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A Data-Driven Power Loss Pattern Recognition for Sustainable Energy Management

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ABSTRACT
Power loss remains a major challenge in smart grids (SGs), making accurate prediction models vital for sustainable energy management. This study employs deep neural networks (DNNs) to predict power loss using key attributes such as temperature, grid load, and environmental factors. Principal component analysis (PCA) identified grid temperature and load as the most influential variables, contributing 40.6% and 15.93% of the total variance, respectively, with selected features accounting for 76.28% overall. Comparative evaluation of DNN architectures showed that the 6-layer model outperformed configurations with fewer layers, achieving an R^2 of 94.5%, the lowest MSE (1.00E-03), RMSE (3.40E-02), and MAPE (4.83%). Although it required slightly longer processing time, its superior predictive accuracy justified its selection. Pearson correlation analysis revealed weak positive relationships between temperature, voltage, and power loss, while regional analysis demonstrated that rising temperatures increase consumption and losses. Overall, the results demonstrate that the proposed DNN-based approach provides a robust and data-driven solution for power loss prediction, supporting improved grid efficiency and sustainability, with future work focusing on real-time data integration and additional environmental factors.

Keywords
DNN, Activation Function, Smart Grid, Power Loss, Performance Metrics, Correlation

1. INTRODUCTION
Energy is a major driver of economic growth [27] and exists in many forms, including kinetic, thermal, chemical, electrical, nuclear, and hydraulic energy [15]. Understanding these forms and their conversions is crucial for efficient energy use and technological progress. This study focuses on electrical energy, which involves generation, transmission, substations, and distribution [14]. Distribution delivers power to consumers, but significant losses occur during transmission. To reduce these losses, utilities use methods like network reconfiguration and capacitor installation for reactive power support ([3], [23]). Machine Learning models are also applied to detect loss patterns and improve energy management [21].

Power loss is the difference between transmitted and received power [20] and is categorized as technical or non-technical. Technical losses result from equipment and conductor resistance, while non-technical losses stem from human error or theft [11] . Power flow analysis determines bus voltages, branch flows, consumption, and total losses [7]. Traditional Newton-Raphson methods can struggle with large datasets, motivating the use of Artificial Intelligence (AI). AI supports energy conversion, harvesting, planning, storage, and overall efficiency improvements [2]. AI integration with smart grids (SG) enables real-time, bidirectional communication and improved fault detection and system control ([10],[19]). AI enhances renewable energy reliability by improving forecasting for solar, wind, and hydro power, supporting decentralized systems, and reducing energy waste through monitoring and real-time recommendations. Predictive analytics also improves maintenance and reduces downtime.

As the energy sector decarbonizes, AI helps optimize consumption and reduce inefficiencies using data-driven techniques such as classification, regression, and unsupervised learning [29]. The large volumes of power system data create opportunities for new data-driven services [3]. Deep Neural Networks (DNNs) are effective for pattern detection and classification across many features. DNNs combined with Pearson correlation can optimize performance metrics such as MSE, RMSE, MAE, MAPE, and R^2. Sustainable energy management focuses on efficient energy use to reduce costs and improve competitiveness [6]. Reducing power loss improves efficiency, lowers fossil fuel reliance, cuts emissions, and supports renewable integration [1]. This study also aims to provide DNN activation function parameters that can be applied to various datasets for energy optimization using AI.

2. LITERATURE REVIEW
1. Conventional methods for identifying power loss in power systems
Power losses in electrical networks include technical and non-technical losses (NTLs), but traditional NTL detection methods such as onsite inspections and reward–penalty policies are inefficient and time-consuming in modern power systems [17]. Earlier approaches relied on manual audits, statistical analysis, and

theoretical loss calculations that lacked accuracy under real operating conditions [26]. Methods such as energy balance and load flow analysis improved system evaluation but were limited by outdated infrastructure and the absence of real-time data [8]. Although analog meters enhanced energy measurement, their inability to store detailed consumption data hindered loss identification and often resulted in estimated billing [18]. These limitations highlight the need for advanced, automated, and data-driven approaches for effective power loss management.

2. The role of SG and Advanced Metering Infrastructure in modern power loss detection

The advent of smart grids (SG) has transformed power systems by enabling multidirectional electricity and information flows, improving operational efficiency and environmental sustainability [5]. Unlike conventional grids with unidirectional power flow, SG support bidirectional communication between utilities and consumers, enabling real-time monitoring and control [16].Through the integration of Advanced Metering Infrastructure (AMI), smart grids provide continuous, granular data on energy consumption and losses across transmission and distribution networks [22].AMI’s two-way communication capability allows utilities to detect irregularities, analyze usage patterns, and improve power loss detection accuracy [19]. Additionally, SG facilitate the efficient integration of distributed energy resources such as solar and wind, adapting to variable generation and load conditions to minimize energy wastage and reduce both technical and non-technical losses ([24]; [12]).

3. Energy Management Systems and Power Loss Mitigation Strategies

Energy Management Systems (EMS) are critical tools in modern power systems for monitoring, controlling, and optimizing energy performance, playing a key role in reducing power losses and improving reliability [28]. Integrated with smart grids and Advanced Metering Infrastructure (AMI), EMS enable real-time data collection and analysis of energy consumption, generation, and distribution, allowing rapid identification of inefficiencies. Core EMS functions include load balancing, demand-side management (DSM), real-time monitoring, and forecasting, which help prevent circuit overloading and minimize technical losses [28]. Through DSM strategies such as smart metering and dynamic pricing, EMS encourage consumers to shift usage away from peak periods, reducing grid stress and energy wastage ([25],[13]). Additionally, EMS supports the integration of variable renewable energy sources by predicting generation and dynamically adjusting grid operations, thereby mitigating supply demand mismatches and enhancing overall system efficiency and sustainability.

3. MATERIAL AND METHODS

The dataset-driven analytical approach, depicted in Fig 1, progresses through the following sequence of activities:(i) Knowledge Base (ii) Rule Base (iii) Data Collection and Description (iv) Data Preprocessing, (v) Model Development, (vi) DNN Model construction (vii) Correlational Patterns (viii) DNN Power Loss pattern.

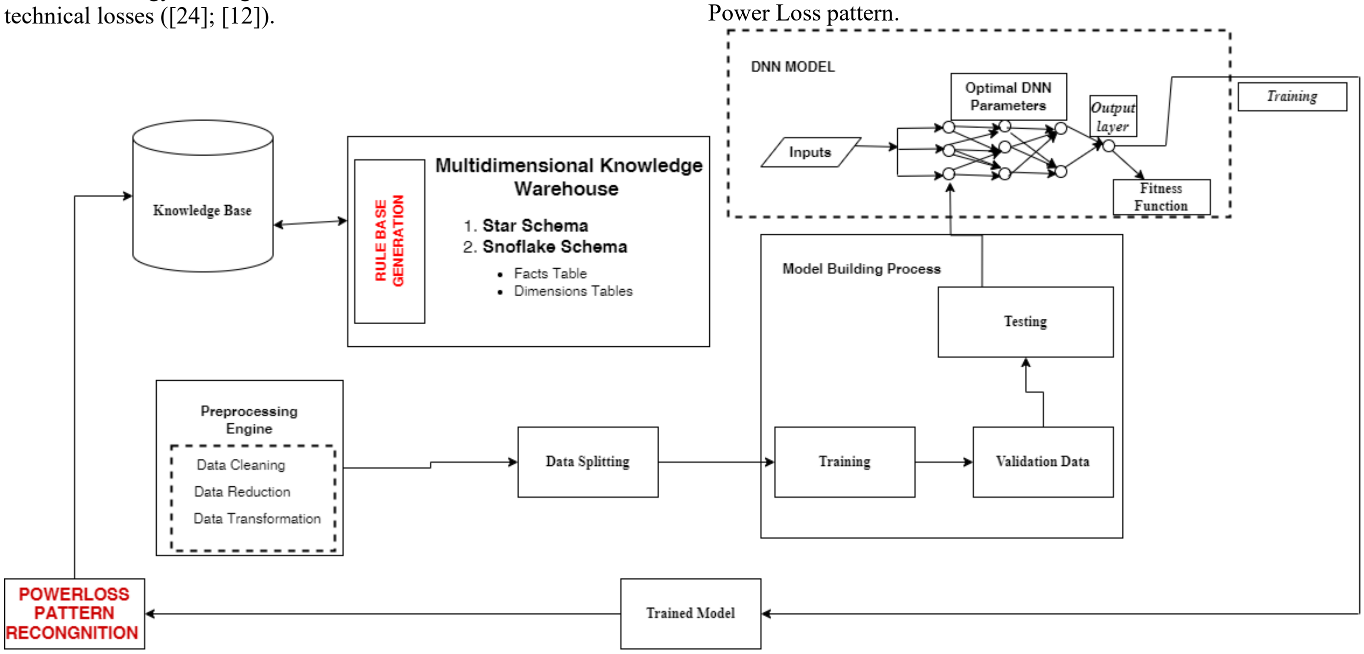

Fig 1: Dataset-Driven Analytic Workflow

In Fig 2, ‘n’ represents the neurons within the hidden layer, while n stands for the number of inputs, and ‘m’ pertains to the count of outputs. Additionally, the variables, x and P_L denote the input and output vectors of the Multi-Layer Perceptron (MLP). These components are linked by specific weights, represented by the vector ‘w_{11}^1 ……w_{mN}^1 ’. The term’ b_1^1 …. b_m^3 ‘denotes the bias vector associated with all neurons except those in the input layer. The inputs are derived from the smart grid profile like the load, temperature and they are represented as x_1 to x_n. The DNN consists of 2 – 6 hidden layers, generating one distinct output: P_L, which indicates power loss. The neural network operates in two main phases: training and testing. During the phase, the architecture depicted in Figure 2 is employed. where the backpropagation algorithm is used to iteratively adjust the network's internal weights for better performance. After training, the testing phase begins. In this stage, when the SG profile is fed into the network, it processes the information and predicts the power loss within the SG. This process enables the evaluation of power loss based on the input profile and the trained DNN model [9].

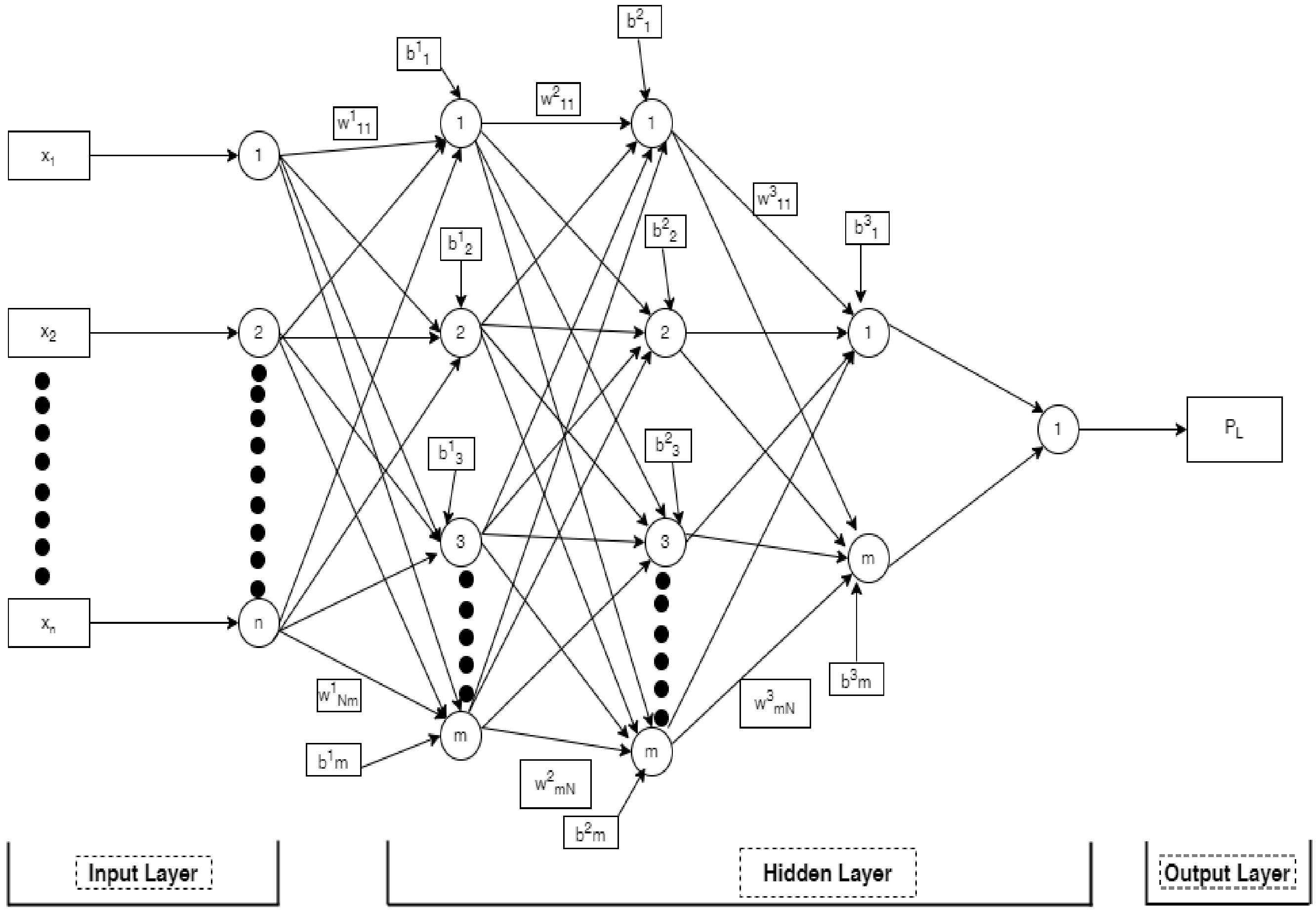

Fig 2: DNN model for SG Dataset-Driven analytics

4. EXPERIMENTAL ANALYTICS AND RESULTS

I. Data Collection and Description

The core of the data collection process focuses on gathering and preparing data from the smart grid source. This study utilizes one distinct dataset for model development, testing, and deployment to enable a comparative analysis in power loss pattern modeling. The dataset is:

a. ***Grid Loss Prediction Dataset***

Grid Loss Prediction Dataset: This dataset encapsulates historical information on power loss incidents within the smart grid. The detailed insights into the dataset are presented in Table 1. This consists of 4,118 rows and 4 columns, representing various features crucial for predicting power loss in a grid. The dataset contains no categorical features, but includes 3 numeric features. Table 2 provides a detailed description of these features: grid1-load (a float64 representing the load data for grid 1), grid1-loss (a float64 representing the power loss data for grid 1), grid1-temp (a float64 representing the temperature data for grid 1), and month_x (a float64 indicating the X-coordinate of the month component). This dataset serves as the foundation for modeling and predicting pattern in the grid power loss based on historical data.

Table 1: Description Statistics for Grid Loss Prediction Dataset

Dataset Name	Dataset Size		Features	
	Rows	Columns	Categorical	Numeric
Grid Loss Prediction	4118	4	0	3

Table 2: Data Description for Grid Loss Prediction Dataset

S/N	Feature/ Attribute	Data Type	Description
1	grid1-load	float64	Load data for grid 1
2	grid1-loss	float64	Power loss data for grid 1
3	grid1-temp	float64	Temperature data for grid 1
4	month_x	float64	X-coordinate of the month component

The key summary measures presented in Table 3 are employed to comprehensively characterize the fundamental properties of the dataset. The count provides a primary indication of the dataset size and confirms the completeness of observations across all variables. The mean (average) offers insight into the central tendency, representing the typical value around which the data points are distributed. The standard deviation measures the degree of dispersion or variability within the dataset, where higher values indicate a wider spread of observations from the mean, suggesting greater fluctuation in the variable. The minimum and maximum values define the lower and upper bounds of the dataset, respectively, thereby establishing the overall range and highlighting potential extremities in the observations. Furthermore, the percentiles (25%, 50%, and 75%) provide a more detailed understanding of the data distribution. The 25th percentile (first quartile) indicates the value below which 25% of the data falls, while the 75th percentile (third quartile) represents the value below which 75% of the observations lie. The 50th percentile, also known as the median, serves as a robust measure of central tendency, particularly in the presence of skewed data, as it divides the dataset into two equal halves.

Collectively, these descriptive statistical measures offer a comprehensive overview of the dataset by capturing its size, central tendency, spread, and distributional characteristics. This foundational understanding is essential for subsequent data preprocessing, feature selection, and model development, as it helps to identify patterns, detect anomalies, and ensure the reliability of the analytical process.

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Table 3: Descriptive Statistics of Grid Loss Prediction Dataset

Statistics	grid1-load	grid1-loss	grid1-temp	month_x
count	4118 .000	4118 .000	4118.000	4118.000
mean	0.528	0.521	0.365	0.643
std	0.181	0.155	0.130	0.358
min	0 .000	0 .000	0.000	0.000
25%	0.398	0.415	0.292	0.333
50%	0.528	0.509	0.358	0.910
75%	0.667	0.628	0.434	0.910
max	1 .000	1 .000	1.000	1.000

II. Data Preprocessing

To facilitate effective data preprocessing and dimensionality reduction, Table 4 and Fig. 3 present the eigenvalues and corresponding explained variance ratios derived from the Grid Loss Prediction dataset. These metrics provide insight into the relative contribution of each attribute to the total variance, thereby highlighting their importance in representing the underlying data structure. The results indicate that the grid-temp attribute possesses the highest eigenvalue (4.46), accounting for approximately 40.6% of the total variance. This suggests that temperature is the most dominant factor influencing variations in power loss within the grid system. Following this, the grid-load attribute contributes 15.93% of the variance with an eigenvalue of 1.75, underscoring its significant role in shaping system behavior and energy consumption patterns. The month_x attribute explains 10.64% of the variance (eigenvalue = 1.17), capturing seasonal or temporal variations that may affect load demand and grid performance. Similarly, the grid1-loss attribute contributes 9.11% of the variance with an eigenvalue of 1.00, reflecting its direct but comparatively smaller influence within the dataset's variability structure. Together, these four principal attributes account for approximately 76.28% of the total variance, indicating that a substantial proportion of the dataset's informational content can be effectively captured using a reduced feature set. This not only enhances computational efficiency but also improves model performance by eliminating redundant or less informative variables, thereby supporting more accurate and robust power loss prediction.

Table 4: Eigenvalues and Ratio of Explained Variance for Grid Loss Prediction Dataset

S/N	Attribute	Eigenvalue	Explained Proportion Ratio	proportion	Commutative
1	grid-temp	4.46	0.40	40.6	40.6
2	grid-load	1.75	0.15	15.93	56.53
3	month_x	1.17	0.10	10.64	67.17
4	grid1-loss	1.00	0.09	9.11	76.28
Total		8.39	0.76	76.28	240.58

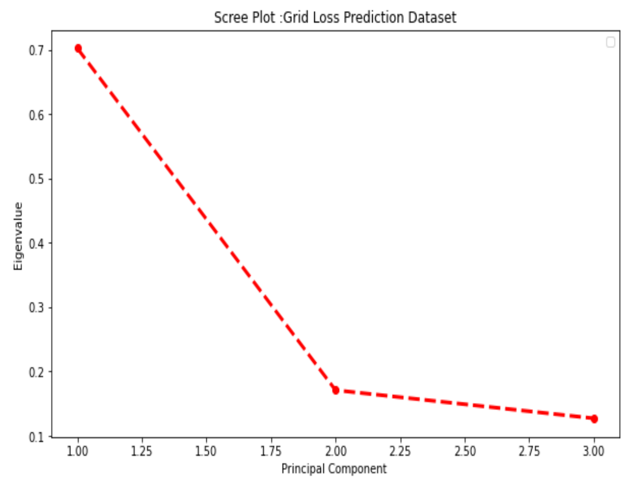

Fig 3: Eigenvalue Representation for Grid Loss Prediction Dataset

Table 5 and Fig. 4 present a comparative analysis of the performance metrics for Deep Neural Network (DNN) models with varying numbers of hidden layers (2, 3, 4, and 6). The results indicate that the 6-layer configuration outperforms the other architectures across multiple evaluation metrics, establishing it as the optimal model for power loss prediction.

The Mean Squared Error (MSE) remains consistently low at 1.00E−03 for the 2-, 3-, and 6-layer models, reflecting accurate predictive performance. In contrast, the 4-layer model exhibits a significant increase in MSE to 2.94E−01, indicating reduced predictive accuracy and highlighting its relative inefficiency. Similarly, the Root Mean Squared Error (RMSE) is lowest for the 6-layer model at 3.40E−02, followed closely by the 3-layer configuration, further confirming the superiority of the deeper network. The coefficient of determination (R^2) reaches its highest value of 9.45E-01 in the 6-layer model, demonstrating its enhanced ability to explain the variance present in the dataset. Additionally, the Mean Absolute Percentage Error (MAPE) is lowest at 4.83E+00 for the 6-layer model, supporting its strong predictive reliability compared to other configurations. Although the training time for the 6-layer model is slightly higher (3.83E−03 seconds), this represents a typical trade-off between computational cost and improved predictive accuracy. Overall, the 6-layer DNN provides a balanced solution, achieving superior accuracy while effectively capturing the variance in the dataset, making it the preferred configuration for robust and reliable power loss prediction in smart grid applications.

Table 5: DNN Performance Comparison with Relu Activation in Different Layers

PERFORMANCE METRICS	HIDDEN LAYERS			
	2	3	4	6
MSE	1.00E-03	1.00E-03	2.94E-01	1.00E-03
RMSE	3.80E-02	3.60E-02	5.43E-01	3.40E-02
MAE	1.90E-02	1.80E-02	5.23E-01	1.90E-02
R2	9.29E-01	9.38E-01	-1.28E+01	9.45E-01
MAPE	5.44E+00	5.28E+00	1.00E+02	4.83E+00
TIME	3.22E-03	2.37E-03	3.47E-03	3.83E-03
MSE	1.00E-03	1.00E-03	2.94E-01	1.00E-03

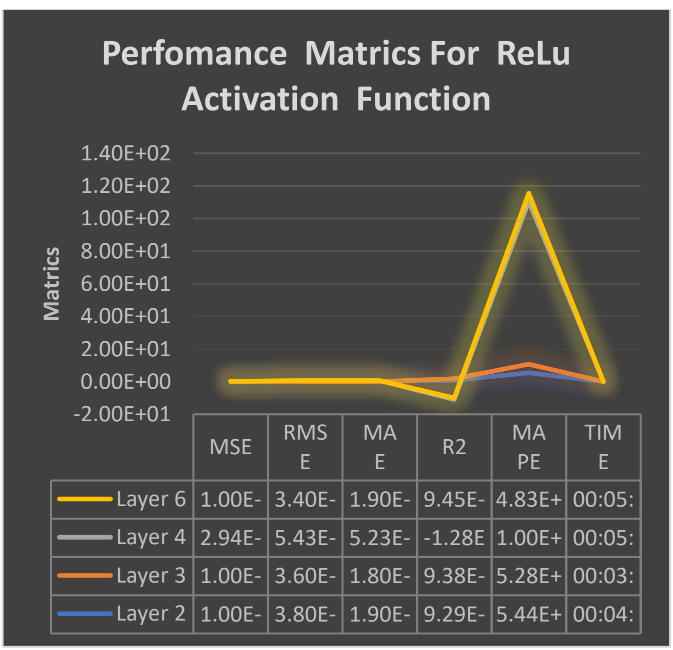

Fig 4: Graph comparing ReLU activation in different layers on SG Loss Prediction Dataset

I. Epoch Generation

Fig 5 visually depicts the graphical representation of MSE, MAE, MAPE and RMSE. The graph provides a clear and concise overview of these error metrics, allowing for a visual assessment of their variations of 500 epochs.

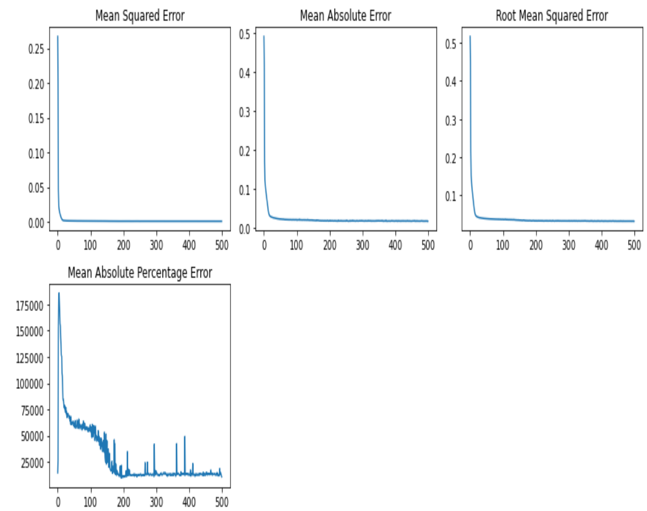

Fig 5: Graphical Representation of Performance During Epoch Evaluation

Fig 6 is pivotal for refining the neural network architecture and adjusting hyperparameters. This iterative process ensures that the model achieves optimal performance on both the training and validation datasets, enhancing its reliability and effectiveness in real-world applications. Figure 6, therefore, serves as a visual compass for navigating the intricate landscape of model training and validation in the context of the presented research. The model achieved its highest performance when using the ReLU activation function, reaching convergence of both training and validation losses at a scale of 1.5 after 500 epochs.

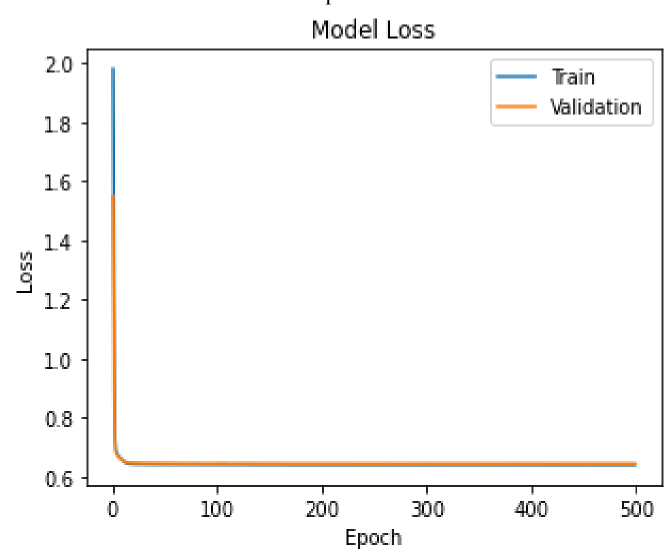

Fig 6: Train and Validation Loss for Smart Grid Loss Prediction Dataset

D. DNN Power Loss Pattern

I. Correlational Patterns

Table 6 depicts the relationship between variables associated with power loss. The Pearson correlation yields a coefficient of 0.02, signifying an extremely weak positive linear relationship between the attributes. Within the context of power loss in a SG, this weak positive correlation suggests that factors such as temperature, voltage levels have significant influence on SG with respect to power loss.

Table 6: Power loss Correlational Analysis

S/N	Correlational Methods	Result
1	Pearson	0.02

In Fig 7, *r* =0.02 indicates a very weak positive linear relationship between the attribute being plotted. The value of *r* represents the Pearson correlation coefficient, which quantifies the strength and direction of the linear relationship between two attributes.

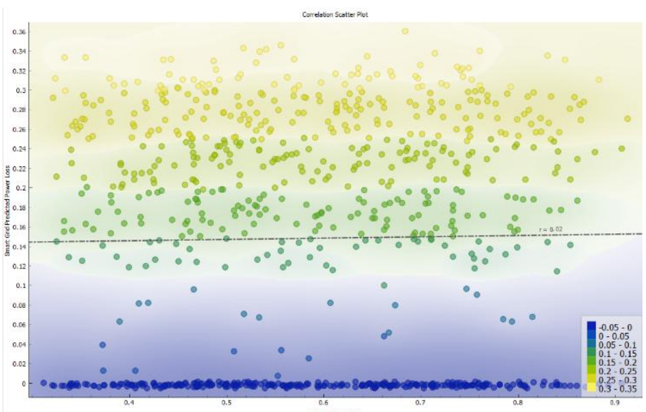

Fig 7: Scatter Plot Correlation Representation

Fig 8 visualizes the relationships between the actual power loss attribute and the predicted power loss attribute within the SG domain. Each scatter plot in the pair plot represents the relationship between these two quantities, making it easy to identify patterns, trends, and correlations.

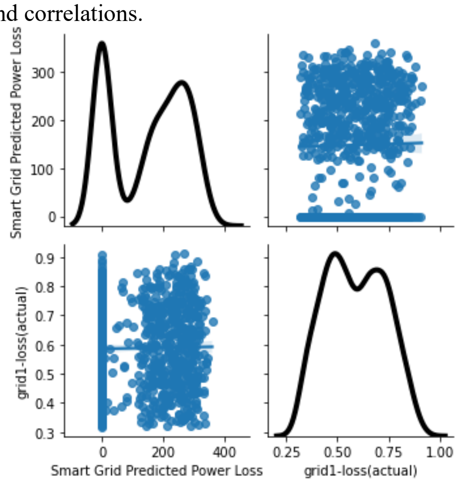

Fig 8: Pair Plots Relationship Representation

II. Detection of Regional Power Loss Patterns in SG

Region **A** in Fig 9 shows higher prediction accuracy without consi dering the influence of demand, and can well reflect the changes of the power loss under the constraints of factors such as power load and temperature. so, it is consistent with the change trend of actual power loss shown in region **B**. The **C** region in Fig 10 signifies that temperature increase will result in a considerable rise in power usage by the load, causing power loss in SG. This power loss happens at point 75 and 95 in power consumption axis while in region **D** indicate that there is no increase in temperature, which suggests that the conditions remain stable or unchanged. This takes place between 0 and 75 moving to 95 and 200 in power consumption axis.

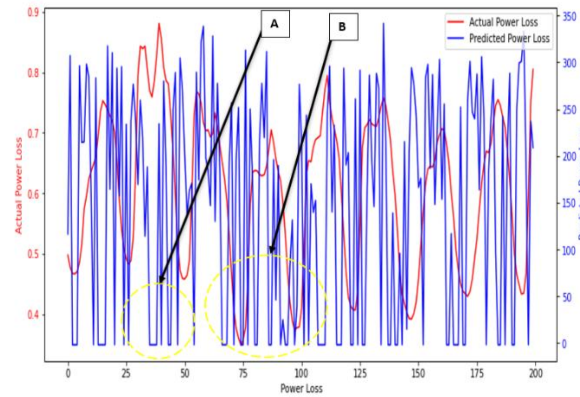

Fig 9: Power loss pattern analytics

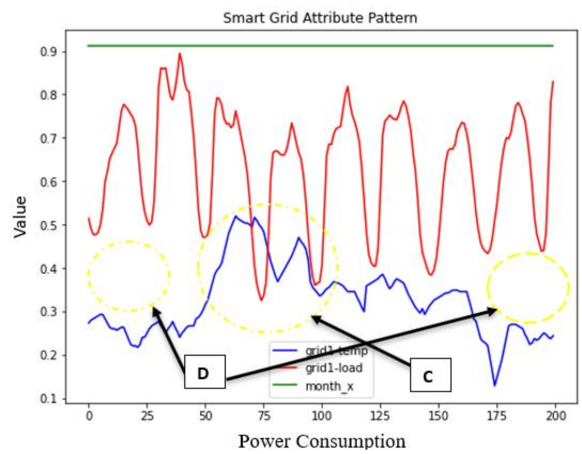

Fig 10: Power loss attribute pattern analytics

5. DISCUSSION

The results of this study provide a comprehensive analysis of the factors influencing grid loss prediction. The preprocessing and dimensionality reduction stage, illustrated in Table 4 and Fig. 3, reveals that grid-temp has the highest eigenvalue (4.46), accounting for 40.6% of the total variance. This highlights its dominant role in affecting variations in power loss. The grid-load attribute contributes 15.93%, while month_x and grid1-loss together add 19.75%, bringing the cumulative explained variance to 76.28%. These findings underscore the critical importance of temperature, load, and temporal factors in accurately modeling grid power loss. Table 5 compares the performance of DNN models with varying numbers of hidden layers (2, 3, 4, and 6) using key evaluation metrics, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), R^2, Mean Absolute Percentage Error (MAPE), and training time. The MSE remains consistently low (~1.00E−03) across the 2-, 3-, and 6-layer models, with the 6-layer DNN demonstrating the best overall performance. This configuration achieved the lowest RMSE (3.40E−02), lowest MAE (1.90E−02), highest R^2 (0.945), and lowest MAPE (4.83), indicating superior predictive accuracy. Although the 6-layer model required slightly more training time (3.83E−03 s), this marginal increase is justified by the substantial gain in accuracy and reliability, making it the most effective and efficient configuration.

Correlation analysis, summarized in Table 6, reveals a weak positive Pearson correlation (r = 0.02) between temperature and voltage fluctuations with power loss, indicating a minimal linear relationship among these variables. However, regional analysis depicted in Fig 9–10 demonstrates that the model effectively captures real-world trends: higher temperatures correspond to increased power consumption and losses, whereas stable temperature conditions are associated with relatively stable power loss patterns. These findings confirm that, despite weak linear correlations, the DNN model successfully identifies complex, non-linear patterns in the smart grid data, supporting accurate and actionable power loss prediction.

6. CONCLUSION

This study demonstrates the effectiveness of using machine learning, particularly DNNs, to predict and analyze power loss in SG. The data-driven approach employed in this research highlighted the critical role of key attributes such as "grid-temp" and "grid-load" in understanding power loss dynamics. These attributes, collectively explaining 76.28% of the variance, underscore the importance of temperature and load-related variables in grid loss prediction. The 6-layer DNN model emerged as the optimal configuration, achieving the highest R^2 value of 94.5%, which signifies its superior predictive performance compared to other models. The model's ability to minimize errors, as indicated by its lowest RMSE and MAPE values, further reinforces its reliability for accurate power loss predictions. While the time complexity of training the 6-layer model was slightly higher than that of simpler models, the gain in accuracy and robustness justifies its selection for real-world grid loss prediction tasks. Moreover, the correlation analysis reveals a weak positive linear relationship between temperature, voltage levels, and power loss. However, the regional analysis indicates that temperature fluctuations significantly impact power usage and loss, particularly in high-demand areas, further validating the need for a data-driven approach to optimize grid performance. the findings of this research contribute to sustainable energy management by providing a predictive model that can assist grid operators in minimizing power loss. By proactively identifying key patterns and external factors influencing grid performance, this approach paves the way for more efficient energy usage, reduced waste, and the promotion of more resilient smart grid systems. Further research can advance this framework by embedding real-time data ingestion within semantic knowledge models and expanding the set of environmental variables used for load profile prediction.

7. ACKNOWLEDGMENTS

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