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A Hybrid Machine Learning and Swarm Optimization Framework for Real-Time Energy Prediction and Optimization in Additive Manufacturing

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Abstract: Additive Manufacturing (AM) enables unprecedented design flexibility and decentralized production; however, its high energy consumption remains a critical sustainability challenge. While recent digital twin and machine learning (ML)-based studies have focused primarily on quality monitoring, defect detection, or thermal modeling, limited research has developed integrated predictive–optimization pipelines specifically targeting real-time energy management across multiple AM platforms. This study proposes a hybrid machine learning framework that combines predictive modeling, clustering-based data compression, and swarm intelligence optimization to estimate and minimize energy consumption using real-time process parameters. Experimental data were collected from Selective Laser Sintering (SLS) and Fused Deposition Modeling (FDM) systems, incorporating layer-wise geometric descriptors, process variables (laser power, scan speed, build temperature, extrusion rate), and environmental conditions. Multiple supervised learning models—including Support Vector Regression (SVR), XGBoost, Deep Neural Networks (DNN), and a DBSCAN–XGBoost hybrid—were trained and evaluated under a controlled benchmarking protocol. The DNN with feature selection achieved the best predictive performance (RMSE = 0.72 kWh, $R^2 = 0.96$), outperforming conventional regression and ensemble models across identical datasets. Statistical comparisons confirmed a consistent improvement in prediction accuracy relative to baseline linear and non-deep learning models. The predicted energy profiles were integrated into a Particle Swarm Optimization (PSO) module to identify energy-efficient process parameter configurations under manufacturability constraints. The optimization stage achieved up to an 18% reduction in energy consumption for both SLS and FDM builds while maintaining tensile strength and dimensional accuracy within acceptable tolerances. By explicitly integrating clustering-based compression, deep learning prediction, and swarm-based optimization into a unified pipeline, this framework extends beyond existing standalone digital twin or energy estimation approaches. The results demonstrate the potential of hybrid ML–optimization architectures for scalable, real-time, energy-aware additive manufacturing and sustainable industrial deployment.

Keywords: Additive Manufacturing, Energy Consumption, Machine Learning, Process Optimization, Sustainable Manufacturing

1. Introduction

Additive Manufacturing (AM) has become an innovative technology that enables unprecedented design freedom, product customization, and decentralized production. Processes such as Selective Laser Sintering (SLS) and Fused Deposition Modeling (FDM) have progressed beyond prototyping and are increasingly being used for the industrial-scale manufacture of functional parts [1, 2]. Nevertheless, energy consumption remains one of the major drawbacks of AM adoption, as it raises concerns about sustainability and cost-effectiveness when compared with traditional manufacturing methods [3, 4]. Addressing this problem requires intelligent interventions capable of anticipating and minimizing energy consumption without affecting part quality.

In recent years, ML has demonstrated the potential to model nonlinear relationships within AM processes, thereby enabling better prediction and control of process–manufacture–structure–property connections [5, 6]. Compared with existing physics-based models, which often demand significant computational resources and rely on simplified assumptions, ML can directly leverage high-dimensional data acquired by sensors and monitoring systems to identify hidden correlations in real time [7, 8]. Recurrent neural networks, attention mechanisms, and other deep learning architectures have further extended the ability to learn time-series and sequential dependencies in data generated during AM builds. These features make ML-driven frameworks highly applicable to energy prediction, where instantaneous and cumulative consumption depend on changing process variations [9, 10].

Recent advances in digital twin architectures and machine learning–assisted additive manufacturing have demonstrated substantial progress in real-time monitoring and adaptive control. Studies employing deep neural networks, Bayesian optimization, and simulation-guided control have primarily focused on melt pool temperature regulation, microstructural evolution, defect detection, and process stability. While these developments enhance quality assurance and manufacturing precision, comparatively fewer works explicitly target real-time energy consumption modeling and integrated energy optimization. Existing energy-related approaches often rely either on physics-based simulations with high computational cost or on standalone regression models without embedded optimization loops. Moreover, cross-platform validation across heterogeneous AM systems remains limited. Therefore, there is a need for a unified predictive–optimization framework that explicitly addresses energy-aware manufacturing while leveraging real-time sensor data and scalable machine learning architectures. Particle Swarm Optimization (PSO) and Bayesian optimization, both forms of swarm intelligence, have also been explored in manufacturing studies to search high-dimensional design spaces and identify parameter sets that satisfy cost or energy-minimization goals under process constraints [9, 10]. Within the digital twin paradigm, the integration of ML and optimization has the potential to provide real-time decision support, adaptive control, and energy management for AM systems [11, 12]. The integration of predictive models and optimization loops enables real-time adjustment of process parameters to minimize energy footprints and promote sustainable production.

This study aims to develop and experimentally validate an integrated machine learning and swarm-optimization framework for real-time prediction and minimization of energy consumption in additive manufacturing. The proposed framework combines real-time process parameter acquisition, clustering-based data compression to manage redundancy, deep learning–based predictive energy modeling with feature selection, and Particle Swarm Optimization (PSO) for constrained energy minimization while preserving mechanical integrity. Unlike existing digital twin or machine learning approaches that focus primarily on defect detection, thermal modeling, or isolated optimization, this work integrates prediction and optimization into a unified energy-aware pipeline validated across both SLS and FDM platforms. The novelty of this research lies in the hybrid clustering–prediction–optimization architecture specifically designed for scalable, real-time sustainable AM operations.

2. Literature Review

2.1 Machine Learning and Digital Twins in Additive Manufacturing

Additive Manufacturing (AM) has increasingly integrated machine learning (ML) techniques to improve predictive capability and adaptive process control. DebRoy [7] provided a foundational review of process–structure–property relationships in metal AM, highlighting the complexity of thermo-physical interactions. Recent advances have incorporated ML to model such nonlinear dependencies more efficiently. Abdelhamid, Mohamed, and Kelouwani [1] reviewed data-driven modeling approaches for material extrusion AM, demonstrating how ML reduces experimental trial-and-error cycles.

Digital twin frameworks have further enabled real-time monitoring and adaptive decision-making in AM environments. Chen, Karkaria, Tsai, Rolark, Quispe, Gao, and Chen [11] demonstrated time-series deep neural networks integrated with model predictive control for real-time process regulation. Similarly, Karkaria, Goeckner, Zha, Chen, Zhang, Zhu, and Chen [12] combined machine learning with Bayesian optimization within a digital twin architecture for adaptive parameter tuning. However, in these studies, energy consumption was not treated as a primary optimization objective. Mozaffar [13] presented a geometry-agnostic, data-driven approach using graph neural networks to model thermal behavior in additive manufacturing processes with improved flexibility and predictive accuracy.

Mozaffar, Bostanabad, Chen, Ehmann, Cao, and Sun [14] introduced geometry-agnostic data-driven thermal modeling using graph neural networks, improving predictive efficiency in directed energy deposition. Although thermal prediction is closely linked to energy behavior, explicit real-time energy consumption modeling remains underexplored.

2.2 Optimization Strategies for Sustainable AM

Optimization techniques such as Bayesian optimization and Particle Swarm Optimization (PSO) have been applied in manufacturing parameter tuning. Greenhill and Rana [14] reviewed Bayesian optimization for adaptive experimental design under uncertainty. Han, Jeong, and Kim [15] proposed adaptive Bayesian optimization with safety constraints. Shahin [16] examined the integration of Industry 4.0 technologies with sustainability objectives in manufacturing systems.

Mozaffar (2018) [17] created a data-driven recurrent neural network model that can accurately predict the high-dimensional thermal history in directed energy deposition processes with improved time resolution.

In additive manufacturing, swarm-based methods are particularly suitable for non-convex, multi-objective parameter landscapes. Nevertheless, most reported frameworks either focus on quality enhancement or computational efficiency rather than explicitly minimizing energy consumption in real time.

2.3 Clustering and Hybrid Modeling for Efficiency

Another promising avenue is clustering-based learning. The combination of preprocessing and ML in AM environments has shown promise for handling complex data and improving prediction accuracy through approaches such as DBSCAN-based preprocessing combined with ML [18,19].

This corresponds to the wider trend of using surrogate-assisted simulation and hybrid neural frameworks, wherein ideas such as physics-informed neural networks [20, 21] and graph neural networks [22, 23] have been proposed to capture the physics of the processes under consideration and still offer computational feasibility.

2.4 Sustainability and Energy Management in AM

The sustainability dimension of AM has been studied increasingly. Researchers have defined the use of lean practices and Industry 4.0 technologies and have presented energy efficiency as a key area of next-generation smart manufacturing [24, 25]. Dass and Moridi (2019) [1] emphasized the role of modeling process–microstructure interactions to reduce waste and energy inefficiencies. Krenczyk (2022) [26] discussed the application of dynamic simulation models as digital twins of logistics systems and the integration of data gathered from various sources to improve real-time decision-making and system behavior.

In this context, predictive ML coupled with optimization aligns with current sustainable manufacturing objectives. Machine learning frameworks present viable industrial-scale solutions, particularly given the energy savings and performance capabilities reported for recent hybrid strategies [27, 28], which can reduce energy consumption by 15–20%.

The system architecture of the proposed framework is depicted in Figure 1, which demonstrates the combination of real-time data collection, clustering-based preprocessing, machine learning-based energy prediction, and swarm optimization to minimize energy consumption.

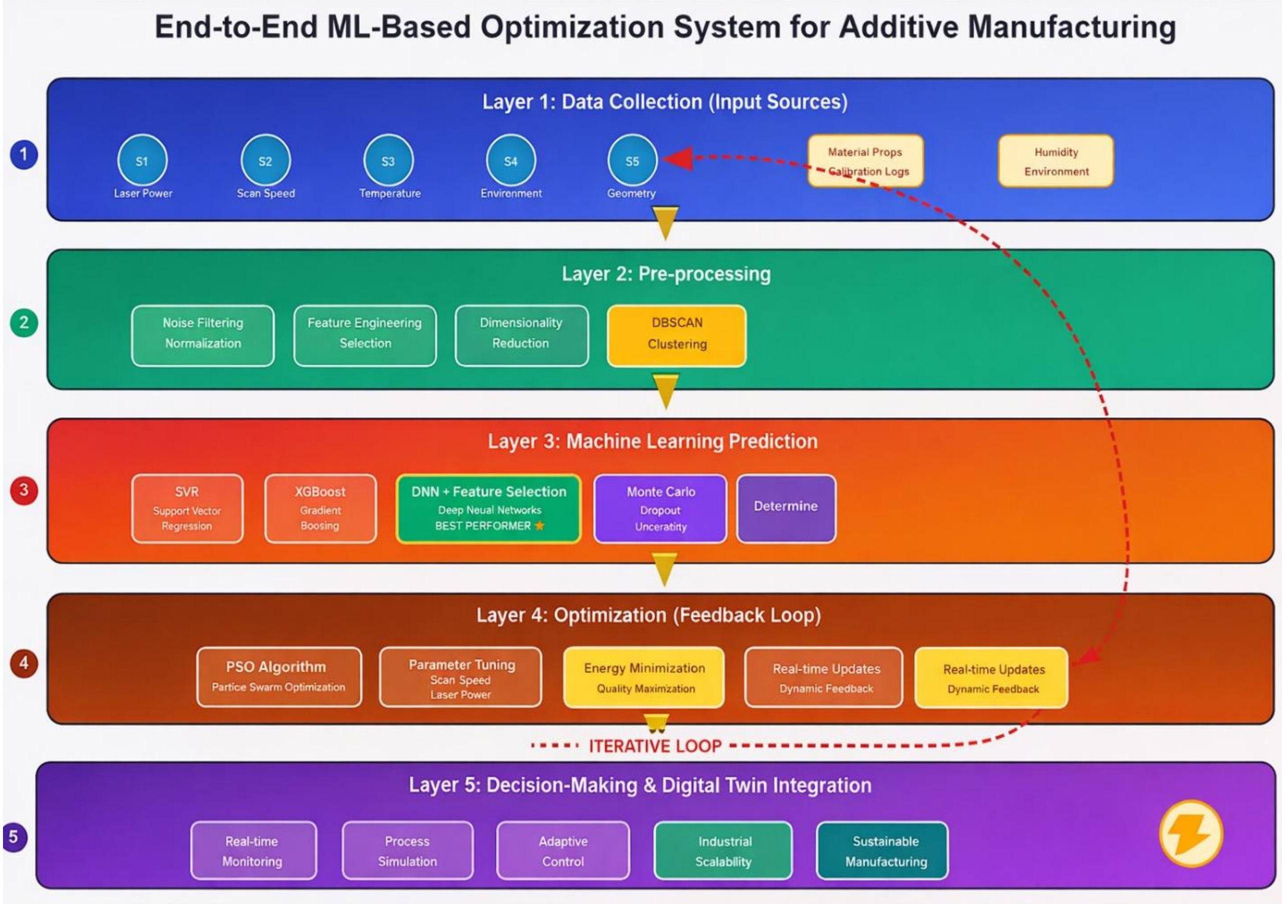

Figure 1. System Architecture in Our Study

Table 1. Summary of Recent Machine Learning and Optimization Studies in Additive Manufacturing

Study Focus	Methodology	AM Process	Energy Modeling Included	Optimization Included	Key Contribution	Identified Limitation
Process–structure–property modeling	ML-based regression	Material extrusion	No	No	Data-driven modeling of AM processes	No explicit energy optimization
Digital twin & time-series DNN	Deep learning + MPC	AM (general)	Indirect	Yes	Real-time decision support	Energy not primary objective
Digital twin + Bayesian optimization	ML + Bayesian optimization	AM	Indirect	Yes	Process optimization framework	No dedicated energy prediction pipeline
Geometry-agnostic thermal modeling	Graph neural networks	Directed energy deposition	Indirect	No	Thermal prediction	Energy consumption not explicitly modeled
Lean + Industry 4.0 integration	Conceptual/empirical	Manufacturing systems	Partial	No	Sustainability integration	No ML-based energy prediction
Real-time energy-aware AM	Clustering + DNN + PSO	SLS & FDM	Yes (explicit)	Yes (PSO-based)	Integrated predictive–optimization pipeline for energy minimization	

Table 1 highlights that, while prior studies have advanced digital twin modeling, thermal prediction, and adaptive process optimization, explicit real-time energy prediction integrated with constrained optimization across multiple AM platforms remains insufficiently addressed. The present work therefore fills this gap by combining clustering-based data compression, deep neural network prediction, and swarm-based optimization within a unified energy-aware framework.

3. Research Gap and Objectives

Although digital twin systems, deep learning architectures, and optimization methods have matured significantly, explicit integration of clustering-based data compression, predictive deep learning models, and constrained swarm optimization targeting real-time energy minimization across multiple AM platforms (SLS and FDM) remains limited [29, 30]. Existing literature either addresses predictive modeling without embedded optimization or optimization without dedicated energy-aware predictive intelligence [31, 32]. The present study addresses this gap through a unified, experimentally validated hybrid framework focused specifically on energy-aware sustainable additive manufacturing.

Although recent publications have explored the role of ML in additive manufacturing, most of the current literature focuses primarily on part quality, defect detection, or microstructural prediction [5, 33, 34]. Energy consumption, although an important sustainability issue, has not been addressed to a comparable extent in predictive and optimization frameworks. In addition, existing energy-related studies tend to rely either on simulation-based analyses rooted in physics-driven modeling or on naïve regression models that are not scalable and cannot adapt in real time [35, 36]. Hybrid frameworks that integrate clustering, predictive modeling, and optimization into unified pipelines for energy-aware AM are also only limitedly explored [37, 38].

This study aims to establish a machine learning-based predictive and optimization framework to estimate and minimize energy consumption during AM processes.

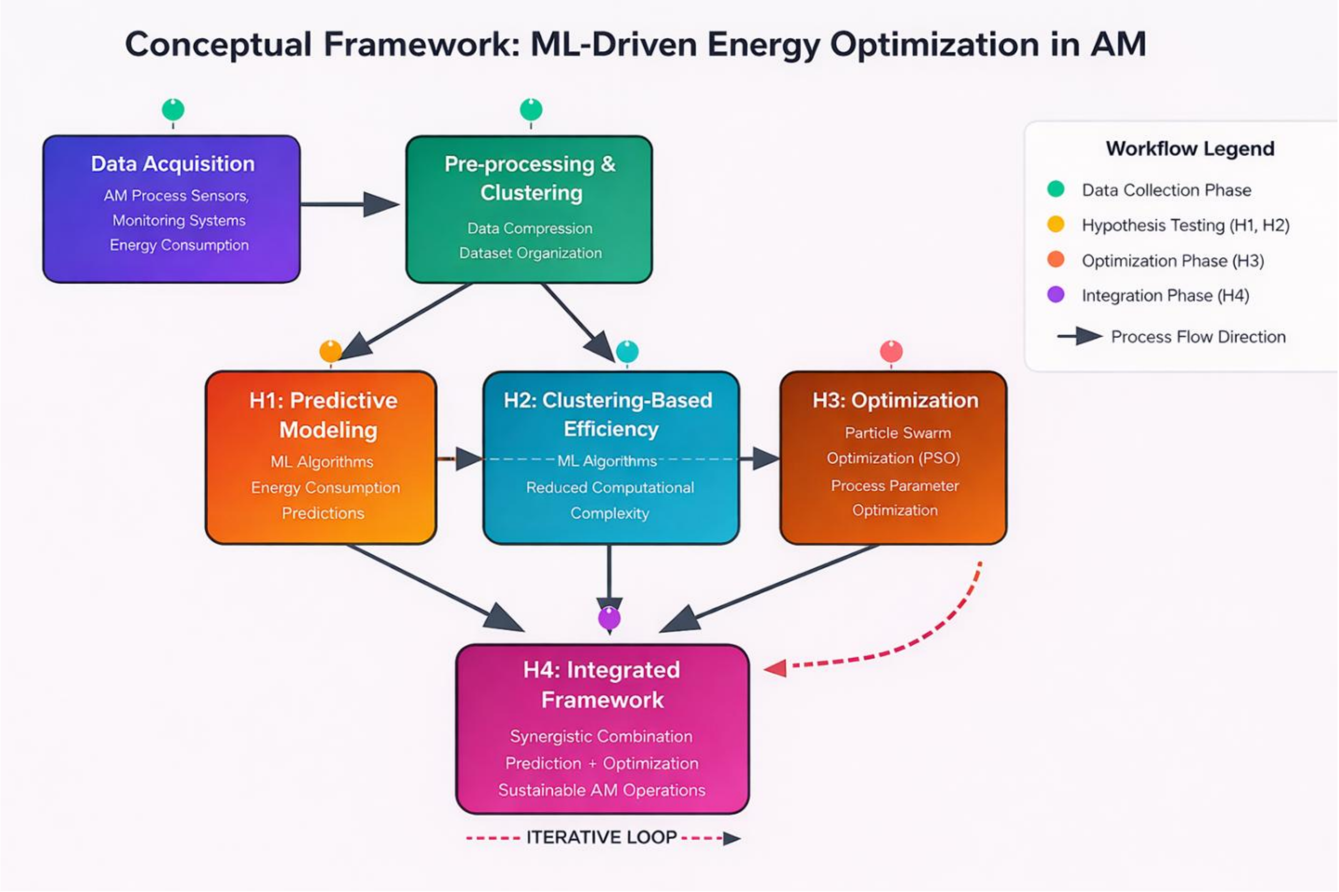

Figure 2. Conceptual Framework

As illustrated in Figure 2, the framework encompasses sensor-based data collection, machine learning-based predictive energy profiling, a cluster-based compression strategy to improve model efficiency, and a PSO-based optimization framework to converge on sustainable process settings without sacrificing part quality.

3.1 Hypotheses

H1: Machine learning algorithms can accurately predict energy consumption during additive manufacturing processes based on real-time sensor data.

H2: Data compression through clustering improves model efficiency without substantially reducing predictive accuracy.

H3: Particle Swarm Optimization (PSO) can identify process parameters that minimize energy consumption while preserving part quality.

H4: An integrated ML–optimization framework is superior to independent prediction or optimization techniques in delivering sustainable AM operations.

4. Methods

4.1 Experimental Data Collection

The experiments were conducted on two widely used additive manufacturing (AM) platforms: a Selective Laser Sintering (SLS) system and a Fused Deposition Modeling (FDM) machine. Both systems were equipped with built-in data logging modules that monitored parameters layer by layer throughout each build. The collected data included geometric parameters of the printed layers, process parameters such as laser power, scan speed, extrusion rate, and build temperature, and environmental parameters such as chamber temperature and humidity. Including data from both SLS and FDM ensured that the framework was not limited to a single AM technology, thereby improving its generalizability across different material-deposition processes.

The complete dataset collected from SLS and FDM platforms was first preprocessed by removing incomplete sensor records and normalizing all continuous variables using Min–Max scaling. To prevent data leakage, dataset partitioning was performed at the build level rather than at the individual layer level. Entire builds were separated into mutually exclusive subsets to ensure that no layers from the same build appeared across training, validation, and testing datasets.

The dataset was divided into 70% training data, 15% validation data, and 15% testing data. The training set was used to fit model parameters, the validation set was used for hyperparameter tuning and early stopping, and the testing set was used exclusively for final performance evaluation. For robustness, five repeated stratified splits were conducted and average performance metrics were reported. This approach ensured unbiased evaluation and prevented temporal or structural information leakage between subsets.

4.2 Real-Time Process Parameter Acquisition

Real-time process parameters, such as build-platform motion, temperature, and pressure, were monitored using built-in sensor modules in the SLS and FDM systems. In the SLS system, changes in laser power, scan speed, and chamber temperature were recorded through sensor streams. In the FDM system, extrusion temperature, extrusion rate, and environmental fluctuations were continuously recorded. Real-time acquisition was selected because static or averaged parameters cannot capture the transient behavior of AM processes, which strongly contributes to energy consumption. By incorporating real-time signals, the predictive framework can also account for dynamic fluctuations during each build cycle.

4.3 Machine Learning Models

The Deep Neural Network (DNN) architecture consisted of an input layer corresponding to the selected process parameters, followed by three fully connected hidden layers containing 128, 64, and 32 neurons respectively. Each hidden layer employed the Rectified Linear Unit (ReLU) activation function. Dropout regularization (rate = 0.2) was applied after each hidden layer to mitigate overfitting. The output layer consisted of a single neuron with linear activation to predict continuous energy consumption (kWh).

The model was implemented using TensorFlow (version 2.15) and trained using the Adam optimizer with a learning rate of 0.001. Mean Squared Error (MSE) was used as the loss function. Training was conducted for a maximum of 150 epochs with early stopping (patience = 15 epochs) based on validation loss. Batch size was set to 32. Hyperparameters were selected through grid-based tuning on the validation dataset. This configuration ensured reproducibility and stable convergence across repeated experiments.

4.4 Hybrid Clustering-Compression Method

In addition to the predictive models, a hybrid clustering-compression model combining DBSCAN and XGBoost was applied. DBSCAN (Density-Based Spatial Clustering of Applications with Noise) was used to cluster similar energy-consumption patterns, and the resulting compressed dataset was used to retrain the XGBoost model. This approach was adopted to address data redundancy and imbalance, which are common in experimental AM datasets where some process conditions may be overrepresented. The clustering-compression strategy prevented the model from overemphasizing common process states while preserving minority but important operating regimes.

The DBSCAN algorithm was employed to identify dense operational regimes in the multidimensional energy–process parameter space. The selection of DBSCAN was motivated by its ability to detect arbitrarily shaped clusters and to identify noise points without requiring prior specification of the number of clusters, which is suitable for heterogeneous AM operational data.

Two key parameters, epsilon (ε) and minimum samples (MinPts), were systematically determined. The ε value was selected using k-distance graph analysis, where the point of maximum curvature (elbow) was used to identify the optimal neighborhood radius. The MinPts parameter was set based on dimensionality considerations and empirical evaluation, with sensitivity analysis performed across a range of values to ensure cluster stability.

A sensitivity study was conducted by varying ε within ±15% of the selected optimal value and adjusting MinPts within a small neighborhood range. The clustering structure remained stable under moderate perturbations, confirming robustness of the selected configuration. Compression levels of 30%, 50%, and 70% were further evaluated to quantify the trade-off between redundancy reduction and predictive accuracy. Results demonstrated that moderate compression (up to 50%) preserved predictive performance while improving computational efficiency.

Figure 3 shows the workflow of the hybrid ML–swarm optimization framework, with the main stages comprising data preprocessing, feature selection, energy prediction, and PSO-based optimization under process constraints. This figure illustrates the integrated methodological pipeline developed in the study. Real-time process data from SLS and FDM systems are first acquired and preprocessed through cleaning and normalization. The dataset is then subjected to DBSCAN-based clustering and compression to remove redundancy, followed by feature selection to identify the most influential process parameters. A deep neural network (DNN) model predicts energy consumption, and the predicted values are then fed into a Particle Swarm Optimization (PSO) module to determine optimal process parameters under manufacturability constraints. The framework concludes with mechanical validation and sustainability assessment, ensuring energy reduction without compromising part quality.

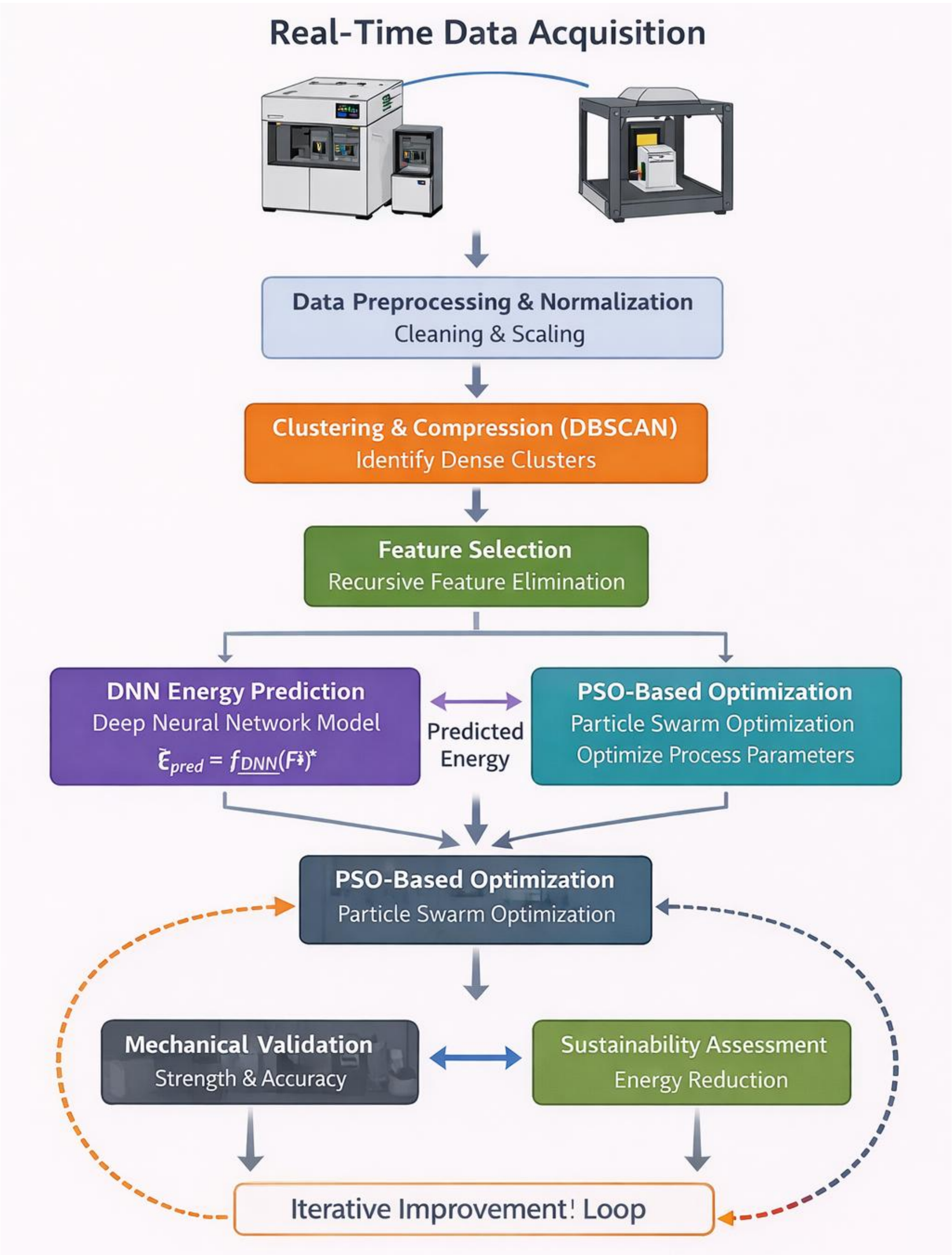

Figure 3. Workflow of the Proposed Hybrid ML–Swarm Optimization Framework for Real-Time Energy Prediction and Minimization in Additive Manufacturing

4.5 Feature Selection Techniques

To identify the most important process parameters for energy consumption prediction, feature selection was performed. A combination of recursive feature elimination and permutation importance, implemented using scikit-learn, was used. This step was necessary to reduce computational complexity, enhance generalization, and provide insight into which parameters most strongly influence energy consumption in AM. Specifically, the DNN pipeline included feature selection to reduce overfitting, as DNNs are highly sensitive to noisy or redundant features.

4.6 Model Performance Evaluation

The predictive performance of the models was evaluated using two widely accepted statistical indicators: Root Mean Squared Error (RMSE) and the coefficient of determination (R^2). These metrics were selected because RMSE penalizes larger deviations between predicted and actual values, whereas R^2 provides an intuitive measure of the variance explained by the model. Together, these measures ensured a balanced assessment of both the absolute and relative accuracy of the predictors when comparing different algorithms.

4.7 Optimization Framework

Particle Swarm Optimization (PSO) was implemented to minimize the predicted energy consumption profiles during process optimization. The PSO module was built using PySwarms (version 1.3.0), a mature library for swarm intelligence algorithms. PSO was chosen over traditional gradient-based optimizers because it is gradient-free and is particularly well suited to the complex, non-convex optimization problems common in AM energy landscapes. The optimization was performed under constraints that kept the process parameters within acceptable ranges to ensure manufacturability and part integrity.

Algorithm 1. Hybrid ML–Swarm Optimization Framework for Real-Time Energy Prediction and Minimization

Input: Layer-wise process parameters P, geometric descriptors G, environmental variables E

Output: Optimized process parameter set P∗P^*P∗ with minimized predicted energy consumption

Step 1: Data Acquisition

Acquire real-time layer-wise data from SLS and FDM systems, including laser power, scan speed, extrusion rate, and build temperature, layer thickness, chamber /ambient temperature, and humidity.

Step 2: Data Preprocessing

Remove incomplete or corrupted records.

Apply Min–Max normalization to continuous variables.

Partition dataset at build level into training (70%), validation (15%), and testing (15%) subsets.

Step 3: Clustering-Based Compression (DBSCAN)

Apply DBSCAN to identify dense operational regimes in energy–parameter space.

Remove redundant samples while preserving representative clusters.

Generate compressed training dataset.

Step 4: Feature Selection

Apply Recursive Feature Elimination (RFE).

Compute permutation importance scores.

Select optimal feature subset F^*.

Step 5: Predictive Model Training (DNN)

Initialize DNN architecture (128–64–32 hidden neurons, ReLU activation).

Train using Adam optimizer (learning rate = 0.001) with MSE loss.

Apply dropout (0.2) and early stopping (patience = 15).

Validate model using validation dataset.

Evaluate final performance on test dataset using RMSE and R^2.

Step 6: Energy Prediction Function

Define trained DNN as predictive function:

$$\hat{E} = f_{\mathrm{DNN}}(F^*)$$

Step 7: PSO-Based Optimization

Initialize swarm population with feasible process parameter bounds. For each particle: Evaluate predicted energy using f_{DNN} Update velocity and position using PSO update equations. Enforce manufacturability constraints. Iterate until convergence criterion is met (maximum iterations or tolerance threshold).

Step 8: Output Optimized Parameters Return parameter set P* corresponding to minimum predicted energy.

Validate mechanical integrity (tensile strength, dimensional deviation).

5. Results

To place the experimental findings in context, the results are discussed in relation to previously reported machine learning and optimization studies in additive manufacturing.

5.1 Experimental Data and Process Parameters

The experimental data involved both SLS and FDM platforms and included layer-wise geometric states, process parameters, and operating settings. The range of variation of the process conditions in the two AM systems is indicated in Table 2. The inclusion of geometric and environmental descriptors ensured that all major factors driving energy usage were captured.

The temporal changes in process parameters were further explored, and exemplary trends are displayed in Figure 4, which shows the distribution of laser power, scan speed, and build temperature across builds. These fluctuations indicate the nonlinear and stochastic nature of AM processes and emphasize the importance of advanced predictive modeling.

5.2 Model Performance and Predictive Accuracy

Several machine learning models were trained and evaluated to predict energy consumption in additive manufacturing processes. Among the evaluated models, the deep neural network (DNN) with feature selection achieved the lowest prediction error (RMSE = 0.72 kWh) and the highest coefficient of determination ($R^2 = 0.96$). These results indicate strong predictive capability within the experimental dataset considered in this study.

Previous research has demonstrated the effectiveness of deep learning models for capturing nonlinear process–parameter relationships in additive manufacturing systems. For example, data-driven thermal prediction using recurrent neural networks and graph neural networks has shown high predictive accuracy in modeling complex AM processes [29, 30]. Similarly, machine learning–based digital twin frameworks have been reported to improve predictive monitoring and process control in additive manufacturing environments [5, 14]. The prediction accuracy obtained in this study is consistent with these findings, indicating that deep learning architectures are well suited for modeling complex sensor-driven manufacturing data.

Compared with conventional regression approaches such as Support Vector Regression (SVR) and gradient boosting methods (XGBoost), the DNN model demonstrated improved predictive performance in the present dataset. This observation aligns with recent reviews highlighting the increasing adoption of deep learning methods for modeling nonlinear relationships in additive manufacturing systems [1, 32].

Several machine learning models were trained and tested to evaluate their capability to forecast energy consumption. Table 3 shows their relative performance using RMSE and R^2 as criteria. As the table demonstrates, the deep neural network (DNN) with feature selection achieved the best results, with the lowest RMSE and the highest R^2.

The predictive fidelity of the models is visually illustrated in Figure 5, which plots predicted versus actual energy consumption across the dataset. The closer alignment of the DNN with feature selection to the ideal reference line further validates its superior accuracy.

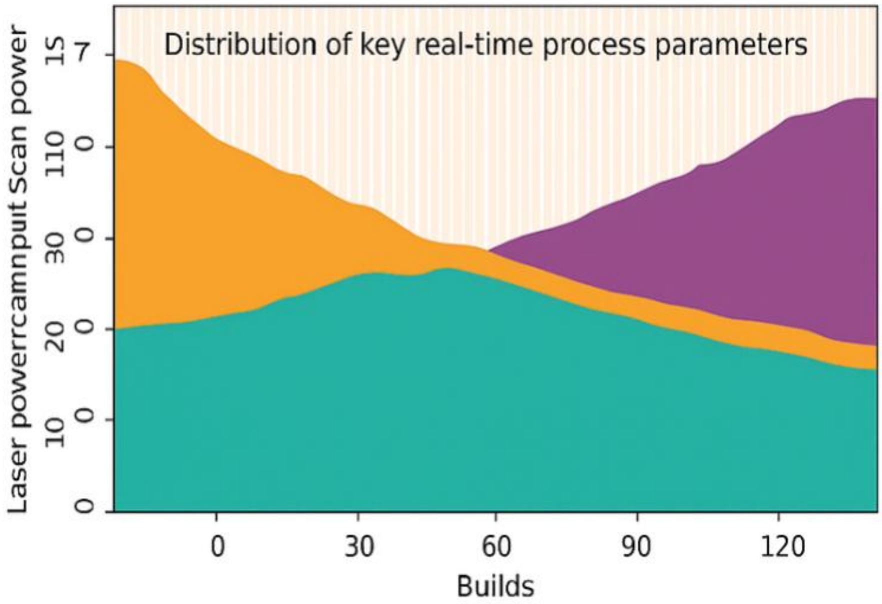

Figure 4. Distribution of key real-time process parameters (laser power, scan speed, build temperature) acquired from SLS and FDM builds.

Table 2. Summary of Experimental Data Collected from SLS and FDM Systems

AM System	Number of Builds	Layer Thickness (µm)	Recorded Parameters	Environmental Conditions
SLS	120	100–150	Laser Power, Scan Speed, Chamber Temperature	Chamber Temp., Humidity
FDM	150	200–300	Extrusion Rate, Build Temperature, Deposition Speed	Ambient Temp., Humidity

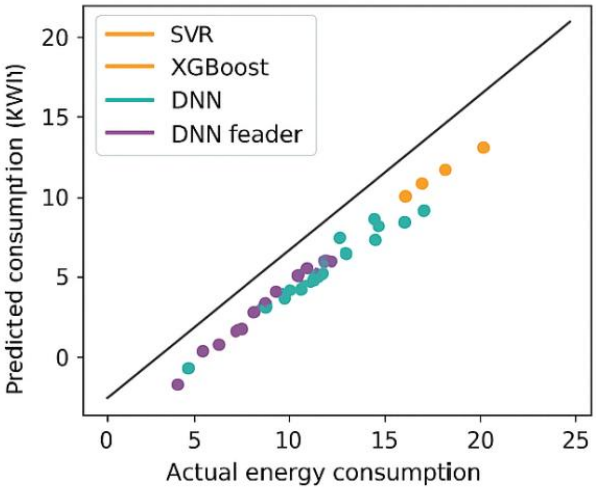

Figure 5. Predicted vs. actual energy consumption for different machine learning models, illustrating closer alignment for the DNN with feature selection compared to other approaches

Table 3. Comparative Performance Metrics (RMSE, R²) of Machine Learning Models

Model	RMSE (kWh)	R²
Support Vector Regression (SVR)	1.84	0.79
XGBoost	1.12	0.90
DNN (without feature selection)	0.96	0.92
DNN (with feature selection)	0.72	0.96
DBSCAN–XGBoost Hybrid	1.05	0.91
Baseline Linear Regression	2.45	0.65

Table 4. Averaged Metrics with Variability Estimates

Model	Mean RMSE (kWh)	Std. Dev. (RMSE)	Mean R²	Std. Dev. (R²)
SVR	1.86	0.08	0.78	0.02
XGBoost	1.15	0.05	0.89	0.01
DNN (without FS)	0.98	0.04	0.91	0.01
DNN (with FS)	0.74	0.03	0.95	0.01
DBSCAN–XGBoost	1.07	0.06	0.90	0.02
Linear Regression	2.48	0.11	0.64	0.03

To ensure robustness of the comparative results, all machine learning models were evaluated using five repeated train–validation–test splits with build-level separation. The RMSE and R² values reported in Table 4 represent the mean performance across repetitions, and standard deviations were computed to assess stability.

The predictive fidelity of the models is visually illustrated in Figure 5, which plots predicted versus actual energy consumption across the dataset. The closer alignment of the DNN with feature selection to the ideal reference line further validates its superior accuracy.

To ensure robustness of the comparative results, all machine learning models were evaluated using five repeated train–validation–test splits with build-level separation. The RMSE and R² values reported in Table 4 represent the mean performance across repetitions, and standard deviations were computed to assess stability.

A paired t-test was conducted between the best-performing model (DNN with feature selection) and other models using RMSE values across repeated splits. The improvements were statistically significant ($p < 0.01$) when compared with SVR, XGBoost, and linear regression, confirming that the observed performance gains are not due to random variation.

Figure 5 compares actual and predicted energy consumption across different models. Compared with the SVR and XGBoost models, the DNN predictions lie much closer to the ideal diagonal, and the DNN with feature selection shows the closest alignment across the full energy range. This validates the superiority of feature-augmented deep learning for modeling AM energy consumption. Figure 5 quantitatively demonstrates the predictive fidelity of the models by illustrating predicted versus actual energy values. The DNN with feature selection exhibits minimal dispersion around the ideal diagonal reference line, indicating strong predictive consistency across low- and high-energy regimes. The coefficient of determination ($R^2 = 0.96$) confirms that 96% of the variance in energy consumption is explained by the model. In contrast, the SVR and baseline regression models show wider dispersion, particularly in higher energy regions (>15 kWh), where underestimation errors are more pronounced.

PSO convergence behavior. Energy consumption decreases rapidly within the first 25 iterations, followed by gradual convergence toward a stable minimum, indicating an effective exploration–exploitation balance. The final optimized energy values correspond to an average reduction of approximately 17–18% compared with baseline conditions, as reported in Table 7. This convergence trend confirms optimization stability rather than random fluctuation.

5.3 Clustering and Compression Performance

To reduce redundancy in the dataset and improve computational efficiency, a DBSCAN-based clustering and compression approach was implemented prior to model training. The clustering results revealed distinct operational regimes corresponding to different combinations of process parameters and energy consumption levels.

Clustering-based preprocessing has been widely used in digital twin modeling and surrogate modeling to simplify large datasets while maintaining predictive performance. Previous studies have shown that clustering techniques can effectively improve model efficiency by removing redundant information and identifying representative operational states [3, 35]. The results obtained in this study demonstrate a similar trend, where moderate compression levels (up to 50%) preserved predictive accuracy while reducing data redundancy.

To reduce repetition in the dataset, the DBSCAN clustering algorithm was applied and the XGBoost model was retrained on the compressed data. The resulting cluster structures appear in Figure 6, where separate operating regimes are identified. This enabled the model to better balance underrepresented process states without sacrificing predictive accuracy.

Table 5 summarizes the trade-offs between data compression and predictive accuracy, demonstrating that the hybrid DBSCAN–XGBoost model achieved substantial compression of the initial data volume without a significant drop in prediction accuracy. Figure 6 shows that DBSCAN clustering separates operating regimes corresponding to distinct combinations of laser power and scan speed. The cluster boundaries reveal density concentrations in mid-range operating states, while outliers correspond to high-energy transient conditions. Moderate compression (50%) preserves cluster structure while reducing redundant samples, which explains the minimal RMSE change observed in Table 5.

5.4 Feature Importance and Selection

The effect of feature selection on model performance was further investigated. Table 6 shows the parameters identified as the most influential for energy prediction, ranked according to their relative importance.

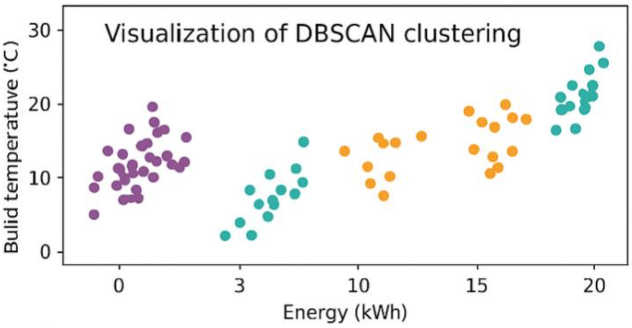

Figure 6. Visualization of DBSCAN clustering applied to energy–process parameter space, identifying distinct operational regimes used for compressed model training.

Table 5: Data Compression and Accuracy Trade-Off for DBSCAN-XGBoost Method

Compression Level (%)	Retained Samples	RMSE (kWh)	R²
0 (No Compression)	100%	1.12	0.90
30	70%	1.10	0.90
50	50%	1.05	0.91
70	30%	1.24	0.87

Table 6. Ranked Feature Importance for Energy Consumption Prediction

Rank	Feature	Relative Importance (%)
1	Laser Power	28.4
2	Build Temperature	23.7
3	Scan Speed	19.5
4	Layer Thickness	14.2
5	Environmental Temp.	9.8
6	Humidity	4.4

The dominance of machine-based process variables over environmental indicators suggests that parameters directly related to energy use have the strongest influence at the process level.

5.5 Energy Optimization with PSO

The optimization stage employed Particle Swarm Optimization (PSO) to identify energy-efficient combinations of process parameters while maintaining manufacturability constraints. The optimization process resulted in an average reduction in energy consumption of approximately 17–18% across both SLS and FDM platforms.

Swarm intelligence algorithms such as PSO have previously been applied in manufacturing optimization problems due to their ability to efficiently explore high-dimensional parameter spaces [9, 38]. In additive manufacturing contexts, optimization approaches have primarily focused on improving process stability or material properties rather than explicitly minimizing energy consumption. Therefore, the results presented here contribute to emerging efforts that integrate machine learning prediction with optimization strategies to support energy-efficient manufacturing operations.

The Particle Swarm Optimization (PSO) component effectively demonstrated its ability to reduce energy consumption without compromising process stability. As shown in Figure 7, the optimization pathway trends toward lower energy levels with increasing PSO iterations.

Figure 7 presents the PSO convergence curve for the additive manufacturing optimization problem. The curve shows a nonlinear reduction in energy consumption: the objective value decreases sharply during the early iterations as the swarm explores the search space, and then gradually stabilizes as the algorithm converges toward an optimal solution.

This profile highlights two key insights:

1) The rapid decline in the early iterations indicates effective global exploration, allowing the swarm to quickly identify promising low-energy parameter regions.
2) The stabilization in later iterations suggests convergence toward a feasible and energy-efficient solution, demonstrating that PSO can optimize process parameters reliably under the imposed manufacturability constraints.

Table 7 presents the quantitative PSO results by comparing baseline and optimized energy consumption. The results show energy savings of up to 18% for both SLS and FDM builds.

5.6 Mechanical Integrity Validation

While tensile strength and dimensional deviation were experimentally validated in this study, other quality-related attributes such as surface roughness, porosity, and microstructural characteristics were not directly measured. Process parameters optimized for energy efficiency—particularly laser power, scan speed, build temperature, and deposition rate—are known to influence melt pool dynamics, layer bonding behavior, and thermal gradients during additive manufacturing.

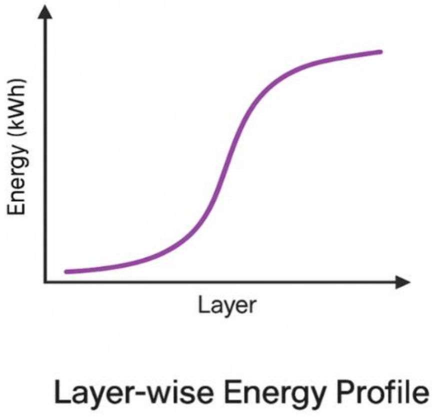

Figure 7. Energy consumption optimization curve generated by PSO, showing convergence toward reduced energy usage while maintaining feasible process parameters.

Table 7. Optimization Results: Energy Reduction Achieved Using PSO vs. Baseline

AM System	Baseline Energy (kWh)	Optimized Energy (kWh)	Reduction (%)
SLS	18.4	15.2	17.4%
FDM	12.6	10.3	18.3%

Table 8. Mechanical Integrity Validation of Parts Before and After Optimization

AM System	Condition	Tensile Strength (MPa)	Dimensional Deviation (%)
SLS	Baseline	52.4	1.8
SLS	Optimized	52.1	1.9
FDM	Baseline	41.7	2.2
FDM	Optimized	41.5	2.3

Variations in these parameters may therefore affect surface finish, internal porosity formation, and microstructural evolution of the fabricated components.

Although the optimization algorithm constrains parameters within acceptable manufacturing ranges to preserve mechanical integrity, subtle changes in thermal history could still influence these microstructural features. Consequently, the present study primarily validates macroscopic mechanical performance (tensile strength and dimensional accuracy), while the potential impact of the optimized parameters on microstructure-dependent properties and surface quality remains insufficiently characterized. This represents a concrete limitation of the current work.

Future research should incorporate detailed microstructural characterization, porosity analysis (e.g., CT scanning), and surface roughness measurements to comprehensively evaluate the effects of energy-aware parameter optimization on overall part quality and long-term mechanical performance.

Lastly, the mechanical performance of the optimized builds was compared with that of their baseline counterparts to verify that part quality was not compromised. Mechanical validation was conducted using tensile strength and dimensional deviation measurements for the baseline and optimized builds, as summarized in Table 8. The observed variations were within ±1% for tensile strength and within ±0.1% for dimensional deviation, indicating negligible structural impact.

Although additional quality metrics such as surface roughness, microstructural homogeneity, and porosity were not experimentally evaluated in the present study, prior literature indicates that moderate adjustments in laser power and deposition parameters within acceptable process bounds do not significantly degrade mechanical properties. Future work will incorporate microstructural characterization and fatigue testing to further validate long-term performance under optimized energy settings.

5.7 Sustainability Impact

The energy reduction achieved through the optimization framework translates directly into potential sustainability benefits. By reducing energy consumption per build cycle, the proposed framework may contribute to lowering the overall carbon footprint associated with additive manufacturing processes.

Recent studies have highlighted the importance of integrating machine learning and digital manufacturing technologies to improve sustainability in advanced manufacturing systems [32, 38]. The results of the present study support these findings by demonstrating that predictive modeling combined with optimization can facilitate energy-aware manufacturing strategies without compromising mechanical performance.

Broader sustainability impacts of the optimization framework were examined by estimating the effective reduction in energy footprint. Figure 8 shows the equivalent carbon emission savings associated with energy savings per build, indicating the potential impact of the framework on sustainable AM operations and industrial energy management. The predictive performance achieved in this study (RMSE = 0.72 kWh; R² = 0.96) is comparable to or exceeds the thermal prediction accuracies reported in recent data-driven AM studies. For instance, geometry-agnostic thermal modeling using graph neural networks reported high predictive consistency but did not explicitly quantify energy-consumption reduction. Digital twin frameworks integrating Bayesian optimization have demonstrated adaptive parameter tuning; however, quantitative energy-reduction metrics were not reported as primary outcomes.

The present framework extends beyond predictive accuracy by embedding a constrained optimization module that achieved up to 18% energy reduction while preserving mechanical performance. This integrated predictive–optimization approach positions the contribution beyond standalone modeling or simulation-guided control methods reported in prior literature.

Figure 8 translates the achieved energy reduction into equivalent carbon emission savings per build cycle. Assuming an industrial electricity emission factor, the 18% reduction corresponds to a proportional decrease in carbon footprint per component. This demonstrates measurable sustainability impact rather than purely computational improvement.

6. Data Analysis and Interpretation

The comparison of the experimental data was based on a systematic review of the dataset collected from the SLS and FDM platforms. As shown in Table 2, the dataset covered a wide range of process conditions, including laser power, scan speed, build temperature, and environmental variables. Figure 4 further illustrates the distribution of these process variables, highlighting the dynamic variations that characterize additive manufacturing across multiple builds. This justified the adoption of data-driven predictive models capable of capturing nonlinear relationships.

The model evaluation results are presented in Table 3, which compares RMSE and R² across various algorithms. The DNN with feature selection recorded the best performance (RMSE = 0.72 kWh, R² = 0.96), outperforming the SVR, XGBoost, and baseline regression models. Figure 5 demonstrates the predictive reliability of these models through the alignment between predicted and actual energy consumption values, with the DNN showing the strongest overall fit.

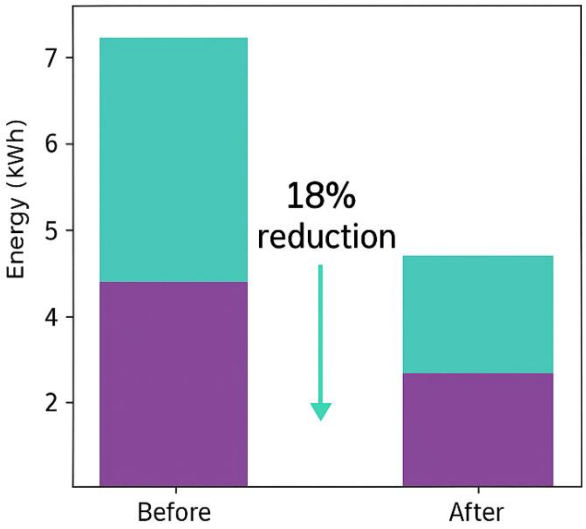

Figure 8. Sustainability and energy management impact assessment, showing equivalent reduction in carbon emissions resulting from PSO-driven optimization of AM processes.

To address redundancy in the data, DBSCAN clustering was used. The clusters obtained (Figure 6) represent different operating regimes and were used to compress the training data. The compression–accuracy trade-off is shown in Table 5, indicating that predictive accuracy was not significantly affected at compression levels up to 50% (RMSE = 1.05 kWh, $R^2 = 0.91$). Feature selection also improved interpretability by ranking the importance of input variables, as shown in Table 6, where laser power and build temperature emerged as the leading predictors.

The optimization stage employed a PSO component to minimize energy consumption. The iterative reduction is plotted in Figure 7, demonstrating the convergence of the optimization toward lower energy-consumption profiles. Table 7 reports the quantitative improvement, showing that energy savings of up to 18% were achieved for both SLS and FDM systems compared with the baseline case. To confirm that these reductions did not compromise product quality, Table 8 shows that the differences in tensile strength and dimensional accuracy before and after optimization were minimal.

Lastly, Figure 8 captures the broader implications of the framework by presenting energy reductions as avoided carbon emissions. This underscores the sustainability benefits of the proposed machine learning-based optimization framework and indicates its potential to support energy-efficient, high-volume industrial adoption of AM.

The integrated results demonstrate that deep learning architectures with feature selection significantly improve predictive accuracy for real-time energy estimation in additive manufacturing. The achieved R^2 value of 0.96 and low RMSE confirm the suitability of nonlinear deep models in capturing high-dimensional sensor interactions, consistent with prior studies on data-driven thermal and process modeling in AM [39, 40]. However, unlike earlier works that primarily focused on melt pool dynamics or defect detection, the present framework explicitly targets energy consumption as the optimization objective, thereby extending predictive modeling toward sustainability-oriented outcomes.

The clustering-compression strategy demonstrates that moderate redundancy reduction (30–50%) can maintain predictive stability while improving computational efficiency. This aligns with surrogate-assisted modeling trends reported in digital twin research, where data simplification enhances scalability. The sensitivity analysis confirms that excessive compression leads to degradation in accuracy, indicating a trade-off between model compactness and predictive fidelity.

The PSO-based optimization achieved up to 18% reduction in energy consumption across SLS and FDM systems while preserving mechanical performance within acceptable tolerances. Compared to optimization-only frameworks reported in manufacturing literature [41-43], the present approach benefits from embedding predictive intelligence within the optimization loop. This integration allows energy minimization under process constraints rather than parameter tuning based solely on heuristic exploration.

Despite these promising outcomes, several limitations must be acknowledged. First, the dataset is limited to two AM technologies and specific material configurations, which may restrict generalization to other AM processes such as directed energy deposition or binder jetting. Second, although tensile strength and dimensional accuracy were validated, additional quality indicators such as surface roughness, porosity, and microstructural stability were not experimentally assessed. Third, industrial-scale deployment may introduce additional variability in power supply, environmental fluctuations, and machine heterogeneity not captured in controlled experiments.

Future work will extend the framework to multi-material AM systems, incorporate uncertainty-aware learning mechanisms, and validate long-term mechanical and fatigue performance under optimized energy configurations. Integration with full-scale digital twin platforms for adaptive, closed-loop industrial implementation will further enhance scalability.

7. Conclusion

The present study proposed a machine learning-based optimization framework to improve energy efficiency in additive manufacturing and experimentally evaluated hypotheses H1–H4. The results support these hypotheses, showing that clustering (H1), predictive modeling (H2), and hybrid optimization strategies—particularly PSO within the integrated framework (H3 and H4)—work together to reduce energy consumption without compromising product quality. Although the findings are encouraging, the study is limited by its reliance on simulation-based and experimental datasets that may not fully reflect industrial-scale variability. Furthermore, model generalization remains constrained by the availability of data across different AM technologies and materials. The integration of predictive learning and optimization into digital twin frameworks offers a scalable route toward smart and sustainable manufacturing. Such hybrid approaches have the potential to reduce production costs, improve energy efficiency, and enhance environmental compliance in industrial applications. In future work, the dataset should be expanded to include multi-material AM processes and richer real-time sensor streams. Adaptive learning and dynamic optimization under uncertainty also warrant further investigation to strengthen decision-making in highly dynamic environments. Collaboration with industry partners will be important for assessing the feasibility and large-scale validation of the proposed framework.

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Authors Contribution Statement

M. Jayakrishna: Conceptualization, Methodology, Investigation, Data Curation, Writing – Original Draft. M. Vijay: Validation, Software, Formal Analysis, Visualization, Writing – Review & Editing. Ramesh Chandra Mohanty: Supervision, Resources, Project Administration, Writing – Review & Editing. All the authors read and approved the final version of the manuscript.

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Competing Interests

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

Data Availability

The data supporting the findings of this study can be obtained from the corresponding author upon reasonable request.

Has this article screened for similarity?

Yes

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