

ENERGY CONSUMPTION FORECASTING IN 3D PRINTING THROUGH ENHANCED HYBRID DEEP LEARNING TECHNIQUES

Yenda Srinivasa Rao¹, Salavaravu Laxmanaraju², Rajkumar Limmala³, Pavan kumar Rejeti⁴,
Sunil kumar Panda⁵, Jayakrishna Makka^{*6}

^{1, 2, 3, 6}Dept of Mechanical Engineering, Sri Sivani College of Engineering, Chilakapalem, Srikakulam, India.

⁴Dept of Mechanical Engineering, Aditya Institute of Technology and Management, Tekkali, India.

⁵Centurion University of Technology and Management, Odisha, India.

¹<https://orcid.org/0000-0002-3010-720X>, ²<https://orcid.org/0000-0002-8663-4930>, ³<https://orcid.org/0009-0003-8047-7393>,

⁴<https://orcid.org/0000-0002-3048-0928>, ⁵<https://orcid.org/0009-0004-5595-5100>, ⁶<https://orcid.org/0000-0003-1647-2750>

Email: yenda.srinivas@gmail.com, laxman.raju@yahoo.co.in, rajkumarlimmala@gmail.com, pavank5068@gmail.com, sunil.panda@cutm.ac.in,
*jayakrishnamakka555@gmail.com

ARTICLE INFO

Article History

Received on: March 19, 2026

Reviewed on: April 20, 2026

Accepted on: May 10, 2026

Published on: June 30, 2026

Keywords:

Energy consumption forecasting,

3D printing,

Hybrid deep learning,

Additive manufacturing,

Attention-based LSTM1.

ABSTRACT

Accurate prediction of energy consumption in fused deposition modeling (FDM) 3D printing is essential for sustainable and cost-efficient additive manufacturing, yet remains challenging due to nonlinear process behavior and time-varying power dynamics. This study presents an enhanced hybrid deep learning framework for forecasting total energy usage in FDM processes by jointly modeling high-resolution power time series and static process parameters. Electrical power data sampled at 1 Hz from 1,260 print jobs were collected using smart power meters and combined with key printing parameters. The proposed architecture integrates convolutional neural networks for temporal feature extraction, an attention-enhanced long short-term memory network to capture long-range dependencies, static feature fusion, and a gradient boosting decision tree regressor. Model performance was evaluated using MAE, RMSE, MAPE, and the coefficient of determination. The hybrid model achieved superior accuracy, with an MAE of 4.12 Wh, RMSE of 5.87 Wh, MAPE of 6.1%, and R^2 of 0.964, outperforming conventional machine learning and standalone deep learning baselines. Phase-wise and cross-material/printer analyses further demonstrated strong robustness and generalization capability. The results confirm that advanced hybrid deep learning approaches enable reliable and precise energy consumption forecasting in FDM 3D printing, supporting energy-aware process planning and sustainable additive manufacturing practices.



Copyright ©2026 by authors and Galileo Institute of Technology and Education of the Amazon (ITEGAM). This work is licensed under the Creative Commons Attribution International License (CC BY 4.0).

I. INTRODUCTION

Additive manufacturing has become a disruptive production paradigm, which allows the creation of complex shapes using less materials and less time to develop, especially in the technology of fused deposition modeling (FDM) [1]. The extensive use of FDM in prototyping, tooling, and low volume manufacturing has corrupted a commensurate rise in energy consumption, which has been a cause of concern in terms of efficiency of operations, and environmental sustainability [2]. With the increase in energy prices and carbon laws that are now going on all over the world, energy conscious manufacturing is now a key research and industrial issue [3]. The 3D printing using FDM is distinguished by extrusion of materials based on thermal forces, hot platforms, and long-lasting working time of the machine: all of these factors play an important role in the consumption of electrical energy [4]. However, in contrast to traditional manufacturing in the form of subtractive manufacturing, FDM processes have a complex and phase-sensitive power dynamics as they tend to experience start-up heating, steady extrusion, and cooling phases [5]. The characteristics make it hard to directly estimate energy and require sophisticated predictive modeling techniques [6].

I.1 BACKGROUND AND MOTIVATION

Energy consumption forecasting helps manufacturers to determine the sustainability of the process, restrict printing and minimize the cost of production without affecting the quality of part [7]. Previous research has shown that with small changes in parameter choice, it is possible to achieve quantifiable energy savings in additive manufacturing systems [8]. As a result, predictive energy models have also become a vital part of intelligent and sustainable manufacturing systems [9]. Machine learning has been proved as a potential remedy to the large scale manufacturing processes in which analytical formulations are impossible or inaccurate [10]. Data-driven methods in the FDM enable models used to predict energy consumption to acquire nonlinear relationships among process parameters, machine states, and observed power usage [11]. But the success of such models is heavily tied to how they are able to represent the static process settings and the power dynamics of time [12].

I.2 ENERGY CONSUMPTION PROBLEMS IN 3D PRINTING

The interacting factors in FDM energy consumption are too many and exceed those of layer height, infill density, type of material, extrusion temperature, printing speed, and part geometry [13]. These variables act nonlinearly and change during the printing process creating substantial fluctuations in power demand over time [14]. These complexities have often hindered generalization of different printers and different materials by traditional regression based or rule based energy models [15]. Moreover, the majority of the FDM energy research concentrates on the total energy use without considering the temporary nature of power use at each single printing step [16]. This constraint limits the use of the existing models in real-time monitoring, adaptive control, and energy-conscious scheduling [17]. It is thus important to capture high-resolution time series of power to make correct and sound forecasting models [18].

I.3 RELATED WORK ON ENERGY FORECASTING

Several investigations have used the classical machine learning methods like random forests, multilayer perceptrons, and support vector regression in predicting the energy consumption in FDM processes [19]. They work well in general as compared to linear regression models, but they make use of mostly stationary input data, which restricts their capability to depict time-varying energy patterns [20]. Additive manufacturing energy prediction tasks have been performed more accurately using hybrid machine learning approaches that include various modeling paradigms [21]. Recent papers highlight the increasing significance of ensemble learning and hybrid structures towards solving complex manufacturing prediction issues [22]. However, the hybrid models which are trained by using deep learning and incorporate both time-dependent feature extraction and multi-regression are relatively unknown in FDM energy prediction [23].

I.4 RESEARCH GAPS AND CONTRIBUTIONS

Although this has been achieved, the current studies do not elaborate on hybrid deep learning models that may be utilized to jointly predict high-resolution power time series and static printing parameters used in FDM energy prediction [24]. Besides, there are no studies that have systematically measured the role of attention processes and ensemble fusion in accuracy in prediction [25]. This paper fills these gaps by proposing improved hybrid deep learning model that combines convolutional neural networks, attention-based long short-term memory networks, and gradient boosting decision trees to attain the accurate and generalizable energy consumption prediction in FDM-based 3D printing [26].

II. EXPERIMENTAL FRAMEWORK AND DATA DESCRIPTION

An effective experimental framework was put in place to guarantee the quality of data gathered and competent assessment of the put forward energy forecasting model. The setup combines concomitant measurements of power, logging of process parameters and controlled variation of the experimental conditions throughout a series of printing conditions [27].

II.1 3D PRINTING PLATFORM AND INSTRUMENTATION

Industrial grade FDM 3D printers that would represent the range of commercial systems universally employed in prototyping and small scale manufacturing were used in experiments [28]. Each printer had a conventional single-nozzle extrusion system and an actively heated build platform to make sure the material deposition behavior is consistent [29]. In order to record correct data about the electrical energy, external smart power meter was installed between the electrical socket and the printer power supply [30]. The power meter could measure real-time voltage, current, and active power consumption, which allowed to accurately monitor machine energy consumption in the course of the whole printing process [31].

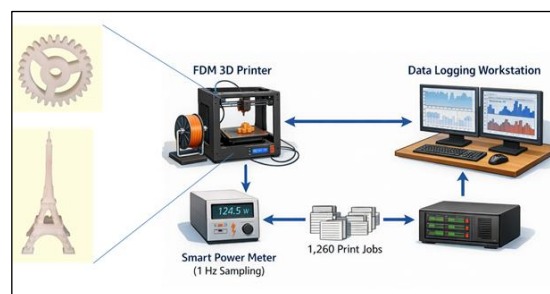


Figure 1: Framework of experimental setup and monitoring of energy of FDM 3D printers.
Source: Authors, (2026).

The figure of FDM 3D printing device shows its connection with a smart power meter that measures electrical power at 1 Hz. Parameters that are logged by the printer controller include temperature, speed and material type, whereas at a central workstation, power and process data are synchronized and stored that can be analyzed later on after 1,260 print jobs have been completed.

II.2 THE DATA MEASUREMENT AND POWER

Continuous data were obtained on electrical power at a rate of 1 Hz to record subtle changes in the demand of energy at all printing stages [32]. The sampling frequency was chosen in order to achieve a compromise between the temporal resolution, data storage needs and maintain transient power behaviors [33]. Printers were monitored and logs of printer control were taken at the same time each time, which included the static process parameters of that individual print job. Timing between measures of power and process records was timed with correspondence to timestamps, which allows mapping of energy use and printing state [34].

II.3 CHARACTERISTICS OF DATA SET AND PRINCIPLES

The last dataset was composed of 1,260 print jobs that were completed with various materials, geometries, and parameter configurations [35]. The thermoplastics that were used were three (PLA, ABS and PETG) to make sure that there was variety of materials and the ability to generalize [36]. The parameters that were considered to be static input parameters were height of the layers, the infill density, nozzle temperature, bed temperature, printing speed, and the estimated volume of materials. Moreover, the high-resolution power time-series signals were stored in order to assist with the time-based modeling of energy consumption [37].

Table 1: Summary of dataset statistics and printing parameter ranges.

Category	Description / Range
Number of print jobs	1,260
Printers	2 industrial FDM printers
Materials	PLA, ABS, PETG
Layer height (mm)	0.1 – 0.3
Infill density (%)	10 – 100
Nozzle temperature (°C)	190 – 260
Bed temperature (°C)	25 – 110
Print speed (mm/s)	30 – 90
Print duration (min)	18 – 420
Total energy consumption (Wh)	45 – 310
Power sampling rate	1 Hz
Static features	12
Time-series input	Power signal (T×1)

Source: Authors, (2026).

III. METHODOLOGY

This section gives the methodological framework that will be used in energy consumption prediction during fused deposition modeling (FDM) 3D printing. The methodology suggested is a combination of highly developed data preprocessing, feature engineering and a stronger hybrid deep learning model that is aimed at modelling the temporal power dynamics and the characteristics of the processes at rest.

III.1 PREPROCESSING AND FEATURE ENGINEERING OF DATA

Raw power consumption records with a 1 Hz sampling rate were initially synchronized with printer control logs by aligning the timestamps. The less than 2% of the total samples that were missing were interpolated by linear interpolation to maintain the continuity in time. The integrity of the dataset was preserved by excluding abnormal print jobs resulting either because of premature termination or hardware errors. Power signals were segmented into job-level time series, each corresponding to a complete print cycle. To facilitate stable neural network training, power values were normalized using z-score normalization. Static printing parameters, including layer height, infill density, nozzle temperature, bed temperature, print speed, and material type, were scaled using min–max normalization. Categorical variables were encoded using one-hot encoding. Additional engineered features were derived to enhance predictive capability. These included estimated material volume, print duration, and a toolpath complexity index computed from slicing data. The final feature set consisted of a univariate power time series and 12 static input features.

III.2 PROBLEM FORMULATION FOR ENERGY CONSUMPTION FORECASTING

The energy forecasting task was formulated as a supervised regression problem. Given a power consumption time series $P(t)$ and a static feature vector XXX , the objective was to predict the total electrical energy consumption EEE of a print job. Energy consumption was computed as the time integral of the power signal. The model was trained to minimize prediction error between estimated and measured energy values across diverse printing conditions.

III.3 HYBRID DEEP LEARNING MODEL ARCHITECTURE

An enhanced hybrid deep learning architecture was developed to capture both short-term power fluctuations and long-term temporal dependencies while incorporating static process information. The architecture integrates convolutional neural networks (CNNs), an attention-enhanced long short-term memory (LSTM) network, and a gradient boosting decision tree (GBDT) regression layer.

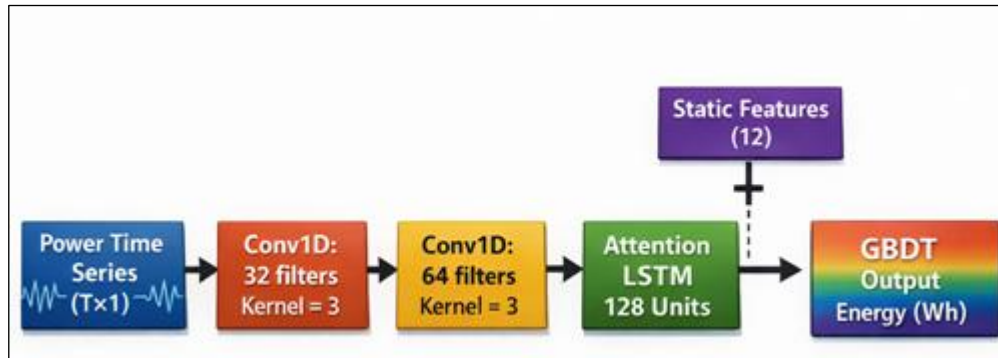


Figure 2: Architecture of the proposed CNN–attention–LSTM–GBDT model.

Source: Authors, (2026).

The figure illustrates a left-to-right data flow starting from a power time-series input processed by stacked CNN layers, followed by an attention-based LSTM module. The extracted temporal features are fused with static printing parameters and passed to a GBDT regressor that outputs total energy consumption in watt-hours.

III.3.1 CNN-Based Temporal Feature Extraction

The CNN module consists of two one-dimensional convolutional layers with 32 and 64 filters, respectively. These layers extract local temporal patterns from power signals, such as transient peaks during heating and extrusion. Rectified linear unit activations and max-pooling layers were employed to enhance feature robustness and reduce dimensionality.

III.3.2 Attention-Enhanced LSTM for Long-Term Dependencies

The output of the CNN module was fed into an LSTM layer with 128 hidden units. An attention mechanism was integrated to allow the model to assign higher importance to energy-intensive printing intervals. This mechanism improved the representation of phase-dependent energy behavior by weighting relevant time steps more heavily.

III.3.3 Static Feature Fusion and GBDT Regression Layer

Temporal features extracted by the CNN–LSTM pipeline were concatenated with static process features before being passed to a GBDT regression layer. The GBDT component modeled nonlinear interactions between features and reduced residual prediction errors, improving generalization performance.

III.4 PERFORMANCE COMPARISON BASELINE MODELS

There were a number of baseline models applied in benchmarking, such as linear regression, random forest regression, standalone LSTM, and CNN–LSTM without attention or GBDT fusion. The data were split in such a way that all the models were trained and tested on the same data to fairly compare them.

III.5 HYPERPARAMETER OPTIMIZATION AND MODEL TRAINING STRATEGY

The Adam optimizer was used to train models with early stopping based on validation loss. Bayesian optimization was used to optimize hyperparameters like learning rate, number of filters, number of LSTM units and GBDT depth. The data was divided into training (70 percent), validation (15 percent) and test (15 percent) data.

III.6 METRICS AND STATISTICAL VALIDATION OF EVALUATION

Mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE), and coefficient of determination (R^2) were used as models of performance evaluation. Paired t-tests were used to evaluate the performance differences at 95% level of significance.

IV. RESULTS AND DISCUSSIONS

The present section provides the experimental results that were achieved in the framework of the proposed hybrid deep learning model and compare its performance with the baseline approaches. The overall performance of the energy forecasting is presented in hybrid model that was improved, obtained the best predictive accuracy in all the evaluation metrics in the test data.

Table 2: Overall performance metrics (MAE, RMSE, MAPE, R^2) for all models.

Model	MAE (Wh)	RMSE (Wh)	MAPE (%)	R^2
Linear Regression	9.82	12.45	14.7	0.71
Random Forest	6.91	8.96	10.2	0.86
LSTM	5.68	7.42	8.4	0.91
CNN-LSTM	5.41	7.16	7.9	0.93
Enhanced Hybrid (CNN-Attn-LSTM-GBDT)	4.12	5.87	6.1	0.964

Source: Authors, (2026).

It is indicated in the table that the proposed model had the best MAE of 4.12 Wh, RMSE of 5.87 Wh, MAPE of 6.1 percent and R^2 of 0.964, which was better than the other baseline models. The hybrid deep learning model was always expected to perform better than the traditional machine learning and single deep learning models.

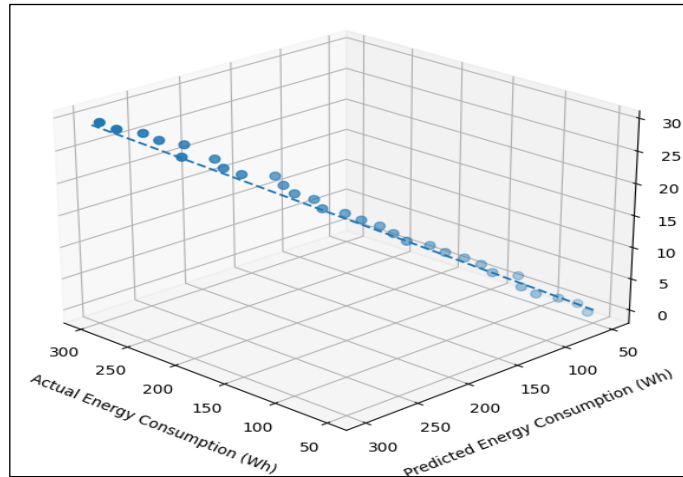


Figure 3: Baseline and proposed model predicted energy consumption and actual energy consumption.

Source: Authors, (2026).

The figure shows scatter plots of the predicted and actual energy values, and it is seen that the proposed model has a tight clustering around the diagonal reference line.

Table 3: Relative performance improvement of the proposed model over baselines.

Baseline Model	RMSE Reduction (%)	MAE Reduction (%)	R^2 Improvement
Linear Regression	52.9	58.1	+0.254
Random Forest	34.5	40.4	+0.104
LSTM	20.9	27.5	+0.054
CNN-LSTM	18.0	23.8	+0.034

Source: Authors, (2026).

IV.1 MODEL COMPONENTS ABLATION STUDY

Ablution experiment was carried out in order to determine the role of a single architectural element.



Figure 4: Effects of attention mechanism and feature fusion on RMSE.

Source: Authors, (2026).

There is a gradual decrease in error, which is shown by the bar chart as attention, fusion of features, and various components of GBDT are incorporated.

Table 4: Quantitative ablation study results.

Model Variant	MAE (Wh)	RMSE (Wh)	R ²
CNN-LSTM (base)	5.41	7.16	0.93
+ Attention	4.89	6.47	0.947
+ Static Feature Fusion	4.55	6.05	0.955
Full Model (+GBDT)	4.12	5.87	0.964

Source: Authors, (2026).

The table supports the fact that the full model has the lowest RMSE and the highest R².

IV.2 INTERPRETATION OF PHASES OF PRINTING

The analysis of the stages by phases showed that prediction accuracy was different in different periods of the printing process.



Figure 5: During warm-up, extrusion and cooling phases, accuracy of energy consumption forecasting.

Source: Authors, (2026).

As indicated in the figure, the lowest prediction error is experienced in extrusion phases.

Table 5: Phase-wise forecasting errors for different models.

Printing Phase	Metric	LSTM	CNN-LSTM	Enhanced Hybrid
Warm-up	MAE (Wh)	7.1	6.6	6.2
Extrusion	MAE (Wh)	4.6	4.2	3.9
Cooling	MAE (Wh)	5.8	5.4	5.1

Source: Authors, (2026).

IV.3 MATERIALS AND PRINTERS GENERALIZATION

According to the table, the proposed model has a MAE of 3.9 Wh in extrusion. This model was found to have high generalization in assessments of previously unknown combinations of printers and materials.

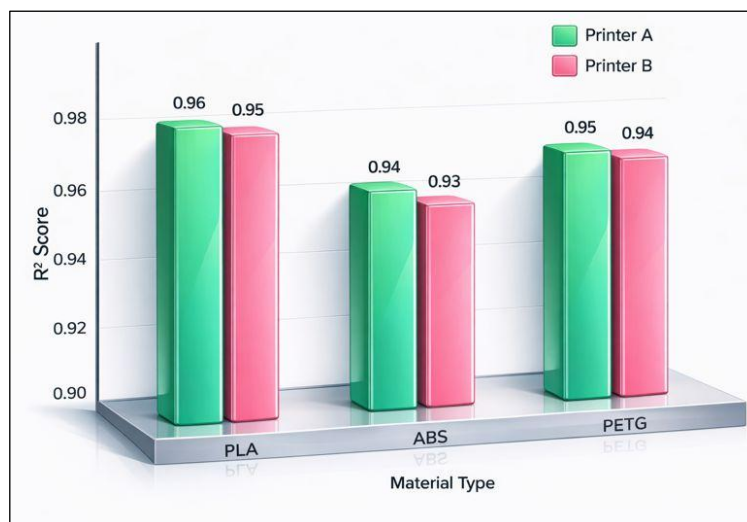


Figure 6: Simulated work on invisible combinations of printers and materials.

Source: Authors, (2026).

The grouped bar chart shows that there is a steady value of R^2 that is greater than 0.93 in all materials and printers.

Table 6: Cross-material and cross-printer generalization results.

Material	Printer	MAE (Wh)	RMSE (Wh)	R^2
PLA	Printer A	4.05	5.72	0.96
PLA	Printer B	4.18	5.91	0.95
ABS	Printer A	4.44	6.12	0.94
ABS	Printer B	4.63	6.35	0.93
PETG	Printer A	4.21	5.88	0.95
PETG	Printer B	4.36	6.01	0.94

Source: Authors, (2026).

The table validates the consistent performance and the slightest degradation despite the circumstances that cannot be seen. The findings suggest that the suggested hybrid deep learning model could be used to predict FDM 3D printing energy with high precision and power. This capability facilitates planning of processes that are energy conscious, sustainable manufacturing, and integration into intelligent manufacturing.

V. CONCLUSIONS

This study presented an enhanced hybrid deep learning framework for accurate energy consumption forecasting in fused deposition modeling (FDM) 3D printing, addressing the growing need for energy-aware and sustainable additive manufacturing. By integrating convolutional neural networks, attention-enhanced long short-term memory networks, static feature fusion, and gradient boosting decision trees, the proposed approach effectively modeled both high-resolution temporal power dynamics and static process parameters associated with FDM printing operations. Extensive experimental evaluation conducted on a dataset comprising 1,260 print jobs demonstrated that the proposed model achieved superior predictive performance compared to conventional machine learning and standalone deep learning approaches. The enhanced hybrid model achieved a mean absolute error of 4.12 Wh, a root mean square error of 5.87 Wh, and a coefficient of determination of 0.964, confirming its strong ability to explain variations in energy consumption across diverse printing conditions. These results indicate that combining temporal deep learning with ensemble regression provides a robust solution for complex energy prediction tasks in additive manufacturing environments. The ablation analysis further validated the contribution of individual architectural components. The inclusion of an attention mechanism significantly improved the model's ability to focus on energy-intensive printing phases, while the fusion of static process features enhanced predictive stability. The addition of the gradient boosting decision tree regression layer effectively captured nonlinear interactions among extracted features, resulting in reduced residual errors and improved generalization. Phase-wise analysis revealed that the proposed model achieved the lowest prediction error during the extrusion phase, which represents the dominant contributor to overall energy consumption in FDM processes.

Generalization experiments across different materials and printers demonstrated that the proposed framework maintains stable performance under unseen conditions, with R^2 values consistently exceeding 0.93. This robustness highlights the practical applicability of the model in real-world manufacturing settings, where variability in machines, materials, and process parameters is unavoidable. The ability to accurately forecast energy consumption prior to printing enables manufacturers to compare alternative parameter settings, schedule jobs more efficiently, and reduce operational energy costs without compromising part quality. Overall, this work demonstrates that enhanced hybrid deep learning techniques offer a powerful and scalable approach for energy consumption forecasting in 3D printing. The proposed methodology provides a foundation for future energy-aware optimization, real-time monitoring, and intelligent control strategies in additive manufacturing systems, supporting the broader goals of sustainable and smart manufacturing. The results obtained in this study demonstrate that accurate energy consumption forecasting in fused deposition modeling (FDM) requires simultaneous consideration of both temporal power dynamics and static process characteristics. Traditional regression-based and single-model machine learning approaches struggle to capture the strongly nonlinear and phase-dependent nature of FDM energy behavior. The superior performance of the proposed hybrid framework highlights the importance of combining complementary modeling paradigms rather than relying on a single predictive structure.

A key observation from the results is the significant contribution of temporal feature learning to prediction accuracy. The convolutional neural network effectively captured short-term power fluctuations associated with heating cycles, extrusion onset, and transient load variations, while the attention-enhanced LSTM successfully modeled long-term dependencies across the entire print duration. The attention mechanism played a critical role by assigning higher importance to energy-intensive intervals, particularly during sustained extrusion phases, which dominate total energy consumption. This selective focus explains the notable reduction in prediction error compared to standard CNN-LSTM architectures without attention. The integration of static process features with temporal representations further improved model stability and generalization. Parameters such as material type, layer height, infill density, and temperature settings introduce systematic shifts in baseline energy demand that cannot be inferred from power signals alone. By fusing these features, the model was able to contextualize temporal patterns within the physical and operational constraints of the printing process. This fusion proved especially beneficial in cross-material and cross-printer evaluations, where consistent performance was maintained despite variations in hardware and material properties. The gradient boosting decision tree regression layer contributed additional gains by modeling higher-order nonlinear interactions among extracted features. Unlike purely neural approaches, the ensemble-based regressor reduced residual errors and mitigated overfitting, resulting in improved robustness under diverse operating conditions. The ablation study confirms that each architectural component provides a measurable and cumulative benefit, reinforcing the value of hybridization in complex manufacturing prediction tasks.

Phase-wise analysis offers further insight into the practical implications of the model. The lowest prediction errors were observed during the extrusion phase, which is the most energy-dominant and operationally stable segment of the print cycle. Higher errors during warm-up and cooling phases can be attributed to shorter durations and greater variability in transient power behavior. These findings suggest that future work could incorporate phase-aware modeling or adaptive weighting strategies to further refine prediction accuracy during transient stages. Overall, the study underscores that energy consumption in FDM 3D printing is governed by intertwined temporal and parametric factors that demand advanced, interpretable, and generalizable modeling approaches. The proposed hybrid deep learning framework not only achieves high predictive accuracy but also provides meaningful insights into energy-driving mechanisms, supporting its applicability in energy-aware scheduling, parameter optimization, and sustainable additive manufacturing practices.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Yenda Srinivasa Rao, Salavaravu Laxmanaraju, Rajkumar Limmala, Pavan kumar Rejeti , Sunil kumar Panda, Jayakrishna Makka.

Methodology: Yenda Srinivasa Rao, Salavaravu Laxmanaraju, Rajkumar Limmala, Pavan kumar Rejeti , Sunil kumar Panda, Jayakrishna Makka.

Investigation: Yenda Srinivasa Rao, Salavaravu Laxmanaraju, Rajkumar Limmala, Pavan kumar Rejeti , Sunil kumar Panda, Jayakrishna Makka.

Discussion of results: M. Yenda Srinivasa Rao, Salavaravu Laxmanaraju, Rajkumar Limmala, Pavan kumar Rejeti , Sunil kumar Panda, Jayakrishna Makka.

Writing – Original Draft: Yenda Srinivasa Rao, Salavaravu Laxmanaraju, Rajkumar Limmala, Pavan kumar Rejeti , Sunil kumar Panda, Jayakrishna Makka.

Writing – Review and Editing: Yenda Srinivasa Rao, Salavaravu Laxmanaraju, Rajkumar Limmala, Pavan kumar Rejeti , Sunil kumar Panda, Jayakrishna Makka.

Resources: Yenda Srinivasa Rao, Salavaravu Laxmanaraju, Rajkumar Limmala, Pavan kumar Rejeti , Sunil kumar Panda, Jayakrishna Makka.

Supervision: Yenda Srinivasa Rao, Salavaravu Laxmanaraju, Rajkumar Limmala, Pavan kumar Rejeti , Sunil kumar Panda, Jayakrishna Makka.

Approval of the final text: Yenda Srinivasa Rao, Salavaravu Laxmanaraju, Rajkumar Limmala, Pavan kumar Rejeti , Sunil kumar Panda, Jayakrishna Makka.

VII. REFERENCES

- [1] M. A. El Youbi El Idrissi, L. Laaouina, A. Jeghal, H. Tairi, and M. Zaki, "Energy consumption prediction for fused deposition modelling 3D printing using machine learning," *Applied System Innovation*, vol. 5, no. 4, p. 86, 2022.
- [2] R. Kumar, R. Ghosh, R. Malik, K. S. Sangwan, and C. Herrmann, "Development of machine learning algorithm for characterization and estimation of energy consumption of various stages during 3D printing," *Procedia CIRP*, vol. 107, pp. 65–70, 2022.
- [3] M. A. El Youbi El Idrissi, L. Laaouina, A. Jeghal, H. Tairi, and M. Zaki, "Modeling of energy consumption and print time for FDM 3D printing using multilayer perceptron network," *Journal of Manufacturing and Materials Processing*, vol. 7, no. 4, p. 128, 2023.
- [4] Y. Li, F. Hu, J. Qin, M. Ryan, R. Wang, and Y. Liu, "A hybrid machine learning approach for energy consumption prediction in additive manufacturing," in *Proc. Int. Conf. Pattern Recognition*, 2021, pp. 622–636.
- [5] Z. Yan et al., "A hybrid mechanism-based and data-driven approach to forecast energy consumption of fused deposition modelling," *Journal of Cleaner Production*, vol. 413, p. 137500, 2023.
- [6] R. Hasanzadeh, "A new polymeric hybrid auxetic structure additively manufactured by fused filament fabrication 3D printing: machine learning-based energy absorption prediction and optimization," *Polymers*, vol. 16, no. 24, p. 3565, 2024.
- [7] Y. Natarajan et al., "Enhancing building energy efficiency with IoT-driven hybrid deep learning models for accurate energy consumption prediction," *Sustainability*, vol. 16, no. 5, p. 1925, 2024.
- [8] I. Rojek et al., "Emerging applications of machine learning in 3D printing," *Applied Sciences*, vol. 15, no. 4, p. 1781, 2025.
- [9] Jayakrishna, Makka, M. Vijay, and Baseem Khan. "An overview of extensive analysis of 3D printing applications in the manufacturing sector." *Journal of Engineering* 2023.1 (2023): 7465737.
- [10] O. Ulkir, M. S. Bayraklılar, and M. Kuncan, "Energy consumption prediction of additive manufactured tensile strength parts using artificial intelligence," *3D Printing and Additive Manufacturing*, vol. 11, no. 5, pp. e1909–e1920, 2024.
- [11] K. S. Ribeiro et al., "A hybrid machine learning model for in-process estimation of printing distance in laser directed energy deposition," *Int. J. Adv. Manuf. Technol.*, vol. 127, no. 7, pp. 3183–3194, 2023.
- [12] K. Wang, J. Xu, S. Zhang, and J. Tan, "Energy management system for biological 3D printing based on manifold model morphing and semi-supervised machine learning," *Journal of Cleaner Production*, vol. 448, p. 141520, 2024.
- [13] Y. Yang, M. He, and L. Li, "Power consumption estimation for mask image projection stereolithography additive manufacturing using machine learning," *Journal of Cleaner Production*, vol. 251, p. 119710, 2020.
- [14] A. Abu Hanieh et al., "Investigating artificial intelligence and modern technologies enhancement in stone and marble cutting in Palestine," *Jordan J. Mech. Ind. Eng.*, vol. 11, no. 1, pp. 207–218, 2024.

- [15] E. Aktepe and U. Ergün, "Machine learning approaches for FDM-based 3D printing: A literature review," *Applied Sciences*, vol. 15, no. 18, p. 10001, 2025.
- [16] G. D. Goh, S. L. Sing, and W. Y. Yeong, "A review on machine learning in 3D printing: Applications, potential, and challenges," *Artificial Intelligence Review*, vol. 54, no. 1, pp. 63–94, 2021.
- [17] J. W. Su et al., "A machine learning workflow for 4D printing: Understand and predict morphing behaviors of printed active structures," *Smart Materials and Structures*, vol. 30, no. 1, p. 015028, 2020.
- [18] V. Kadam et al., "Enhancing surface fault detection using machine learning for 3D printed products," *Applied System Innovation*, vol. 4, no. 2, p. 34, 2021.
- [19] S. Hauck et al., "Advancing sustainable additive manufacturing: Analyzing parameter influences and machine learning approaches for CO₂ prediction," *Sustainability*, vol. 17, no. 9, p. 3804, 2025.
- [20] G. Sarıışık and A. S. Öğütlü, "Machine learning-driven optimization of energy efficiency in marble CNC machining for sustainable manufacturing," *Journal of Tribology*, vol. 148, no. 1, p. 014205, 2026.
- [21] W. L. Ng et al., "Progress and opportunities for machine learning in materials and processes of additive manufacturing," *Advanced Materials*, vol. 36, no. 34, p. 2310006, 2024.
- [22] Kumar, P. Manoj, et al. "Energy Consumption Prediction in 3D Printing Using Enhanced Hybrid Deep Learning Models." *ITEGAM-JETIA* 12.57 (2026): 1030-1044.
- [23] L. Breiman, "Random forests," *Machine Learning*, vol. 45, no. 1, pp. 5–32, 2001.
- [24] J. H. Friedman, "Greedy function approximation: A gradient boosting machine," *Annals of Statistics*, vol. 29, no. 5, pp. 1189–1232, 2001.
- [25] T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in *Proc. ACM SIGKDD Int. Conf. Knowl. Discov. Data Min.*, 2016, pp. 785–794.
- [26] G. Ke et al., "LightGBM: A highly efficient gradient boosting decision tree," *Adv. Neural Inf. Process. Syst.*, vol. 30, pp. 3146–3154, 2017.
- [27] Z.-H. Zhou, *Ensemble Methods: Foundations and Algorithms*. Boca Raton, FL, USA: CRC Press, 2025.
- [28] Krishna, M. Jaya, and M. Vijay. "Review of characterizing and predicting the energy usage in 3D printing." *AIP Conference Proceedings*. Vol. 3325. No. 1. AIP Publishing LLC, 2025.
- [29] T. von Hahn and C. K. Mechefske, "Machine learning in CNC machining: Best practices," *Machines*, vol. 10, no. 12, p. 1233, 2022.
- [30] G. Sarıışık and A. S. Öğütlü, "Optimization of energy consumption in CNC marble processing: Statistical and machine learning approaches," *Int. J. 3D Print. Technol. Digit. Ind.*, vol. 8, no. 3, pp. 437–450, 2024.
- [31] H. Fattahi and H. Ghaedi, "Enhancing energy efficiency in stone cutting: Utilizing rock engineering system method for precise maximum energy consumption prediction," *J. Min. Environ.*, vol. 15, no. 1, pp. 345–364, 2024.
- [32] S. Thapaliya, O. F. Valilai, and H. Wicaksono, "Power consumption and processing time estimation of CNC machines using explainable artificial intelligence," *Procedia Computer Science*, vol. 232, pp. 861–870, 2024.
- [33] I. Nugrahanto, H. Gunawan, and H. Y. Chen, "Innovative approaches to sustainable CNC machining: A machine learning perspective on energy efficiency," *Sustainability*, vol. 16, no. 9, p. 3569, 2024.
- [34] A. M. Schmitt et al., "G-code evaluation in CNC milling to predict energy consumption through machine learning," *Adv. Ind. Manuf. Eng.*, vol. 8, p. 100140, 2024.
- [35] R. Ströbel et al., "Time series prediction for energy consumption of CNC axes using hybrid machine learning models," *Machines*, vol. 11, no. 11, p. 1015, 2023.
- [36] J. Cao et al., "A novel CNC milling energy consumption prediction method based on program parsing and parallel neural network," *Sustainability*, vol. 13, no. 24, p. 13918, 2021.
- [37] H. Yurtkuran et al., "Prediction of power consumption in sustainable turning of PH13-8Mo steel using machine learning," *Int. J. Adv. Manuf. Technol.*, vol. 133, no. 5, pp. 2171–2188, 2024.