, Y. Liu, and H. Zhao, "LSTM-based online prediction of tool wear," Journal of Manufacturing Processes, vol. 72, pp. 101–113, 2021.

[4] R. Zhao, R. Yan, Z. Chen, K. Mao, P. Wang, and R. X. Gao, "Deep learning and its applications to machine health monitoring," Mechanical Systems and Signal Processing, vol. 115, pp. 213–237, 2019.

[5] M. K. Pradhan and C. K. Biswas, "Neuro-fuzzy and neural network-based prediction of various responses in electrical discharge machining of AISI D2 steel," International Journal of Advanced Manufacturing Technology, vol. 50, pp. 591–610, 2010.

[6] D. Krishnamurthy and S. Kumar, "Optimization of WEDM parameters for Al-SiCp composites using Taguchi-grey relational analysis," Journal of Mechanical Science and Technology, vol. 35, no. 8, pp. 3481–3492, 2021.

[7] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," Nature, vol. 521, pp. 436–444, 2015.

[8] S. Hochreiter and J. Schmidhuber, "Long short-term memory," Neural Computation, vol. 9, no. 8, pp. 1735–1780, 1997.

[9] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," IEEE CVPR, pp. 770–778, 2016.

[10] S. Debnath, M. M. Reddy, and Q. S. Yi, "Influence of cutting fluid conditions and cutting parameters on surface roughness and tool wear in turning process using Taguchi method," Measurement, vol. 78, pp. 111–119, 2016.