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Ensembled Model of Random Forest and Artificial Neural Network for Short-Term Electric Load Forecasting

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ABSTRACT

The research focuses on secure short-term electric load forecasting using Random Forest and Artificial Neural Network (RF-ANN) models. Accurate forecasting is crucial for maintaining power system stability and efficiency. Inaccurate forecasting can lead to financial losses, increased load shedding events, and decreased customer satisfaction. Techniques like the State Space Method, Stochastic Time Series, Multiple Linear Regression, General Exponential Smoothing, Knowledge-based Expert Approach, and Machine Learning Approach have been used. The dataset from Transmission Company of Nigeria(TCN) was divided into a 70% training and 30% testing set, and performance accuracies were evaluated using Mean Squared Error, Mean Absolute Error, Root Mean Squared Error, and Mean Absolute Percentage Error. The model achieved an accuracy of 1.73. While RMSE has an accuracy of 1.50899, MSE has 2.27704, and MAE accuracy of 0.00521. The study aims to strike a balance between accurate predictions and ethical data treatment.

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I. INTRODUCTION

In the field smart grid, another significantly vital research area is forecast for load; it ranges from traditional time series analyses to recent machine learning approaches and mostly focuses on forecasted aggregate electricity consumption [13]. When Compared to the traditional power grid, smart grids offer more efficient, intelligent, reliable, and sustainable power services by utilizing the state-of-the-art infrastructures and information technologies. The role Load forecasting plays in smart grids is crucial. It is of fundamental importance for utility providers to model and forecast power loads in advance, to strike a balance between production and demand, to decrease the production cost, and to implement various pricing schemes for demand response [6]. In modern smart grids, load forecasting plays a critical role in enabling utilities to deliver stable and uninterrupted power. By accurately predicting future demand with minimal error, decision-makers can optimize resource allocation, reduce reliance on load shedding, and enhance system reliability. Load prediction with less percentage of error can save millions of dollars to utility companies [11]. As power systems advance, the necessity and impact of accurate load forecasting have become very important. It is not only an important part of power system dispatching, operation, and planning, but also the foundation of economic operation and safe operation of the power system [16].
Smart grids demand an uninterrupted and reliable electricity supply, which depends on accurately predicting present and future load demand with minimal error. To meet this need, researchers and utility stakeholders have advanced state-of-the-art load forecasting methods that support informed decision-making and system optimization. Load forecasting is used to control several operations and decisions such as dispatch, unit commitment, fuel allocation, and off-line network analysis [11]. By providing insight into future consumer demand, load forecasting allows utilities to address mismatches between generation capacity and load in a timely manner. Within smart grids, this predictive function plays a pivotal role in minimizing generation costs, enhancing operational efficiency, and supporting well-structured utility management, underscoring its strategic importance to the power sector. Load demand variability arises from a combination of external and operational factors, including climate conditions, seasonal changes, special events, and network disturbances. In the context of smart grids, load forecasting equips utilities with the ability to anticipate demand patterns and make informed decisions on generation scheduling, market participation, load management, and infrastructure development. Having been an established area of research for decades, load forecasting

remains central to accurately estimating both the scale and geographic distribution of electricity demand across short-, medium-, and long-term horizons.

Electricity load forecasting has long been recognized as essential to the economic operation of power systems. Within smart grids, its value is amplified as accurate forecasts allow utilities to minimize costs by guiding decisions on unit commitment, economic dispatch, fuel distribution, and real-time network optimization. According to [15], the operating cost is increased due to the forecasting errors (either positive or negative). Consumer-level load forecasting enhances energy management by allowing households and businesses to anticipate their electricity needs. In parallel, utilities leverage these forecasts to plan for future demand and generation capacity. In the context of smart grids, this collaborative forecasting framework is key to optimizing system efficiency and supporting informed decision-making.

Short-Term Load forecasting is key module for the energy management system (EMS) unlike the power system platform and has been very rigorously developed in recent decades. However, is with the rapid development of the economy, the load consumption has been increasing, and the power load fluctuations have become more substantial [7]. This study aims to predict the short-term, day-ahead demand for power. The case study for this paper is the TCN power system data from 2019–2024. It's crucial to remember that this kind of dataset raises privacy issues. In order to address this, the study used the differential privacy technique in the context of short-term electric load forecasting. The goal was to create a model that could make precise forecasts while maintaining the privacy of each person's unique energy usage habits.

II. RELATED WORK

So many different approaches have been applied to minimise the large gap between actual generation and electricity demand that could leads to shortages or surplus in power supply. Notable amongst them is the work by [2] who suggested load-shedding as a great way to cut the gap between the excess demand and supply of electricity. Utility providers employ load-shedding as a demand-management strategy, temporarily disconnecting specific areas from supply to mitigate stress on the grid. This controlled intervention prevents large-scale outages, ensures system stability, and allows portions of the network to remain operational. In smart grid environments, such actions are increasingly optimized through predictive analytics and real-time monitoring. Load-shedding is frequently planned in advance to optimize the allocation of electricity demand across the grid. Nevertheless, it may also occur

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reactively when generation shortfalls arise, particularly if primary energy sources are unable to maintain adequate supply."

Even if load-shedding means temporarily powering down some customers, it is better than shutting the entire system down and it helps avoid damage to the grid that could cause long-term blackouts [1].

If unmanaged, sudden increases in electricity demand can cause severe and prolonged grid collapse. Load-shedding mitigates this risk by maintaining the critical balance between generation and consumption. Although effective in protecting overall system stability, it imposes temporary inconvenience on many affected consumers. When load-shedding goes on for extended periods, it could create unsatisfied utility customers, cuts revenue for the energy supplier and surges can occur when restoring power afterward, damaging appliances and equipment [2]. Efficient load-shedding cannot take place without an adequate load-forecasting plan. The effectiveness of load-shedding largely depending on the load-forecasting data.

While recent research has introduced several novel methodologies in electricity load forecasting, the need for models that are both more precise and robust remains essential to address the complex decision-making requirements of smart grids [17]. An accurate estimation of variation in the future electric load is very crucial for both electric utility companies and consumers due to its application in the decision-making and operation of the power grid [6]. The foremost challenges in electricity load forecasting are the influence of external and behavioural factors, including variable climate conditions, temperature, humidity, occupancy, calendar effects, and social conventions. Accurately modelling the relationship between these variables and consumption patterns is difficult due to the stochastic and non-linear behaviour of end-users. The advent of advanced metering infrastructure (AMI), communication platforms, and sensing technologies in smart grids now provides the capability to monitor, record, and analyse these drivers with greater granularity. Within this framework, load forecasting—long recognized as a core application of time-series analysis—is typically classified according to forecasting horizon and purpose. One classification that is commonly considered by researcher based on a forecasting horizon [9]. Load forecasting is often classified according to three-time horizons: short-term, medium-term, and long-term. Short-term forecasts, typically spanning one hour to one week, are used by TSOs, DSOs, and power generation firms to optimize operational scheduling, assess load flows, and prevent congestion in transmission lines. Medium-term forecasts, which cover a period of one week to one year, enable utilities to plan network configuration, schedule maintenance activities, and secure fuel supplies, thereby enhancing system reliability. Long-term forecasts, extending beyond one year, are critical for large-scale infrastructure development and policy formulation, including grid expansion, substation design, and long-term energy strategies pursued by governments and utilities. And this is especially true for deregulated energy market, where the capital expenditure of future stakeholder may drastically vary on the future energy consumption [2].

Accurate short-term load forecasting (STLF) is important for economic power generation and maintaining system security. By lowering operational costs, STLF provides measurable financial benefits to utilities. Its importance is further magnified in deregulated electricity markets, where precision in demand forecasting directly influences market performance and decision-making. To correct the forecast inaccuracy, the utility must buy or sell power in the real-time market, but it comes at the expense of higher real-time prices [14].

As the demand for precise short-term load forecasting in power systems intensifies, the exploration of advanced machine learning techniques becomes imperative. Random Forest, a versatile ensemble learning algorithm, has demonstrated success in various domains, yet its application and performance in short-term load forecasting remain underexplored.

Traditional machine learning techniques have shown considerable effectiveness in short-term load forecasting (STLF), particularly for fitting non-linear load features that challenge conventional techniques. Among these, artificial neural networks (ANNs) are the most frequently employed, serving as a standard approach for constructing accurate forecasting models. ANN has occupied the dominant position of STLF and has gained significant improvements of forecasting performance because of its ability to build accurate nonlinear relationships between loads and related factors [7]. Nevertheless, drawbacks of ANN-based electricity load forecasting mainly covering the subjective determination of model structures. [10] presents a short-term power load forecasting model using the random forest algorithm, which improves prediction accuracy and reduces model variability. The model was evaluated using historical hourly load records from four transformer substations at the University of Beira Interior, Portugal. Experimental results demonstrated its accuracy in short-term load prediction, including hourly forecasts and one-day-ahead demand estimation. Also, [5] propose a method based on empirical wavelet transform and random forest to address strong randomness and low forecasting accuracy in short-term electric load. The method extracts noise, decomposes data into low or high frequencies, and uses these decomposed modes as characteristic

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variables for random forest forecasting. This method has advantages in characterization of non-stationary signal characteristics, time domain analysis, and accurate results even after data features are lost.

[4] additionally presents a hybrid Long Short-Term Memory Recurrent Neural Network (LSTM-RNN) and Random Forest (RF) model for accurate forecasting of photovoltaic (PV) system output in sustainable aquaponic systems. The model integrates the sequential learning capacity of LSTM-RNN with the feature selection and non-linear handling capabilities of Random Forests. This hybrid approach yields improved predictive accuracy for parameters including voltage, current, power, and irradiance. Furthermore, its scalability and adaptability highlight its potential as an effective tool for energy optimization and cost reduction in smart grid operations.

LOAD FORECASTING

Without dedicated metering, estimating the electricity consumption of individual equipment in large facilities is a non-trivial task [20]. Device usage tends to be random, and the operational patterns of one load may vary considerably from those of other appliances connected to the same system. There is often a large diversity in individual loads, yet when these individual loads are summed into one larger facility load, patterns emerge that can be statistically predicted [9].

Four main factors influence electrical load are Time, Weather, Economic, and Random effects. Time factor Given its importance in understanding and forecasting patterns of energy consumption, the time factor is a critical component in electric load forecasting. According to [14], time-related factors aid in capturing the natural fluctuations and periodicities in load data, which are crucial for precise and trustworthy load forecasting. Temporal Patterns, Temporal trends, including daily, monthly, and seasonal fluctuations, are commonly observed in load data. For instance, at some hours of the day (peak hours) and other times (off-peak hours), there is a tendency for electricity usage to be higher. The load may also change depending on the day of the week, month, or season. Seasonality is the term used to describe the regular variations in load patterns brought on by weather variations and other external variables[18]. Because heating and cooling systems are used more frequently in the summer and winter, many places see greater rates of power usage throughout these seasons. The time of day is important for load forecasting since different hours have varied patterns of electricity usage. For short-term load forecasting, precise modelling of load fluctuations throughout the day is crucial. Patterns of electricity use can be affected by the day of the week. Weekdays might see higher levels of industrial and commercial loads, for instance, but weekends might see differing consumption patterns because of lower levels of industrial activity and higher levels of residential loads [9]. Holidays and other unique occasions that may have an impact on power use must be taken into consideration by load forecasting algorithms. There may be variations in load patterns between ordinary weekdays and weekends and public holidays or large events. The time span for which the forecast is made (example a few hours, a day, or many days ahead) is referred to as the forecasting horizon. While long-term forecasting may concentrate more on seasonal trends, short-term load forecasting must account for fine-grained variances [19]. In most cases, electric load data is handled as a time series, with each data point having a unique time stamp assigned to it. To estimate the time component and forecast burden, time series analysis techniques like Prophet, Seasonal Autoregressive Integrated Moving Average (SARIMA), and Autoregressive Integrated Moving Average (ARIMA) are frequently utilized Forecasting models must include time-related variables and seasonal components in order to capture the time factor in electric load forecasting efficiently [17]. Additionally, the data can be changed to make it appropriate for modelling the temporal patterns using data pre-processing techniques like lagging and differencing [4]. Precise integration of the time factor enhances the accuracy and dependability of load projections, which are necessary for effective power system operation, planning, and resource management [19].

Since weather has a direct impact on power usage, weather parameters are important in the forecasting of electric loads. The Institute of Electrical and Electronics Engineers states that adding weather-related variables to load forecasting models facilitates the capture of the effects of temperature, humidity, wind speed, and other meteorological elements on energy demand [3]. Temperature and humidity are key meteorological variables influencing electricity consumption. Hot weather increases the need for cooling devices, while colder months may increase heating systems[21]. Wind speed and solar irradiance also impact electricity use. Seasonal variations, such as severe weather, can lead to increased energy usage for heating and cooling [12]. Weather forecasting models can be improved by incorporating short-term weather forecasts into load forecasting. Historical weather data can be connected to load data to incorporate weather aspects into electric load forecasts. Machine learning models can help identify the association between meteorological variables and power use patterns. Weather-informed load forecasting is crucial for effective demand response programs and grid stability management [6].

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Economic Factor

Economic factors influence patterns of power consumption and overall energy demand, making them important for electric load forecasting [21]. A more thorough knowledge of how economic conditions affect energy demand is made possible by the incorporation of economic variables into load forecasting models [8]. Energy consumption is influenced by a nation's economic growth, with increased commercial and industrial activity leading to increased demand for electricity. Industrial sectors like production and manufacturing use a lot of electricity, and a thriving economy can result in increased demand from businesses. Residential energy usage is also influenced by factors like housing markets, income levels, and employment rates. Economic conditions can influence consumer behaviour, leading to variations in energy use. Energy efficiency initiatives, government initiatives, and urbanization can also impact electricity usage.

Relevant economic data is gathered and combined with load data to incorporate economic aspects into electric load forecasts. The associations between economic variables and patterns of power use can then be examined using machine learning models, such as hybrid models, time series models, and regression-based models [13].

Utilities and energy suppliers can make better judgments about capacity planning, resource allocation, pricing strategies, and demand-side management by taking economic aspects into account when projecting load. Additionally, it helps in improving energy generation and distribution to meet the dynamic demand in an economically efficient manner and anticipates variations in load in reaction to economic swings [9].

METHODOLOGY

III. ANALYSIS AND RESULTS

The research Designed a short-term electric load forecasting architecture and develop an ensembled model (RF-ANN) by fusing Artificial Neural Networks with Random Forest. Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) are used to assess the performance of the RF-ANN ensemble model. The results are then compared with the base paper [6]. The goal of the study is to predict the short-term, day-ahead demand for power. The case study for this paper is the TCN power system data from 2019–2024.

It's crucial to remember that this kind of dataset raises privacy issues. In order to address this, the study used the differential privacy technique in the context of short-term electric load forecasting. The goal was to create a model that could make precise forecasts while maintaining the privacy of each person's unique energy usage habits.

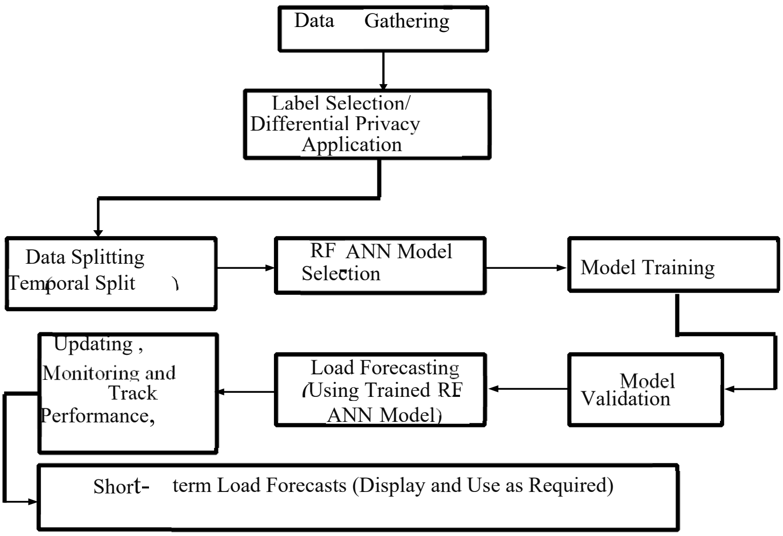

Fig.1 Proposed Short-Term Load Forecasting Architecture

The Short-term electric load forecasting architecture **Fig.1** above predicts electricity demand for hours or days ahead. The system ingests meter data, weather forecasts, and other relevant info. It then cleans and prepares this data for machine learning or statistical models trained on historical data. These models forecast future demand, and the results are visualized for informed decision-making.

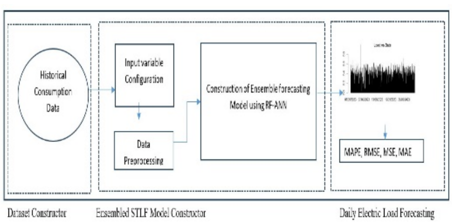

Fig.2 RF-ANN STLF Model

The model as shown in **Fig.2** above is implemented in three main steps, dataset constructor (data gathering), ensembled STLF Model constructor (RF-ANN), and result constructor (model evaluation and performance measurement). This research used a baseline approach based on some libraries for feature selection through variance threshold. A predictive model is trained by deriving a function that links inputs to outputs as defined by the training data. To improve robustness, ensemble libraries are employed to filter out features with training set variance below a predetermined threshold.

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STLF IMPLEMENTATION WORKFLOW

The Short-Term Load Forecasting follows a data-driven workflow. It starts by collecting power meter readings, weather forecasts, and other relevant data. This data is then cleaned and formatted for machine learning models. These models, trained on historical data, predict future electricity demand. Finally, the results are visualized for informed decision making by grid operators.

Data gathering

The Dataset from 2019-2024 was gathered from the Transmission Company of Nigeria (TCN). The dataset contains over 100,000 records consisting of about 18 fields.
Data Preprocessing (Merge, Handle Missing Data, Feature engineering, Normalize)
The acquired dataset was pre-processed using pandas and scikit-learn packages. A few portions of the dataset contain missing values which were corrected.

Label selection/ differential privacy application

Implementing differential privacy in short-term load forecasting is a complex but important task, as it involves protecting the privacy of sensitive energy consumption data while still making accurate predictions.
Data Collection and Aggregation: Collect energy consumption data from various sources, such as smart meters, IoT devices, or historical records. Aggregate the data in a privacy preserving manner to protect individual consumption values.

Data Preprocessing: Anonymize data: Replace specific customer identifiers with pseudonyms or anonymize user IDs.

Add noise: Inject controlled noise into the consumption data to prevent the identification of individual users. This should be done in a way that does not significantly affect the overall accuracy of the load forecasts.

Model Training: Short-term load forecasting can be achieved using suitable machine learning architectures, such as RF-ANN hybrids, trained on differentially private, pre-processed datasets. The application of differential privacy mechanisms ensures confidentiality of consumer data while enabling accurate and reliable model development. Common mechanisms include Laplace noise addition and the use of privacy budgets. Set the privacy parameters (delta) to control the trade-off between privacy and utility. Smaller values of epsilon provide stronger privacy but may reduce utility.

Evaluation: Evaluate the performance of the differential privacy-protected model using standard metrics like Mean Absolute Error (MAE), Mean Squared Error (MSE), or root mean square error (RMSE). Compare the model's performance with non-differentially private models to assess the trade-off between privacy and accuracy.

Data splitting (temporal split)

The dataset was divided into training and testing sets. The training data contains historical records, while the testing data covers the future time periods for validation. The temporal split was done based on 70/30 ratio. 70 percent of the dataset for training while the remaining 30 percent for testing.

RF-ANN model selection
Ensembled model of Random Forest (RF) and Artificial Neural Network was selected.

Model Training : The training dataset was provided to the selected RF-ANN forecasting model. The model learns from the training data to identify patterns and relationships in the features to predict future load values.

Model Validation (predict on test data)
The trained model was used to predict the load values on the testing data (future time periods).

The predicted values were compared with the actual load data to assess the model's performance.

Load forecasting (using trained RF-ANN model)
The trained and validated RF-ANN ensembled model is now used to make short-term load forecasts for future time periods with better accuracy. Monitoring and updating (track performance, retraining) Monitor Model Performance: Continuous tracking of the forecasting model's accuracy and performance is required to detect any degradation over time. Retrain the Model: Periodically it is required we retrain the model with new data to adapt to changing load patterns and maintain forecast accuracy.

IV. DISCUSSION

DIFFERENTIAL PRIVACY

Differential privacy is a mathematically defined framework for privacy preservation, designed to protect the confidentiality of individual data points in statistical datasets while maintaining the utility of aggregate information. The main goal of differential privacy is to allow the extraction of accurate aggregate information from a dataset while preventing the disclosure of sensitive information about any specific individual within that dataset. Differential privacy represents a critical advancement in the field of privacy-preserving technologies, providing a robust and principled approach to balancing the need for accurate data analysis with the imperative to protect individual privacy. As the digital landscape continues to evolve, the adoption of differential privacy techniques is likely to increase in various sectors that handle sensitive data. Differential privacy plays a crucial role in short-term electric load forecasting by providing a privacy-

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preserving framework for collecting, analysing, and sharing individual energy consumption data. The integration of differential privacy in this context aims to protect the confidentiality of sensitive information while enabling accurate load forecasts.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	CustAcct	CustomerINFO	DTR	TRM	Feeder	Hour	Load	FORECAST	Difference	MAX Ener	smartmet	Date	CustomerName	TariffCatego	Tariff Clas
2	701525311		HOME_SECURITY_1_		AT2_GWARINPA F	7	33.8	12	21.8		smartmet	23/02/2024	Abdullahi Abubaka	PREPAID	R2
3	702625246	07067351763	4A_S22		AT3_H31_PL_PL	8	32.7	12	20.7		smartmet	23/02/2024	Apo Legislativeqtr:	PREPAID	R2
4	700927360	8036141866	GRA 2_MP04_001		AT2_MBP_C3_2B	5	32.5	12	20.5		smartmet	23/02/2024	Yusuf Shuaib . , Ch	PREPAID	R2
5	700929959		GRA 1_MP04_001		AT2_MBP_C3_2B	9	27.8	12	15.8		smartmet	23/02/2024	Promise Moulee	PREPAID	R2
6	701482501		MOPOL_GWP02_001		AT4_DAWAKI FDF	12	27.14	14.85	12.29		smartmet	23/02/2024	Dr Agbai-Eke	PREPAID	R2
7	701351711		13RD_SS_GWP01_0C		AT2_GWARINPA F	14	27.1	13	14.1		smartmet	23/02/2024	Idu James Oche .	PREPAID	R2
8	703812098		AT7_FDR 1 (AKWANC		AT7_FDR 1 (AKW/	12	26.9	13	13.9		smartmet	23/02/2024	Habiba Usman.	PREPAID	R2
9	704274305	07036527419	AT2_MBP_1A_C3		AT2_MBP_C3_1A	11	26.4	12	14.4		smartmet	23/02/2024	Zondo T Sakala , M	PREPAID	C1
10	702761161	8061668500	GW_L36_L2_FD3		GW_L36_L2_FD3	13	25.81	14.85	10.96		smartmet	23/02/2024	Shakuibo C. Musa	PREPAID	R2
11	701925761	08037014381/07	FD1_K2		AT4_KUBWA FDR	14	25.44	14.85	10.59		smartmet	23/02/2024	Gen. Hassan Aliyu	PREPAID	R2
12	704115041		BABA OLD SOLDIER S		AT9_K4_PL_PL	10	25.43	14.85	10.58		smartmet	23/02/2024	Alh. Farouksulema	PREPAID	R2
13	700702946		HVDS 54 S/S NYANYA		AT9_K4_A23_FD9	3	25.4	12	13.4		smartmet	23/02/2024	Daniel Onyemaech	PREPAID	R2
14	701677296	8038699002	DAWAKI_AT4		AT4_DAWAKI FDF	10	25.1	12	13.1		smartmet	23/02/2024	Onirobo Godwin	PREPAID	R2
15	703262339	8135551451	Hajiya zara s/s_CKK_		GW_L36_PL_PL	4	24.3	12	12.3		smartmet	23/02/2024	Emmanuel Kure .	PREPAID	R2
16	700400343	8168849147	NAVY ESTATE JUNCTI		AT9_K2_PL_PL	9	24.19	13.5	10.69		smartmet	23/02/2024	Hon. Anthonia Ast	PREPAID	R2
17	703666114		BURATAI S/S MARAR		AT9_K5_J32_FD7	4	24.16	14.85	9.31		smartmet	23/02/2024	Mathias Obeka .	PREPAID	R2
18	704069406	8035901726	ALBARKA COMM S/S		AT9_K4_J22_FD3	1	24	19.5	4.5		smartmet	23/02/2024	Mr Rapheal Adeniy	PREPAID	R2
19	701784855		FD3_K2		AT4_KUBWA FDR	2	23.8	10.7	13.1		smartmet	23/02/2024	Mustapha Abdul .	PREPAID	R2

Fig 3. Sample of the dataset before application of differential privacy

Above **Fig 3.** is a sample of dataset containing sensitive personally identifiable information about the customers. It clearly revealed the CustomerName, Contact_Info, and other detail that shouldn't be publicly disclosed. Differential privacy settings could help conceal all these details while achieving the primary target of load forecasting.

Table 1. Sample of Load prediction using RF- ANN Ensembled model

Feeder	load	Predicted	Date
	FORCAST		
33KV FDR H5	367.3	369.03	24/02/2024 00:00:00
33KV WUSE II FDR	172.2	173.93	24/02/2024 00:00:00
33KV FDR H31	44.93	46.66	24/02/2024 00:00:00
33KV FDR H33	84.28	86.01	24/02/2024 00:00:00
33KV FDR L31	23.8	25.53	24/02/2024 00:00:00
33KV FDR H21	45.88	47.61	24/02/2024 00:00:00
33KV CFDR 8	101	102.73	24/02/2024 00:00:00
33KV BWARI FDR	38.9	40.63	24/02/2024 00:00:00
33KV FDR L36	19.4	21.13	24/02/2024 00:00:00
33KV LIFE CAMP FDR	18.96	20.69	24/02/2024 00:00:00

above **Table 1.** shows result of electric load forecast using the RF-ANN model with Mean Absolute Percentage Error (MAPE) of 1.73%. This explains the difference between the actual load and the predicted load for a particular time. The application of differential privacy concealed all the sensitive customer details in the test dataset.

The scatter plot of RF-ANN Model in **Fig. 4** below shows the relation between the Actual and the predicted Load based on RF-ANN model trial. The gap between the Actual and the predicted stood at 1.73% based on Mean Absolute Percentage Error (MAPE) metric performance measurement. Overall, this results in a smaller load gap between the predicted and actual loads. The scatter plot's datapoints appear to be clustered together and show a strong correlation with the load data.

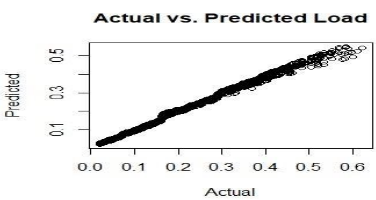

Fig 4. Scatter plot trial of RF-ANN Model

The line graph of Load versus Date below shows the relationship between Actual load and Date based on the original dataset acquired. However, the dataset splitted (70/30), 70 for Training set and 30 for Testing.

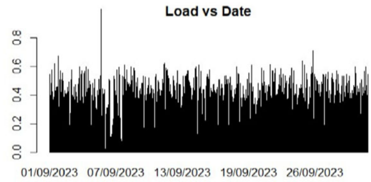

Fig 5. Load vs Date Line Graphs

Model Performance Accuracies

In this section, the performance of each model is measured based on the four metrics stated in the objective: MAPE, MAE, MSE and RMSE and the comparison of the five algorithms' test results.

Random forest model performance

The Random Forest (RF) model performed relatively well with MAPE of 5.16, MAE of 0.00411, MSE of 4.59472 and RMSE of 2.14353. **Table 2** below summarizes the performance metric of the Random Forest Model.

Table 2. Random Forest Model Performance Accuracy

Metrics	Accuracy (%)
MAPE	5.16
MAE	0.00411
MSE	4.59472
RMSE	2.14353

Artificial neural network performance

The Artificial Neural Network (ANN) achieved reliable forecasting accuracy, reflected in performance metrics of MAPE (4.32), MAE

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(0.09176), MSE (0.01256), and RMSE (0.11207). **Table 3** below summarizes the performance metric of the ANN Model.

TABLE 3. ANN MODEL PERFORMANCE ACCURACY

Metrics	Accuracy (%)
MAPE	4.32
MAE	0.09176
MSE	0.01256
RMSE	0.11207

Support vector regressor performance

The Support Vector Regressor (SVR) model performed relatively well with MAPE of 7.14, MAE of 0.00411, MSE of 4.59472 and RMSE of 2.14353. **Table 4** below summarizes the performance metric of the SVR Model.

TABLE 4. SVR MODEL PERFORMANCE ACCURACY

Metrics	Accuracy (%)
MAPE	7.14
MAE	0.00411
MSE	4.59472
RMSE	2.14353

Ensembled ANN-SVR performance

The Ensembled model of Artificial Neural Network (ANN) and Support Vector Regressor (SVR) performed relatively well better than the single model of Random Forest, Artificial Neural Network and Support Vector Regressor. The ANN-SVR has MAPE of 3.29, MAE of 0.11411, MSE of 2.59472 and RMSE of 1.61081. **Table 5** below summarizes the performance metric of the ANN-SVR Model.

TABLE 5. ANN-SVR MODEL PERFORMANCE ACCURACY

Metrics	Accuracy (%)
MAPE	3.29
MAE	0.11411
MSE	2.59472
RMSE	1.61081

Ensembled RF-ANN performance

The Ensembled model of Random Forest (RF) and Artificial Neural Network (ANN) outperformed the other models when tested with the same dataset features. It outperformed the single model of Random Forest, Artificial Neural Network, Support Vector Regressor and the ensembled model of ANN-SVR. The RF-ANN has MAPE of 1.73, MAE of 0.00521, MSE of 2.27704 and RMSE of 1.50899. **Table 6**. below summarizes the performance metric of the RF-ANN Model.

TABLE 6. RF-ANN MODEL PERFORMANCE ACCURACY

Metrics	Accuracy (%)
MAPE	1.73
MAE	0.00521
MSE	2.27704
RMSE	1.50899

Model Performance Comparison

Metrics for performance evaluation are used to show how productive the proposed techniques are. **Table 7.** summarizes the metrics and their corresponding performance values.

Table 7. Model Performance Comparison

Metrics	SVR	RF	ANN	ANN SVR	RFANN
MAPE	7.14	5.16	4.32	3.29	1.73
RMSE	2.14353	2.14353	0.11207	1.61081	1.50899
MSE	4.59472	4.59472	0.01256	2.59472	2.27704
MAE	0.00411	0.00411	0.09176	0.11411	0.00521

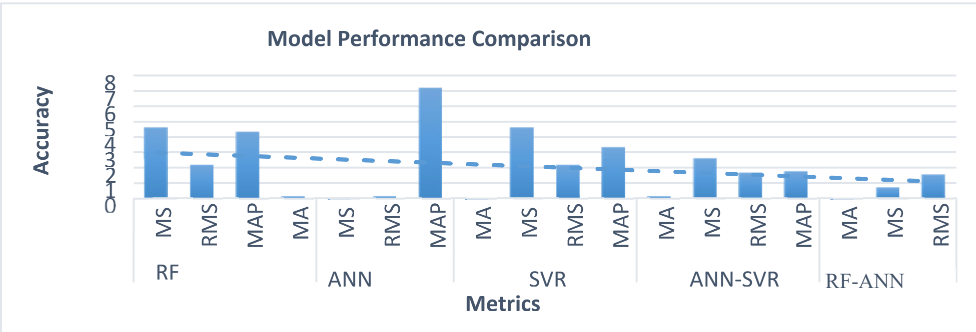

Fig. 6 Model Performance Comparison Chart.

When the RF, ANN, SVR, and ANN-SVR were trained with the same parameters and data, different MAPE outcomes were achieved for every scenario. But every time the RFANN was trained using the identical settings and data, it produced the same MAPE findings. This demonstrates that the RF-ANN produced better outcomes. As a result, utilizing RF-ANN instead of RF, ANN, SVR, and ANN-SVR for short-term (one hour) load forecasting shows to be more reliable. Further research has revealed that the load forecast numbers obtained were most strongly influenced by the most recent 24 hours of historical load data. The researchers Created Safe, Short-Term Electric Forecasting Electric Loads in the Short-Term architecture for load forecasting. An incorporated differential privacy mechanism was designed into the architecture. Using Random Forest forecasting and an Artificial Neural Network for Python programming, create an ensembled model (RF- An RF-ANN Model for Short-Term Load ANN). anticipating the short-term electric load. Utilizing Mean 0.00521, MSE of 2.27704, RMSE of Absolute Error (MAE), Mean Squared 1.50899, and an

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exceptionally low MAPE of Error (MSE), Root Mean Squared 1.73, the RF-ANN Model produced an MAE of the ANN ensemble model that outperformed the Error (RMSE) and Mean Absolute result from the baseline paper [1].

TABLE 8. RF-ANN MODEL PERFORMANCE ACCURACY

Metrics	Accuracy (%)
MAPE	1.73
MAE	0.00521
MSE	2.27704
RMSE	1.50899

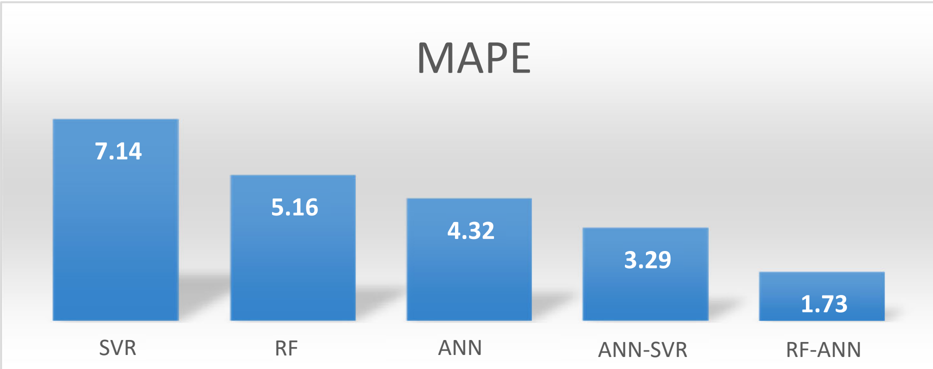

Fig. 7: MAPE Comparison across sample Models.

V. CONCLUSION

The study presents an ensembled RF-ANN short-term electric load forecasting model, demonstrating better outcomes than other models. The research aims to explore the application of differential privacy techniques in short-term electric load forecasting, ensuring accurate predictions while preserving individual energy consumption patterns' privacy. The research questions how to design and implement a robust differential privacy framework, ensuring insights are valuable for energy planners and operators without compromising user information. This research contributes to the development of privacy-preserving methodologies in energy forecasting, striking a balance between accurate predictions and ethical data treatment. Future area will involve better accuracy, tunning and reliability can be achieved by the ensembled (RF-ANN) model with training larger electric load dataset. The limitation of the research model does not include weather as one of the influencing aspects because it is unpredictable and using shaky data to train the algorithm would produce poor forecasting performance. However, if the weather can be reliably anticipated, the model's performance will improve.

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VII. REFERENCES

[1] Abad, L. A., Sarabia, S. M., Yuzon, J. M., & Pacis, M. C. (2020). A Short-Term Load Forecasting Algorithm Using Support Vector Regression & Artificial Neural Network Method (SVR-ANN). *2020 11th IEEE Control and System Graduate Research Colloquium, ICSGRC 2020 - Proceedings*, 138–143. https://doi.org/10.1109/ICSGRC49013.2020.9232630

[2] Ahmad, W., Ayub, N., Ali, T., Irfan, M., Awais, M., Shiraz, M., & Glowacz, A. (2020). Towards short term electricity load forecasting using improved support vector machine and extreme learning machine. *Energies*, *13*(11). https://doi.org/10.3390/en13112907

[3] Ashfaq, T., & Javaid, N. (2019). Short-term electricity load and price forecasting using enhanced KNN. *Proceedings - 2019 International Conference on Frontiers of Information Technology, FIT 2019*, 266–271. https://doi.org/10.1109/FIT47737.2019.00057

[4] Dewi, T., Mardiyati, E. N., Risma, P., & Oktarina, Y. (2025). Hybrid Machine learning models for PV output prediction: Harnessing Random Forest and LSTM-RNN for sustainable energy management in aquaponic system. *Energy Conversion and Management*, *330*, 119663. https://doi.org/10.1016/J.ENCONMAN.2025.119663

[5] Fan, G. F., Zhang, L. Z., Yu, M., Hong, W. C., & Dong, S. Q. (2022). Applications of random forest in multivariable response surface for short-term load forecasting. *International Journal of Electrical Power and Energy Systems*, *139*. https://doi.org/10.1016/J.IJEPES.2022.108073

[6] Hafeez, G., Alimgeer, K. S., & Khan, I. (2020). Electric load forecasting based on deep learning and optimized by heuristic algorithm in smart grid. *Applied Energy*, *269*. https://doi.org/10.1016/j.apenergy.2020.114915

[7] Ibrahim, B., Rabelo, L., Gutierrez-Franco, E., & Clavijo-Buritica, N. (2022). Machine Learning for Short-Term Load Forecasting in Smart Grids. *Energies*, *15*(21). https://doi.org/10.3390/en15218079

[8] Li, Y., Zhang, S., Hu, R., & Lu, N. (2021). A meta-learning

ISSN 2636-9680
eISSN 2682-9266

based distribution system load forecasting model selection framework. *Applied Energy*, *294*. https://doi.org/10.1016/j.apenergy.2021.116991

[9] Madrid, E. A., & Antonio, N. (2021). Short-term electricity load forecasting with machine learning. *Information (Switzerland)*, *12*(2), 1–21. https:// doi.org/10.3390/info12020050

[10] Magalhães, B., Bento, P., Pombo, J., Calado, M. do R., & Mariano, S. (2024). Short-Term Load Forecasting Based on Optimized Random Forest and Optimal Feature Selection. *Energies 2024, Vol. 17, Page 1926*, *17*(8), 1926. https://doi.org/10.3390/EN17081926

[11] Mamun, A. Al, Sohel, M., Mohammad, N., Haque Sunny, M. S., Dipta, D. R., & Hossain, E. (2020). A Comprehensive Review of the Load Forecasting Techniques Using Single and Hybrid Predictive Models. In *IEEE Access* (Vol. 8, pp. 134911– 134939). Institute of Electrical and Electronics Engineers Inc. https://doi.org/10.1109/ACCESS.2020.3010702

[12] Moon, J., Jung, S., Rew, J., Rho, S., & Hwang, E. (2020). Combination of short-term load forecasting models based on a stacking ensemble approach. *Energy and Buildings*, *216*. https://doi.org/10.1016/j.enbuild.2020.109921

[13] Rafi, S. H., Al-Masood, N., Deeba, S. R., & Hossain, E. (2021). A short-term load forecasting method using integrated CNN and LSTM network. *IEEE Access*, *9*, 32436–32448. https://doi.org/10.1109/ACCESS.2021.3060654

[14] Singh, P., & Dwivedi, P. (2018). Integration of new evolutionary approach with artificial neural network for solving short term load forecast problem. *Applied Energy*, *217*, 537–549. https://doi.org/10.1016/j.apenergy.2018.02.131

[15] Wu, K., Wu, J., Feng, L., Yang, B., Liang, R., Yang, S., & Zhao, R. (2021). An attention-based CNN-LSTM-BiLSTM model for short-term electric load forecasting in integrated energy system. *International Transactions on Electrical Energy Systems*, *31*(1). https://doi.org/10.1002/2050-7038.12637

[16] Xiuyun, G., Ying, W., Yang, G., Chengzhi, S., Wen, X., & Yimiao, Y. (n.d.). *Shortterm Load Forecasting Model of GRU Network Based on Deep Learning Framework.*

[17] Elmousaid, R., Drioui, N., Elgouri, R., Agueny, H., & Adnani, Y. (2024). Ultra-short-term global horizontal irradiance forecasting based on a novel and hybrid GRU-TCN model. *Results in*

Engineering, *23*(May), 102817. https://doi.org/10.1016/j.rineng.2024.102817

[18] Abdelsattar, M., Ismeil, M. A., Menoufi, K., Moety, A. A., & Emad-Eldeen, A. (2025). Evaluating Machine Learning and Deep Learning models for predicting Wind Turbine power output from environmental factors. In *PLoS ONE* (Vol. 20, Issue 1 January). https://doi.org/10.1371/journal.pone.0317619

[19] Fose, N., Singh, A. R., Krishnamurthy, S., Ratshitanga, M., & Moodley, P. (2024). Empowering distribution system operators: A review of distributed energy resource forecasting techniques. *Heliyon*, *10*(15), e34800. https://doi.org/10.1016/j.heliyon.2024.e34800

[20] Zelios, V., Mastorocostas, P., Kandilogiannakis, G., Kesidis, A., Tselenti, P., & Voulodimos, A. (2025). Short-Term Electric Load Forecasting Using Deep Learning: A Case Study in Greece with RNN, LSTM, and GRU Networks. *Electronics (Switzerland)*, *14*(14), 1–24. https://doi.org/10.3390/electronics14142820

[21] Dewi, T., Mardiyati, E. N., Risma, P., & Oktarina, Y. (2025). Hybrid Machine learning models for PV output prediction: Harnessing Random Forest and LSTM-RNN for sustainable energy management in aquaponic system. *Energy Conversion and Management*, *330*(March). https://doi.org/10.1016/j.enconman.2025.119663

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