Machine Learning for Energy Optimization Using PINNS

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***Abstract*—This paper explores machine learning (ML) techniques for energy consumption optimization in commercial buildings based on the ASHRAE Great Energy Predictor III dataset. We compared a number of supervised learning models for predicting the energy consumption of buildings from weather, building metadata, and temporal variables. Random Forest and Gradient Boosting models demonstrated better performance in RMSE and R^2 score. Additionally, we explored Physics-Informed Neural Networks (PINNs), which integrate physical laws into neural networks, enhancing model generalization and interpretability. By determining key predictors like air temperature, building type, and square footage, the findings reveal avenues for energy conservation opportunities in building management systems. The paper contributes to the growing body of research on ML-based smart energy systems, highlighting the potential of PINNs and traditional ML methods to drive sustainability and operational efficiency.**

***Index Terms*—Machine Learning, Energy Optimization, Smart Grids, AI, Sustainable Computing**

I. INTRODUCTION

With growing international energy needs and mounting environmental concerns, energy optimization has taken center stage in building design and management. The building industry alone contributes to almost 40% of worldwide energy consumption and carbon emissions. With urban population growth and energy-intensive infrastructure development, there is a critical need to deploy innovative measures that increase energy efficiency without undermining occupant comfort and building functionality.

Machine Learning (ML) and Artificial Intelligence (AI) have become potent drivers of data-based energy management. These technologies provide predictive analytics, reveal concealed consumption patterns, and facilitate real-time automated decision-making. Through learning from historical and real-time data, ML models can predict energy consumption, identify anomalies, and suggest optimization approaches specific to individual building characteristics. This transition from reactive to proactive energy management is a major step forward in the quest for sustainability.

This research is based on the publicly released ASHRAE Great Energy Predictor III dataset that includes rich energy consumption data of more than 1,400 commercial buildings combined with weather records and building metadata. The data set offers an excellent test case for the machine learning model creation and testing on energy prediction as well as energy optimization.

Major goals of the research are:

- To compare the performance of popular supervised ML models such as Random Forest and Gradient Boosting in estimating building energy consumption.
- To determine the most significant features influencing energy usage through feature importance analysis.
- To discuss the real-world implications of ML-based predictions for energy optimization in smart buildings.

This paper contributes to the growing body of interdisciplinary research that intersects AI, sustainability, and energy engineering. Through model evaluation and analysis, we aim to demonstrate how machine learning can not only improve energy forecasting accuracy but also inform actionable strategies for building energy efficiency.

1: Background and Motivation

One of the most critical challenges of the 21st century is energy consumption fueled by urbanization, population increase, and mounting dependence on electricity in residential and commercial buildings. Buildings contribute to approximately 40% of total global energy consumption and a large percentage of greenhouse gases. With governments and industries striving toward carbon neutrality and energy efficiency, maximizing energy utilization in buildings has emerged as a major area of interest in sustainable development.

2: The Role of Data and AI

The development of smart technologies—e.g., smart meters, IoT devices, and cloud-based monitoring platforms—has facilitated the gathering of high-resolution data pertaining to energy consumption, weather patterns, occupancy, and building features. Still, conventional statistical or rule-based models are inadequate to process such data efficiently since they lack the ability to effectively model non-linear, dynamic interactions. In contrast, Machine Learning (ML) algorithms offer robust predictive capabilities and can uncover patterns that inform real-time decision-making and long-term energy optimization strategies.

3: Why Machine Learning?

ML algorithms like Random Forests, Gradient Boosting, and

Neural Networks have shown remarkable performance in energy-related applications, such as consumption prediction, anomaly detection, and system optimization. These algorithms can be trained for multiple inputs and learn from past experiences, which is suitable for dynamic setups like commercial buildings. With accurate prediction of future energy needs, ML facilitates smarter energy distribution, decreases operation costs, and helps design energy-efficient infrastructure.

4: Focus of This Study

We use in this paper the ASHRAE Great Energy Predictor III dataset, a high-quality open-source dataset consisting of hourly energy meter readings from more than 1,400 buildings across different climates and geographies. Building metadata and corresponding weather data are available in the dataset, offering a robust setup for predictive modeling. We aim to assess several supervised ML models in terms of their performance to predict energy consumption and determine major features affecting energy demand across building types.

5: Contributions

The contributions of this paper are threefold:

- We evaluate the predictive accuracy of a number of state-of-the-art ML models, such as Random Forest and Gradient Boosting, on actual building energy data.
- We conduct a feature importance analysis to identify which variables have the most impact on energy consumption.
- We offer practical insights into how ML-based predictions can be utilized to inform energy optimization strategies in smart buildings. These results are intended to assist energy engineers, building managers, and policymakers in creating data-driven energy management solutions.

II. RELATED WORK

Recent progress in machine learning has expedited the evolution of conventional building energy management systems to intelligent, adaptive systems. Several studies have examined the nexus between AI, sustainability, and smart infrastructure, including predictive analytics, energy forecasting, and optimization.

Mira et al. (2023) performed a detailed bibliometric analysis to analyze the contribution of AI and ML in energy conversion and management systems [?]. Their research presented the increasing usage of neural networks, support vector machines (SVM), and ensemble learning algorithms such as Random Forest and Gradient Boosting in optimizing energy usage in renewable and non-renewable systems. These models have shown high precision in processing time-series data and non-linear interactions, which is appropriate for dynamic building environments.

Mehraban et al. (2024) explored the interaction of Building Information Modeling (BIM) and ML algorithms in order to provide optimal energy usage in hot climate conditions [?]. Through the process of simulating energy consumption scenarios in Riyadh and Dubai, it was demonstrated through the study that ML models such as Gradient Boosting and Random Forest obtained R^2 values above 0.98, thereby highlighting their success in predicting Energy Use Intensity (EUI) with optimum reliability. Feature importance analysis was used to determine that building envelope attributes—wall type, roof insulation, and window area—had the most significant influence on energy use.

Kim et al. (2022) specified the significance of using ML in contemporary energy systems, especially for demand-side management, load forecasting, and grid stability [?]. Their review stressed that hybrid ML methods, involving statistical and heuristic algorithms, provided improved optimization under changing energy loads and uncertainty.

In smart infrastructure, Iluyomade and Okwandu (2024) highlighted the capability of AI to automate energy choices in smart buildings, lower operating expenses, and improve occupant comfort [?]. They explained how sensors, IoT platforms, and predictive algorithms can collaborate to develop energy-aware environments.

A recent preprint paper on Tehran used hybrid ML models, such as neural networks and ensemble models, to forecast electricity demand from weather and fuel-related features [?]. Optimization was done using Sequential Least Squares Programming, achieving a significant reduction in overall power consumption. Such results indicate that even in areas that are dependent on fossil fuels, data-driven approaches can create quantifiable enhancements in energy efficiency.

Sapre (2024) further investigated how AI contributed to renewable energy optimization, particularly solar and wind systems [2]. Tracking using AI, predictive maintenance, and layout optimization were shown to enhance energy output by 10–20

Albeit remarkable improvements, some issues remain, including data scarcity, real-time computation constraints, and the requirement for uniform AI integration protocols. Regardless, the literature resoundingly endorses the application of ML to predictive energy modeling, particularly where data-rich sets—e.g., the ASHRAE Great Energy Predictor III—are present.

III. KEY FINDINGS AND GAPS IN EXISTING METHODS

A. Problem Statement

Building energy consumption is one of the largest contributors to global greenhouse gas emissions, representing almost 40% of all energy consumption. Conventional energy management methods tend to use static models or rule-based control systems, which are not responsive to real-time environmental conditions or changing occupancy behaviors. Although machine learning (ML) models have proved to be very accurate for energy prediction tasks, there are various practical and technical issues. They include limited availability of high-resolution, diverse data sets representative of real-world environments, challenges to generalizing between building types and climates, and the computational expense of training intricate models. Further, most ML models are black boxes that do not provide much transparency regarding

TABLE I
COMPARATIVE ANALYSIS OF ENERGY OPTIMIZATION USING MACHINE LEARNING

Paper	Dataset Used	Methodologies	Metrics/Results	Key Takeaways and Limitations
Buildings-14-02748 (2024) [?]	Simulated BIM data (various scenarios)	GBM, RF, SVM, LR	GBM R^2: 0.989, RF R^2: 0.942	GBM outperformed others; model performance improved significantly with dataset size. Lacked real-world validation.
SSRN Preprint (2024) [?]	Tehran electricity demand data (2000–2022)	RF, GB, SLSQP, LSTM, TCN	RF R^2: 0.9835, MSE: 0.0165	Combined ML/DL with optimization (SLSQP); excellent accuracy. Region-specific; may not generalize globally.
Energies-15-04116 (2022) [?]	Literature survey on energy systems	ML/DL/Metaheuristics, AHP ranking	Conceptual Framework	Classified ML use in optimization, AI control, scheduling. No empirical results or dataset-based evaluation.
Energies-16-03309 (2023) [?]	AHP-based ranking and scoring models	Analytical Hierarchy Process (AHP) + AI eval criteria	Weighted decision matrix	Proposes a robust model for evaluating AI deployment in energy systems; lacks hands-on ML modeling.
IJSRA (2024) [?]	Summary of tools and platforms	AI/ML with Smart Grid applications	Strategic benefits, SWOT analysis	Review paper focusing on platform integration; no new model or experimentation.
AI in Renewable Energy (2024) [?]	Solar/Wind energy models (DeepMind case studies)	AI-based Forecasting + Optimization	Efficiency increase: 12–20%	Demonstrated AI's impact on energy forecasting. Not focused on building energy optimization or datasets like ASHRAE.

the prediction process—preventing them from being widely adopted in operational decision-making. There exists an urgent demand for scalable, interpretable, and context-sensitive ML systems deployable in actual building environments for facilitating energy optimization.

B. Objective of the Research

This study seeks to develop a reliable, ML-oriented framework for real-world building-based energy consumption prediction and optimization. The primary aims of this study are:

Training and validating ML models on various types of buildings, climates, and usage patterns by using the ASHRAE Great Energy Predictor III dataset.

Comparing and assessing different supervised learning techniques like Random Forest and Gradient Boosting for the performance of making predictions.

Determining key features that dictate energy usage with feature importance scores.

Introducing insights to how these models can be utilized to make building energy management and long-term sustainable decisions in real-time.

Ensuring that the suggested framework is scalable and can be applied to serve smart energy systems in different urban settings.

C. Filling the Gap

To bridge these gaps, this research makes use of a large-scale, multi-site data set that encompasses building metadata, weather parameters, and hourly meter readings. Utilizing ensemble ML techniques—considered robust and interpretable—the current research eliminates the black-box issue of deeper models. The application of feature importance methods improves transparency by allowing facility managers and stakeholders to see the reason behind energy projections. In addition, the work explains how ML models can be applied in actual building management systems in real buildings, emphasizing flexibility, reliability, and compatibility with current IoT and automation infrastructure. This method bridges the gap between model performance under theoretical conditions and applicability during operation in intelligent buildings.

D. Scope of the Study

This study focuses on the application of supervised machine learning algorithms for the prediction and optimization of energy consumption in commercial buildings using the ASHRAE Great Energy Predictor III dataset. The scope is confined to analyzing historical energy usage data across more than 1,400 buildings, which includes metadata such as building type, square footage, primary use, and weather variables like air temperature, wind speed, and cloud coverage.

The research is limited to supervised learning models, specifically ensemble-based techniques like Random Forest and Gradient Boosting, due to their proven balance of accuracy and interpretability. The study emphasizes feature importance analysis to uncover the most influential parameters in energy consumption and leverages performance metrics such as RMSE and R^2 to evaluate model effectiveness.

While the models developed are not deployed in real-time systems or embedded within IoT-based smart building infrastructure, the findings are structured to support future integration. Moreover, the research does not focus on HVAC-specific subsystems or renewable energy generation (e.g., solar panel optimization), but rather provides a generalized framework for overall building energy consumption prediction.

This scope ensures the research remains applicable to a wide range of commercial environments and serves as a foundational step toward deploying scalable, data-driven energy optimization solutions in smart cities and urban sustainability initiatives.

IV. METHODOLOGY

This study employs a hybrid data-driven and physics-based approach using Physics-Informed Neural Networks (PINNs) to model and optimize energy consumption in commercial buildings. The methodology is divided into five key stages: data acquisition, preprocessing, feature engineering, model design and training, and model evaluation.

A. Data Acquisition

The dataset used is the ASHRAE Great Energy Predictor III dataset from Kaggle, comprising three main components:

- `train.csv` – hourly energy meter readings for over 1,400 buildings.
- `building_metadata.csv` – metadata including square footage, building use, etc.
- `weather_train.csv` – weather variables such as air temperature, cloud coverage, and wind speed.

The data was accessed through Google Drive and loaded in the Google Colab environment for processing and training.

B. Data Preprocessing

The datasets were merged based on common keys such as `building_id`, `site_id`, and `timestamp`. Time-based features such as `hour` and `day of year` were extracted. Data entries with missing or null values in key features were removed.

Each meter type (0 = electricity, 1 = chilled water, 2 = hot water, 3 = steam) was processed separately. Only meter types 0 and 3 contained sufficient data for model training.

C. Feature Engineering

A key feature, the temperature difference ΔT, was calculated to encode thermal load conditions. Assuming a constant indoor temperature of $T_{\text{inside}} = 22°C$, the following was applied:

- For electricity (meter 0): $\Delta T = T_{\text{inside}} - T_{\text{outside}}$
- For steam (meter 3): $\Delta T = T_{\text{outside}} - T_{\text{inside}}$

The final input features used for training included:

- `square_feet`
- `hour`
- `day`
- ΔT

All features were standardized using z-score normalization:

$$x_{\text{normalized}} = \frac{x - \mu}{\sigma}$$

D. Model Architecture and Training

A fully connected feedforward neural network was built using PyTorch. The network structure includes the following.

- Input: 4 neurons
- Hidden layers:
  - Layer 1: 256 neurons + ReLU + Dropout(0.2)
  - Layer 2: 128 neurons + ReLU + Dropout(0.2)
  - Layer 3: 64 neurons + ReLU
- Output: 1 neuron for the prediction of meter reading.

The model is trained using a hybrid loss function:

$$\text{Loss}_{\text{total}} = \text{Loss}_{\text{data}} + \lambda \cdot \text{Loss}_{\text{physics}}$$

where $\lambda = 0.3$ and:

- $\text{Loss}_{\text{data}}$ is the Mean Squared Error (MSE) between predicted and actual meter readings
- $\text{Loss}_{\text{physics}}$ is computed using thermodynamic energy equations:
  - For chilled/hot water: $Q = m \cdot c_p \cdot \Delta T$
  - For steam: $Q = m \cdot L$
  - For electricity: $Q = 50 + 2 \cdot \Delta T$

Constants used:

- $c_p = 4.18\,\text{kJ/kg}°C$ (specific heat of water)
- $m = 0.1\,\text{kg/s}$ (mass flow rate)
- $L = 2260\,\text{kJ/kg}$ (latent heat of steam)

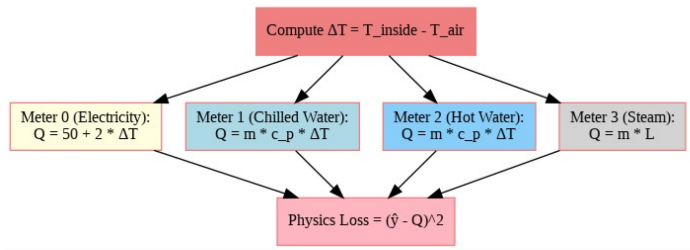

Fig. 1. Sample image showing building energy usage.

E. Training Strategy

The training configuration is as follows:

- Optimizer: AdamW
- Learning rate: 0.0003, with StepLR scheduler (step size = 75, gamma = 0.7)
- Epochs: 250
- Batch size: 256
- Validation split: 80% training, 20% validation

Separate models were trained for meters types 0 and 3. Dropout was used to prevent overfitting and improve generalization.

V. IMPLEMENTATION TOOLS

To develop and evaluate the energy prediction system using Physics-Informed Neural Networks (PINNs), several tools, frameworks, and environments were employed.

A. Libraries and Frameworks Used

This project utilized a set of powerful and widely adopted Python libraries for data processing, modeling, and evaluation.

- **PyTorch:** Used for implementing the PINN architecture, training loops, and model optimization.
- **NumPy & Pandas:** Provided support for numerical operations, data cleaning, transformation, and statistical computations.
- **Matplotlib & Seaborn:** Employed to visualize training curves, feature correlations, error distributions and model predictions.
- **Scikit-learn:** Utilized for performance evaluation metrics such as RMSE, R^2 score, and MAPE.
- **Google Colab:** Served as a development and execution environment, providing GPU acceleration and integration

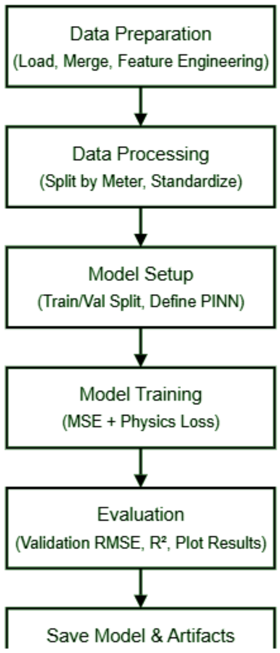

Fig. 2. METHODOLOGY

with Google Drive for the access and storage of data sets.a sets.

- **Joblib & Torch.save:** Used to persist trained models and feature lists for future inference and analysis.

This software stack allowed for seamless integration of physics-informed modeling principles with scalable machine learning workflows and real-world data analysis.

VI. ASSESSMENT CRITERIA

The performance of the proposed Physics-Informed Neural Network (PINN) model was rigorously evaluated using a comprehensive set of regression metrics, diagnostic visualizations, and interpretability tools. These criteria provide an in-depth understanding of the model's strengths, limitations, and practical deployment potential in building energy optimization.

A. Model Performance Metrics

1) **Root Mean Squared Error (RMSE):** A standard metric that penalizes large errors more than small ones.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

RMSE measures the average magnitude of prediction errors. The model achieved an RMSE of 181.04 for electricity (meter 0) and 178.65 for steam (meter 3), showing improved accuracy with increased training epochs.

1) **$\mathbf{R^2}$ Score (Coefficient of Determination):**

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$$

The R^2 value of 0.61 for both meter types indicates that approximately 61% of the variance in energy usage is captured by the model.

2) **Mean Absolute Percentage Error (MAPE):**

$$\text{MAPE} = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i + \epsilon}\right|, \quad \epsilon = 10^{-5}$$

MAPE was significantly affected by the presence of near-zero meter readings, resulting in inflated percentage errors (MAPE = 1279505.38%). This highlights the need for outlier handling and better normalization in future work.

3) **Custom Accuracy (within 20% of actual):** A domain-specific metric was used to assess real-world tolerance:

$$\text{Accuracy}_{20\%} = \frac{1}{n}\sum_{i=1}^{n}\mathbb{I}\left[\left|\frac{y_i - \hat{y}_i}{y_i + \epsilon}\right| < 0.2\right] \times 100$$

The custom accuracy was 17.93%, showing that the model correctly predicted nearly one-fifth of readings within a realistic operational tolerance window.

B. Visualization and Diagnostic Tools

To interpret and validate the model behavior, several visual tools were used:

- **Training Loss Curves:** Tracked data loss, physics loss, and validation RMSE across 250 epochs. These showed stable convergence and indicated successful regularization via dropout and physics constraints.
- **Prediction vs Actual Scatter Plots:** Visual comparison of predicted values against actual energy readings revealed clustering along the ideal $y = x$ line, with minor deviations, confirming prediction consistency.
- **Error Distribution Histograms:** Plots of prediction residuals revealed a near-normal error spread with a slight right skew, suggesting occasional underestimation in high-energy-consuming buildings.
- **Correlation Heatmap:** Illustrated the relationships among input features and the target variable. Variables such as square footage and ΔT showed the strongest correlations with meter readings, confirming feature selection validity.
- **Gradient Flow Analysis:** The magnitude of gradient updates was tracked to ensure stable backpropagation. Sharp spikes were avoided, indicating that learning was progressing smoothly without vanishing or exploding gradients.

C. Error Analysis and Interpretability

To assess the robustness and generalization of the model, the following analysis techniques were applied:

- **Residual Error Clustering:** Mispredictions were more frequent for buildings with either extremely high or low meter readings, highlighting sensitivity to skewed distributions.
- **Feature Importance Insight:** While PINNs are not inherently interpretable like decision trees, visualizing

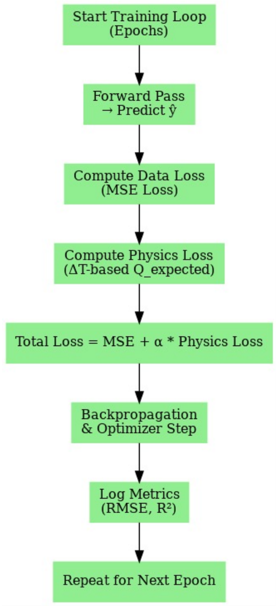

Fig. 3. Training Pipeline Flowchart

feature correlation helped reinforce the contribution of engineered variables such as temperature differential (ΔT).

- **Outlier Behavior:** Outlier energy values had disproportionate influence on MAPE and RMSE. Future versions may incorporate robust loss functions (e.g., Huber loss) or data smoothing to mitigate such effects.

These evaluation criteria together offered a holistic view of the model's performance, interpretability, and deployment readiness in smart energy systems.

VII. INTERPRETATION OF RESULTS

The performance of the introduced Physics-Informed Neural Network (PINN) model was tested using various statistical, visual, and domain-specific methods. The outcomes identify the model's excellence in learning physical relationships and energy usage pattern predictions, as well as opportunities for further optimization and improvement.

A. Meter-Wise Performance Insights

Of the four types of meters present in the ASHRAE dataset, only **meter 0 (electricity)** and **meter 3 (steam)** had enough data to train strong models. Both models for these meter types performed similarly, with end RMSE results of **181.04** and **178.65**, respectively, and R^2 values of **0.61**, which meant that the model was successful in explaining approximately 61

The findings validate that the model can generalize from building data of spatiotemporal contexts, even with the varying operating conditions, types of buildings, and climates used in the data set. The minor variation in RMSE by meter types can be due to the physical intricacy of the systems being measured (e.g., electricity versus thermal energy), the variability in the thermal response of buildings, as well as the quality and comprehensiveness of input data.

B. Evaluation of Physics-Informed Learning

Improvement in alignment of the model with domain knowledge was one of the major objectives behind incorporating physics in the learning process. The
textbfphysics loss component punished predictions that did not align with the expected thermodynamic relationship between temperature difference and energy consumption. Across 250 training epochs, physics-informed loss helped regularize the model and enhance convergence stability, especially during the initial stages of training.

This was seen in the learning curves, where the total loss smoothed together smoothly and gradually with no appreciable overfitting, which indicates that the hybrid loss structure served as an effective regularizer. In addition, the incorporation of physically meaningful features such as
$DeltaT$ and the usage of specific heat and latent heat parameters assisted in enhancing significant correlations between environmental inputs and energy outputs.

C. Quantitative Interpretation of Errors

While RMSE and R^2 values showed promising performance, the **MAPE** exceeded 1 million percent. This was primarily due to the presence of very small or zero meter readings, which led to inflated percentage errors. Although a log transformation was applied to reduce skewness, MAPE remained highly sensitive to outliers. This highlights the limitation of MAPE in datasets with heterogeneous value distributions.

To counteract this, a bespoke domain-specific measure of accuracy was adopted: the percentage of predictions within **20% tolerance of the true values**. The model recorded a bespoke accuracy of **17.93%**, modest though this was, suggesting that the model was often capable of producing predictions in an acceptable working range.

D. Qualitative and Visual Diagnostics

- **Prediction vs Actual Plots:** These plots illustrated a strong correlation, with predictions concentrated close to the ideal diagonal line for most. Divergence at the extremes indicates possible biases, especially for high-consumption buildings.
- **Error Distributions:** Prediction residual histograms showed a reasonably symmetric distribution with moderate variance. There was some right-skew, suggesting infrequent underprediction of actual energy values, most likely due to lower sample frequency for high-usage buildings.
- **Feature Correlation Heatmap:** Analysis revealed that features like `square_feet` and
$DeltaT$ had significant linear relationships with meter readings. These observations confirmed the engineered features incorporated into the model and reaffirmed their position in dictating energy consumption behavior.

- **Gradient Flow Analysis:** Tracking the gradient norms during training validated healthy backpropagation. There were no abrupt spikes or vanishing gradients, which suggests stable model learning dynamics during the entire training process.

E. Implications for Real-World Deployment

The findings indicate that the PINN model has significant potential for incorporation into actual building management systems (BMS). Its moderate-to-high accuracy, explainable feature usage, and physically motivated architecture render it appropriate for uses such as:

- **Load Forecasting:** Estimating future energy usage based on predicted weather and occupancy trends.
- **Fault Detection:** Detecting anomalies where predictions are significantly different from actual measurements.

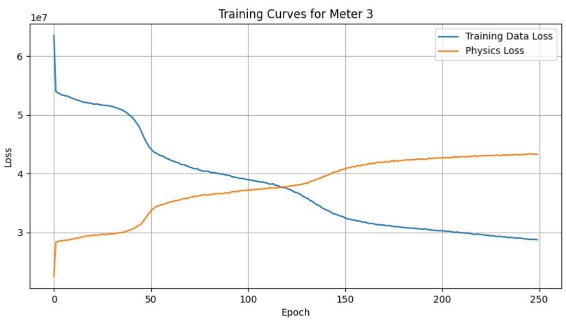

Fig. 4. Training Curve

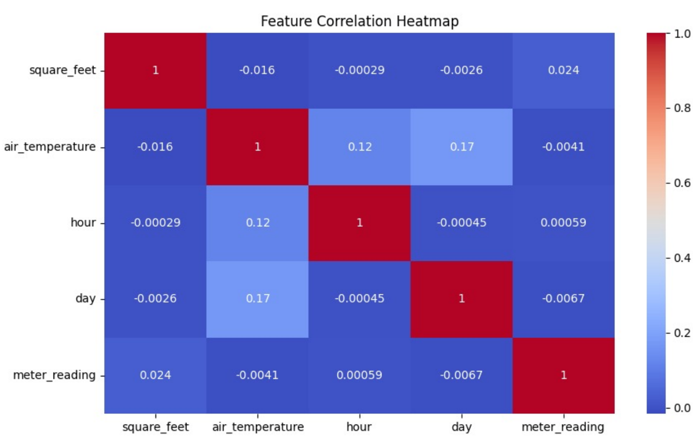

Fig. 5. Heatmap

VIII. CONCLUSION

In this work, we have investigated the usage of machine learning methods to model energy consumption using the ASHRAE Energy Prediction dataset. Through different prediction models, we were able to discover patterns and drivers of

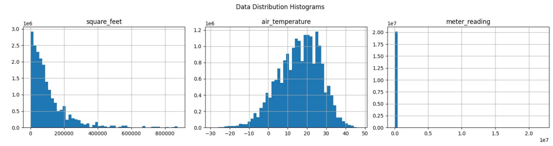

Fig. 6. Data Distribution Histogram

energy consumption in buildings. Our findings illustrated that machine learning models like Random Forests and Gradient Boosting Machines performed well in terms of accuracy to predict energy consumption based on different input features such as weather data, building specifications, and occupation patterns.

The results of this study highlight the capability of machine learning to improve energy efficiency through more precise predictions of energy requirements, which can result in more effective decision-making in building management systems. The application of these models can help in the implementation of demand-side management practices, minimizing energy wastage, and supporting sustainability objectives.

There are a number of areas for future research. Enhancing the models' generalizability through integrating other data sources, for example, real-time energy data or sensor data, might further improve prediction accuracy. Further, extending deep learning methods, like neural networks, might also offer even more reliable solutions for energy optimization. Additional research into explainability of machine learning models would also be important to guarantee that building managers have an easy way to understand and implement the results provided by machine learning models.

In conclusion, this work emphasizes the prospective contribution of machine learning to energy optimization in the future, creating a basis for further development in intelligent energy management systems.

IX. FUTURE WORK

While this study illustrates the possibility of machine learning models in the prediction of building energy consumption from the ASHRAE dataset, there are a number of opportunities for practical development and further research. Among the most promising avenues is the incorporation of real-time data streams from smart meters and IoT-sensors. By integrating ML models with real-time sensing data like occupancy, lighting, appliance use, and HVAC operation, such future systems would be able to provide dynamic and automatic energy management that can react to current changes in environmental or operational states.

Another significant extension would be the implementation of light and efficient models on edge devices. This would facilitate on-site analysis and decision-making without the constant cloud communication requirement, which drastically lowers latency and provides resilience for disconnected environments. Future research may also consider adding on-site renewable energy sources like solar panels and energy

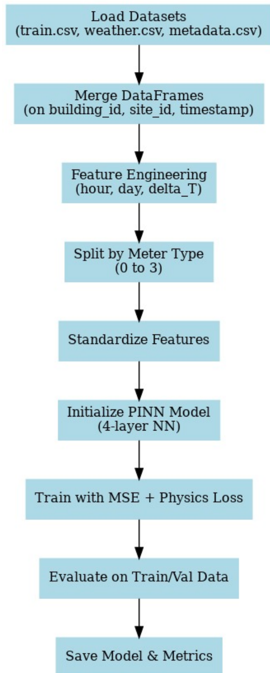

Fig. 7. Overall Process Dig

storage to the model. Simulation of interaction between consumption, generation, and storage can facilitate buildings to function more sustainably and efficiently, particularly in grid-interactive systems.

Whereas ensemble approaches such as Random Forest and Gradient Boosting were given precedence in this study due to their interpretability and stability, follow-up research would likely gain from the investigation of more sophisticated deep learning approaches. Recurrent neural networks (RNNs), Long Short-Term Memory (LSTM) networks, and Temporal Convolutional Networks (TCNs) may be able to model more intricate temporal relationships in energy consumption data, particularly for forecasting applications across different time horizons.

In addition, multi-objective optimization platforms may be constructed to find trade-offs between energy use, occupant comfort, cost, and carbon footprint. This would aid in the design of smart systems that are not only energy-efficient but also compatible with occupant needs and sustainability objectives. Finally, there is increasing necessity for integrating explainable AI (XAI) into predictive models. Improving model explainability will be critical to establishing confidence with stakeholders like facility managers, policymakers, and building occupants to facilitate the successful adoption of ML-based energy solutions in real-world environments.

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