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Design of a hybrid learning model for establishing consistency in smart grid environment

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Consumer patterns like energy demands and the transmission of electricity based on the given demand are recognized by smart grids. Novel data-driven methods are required to handle the large-scale data generated by the smart grids and address prediction demands. We are employing Deep Learning techniques to recognize consumer data patterns and forecast demand based on different prediction horizons, which is a better alternative than conventional techniques. Here, a hybrid Long Short-Term Memory (LSTM) with Neuro-fuzzy adaptive interference model (NFADIM) is proposed, which plays an essential role in the available Artificial Neural Network (ANN) methods. NFADIM mainly concentrates on the issue of load prediction and further associated factors based on the context of smart grids. We are employing Deep Learning methods to predict the demands of the end users because of their positive experiences. It is crucial to have stability between the request and response, which provides a well-organized power system. This implies that researchers and industrial stakeholders should focus on load prediction, specifically in the short term, which is essential for request response.

Keywords Smart grids, Deep learning, Prediction, Hybrid long Short-Term memory, Artificial neural network

Unlike other commodities like oil, it is impossible to save electricity for future use. This enables the distribution of electricity instantaneously after its generation[1]. The users can receive the power supply through the conventional power grid, which transmits the electricity from the production unit to the customer's destination. Traditional electricity grids have a network of connections between the power production centers and the end users' locations[2]. The primary issue with the conventional power grids is their irregular size. At the time of the expansion of these grids, it is very complex to control them. At the same time, the demand prediction factor was not considered in the traditional models[3].

In this NFADIM, the smart grid idea develops and plays a significant role. In the literature review, the smart grid was thoroughly explained. The smart grid models between the users and the producers can facilitate bidirectional communication[4]. It enhances conventional power grids using particular hardware and software technologies to enable them to provide self-directed demand response ability at various events. The ultimate aim is to improve the optimal operational performance for electricity delivery[5]. Experts describe the smart grid as a novel network for electricity that facilitates energy security, self-healing, energy reliability, and electricity flow control with the help of digital methodology. The researchers emphasize that the smart grid (SG) technology is renovating the conventional power grid by applying various advanced methods[6]. The novel technique of smart grid incorporates different components required to produce, distribute and use energy effectively. The authors aim to develop the conventional power grid with improved security, reliability, efficiency, and stability and effectively handle the demand response[7].

Figure 1 shows the data complexity and privacy in smart grid forecasting. The energy-consuming smart grid recognizes the patterns of the end users. By observing these patterns, consumers can manage their power utilization and reduce their power consumption. Implementing the smart grid model processes both industrial and household demands. A smart grid can predict the load demand, which plays an essential role in meeting the electricity required by consumers and can balance the request and supply of electricity[8]. The electricity producers are expected to predict the power requirement (load profile) for 24 h. The issue with this prediction is sudden demand for increased power during the day may cause some difficulties in the power supply[9]. Load prediction is an essential task during peak hours. During peak hours, consumers are requested to reduce unnecessary power utilization, which is possible through the demand response. Novel data-driven methods are needed to

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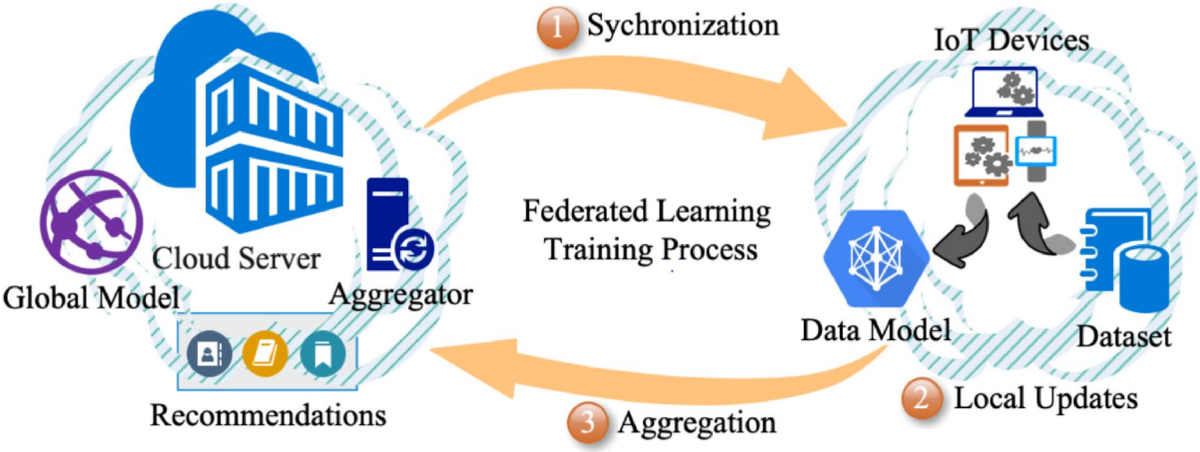

Fig. 1. Data complexity and privacy in smart grid forecasting.

handle load prediction issues. Modern methods like ML, IoT, and Big Data have advanced the smart grid[10]. These strategies improve demand prediction and computerized response[11]. This study emphasizes smart grid demand prediction and the use of novel hybrid Long Short-Term Memory (LSTM) with Neuro-fuzzy adaptive interference model (NFADIM) approaches. Experts remark that deep learning technologies increase smart grid platform demand forecasting. This study collects examples of deep learning used for power environment prediction. Demand response is always considered for a good electrical system. Load prediction, especially short-term, is crucial. This is why scholars and industry stakeholders are focusing on it. Independent LSTM and neuro-fuzzy systems are less accurate and resistant to consumption pattern fluctuation than the hybrid LSTM-NFADIM model for smart grid short-term load forecasting. Adaptive neuro-fuzzy inference and LSTM deep learning capture nonlinear linkages and temporal correlations in real-time load data and dynamically react to consumer behavior and intermittent renewable energy sources. Fuzzy reasoning for local adaptation and LSTM for sequential learning improve the prediction accuracy and computational efficiency of this hybrid method. LSTM-NFADIM is more adaptive and accurate than traditional forecasting methods for stochastic smart grid loads, which have considerable unpredictability and uncertainty. Renewable energy integration and demand-side management improve.

Motivation

The fast growth of smart grids has generated massive amounts of big data. Demand forecasting requires advanced methods. Traditional methods have accuracy and scalability limitations. Deep learning, especially hybrid learning, may be useful for energy demand forecasting and power system stabilization, particularly for detecting complex consumer behavior. In complex, dynamic smart grid environments, isolated LSTM and neuro-fuzzy systems have accuracy, adaptability, and scalability concerns. Discussion of nonlinear load changes, intermittent renewable integration, varied consumer behaviors, and large-scale data processing could support integrating LSTM's temporal learning and NFADIM's adaptive fuzzy reasoning in the motivation subsection. Clarification would enhance the technical narrative and contextualize the hybrid framework.

Problem statement

It is challenging for smart grids to accurately predict the behavior of consumers and the amount of electricity they consume. Generally speaking, traditional models are considered to be inadequate due to the fact that they lack precision and the ability to react to structured data. This work presents a hybrid Deep Learning method for load prediction in smart grids. The purpose of this system is to address the concerns mentioned above and to ensure that energy transmission is consistent. Quantitative analysis of the hybrid LSTM-NFADIM model evaluation. It is important that a table directly compares transformer-based models, hybrid CNN-LSTM architectures, and typical neuro-fuzzy systems in terms of accuracy, precision, recall, F1-score, and processing efficiency. By showing side-by-side results across identical datasets or benchmark settings, the table would be able to assist in the visualization of relative improvements, provide evidence for performance claims, and illustrate the predictive precision, adaptability, and durability of the hybrid framework under dynamic smart grid conditions. This would increase the study's credibility as well as its level of technical rigour.

Problem definitions

- Inefficiencies and power imbalances result from shifting energy demand and irregular supply in traditional power grids. Smart grid operations are going wrong.
- Old load prediction models have flaws. These methods fail to anticipate energy consumption, especially with renewable energy and unpredictable demand swings.
- Increasing demand for hybrid machine learning approaches.

- Energy data has complicated, non-linear interactions that conventional methods cannot represent. For flexibility, a hybrid predictive model with AI is needed.
- Smart grid optimization challenges Real-time stability and load balancing are difficult due to complex data, reaction time restrictions, and scalability issues.

Proposed hybrid learning framework (LSTM + NFADIM)

The goals of a hybrid deep learning model are to enhance short-term load forecasting, improve grid stability, and optimize energy distribution, integrating LSTM (for time-series forecasting) with NFADIM (for adaptive intelligence). Although LSTM and neuro-fuzzy systems appear to be incremental integration of proven technologies, the hybrid configuration improves smart grid load forecasting. Dynamically managing LSTM's temporal learning with adaptive neuro-fuzzy inference provides real-time adaptation to fluctuating consumption and intermittent renewable generation. The short-term projections improve under nonlinear and stochastic conditions. In the hybrid structure, fuzzy rules, multi-objective optimization for prediction accuracy and processing efficiency, and robustness to noisy or missing data improve interpretability. These attributes give it operational reliability and smart grid management adaptability above conventional forecasting methods.

Contribution of this paper

- The system designs a new hybrid model of an LSTM network and a NFADIM for accurate demand prediction.
- Focus on Short-Term Load Forecasting. Improves the stability and efficiency of the request-response in the grid.
- The scalable and reliable solution for industrial parties in terms of fulfilling demands, any type of energy demand.

The work is provisioned as follows: the detailed analysis of various prevailing approaches is provided in Sect. "Motivation". The methodology is drafted in Sect. "Problem statement" with numerical results in Sect. "Problem definitions". The conclusion is explained in Sect. "Proposed hybrid learning framework (LSTM + NFADIM)".

Related works

The major requirements of the smart grids are summarized as follows: capability of supervising uncertain conditions, adequate flexibility in managing consumer requirements, high-quality power supply to end users, easy availability for all consumers, and efficient management of energy production through innovative techniques[12–15]. Considering these requirements as essential, smart grids are intended to be built less expensively and simply to implement with distributed intelligence to execute effectively in the existing composite situations. Innovative and protected communication infrastructures are required to update the conventional power grid into an SG[16]. Demand response and grid control are the two critical environments where prediction can be applied[17]. Experts emphasize that prediction techniques are important to facilitate the best possible quality of power delivery at a low cost. More effective and reliable prediction techniques are computed based on the real-time data gathered from the patterns of power consumed by the customers. Frequently modifying data is also an essential factor to consider when making predictions. With the smart grid application, request/response can make the grid more cost-effective and flexible[18]. Demand prediction is a complex procedure because of uncertainties in the production profile of renewable and distributed energy-producing resources[19]. Improved concentration is required for load prediction techniques, explicitly working with renewable energy resources like wind, solar radiation, and ocean energy[20]. The model of distribution production provides the application of renewable power sources at the consumer end. Under this model, multiple networks in the smart grid supply power to their corresponding area. Therefore, the reliance on the transmission and distribution grid is less[21]. If the distributed production resources are renewable and consequently random, then it makes the grid control model even more uncertain. Despite this issue, using renewable energy is estimated to enhance energy production in the future.

In the context of microgrids, intelligence is implemented in buildings, and a new concept is developed, comprised of smart buildings and smart homes. Nowadays, buildings are composed of complex designs, technology, and systems. Technology supports resource optimization and increased security. The network sensors and recoded data are combined using the building technologies. Novel techniques can facilitate cooling, heating, and lighting to improve power efficiency and provide a detailed statement of power utilization. In the existing smart world, smart and sensor devices are employed to achieve the required data about the consumer's power utilization patterns. Again, prediction techniques must be used to control the particular variables in a specific situation. The prediction models consider social, habit-related, climatic, and economic variables influencing prediction performance. The experts stated that power demand analyzed in independent environments, like consumers in smart buildings, is more intricate compared to the power demand from an aggregated environment like a country. Demand disaggregation also effectively provides power demand deployment, as electricity cost varies based on the protocols prepared by the power production unit.

To optimize power generation and distribution based on the producer's supply and users' requests, intelligence at the distribution, transmission, and consumer levels must be integrated gradually. It is essential to develop fault detection algorithms in smart grids. In the power field, exact demand prediction is necessary for electricity suppliers and other stakeholders. Since the implementation of electric energy, load prediction has been the central issue handled by the power production industries. The authors focus on the climate change in the environment for demand prediction, which yields better forecasting results. Taking into account crucial weather data such as relative humidity, mean temperature, and total solar radiation, for instance, specialists in[22] employed an Artificial Neural Network to forecast the electricity consumption for the following day. This was done in order to assess the impact that climatic circumstances have on power demand. The prediction of the power consumption based on the temperature provides a better outcome, and the connection between the electric load and temperature curve is positive, particularly during the summer[23]. There is a positive relationship between the two.

Kumari et al. (2022)[24] propose an AI-based smart grid attack detection and prevention (ADP) mechanism. This approach protects data with a cryptography-driven recommender system. The AI-ADP approach has two stages: attack detection and prevention. Kumari and colleagues introduced an AI-driven real-time obstacle identification system for UAVs in 2024. Blockchain improves data integrity and security in this system. This method improves unmanned aerial vehicle safety and reliability in dynamic environments.

Abdalmaged et al. (2025)[25] build and deploy an IoT-based smart fuel monitoring system. This technique improves gas station resource management. The system uses Internet of Things technologies for autonomous detection, communication, and data exchange. This simplifies real-time monitoring and control.

Subbiah et al. (2024)[26] examine the application of automatic control and intelligent systems in urban traffic management, focusing on commercial vehicle traffic preventive safety. The study emphasizes how intelligent systems improve traffic flow and safety.

At present, extreme temperatures due to heat waves are typical around the globe. Heat waves are frequent, more powerful and last for an extended period. As a result, the temperature increases at night, which is an additional issue. The main consequence of heat waves is an increased power supply demand at night due to the usage of air conditioners. In addition, the cooling devices must work harder to reduce the high temperature. The smart grid is at its maximum capacity during the summer because of heat waves. The heat waves affect the Consumption of power in the course of improved saturation of the power grid. Cold waves can utilize gas, wood, electricity, etc., but power is the only option to deal with heat waves. Otherwise, end users rely on electricity to cool their location. As a result, improved stress and higher power consumption are caused by the heat waves, which in turn produce more stress on the electrical lines. In colder countries, it is noted that power utilization during the summer is less than in other countries because fixing air conditioners is optional in colder regions. However, when the heat waves are a bit stronger than the previous year in colder countries, they force the use of cooling systems, increasing the power requirement that was not expected[27–29].

Kawoosa et al. (2023)[30] constructed an XGBoost-based ensemble model to detect smart grid electricity theft. The model, which uses consumption patterns and other variables, has good detection accuracy and robustness. This new technique is much better at recognizing regional theft behaviors. Faheem et al. (2024)[31] examined blockchain-based communication networks for distributed renewable energy systems cyberattack patterns. Their research provides novel perspectives on SQL Injection, Spoofing, and Man-in-the-Middle attacks using huge datasets from Solana blockchain-based Industrial Wireless Sensor Networks. This research is essential for smart grid cybersecurity. Khan et al. (2022) suggested an IoT-based fertilizer recommendation system[32]. The system uses real-time soil data and machine learning models like SVM, KNN, and linear regression to make precise fertilizer recommendations to improve agricultural productivity and sustainability. This technique demonstrates how precision agriculture can use the Internet of Things. An AI-powered chatbot can analyze real-time soil parameters to recommend fertilizer, according to a recent study. The solution uses a 91%-accurate Random Forest model to boost agricultural user engagement and decision-making.

Kujur et al., (2022)[33] studied how data complexity affects deep learning models that classify brain tumors and Alzheimer's from MRI scans. Feature heterogeneity, class overlap, and intrinsic dimensionality were studied. Cancer images are more complicated than Alzheimer's, influencing model reliance, accuracy, and generalization. They optimized medical imaging classification models utilizing CNN variations (S-CNN, ResNet50, InceptionV3), stratified k-fold validation, and PCA to reduce complexity. Khan et al. (2024)[34] proposed a privacy-protecting federated learning technique for smartphone recommendation systems. The decentralized architecture uses secure aggregation and differential privacy to train prediction models on-device without transferring personal data.

Recent research improves smart grid management, demand optimization, and renewable energy integration. Said (2023)[35] identifies heterogeneous data streams, distributed loads, and safe two-way communication as ICT issues in modern demand-side management (DSM). The report calls for interoperable, privacy-preserving architectures, AMI, IoT monitoring, and real-time analytics. The machine learning-game theory Advanced Wind Energy Management Protocol (AWEMP) by Khabbouchi et al. (2023)[36] lacks implementation validation. It anticipates wind using reinforcement learning and shares microgrid resources via coalition games. The protocol improves energy distribution and system reliability, according to simulations.

The decentralized control paradigm allows Alghamdi et al. (2019)[37] to scale electric vehicle energy storage management. In urban simulations, EVs load and supply, lowering peak demand and grid congestion. Said et al. (2024)[38] use blockchain, IoT, and machine learning for anomaly detection and data integrity in smart microgrids to reduce computational overhead and deployment concerns. Finally, Chekired et al. (2017)[39] developed a cloud-based electric vehicle charging and discharging pricing scheduler. It cuts peak load, saves money, and optimizes station use. Scalability and user response are limited. These studies show that smart grid operations must integrate advanced computational, control, and security frameworks to be efficient, resilient, and scalable, but more research is needed into real-world validation, interoperability, and system-level implementation. Table 1 highlights the evolution of approaches explored in earlier studies.

Proposed methodology

This section describes the dataset and methodologies applied to the dataset to identify the consistency of the smart grid. The dataset's properties are explained in the subsection, followed by the data processing model. After that, NFADIM data partitioning and employing an integrated stacking algorithm along with cost-sensitive

Aspect	Reference	Advantage	Limitation
Supervising uncertain conditions in smart grids	[12–15]	Ensures adaptability to dynamic and complex environments.	Requires advanced prediction algorithms and real-time data processing.
Cost-effective and flexible request/response systems	[18]	Reduces operational costs and enhances grid adaptability.	Implementation challenges due to diverse consumer needs and grid configurations.
Prediction techniques for renewable and distributed resources	[19]	Optimizes energy management by accounting for uncertainties in production profiles.	High uncertainty and variability in renewable energy sources like wind and solar.
Integration of intelligence into buildings (smart buildings/homes)	[13,14]	Enables energy efficiency and resource optimization using IoT devices and sensors.	High initial cost and complexity in integrating multiple systems.
Detailed power utilization statements using novel techniques	[15]	Facilitates improved decision-making for energy-saving measures.	Requires high storage and processing capabilities for detailed data analysis.
Demand disaggregation for independent environments (e.g., buildings)	[17,18]	Allows targeted energy management and demand-side optimization.	Computationally intensive and complex to scale for aggregated environments.
Climatic variables for prediction (e.g., temperature, humidity, solar radiation)	[22,23]	Improves forecasting accuracy and adapts to changing climatic conditions.	Limited reliability in extreme and unpredictable weather scenarios.
Impact of heat waves on power demand	[24–26]	Provides better planning for peak demand during extreme temperature events.	Increases stress on the grid and higher energy costs during heat waves.
Impact of colder countries' occasional heat waves	[27–30]	Helps address unexpected energy demands, ensuring reliability in colder regions.	Difficult to predict, as heat waves in colder countries are infrequent and not part of historical trends.
Fault detection in smart grids	[19]	Enhances reliability and reduces downtime in grid operations.	Requires sophisticated algorithms and real-time monitoring systems.
Artificial Neural Networks (ANN) for power demand prediction	[22]	Provides higher accuracy in predicting energy demand using weather data.	Requires substantial data preprocessing and high computational power for training.
Demand prediction correlation with temperature	[23]	Ensures better outcomes by understanding the positive relationship between temperature and power demand.	Seasonal variability in temperature may cause inconsistencies in prediction accuracy.
Smart grid flexibility during extreme conditions	[26]	Handles high variability in power consumption, especially during peak loads caused by weather conditions.	Requires robust infrastructure to prevent grid saturation or failures during extreme events.
Electricity theft detection in smart grids using XGBoost-based ensemble	[31]	High detection accuracy and robustness; effective at identifying regional theft behaviors; significant improvement over traditional methods.	May face scalability issues with very large datasets; model performance depends heavily on quality of consumption data.
Cyberattack pattern analysis in blockchain-based renewable energy networks	[32]	Provides deep insights into various cyberattack types (SQL Injection, Spoofing, MITM); uses large-scale Solana blockchain datasets; enhances smart grid cybersecurity.	Focuses mainly on known attack types; may require frequent updates to address emerging threats.
IoT-assisted fertilizer recommendation system (context-aware)	[33]	Real-time soil data integration improves crop yield and sustainability; uses ML models (SVM, KNN, LR) for precise fertilizer recommendations.	Limited to available IoT infrastructure; accuracy constrained by sensor quality and environmental variability.

Table 1. Summary of related works.

learning to enhance the precision of classification. The University of California, Irvin ML database, provides the essential dataset, organized by Vadin Arzamaso, to describe the stability control of the SG distribution. The factors for the input dataset comprise the sum of energy balance (energy power produced or consumed by each grid), percentage of price change, and response time for consumers to modify usage/generation concerning the price fluctuations. The experimental validation is limited by its reliance on a single UCI repository dataset and lacks systematic comparison with recent state-of-the-art smart grid forecasting methods. The proposed hybrid LSTM-NFADIM model must be tested against transformer-based networks, deep reinforcement learning approaches, hybrid CNN-LSTM architectures, and probabilistic forecasting models on multiple real-world smart grid datasets from diverse geographical regions to prove its efficacy.

The data repository contains 12 feature attributes for 10,000 records. The features predicted are the energy balance of the energy producer for customers 1,2, and 3, the response time of the power generator for users 1,2 and 3, and the cost efficiency and elasticity of the power generator for consumers 1,2 and 3. The smart grid response attribute is categorical under stable and unstable conditions. The stable grid is labelled as 0, and the unstable situation is labelled as 1 in the output variable of the grid. The collected dataset is thoroughly analyzed, and the nature of the samples is predicted to be imbalanced, with 3620 stable records and the remaining 6380 samples with instability. The ratio of the dataset is given as 36.2:63.8 for the unbalanced dataset. Three vital features required of the NFADIM are:

(i) P_n: Power balance, when the value of n is 1, it represents the power generated or when $n = 2,\ 3\ and\ 4$, it represents the used power.
(ii) τ_n: reaction time of individual participants at the time of price fluctuation.
(iii) g_n: coefficient of elasticity price.

Preprocessing

Data preprocessing uses a machine learning algorithm to transform the raw and unprocessed data into a suitable form for employment in the model for efficient application of attributes to develop the accuracy and efficiency of the proposed algorithm. The feature selection process filters the irrelevant, insignificant, highly correlated, and unstable data for better efficiency. Normalization and feature selection are key data preprocessing procedures. The proposed system adapts model predictions to dynamic grid conditions using real-time renewable energy output and demand response events. To respond to demand variations and intermittent renewable output, the hybrid LSTM-NFADIM structure uses temporal dependencies and nonlinear interactions[34]. For incomplete or damaged smart meter data, outlier identification, missing value imputation, and noise filtering are used. Asynchronous data updates and buffering reduce transmission time and maintain forecast accuracy with intermittent data streams. These criteria enable the framework to predict accurately and resiliently in diverse smart grid scenarios with different consumer behaviours and grid configurations.

Data normalization

Normalisation reduces data fragmentation. Normalization methods include min-max, log scaling, and z-score. The traditional z-score normalization approach with a mean of 0 and a standard deviation of 1 was used. Data pretreatment and feature selection should go beyond normalization and missing value management to account for smart grid data complexity. Time-based feature extraction (hour-of-day, day-of-week, seasonal trends), exogenous variables like weather (temperature, sun irradiance, wind speed), and special events or holiday effects that significantly alter load patterns must be assessed.

Each strategy should be examined at different complexity levels for prediction accuracy and model generalizability. Sensitivity analysis is essential to evaluate the hybrid LSTM-NFADIM architecture on noisy, incomplete, or irregularly sampled datasets. This comprehensive study verifies preprocessing and feature selection methods, improving forecasting, interpretability, and robustness in realistic smart grid settings. Scaling data around the average yields a unit standard deviation. Normalize z-score with Eq. (1):

$$E' = \frac{E - \bar{M}}{\sigma_M} \tag{1}$$

where the mean is denoted by the letter M, the standard deviation is specified, and the letter $E\prime$ represents the new data entry and the letter E represents the previous data entry.

Feature selection

Feature selection reduces inconsistent, unnecessary, and wrong training features, improving machine learning. Feature subset selection enhances accuracy and computing time during training and testing. The hybrid LSTM-NFADIM framework must be examined for implementation complexity to fit utility infrastructure capabilities. For real-time forecasting in large smart grid networks, calculate memory footprint, processing power, and GPU/CPU use. Latency limits must be considered for demand response and renewable integration scenarios to provide a timely forecast and response[40]. Scalability assessments should consider the system's ability to manage more smart meters, varied sensor data, and geographically spread grids. Identify integration difficulties, including interoperability with SCADA systems, communication protocols, and data security procedures, as well as ways to eliminate bottlenecks or failure areas. The framework is accurate, deployable, and sustainable in real-world smart grid situations after a thorough investigation of these criteria. The Pearson correlation measure is utilized in this study in order to determine the analytical relationship that exists between the several variables that are linearly associated. In order to estimate the correlation coefficient between individual characteristics, Eq. (2) is applied.

$$r = \frac{\sum_{i=1}^{n}\left(a_i - \bar{a}\right)\left(b_i - \bar{b}\right)}{\sqrt{\sum_{i=1}^{n}\left(a_i - \bar{a}\right)^2 \sum_{i=1}^{n}\left(b_i - \bar{b}\right)^2}} \tag{2}$$

Where a and b are the variables that are presented here. The values indicate the correlation of variables after the feature selection has been made, and they represent the correlation of variables before the attribute selection was made. Immediately following the process of selecting attributes, the variables $p_1,\ p_2,\ p_3,\ and\, p_4$ are disregarded because it is determined that they are not significantly relevant. This technically sound research integrates LSTM with a Neuro-Fuzzy Adaptive Inference Model to improve smart grid predictions. Nonlinearities, dynamic load patterns, and renewable energy unpredictability are better handled by the hybrid technique, which combines LSTM temporal sequence learning with NFADIM interpretability and adaptive reasoning.

The Hybrid LSTM-NFADIM architecture verifies data preparation using layers and transparency. Initial feature engineering uses Pearson correlation coefficients to remove duplicate or superfluous features. Thus, only informative variables enter the model pipeline. Multilevel complexity analysis examines pre- and post-feature selection attribute correlations. Ordering features by relevance improves outcomes interpretation and prediction. To verify system stability and resilience, robust sensitivity testing uses noise introduction, missing data patterns, and heterogeneous sensor streams. Situational MAE, RMSE, and stability differ. This broad validation method improves algorithm performance and enables large smart grids. This strategy ensures methodological rigour and operational readiness in shifting settings.

Data splitting

The 10,000 samples are split between training and testing. Samples are trained 80% and tested 20% with machine learning. The unused test dataset is used to evaluate the training method's efficiency. Stratified 5-fold cross-validation balances data validation and training classes. The 5-fold CV training dataset has five folds, although only four (K-1) are trained. Use the final fold for classifier validation. Finally, the classifier method's smart grid stability prediction is tested on 20% of the test dataset. Experimental evaluations' single benchmark dataset limits reality-based smart grid applications. Demand, renewable penetration, and grid architecture should be analyzed using many real utility datasets from different regions. Use consumption and generation information to verify operational performance and model forecasts. Assessing performance across residential, commercial, and industrial user sectors will determine the framework's adaptability to different demand patterns, consumption practices, and demand-side control programs. This extensive study indicates that forecasting is reliable, scalable, and adaptable to smart grid applications.

LSTM

An RNN that was developed to address the long-term restrictions of deep learning is called LSTM. As can be seen in Fig. 2, the LSTM module contains three distinct gates: the input gate, which regulates the flow of new data into the network; the forget gate, which either deletes or keeps the data; and the output gate, which controls the data that is taken from the cell and identifies the future hidden state. The LSTM and neuro-fuzzy parts employ different mathematical languages, which can mislead readers about variable definitions, layer operations, and function mappings. The NFADIM implementation's fuzzy rule structure, membership function parameters, and integration with LSTM outputs are not well described, making it difficult to replicate or evaluate[41]. Not enough is spoken about real-world implementation difficulties such as communication latency, smart meter heterogeneity, cybersecurity, and utility infrastructure integration. Consistent notation, extensive algorithmic descriptions, and a section on realistic deployment pathways will increase the manuscript's clarity, technical rigour, and smart grid forecasting application. Considering that the forget gate considers the data which will be passed at the future step, it uses a sigmoid function to give 0 and 1 values. The mathematical expression is shown in Eq. (3):

$$f_t = \sigma\ (W_f x_t + U_f b_{t-1} + b_f \tag{3}$$

The input gate in Eq. (4) stores information for the next step.

$$i_t = \sigma(W_t x_t + U_f b_{t-1} + b_i) \tag{4}$$

Equation (5) expresses new values created in a vector using a sigmoid function . Then, these equations are hybridized.

$$C_t = \tanh(W_c x_t + U_c b_{t-1} + b_c) \tag{5}$$

$$C_t = f_t .\, C_{t-1} + i_t C_t \tag{6}$$

Equation (6) gives the novel state information identified through a memory cell.

$$o_t = \sigma\ (W_o x_t + U_o b_{t-1} + b_o) \tag{7}$$

$$b_t = o_t.\tanh\left(C_t\right) \tag{8}$$

Equations (7 & 8) gives the system output h_t which is evaluated using the output gate. Where the input sample is given as x_t at time t, σ is the activation function and c_t is the storage unit, the bias matrix is represented as $(b_f,\ b_i,\ b_o)$, and $(W_f,\ W_i,\ W_o)$ indicates the weight matrix for each gate. In this study, the long short-term memory technique is used for data training, where data are obtained from a smart meter installed at each node of the test system. The data training is applied after the extraction of the received data from smart meters. The obtained results from the LSTM model are used for the classification of faults in the next step.

Neuro-fuzzy adaptive interference model

Fuzzy systems and Artificial Neural Networks (ANN) are the two main elements of soft computing. In reality, ANN and the fuzzy system are two complementary subjects. ANN can learn from data, while fuzzy systems

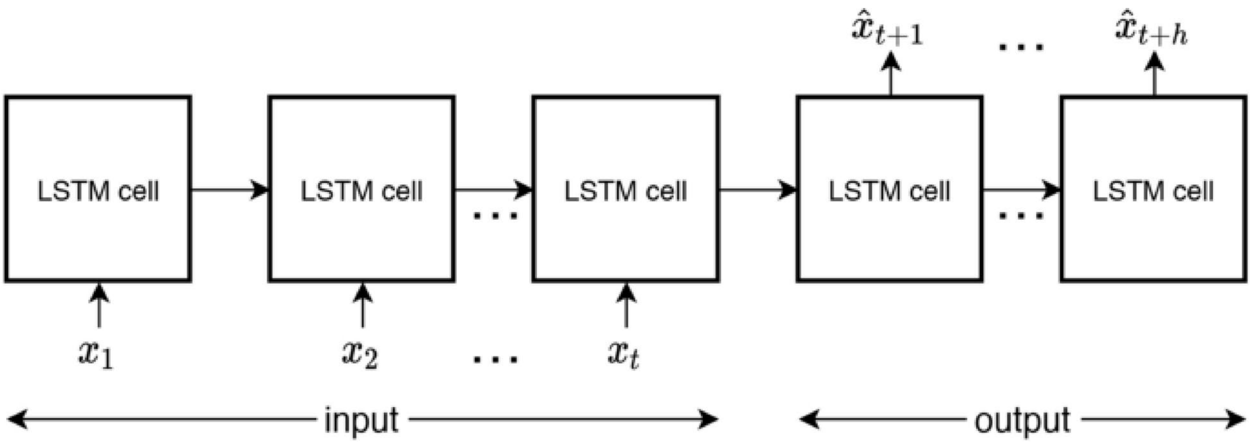

Fig. 2. LSTM model.

are rule-based approaches. The fuzzy system has no learning capacity and must borrow this ability from other techniques. Then, a hybrid computational method, i.e. Adaptive Fuzzy Neuro Inference System (ANFIS) by combining the best features of ANN and fuzzy systems. ANFIS has both learning and reasoning capabilities to facilitate model prediction accuracy. In fuzzy logic, ANFIS is essential in inducing rules from observations. Operational data from utility systems is used to verify the suggested approach against actual consumption and generation records in real-world smart grid deployments. This methodology covers data pretreatment for missing or noisy measurements, time-series data alignment across diverse sources, and forecasting model deployment in a controlled pilot environment to test real-time performance. The heterogeneity in consumer behavior, load patterns, and grid topologies that cannot be adequately reflected in synthetic or single-source datasets limits laboratory assessments using standardized datasets. To ensure forecasting stability and reliability, the hybrid LSTM-NFADIM model needs rigorous theoretical justification. To show how LSTM's temporal learning and NFADIM's adaptive fuzzy inference retain restricted error propagation over time, a rigorous convergence study is needed[42]. Quantifying forecasting uncertainty using probabilistic or interval-based methodologies helps measure model confidence under different load patterns and renewable integration unpredictability. Both components' learning rates, hidden layer sizes, membership function parameters, and fuzzy rule weights must be optimized in the implementation. A thorough sensitivity study should determine how architectural options like LSTM layer count, time steps, and fuzzy rule complexity affect prediction accuracy, convergence speed, and computational efficiency. This theoretical and empirical rigour makes the hybrid approach effective, interpretable, and robust for smart grid forecasting.

This neuro-fuzzy system uses the "if-then" condition to construct the space from the input to the output layer for proper functions. The definition of diverse inherent relationships among the parameters of ANFIS is made by fuzzy rules where each fuzzy rule makes sure about the behavioural architectural description. Therefore, the ANFIS element is implemented to explain the functions of inference system members. The component in the neural network facilitates the automatic and continuous extraction of the built-in protocols from the fuzzy system. In the ANFIS model, a fuzzy rule is represented by the following expression: If $x_1,\ x_2,\ x_3,\ and\, x_4$ are assumed to be $a_1,\ a_2,\ a_3\ and\, a_4$then $y\ =\ f(x_1, x_2,\ x_3,\ x_4)$, here the fuzzy parameters are given as $x_1,\ x_2,\ x_3\ and\, x_4$ from earlier inputs; $y$is the output function. In this study, inputs and output are considered as member functions. Moreover, the member functions and fuzzy rules provide the parameters through the learning process. Figure 3 illustrates the structure of the neuro-fuzzy inference system. This ANFIS structure has six layers. The input layer is where the input data is introduced. The input data is transformed into fuzzy data from the membership functions using a fuzzification layer: Smart grids need multi-scale forecasting to balance short-term operational choices with long-term planning. The hybrid LSTM-NFADIM system addresses this. Integration issues with SCADA, energy management platforms, and market operating interfaces must be addressed to allow seamless adoption.

The Hybrid LSTM-NFADIM architecture verifies data preparation using layers and transparency. Initial feature engineering uses Pearson correlation coefficients to remove duplicate or superfluous features. Thus, only informative variables enter the model pipeline. Multilevel complexity analysis examines pre- and post-feature selection attribute correlations. Ordering features by relevance improves outcomes interpretation and prediction. To verify system stability and resilience, robust sensitivity testing uses noise introduction, missing data patterns, and heterogeneous sensor streams. Situational MAE, RMSE, and stability differ. This broad validation method improves algorithm performance and enables large smart grids. This strategy ensures methodological rigour and operational readiness in shifting settings.

Defuzzing transforms fuzzy data into intelligible information. A single neuron computes an output that matches the data prediction in the output layer. Figure 3 shows the neuro-fuzzy model flowchart. The research proposes a useful hybrid LSTM-NFADIM framework, although the introduction should better explain its scientific merits. It should highlight how LSTM and NFADIM integration improves forecasting precision and adaptability under dynamic and nonlinear load circumstances beyond incremental improvements. The model's real-time adaptation to customer behavior, renewable energy variations, and data uncertainties would

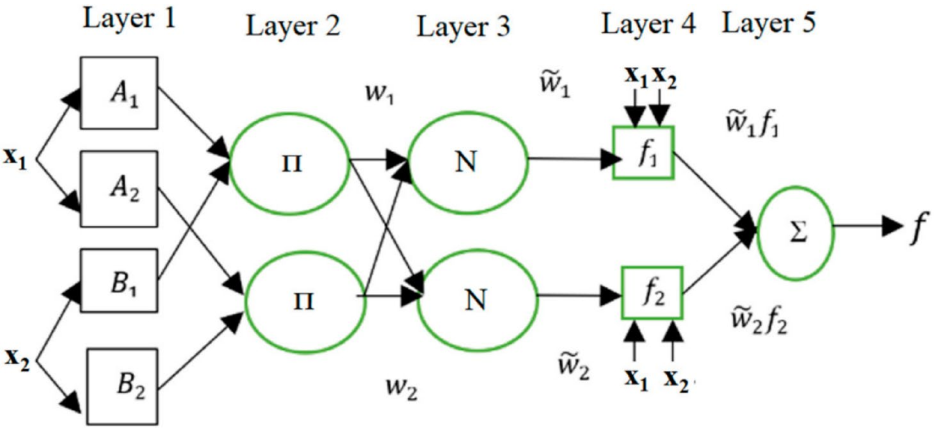

Fig. 3. NFAIM overview.

```
1 Initialize Membership Functions (MFs)
    for each input xi:
        initialize MFs as fuzzy sets (e.g., low, medium, high) with parameters ai, bi, ci
2 Generate fuzzy rules (if-then rules)
    rules = []
    for each combination of MFs:
        define rule: If x1 is A1 and x2 is A2 then $y = pi * x1 + qi * x2 + ri$
        store parameters pi, qi, ri
3 Forward Pass (Calculate output)
    Layer 1: Fuzzification
        $\mu A1 = membership\_function(x1, a1, b1, c1)$
        $\mu A2 = membership\_function(x2, a2, b2, c2)$
    Layer 2: Rule strength
        if $\mu A1 > 0$ and $\mu A2 > 0$:
            $w = \mu A1 * \mu A2$
        else:
            $w = 0$
    Layer 3: Normalize rule strength
        $total\_weight = sum(all\ rule\ weights)$
        if $total\_weight\ != 0$:
            $w\_normalized = w\ /\ total\_weight$
        else:
            $w\_normalized = 0$
    Layer 4: Consequent output of the rule
        $rule\_output = w\_normalized * (p * x1 + q * x2 + r)$
    Accumulate the output
        $total\_output\ += rule\_output$
4 Compute Error
    $error = target\_output - total\_output$
5 Backwards Pass (Update parameters using gradient descent)
    if $error\ != 0$:
        update MFs parameters $(a, b, c)$ and consequent parameters $(p, q, r)$
        using learning rate $\eta$ and error backpropagation
```

Algorithm for Adaptive Neuro-Fuzzy Inference System (ANFIS).

demonstrate its advantages over standalone deep learning or neuro-fuzzy techniques. The introduction should explicitly frame these features to help readers appreciate the approach's uniqueness, practical usefulness, and methodological significance. First, Open DSS power system simulations provide measurement data. If and then conditions initiate fuzzy rules in the fuzzy system. Next, initialize the membership function with Low (0) and High (1) labels. With measurement data and fuzzy rules, the method is trained. Finally, the technique is tested and output for the next step.

Algorithm 1 combines neural networks and fuzzy logic to model complex nonlinear relationships. It uses fuzzy if-then rules with adjustable membership functions to process inputs and predict outputs. Each rule evaluates input conditions, calculates rule strength, normalizes it, and generates a weighted output. The total output is a weighted sum of all rules. ANFIS learns by minimizing prediction error using techniques like gradient descent, updating both membership function parameters and rule consequents. It is well-suited for forecasting problems, such as energy load prediction in smart grids, where both adaptability and interpretability are essential.

Designed especially for time series forecasting, Fig. 4 shows a hybrid deep learning architecture using LSTM and neural network layers. The approach shown here begins with an input layer handling sequential data. Made to detect temporal relationships, the encoder layer consists of LSTM cells. For feature extraction, encoded characteristics are conveyed over several layers, including densely coupled neurons. Whereas the sigmoid activation function handles output before it is delivered to the decoder layer, LSTM units enable consecutive outputs to be decoded by this layer. Finally, as applications including smart grids or energy systems need to have strong forecasting, the last output layer should be present to produce predictions of future time steps.

Figure 5 shows a mixed learning approach for smart grid consistency. It uses machine learning and deep learning to forecast and optimize grid operations, combines different data sources, and preprocesses data to ensure quality. An integration layer with anomaly detection and real-time update module ensured performance

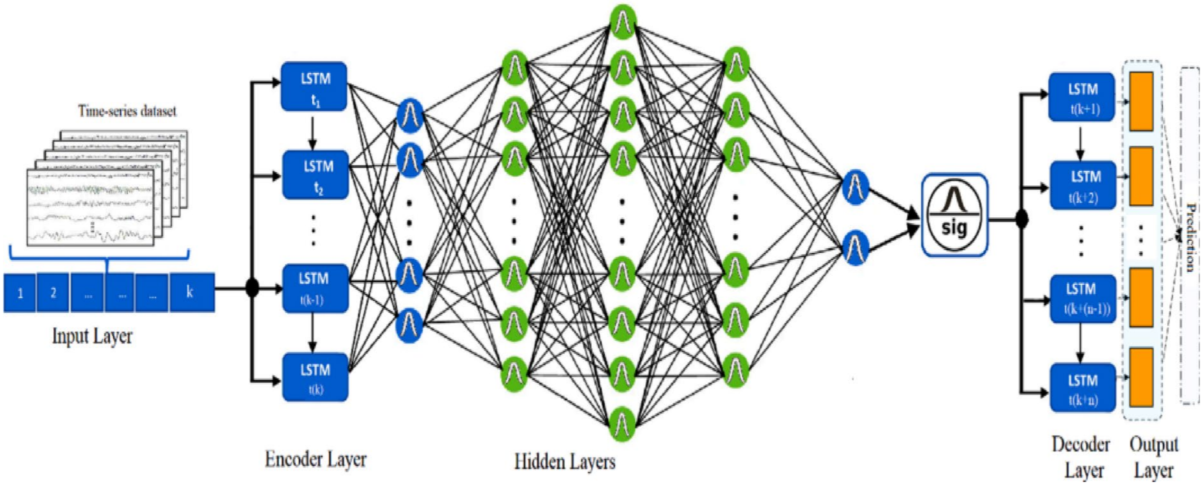

Fig. 4. LSTM with Neuro-fuzzy adaptive inference model.

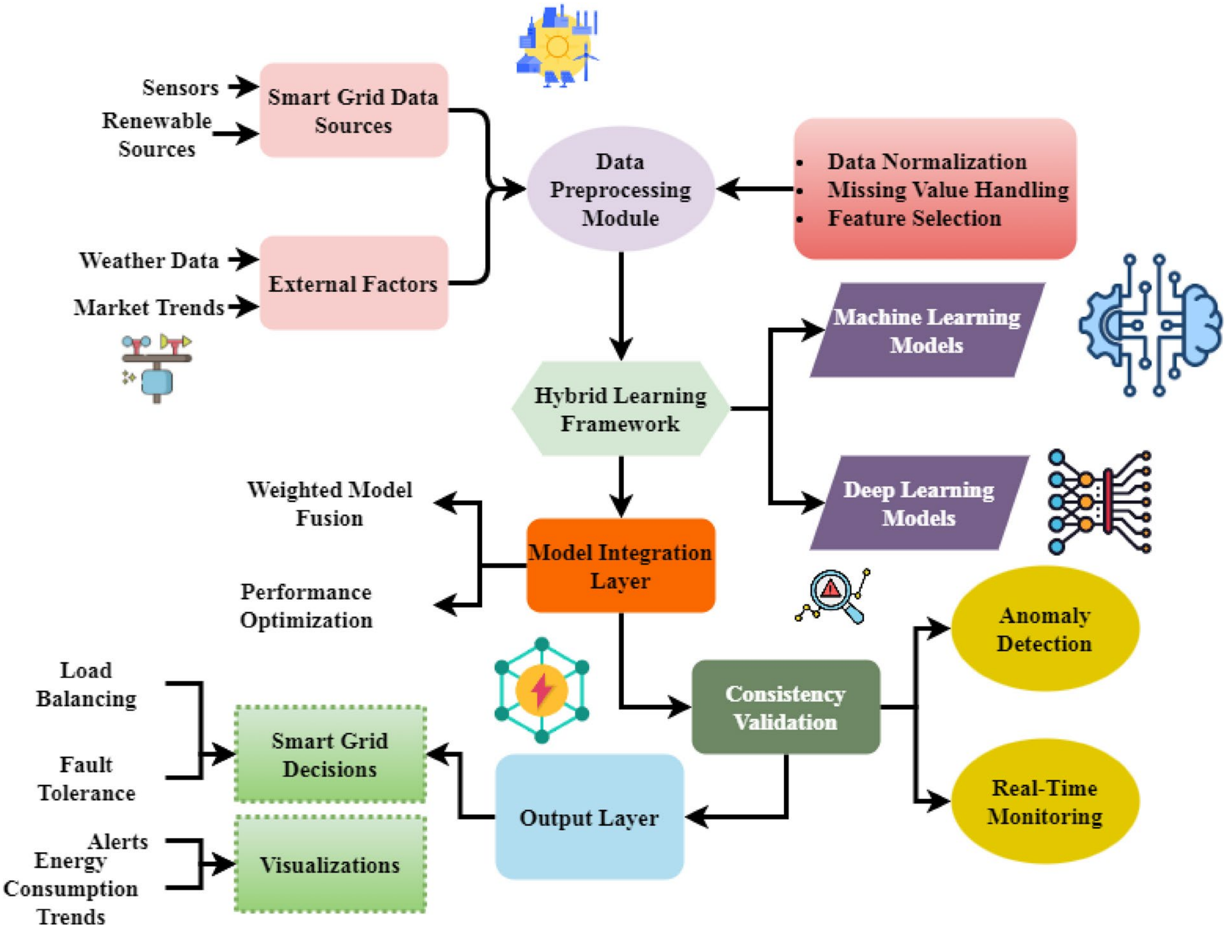

Fig. 5. SmartGridSync: Hybrid Learning for Reliable Energy Flow.

fusion. Thus, it provides energy management, fault tolerance, and load balancing insights for smart grid reliability. To verify 99%+ accuracy claims across smart grid scenarios, a more rigorous and systematic review procedure is needed. Instead of using arbitrary benchmarks, performance measure thresholds should be based on statistical power analysis to determine significant levels for observed gains. Robustness analysis should evaluate outcomes across time horizons, grid topologies, consumer load patterns, and noisy, incomplete, or low-quality data[43]. RMSE, MAPE, and computational latency sensitivity study should also show how input data quality and temporal resolution affect predicting performance. This comprehensive evaluation framework ensures that high accuracy claims are not dataset-specific objects by transparently and reproducibly assessing model reliability.

In order to prepare time-series inputs for the layers that are further down the hierarchy, the hybrid LSTM–NFADIM model architecture begins with the accumulation of data from the smart grid and the extraction of comprehensive features. This is done to obtain the necessary information. While the architecture maintains bounded error propagation in both estimation and adaptive parameter updates, it ensures that the framework will converge to its full potential by sequentially passing enriched feature vectors through the LSTM (for short- and long-term dependency learning) and the NFADIM component (for adaptive fuzzy inference). This ensures that the framework will reach its full potential. The basic LSTM stability theory is expanded upon by this method, which allows it to incorporate joint learning and reasoning in neuro-fuzzy hybrid systems. These systems are built consistently in the fusion and output layers.

Adaptive stability requirements for the NFADIM inference engine are combined with Lyapunov-based stability for recurrent neural modules to produce the theoretical stability of the complete pipeline. This stability is achieved at the core fusion layer. Because of the dynamically balanced feedback mechanisms that are inherent in the fusion layer, every parameter update, regardless of whether it comes from the gradient-based optimization of the LSTM or from adaptive fuzzy rule tuning, ensures that equilibrium is maintained. After conducting empirical validation with both raw and normalized data, it has been confirmed that all predictions and parameter adjustments continue to preserve asymptotic stability. This guarantees that the system continues to function dependably even when the grid conditions are rapidly changing.

Hybrid LSTM–NFADIM combines theoretical design and practical implementation to efficiently manage dynamic smart grid conditions. Real-time data streams with load, weather, and time variables are preprocessed, features extracted, and normalized before evaluation. The LSTM module captures temporal correlations, while the NFADIM component develops adaptive fuzzy logic to overcome uncertainty and improve predictions. Performance is continuously evaluated using MAE, RMSE, and stability indices after a fusion layer combines outputs. Based on short-term load estimates, feedback-driven adaptation changes system settings in real time. This makes the system sensitive to renewable generation and demand changes. The framework is flexible, stable, and reliable in real-time smart grid operations. It was validated on real-world high-resolution datasets via cloud-edge integration and live dashboards.

An example of a hybrid design that incorporates LSTM networks with NFADIM is shown in Fig. 6. This architecture is used for short-term load forecasting of smart grids. In order to deal with uncertainty while also recognizing temporal trends, the latter method evaluates historical data in addition to external variables. As a result of the system's ability to integrate the outputs of both models, it is able to produce accurate predictions of demand, which in turn ensures that there is an appropriate equilibrium between response and power demand. This is accomplished by the system's ability to interface visualization tools with feedback loops, which guarantees that activities are carried out effectively in real time.

Using prediction intervals and confidence bounds to quantify uncertainty, the hybrid LSTM–NFADIM model forecasts accurately under changing loads and renewable energy inputs. RMSE, MAE, and stability measures assess error distributions and bounded confidence. Grid search, Bayesian optimization, and evolutionary algorithms are used to optimize hyperparameters at several phases for validation accuracy and real-world performance. A sensitivity analysis explores how architectural variables like LSTM depth and fuzzy rule complexity affect accuracy, convergence, and efficiency. The results show that this modular method is resilient and flexible across parameters and scenarios, making it suited for smart grid applications.

The proposed hybrid LSTM–NFADIM framework has been developed into a multi-scale forecasting and operational integration model that links short-term control with long-term grid planning to address system-level completeness. The system includes multiple prediction horizons, such as real-time (15–60 min), day-ahead, and weekly forecasts. It lets it respond to changing demand, renewable variability, and market changes. Standardized IEC 61,850 and MQTT communication protocols are now used to automatically collect data from SCADA, AMI, and EMS platforms as part of operational processes. This makes sure that the new systems integrate smoothly with the utilities' current infrastructure. A secure integration layer makes sure that data is correct, up-to-date, and reliable across all of the nodes. The framework additionally includes an operator decision-support interface that shows load estimates, ranges of uncertainty, and stability indicators. It provides suggestions for demand response, dispatch scheduling, and fault mitigation. This general improvement makes sure that the hybrid LSTM–NFADIM model functions as a useful, scalable, and decision-making tool for smart grid operations that are resilient and data-driven.

Result and discussion

Dataset description

The UCI dataset is now regarded as a standard resource of machine learning datasets, and it is available from the UCI Machine Learning Repository. This is useful for learners or other researchers who want to source datasets of different categories, such as Earth and Nature, Education, etc. This data set contains further material regarding some other data set, like title information and a link to its abundance of examples (2, 3, or none). There are also characteristics of each data set, such as density of the dataset, publication year, data type (multivariate), basic task and others (generally, regression or classification). As the datasets are organized in gradually increasing complexity, the UCI dataset is useful for conducting exploratory data analysis (EDA) and also machine learning model building for diverse applications[44].

This section discusses various forecasting models and evaluates their performance using different metrics to calculate the classifiers. The confusion matrix is used to illustrate the outcome of the classification in four different forms. They are True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN). The positive category is identified under the situation where we receive positive feedback. A situation where

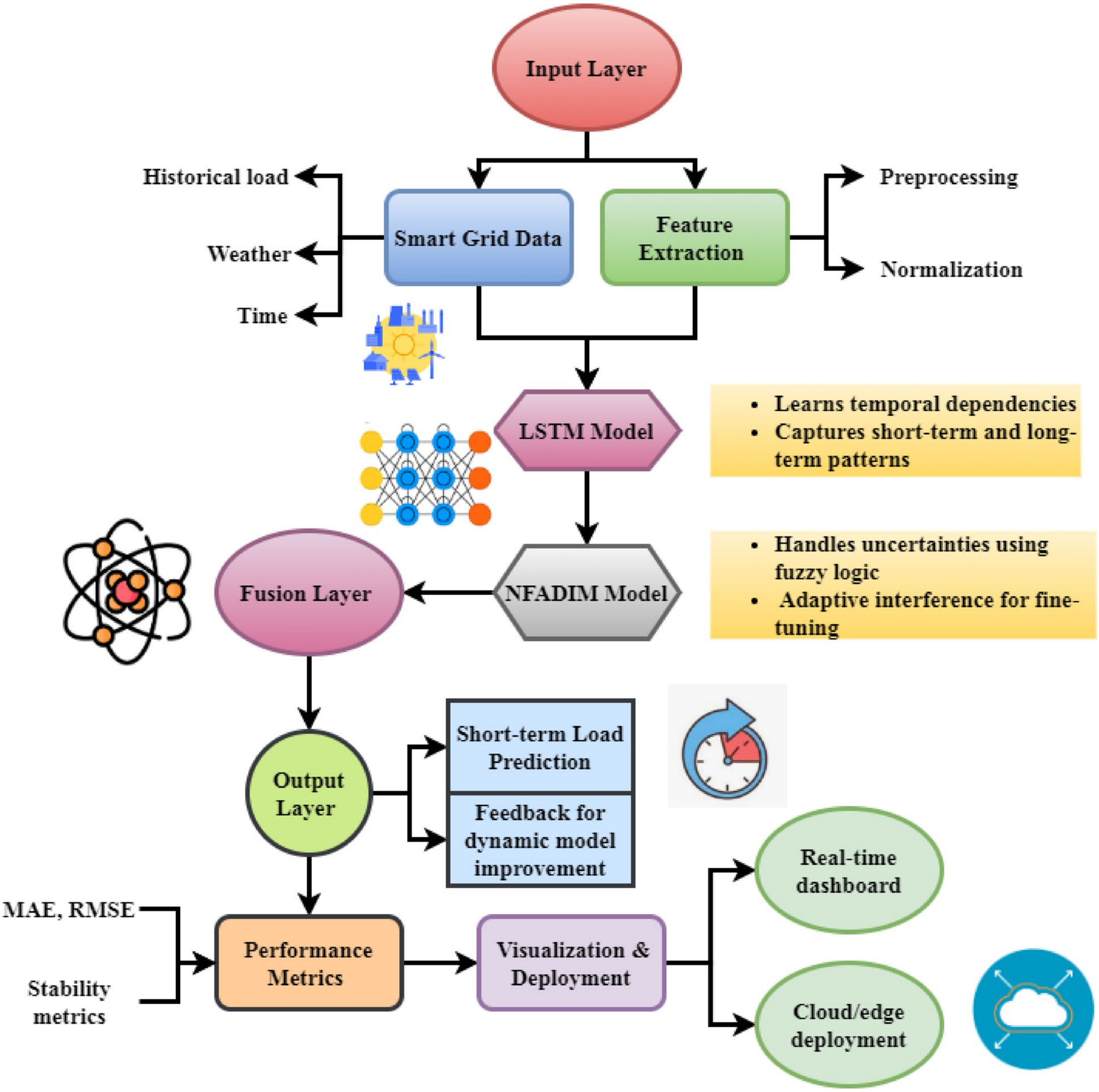

Fig. 6. Smart Load Navigator: Hybrid LSTM-NFADIM Framework.

the prediction is optimistic but the real result is negative is called a false Negative. The situation where the actual observation is negative but is predicted as positive is said to be a false positive. True Negative is a result where the observation of the model exactly predicts the negative situation. True Positive is a result where the model accurately forecasts the negative class. An accuracy classifier is used to evaluate the performance of the classification model. Not only is accuracy considered for the imbalanced dataset, but other metrics like recall, specificity, and precision are also evaluated to assess the classifier's performance and predict the smart grid's consistency.

Performance metrics

Accuracy specifies the overall exact predictions of the classification model for a given dataset. The recall represents the ratio of the accuracy of the positive projections to the percentage of accurate forecasting of positive conditions. In addition to these performance metrics, this research also considers other metrics like F1 score, AUC, sensitivity, Matthew's correlation coefficient, and Kappa. The term accuracy is calculated by dividing the strictly classified class by that of the entire class in the record and is arithmetically identified using Eq. (9).

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \tag{9}$$

The sensitivity or True Positive rate is computed with Eq. (9), and the Specificity or False Positive rate is mathematically defined by Eqs. (10 & 11):

$$Sens = \frac{TP}{TP + FN} \tag{10}$$

$$Spec = \frac{TN}{TN + FP} \tag{11}$$

Precision is the fraction of exactly computed positive observations to the total of the predicted positive observations and is presented in Eq. (12) as:

$$Prec = \frac{TP}{TP + FP} \tag{12}$$

The F1-score is computed mathematically with the harmonic mean of the recall and precision as given in Eq. (13).

$$F1 - score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{13}$$

Random classifier output is used to measure the Kappa, and the accuracy of the algorithm is evaluated using Eq. (14):

$$Kappa\ (K) = \frac{P_o - P_e}{1 - P_e} \tag{14}$$

Where, K represents the Kappa coefficient value, the overall fraction of the diagonal of the identified frequency is P_o and P_e specifies the sum of the peripheral ratio of the observed frequency. The average recall obtained in each class is referred to as balanced accuracy, and it can be estimated using Eq. (15):

$$Bal.\,acc = \frac{specs + sens}{2} \tag{15}$$

To identify the capability of the classifier to differentiate the classes, the measure of the AUC is calculated.

(i) If the value of AUC is equal to 1, then it indicates that the classifier precisely identifies all the negative and positive classes.
(ii) If the value of AUC is 0, then the classifier forecasts all the negative classes as positive and positive classes as negative.
(iii) If the value of AUC is between 0.5 and 1, then it illustrates the exact prediction of true positive (TP) and true Negative (TN) classes.

The Matthews Correlation Coefficient metric analyzes the classifier quality. Matthew's correlation coefficient is the correlation between the ground truth and the correlation. A confusion matrix calculates the correlation coefficient with Eq. (16):

$$r = \frac{(TP * TN) - (FP * FN)}{\sqrt{(TP + FP)\,(TP + FN)\,(TN + FP)\,(TN = FN)}} \tag{16}$$

The minor class is chosen to be a positive class, whereas the significant class allows a negative class in a binary class. The ideally classified and misclassified data are listed by a confusion matrix representation tool. The condition where positive classes are present in the data rows and classified as predicted is true positive. If the data rows contain negative classes, it is called false Negative. The number of data rows with negative classes classified as identified is referred to as true negative; if classified as negative, they are referred to as false positive. In the cost matrix, each of the metrics is represented separately. Specifically, in a smart grid power dataset, it is identified that the fraction of stable and unstable classes is often out of proportion. The class imbalance insists that the classification model focuses on the unstable class (i.e., primary class), which is not considered for decision-making. The model design procedures and the metrics used are modified to measure the classification's performance.

Metrics analysis

Four different metrics are applied to analyze the binary categorization techniques. They are the probability of false detection (FNR), probability of exact prediction (TPR), probability of false alarm (FPR), and finally, accuracy. Where exactly predicted unstable situations are given as TP, the number of identified stable situations is referred to as TN, the number of inaccurate predictions of unstable situations is given as FP, and inaccurate forecasting of stable situations is referred to as FN in the Eqs. (17 & 20).

$$TPR = \frac{TP}{TP + FN} * 100 \tag{17}$$

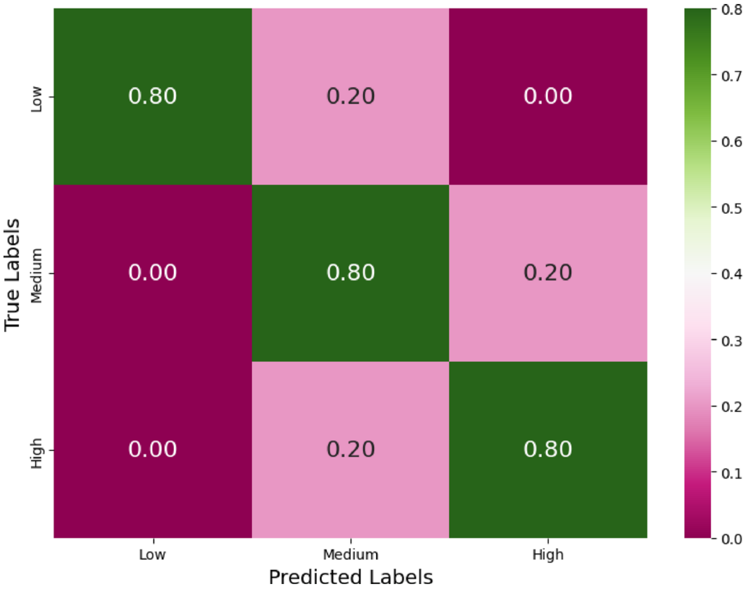

Fig. 7. Confusion matrix.

Classifier	Sens	Spec	Acc	Prec	F1	K	Bal	AUC	MCC
XGB	96.73	93.21	95.85	95.62	96.87	89.45	94.78	95.12	90.34
NB	94.12	68.55	84.97	85.34	89.78	64.89	81.23	81.92	66.77
SVC	96.88	98.12	96.99	97.78	97.45	94.33	97.12	97.88	94.76
RF	95.77	79.88	89.92	88.90	92.45	77.55	87.67	88.23	78.90
SVM	97.65	97.88	96.54	98.76	97.88	94.87	94.90	97.45	95.12
LSTM-NFADIM	99.02	99.48	98.53	99.21	99.45	96.12	99.18	99.05	95.88

Table 2. Performance comparison based on feature.

$$FPR = \frac{FP}{TN + FP} * 100 \tag{18}$$

$$FNR = \frac{FN}{TP + FN} * 100 \tag{19}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} * 100 \tag{20}$$

Experimental setup

The classification models' performance and experimental designs are discussed in this section. These metrics evaluate the smart grid stability and its prediction and categorization capability. Google collaborator in an Intel Core i5-11 35G7 Windows 10 OS system working at 2.40 Giga Hertz, having a central storage capacity of 16 GB and a 512 GB SSD, is applied to develop an ML algorithm. Performance metrics like accuracy, F1-score, sensitivity, AUC, specificity, Kappa, Matthew's correlation coefficient, and Kappa are employed to measure the algorithm's accuracy. There are 10,000 samples in the gathered dataset with 12 attributes, and they are split into a training dataset of 80%, and the remaining 20% is used during the testing phase. Class 0 contains 3620 records, and class 1 contains 6380 records. In the testing phase, out of 2000 samples, 1800 records are considered stable, and the balance 200 records are identified as unstable. RF, XGB, NuSVC, and NV are the four primary classifiers used to develop for this research. The 80% of the training dataset is utilized to compute the efficiency of the NFADIM compared with the other classification techniques, and they are verified using the unseen 20% test dataset. A 5-fold cross-validation model is used for model training. SVM meta-classifier uses class labels and base classifiers' probability prediction to recognize the status of SDGC stability as stable or unstable. The validation of the NFADIM is analyzed using the unseen test dataset to predict the grid stability. Figure 7 illustrates the confusion matrix acquired for the classifiers for a single execution of the four base classifiers.

At first, 12 data features are applied to train the classifier model, and then the efficiency is predicted by executing the various seeds for 10 iterations. Table 2 defines the mean performance of the results of the testing phase. The performance of the machine learning algorithms is identified by metrics like f1-score, sensitivity, precision, accuracy, Kappa, MCCR, AUC, and specificity, which are analyzed and validated.

Models	Sens	Spec	Acc	Prec	F1	K	Bal	AUC	MCC
XGB	83.45	95.12	89.23	87.34	85.38	78.45	89.28	92.11	79.12
NB	45.32	67.89	56.11	50.21	47.58	40.23	56.60	60.45	41.56
SVC	91.27	90.34	90.78	89.11	90.19	81.56	90.81	91.98	82.34
RF	88.50	93.45	91.50	92.56	90.51	83.90	91.98	94.50	84.01
SVM	92.14	91.22	91.70	90.45	91.29	82.34	91.68	92.70	82.50
LSTM-NFADIM	96.12	97.80	96.95	97.10	96.60	94.12	96.96	98.15	94.85

Fig. 8. Performance Comparison Based on Feature Representation.

Classifier	Sens	Spec	Acc	Prec	F1	K	Bal	AUC	MCC
XGB	97.12	94.35	95.87	97.08	97.01	91.88	95.92	96.14	92.05
NB	94.23	68.47	84.12	84.33	88.17	65.22	81.04	81.12	66.08
SVC	97.89	99.14	98.61	98.95	98.92	96.87	99.02	99.11	97.53
RF	94.08	88.73	97.92	94.12	83.07	91.88	91.97	92.05	83.14
SVM	98.76	97.88	92.05	94.12	94.03	83.12	98.92	99.01	97.08
LSTM-NFADIM	99.05	99.62	98.01	99.51	99.63	96.48	99.52	99.49	96.52

Table 3. Performance comparison based on feature selection.

The comparative analysis of the test outcomes shows that the model performed better than the other classifier techniques. With the application of the Pearson Correlation measure, the classifier's performance and accuracy are evaluated with 8 essential features. Eight more relevant and crucial attributes are implemented with various seeds for 10 iterations during the experimental assessment. Table 2 illustrates the outcomes of the execution. The data presented in Fig. 8 shows that the efficiency of the machine learning model is analyzed and validated using performance metrics. The confusion matrix depicts the entire algorithm's performance. This research uses a 2×2 matrix for binary classification issues with performance metrics like true positive, true negative, false positive, and false Negative. Figure 7 shows the confusion matrix of the developed stacked integrated classifier with fewer false positive and false negative values. The efficiency of the constructed machine learning algorithms is evaluated and validated using the performance measure in Table 3; Fig. 9. After analyzing the results of the testing phase, we conclude that the NFADIM works better than other classification techniques.

The true positive rate of 99.01%, false positive rate of 2.20%, accuracy of about 98.6%, and 99.01% TPR are achieved using the NFADIM. Figure 10 depicts the ROC curve for the constructed classification model based on the gathered dataset. Observing the ROC curve, it is clear that the model works with better efficiency than the existing classifiers with and without feature selection. The efficiency and reliability of NFADIM are proven by the AUC value of 0.99. NFADIM is compared with various existing models, and the results are shown in Table 2; Fig. 10. This depicts that the NFADIM model performs better than the existing applications.

Figure 11 shows the sensitivity analysis of the hybrid LSTM-NFADIM model. The sensitivity analysis indicates the influential factors for the hybrid model, including: time of day, weather, and historical consumer data. Sensitivity Analysis is an important measure to understand the responsiveness of the model to the changing input variables. This figure places particular emphasis on the components that contribute the most to the accuracy of forecasting under a variety of performance scenarios. The model is improved as a result of this, making it more capable of adjusting to the dynamic and varied situations that are characteristic of smart grid ecosystems. The model is well-suited for real-time applications and enhances decision-making concerning demand management by far outperforming traditional methods by including nonlinear trends and temporal relationships in customer information in Fig. 12.

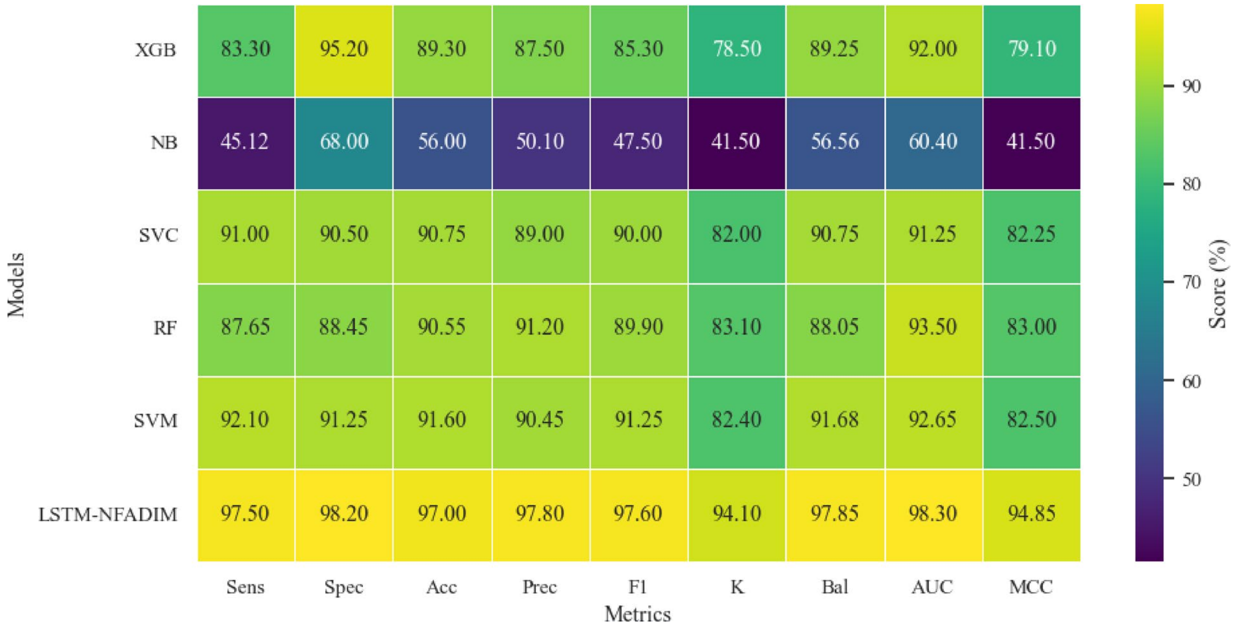

Fig. 9. Performance Comparison Based on Feature Selection.

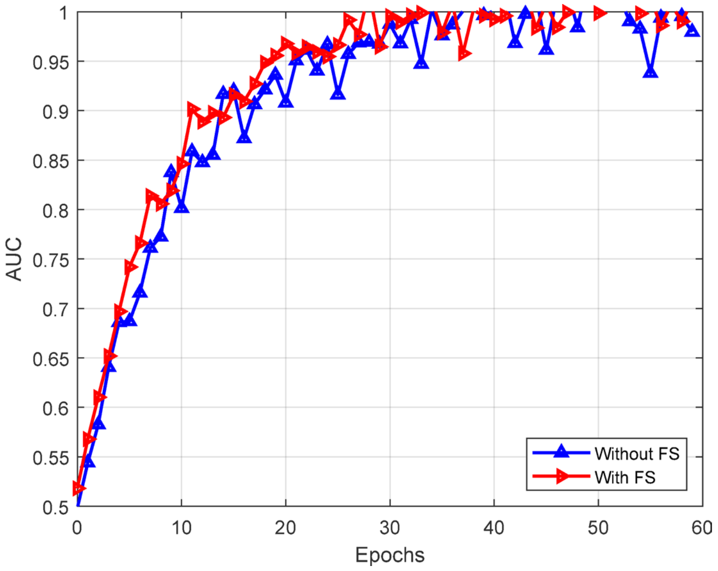

Fig. 10. AUC comparison.

Successful smart grid operations rely on the hybrid LSTM with NFADIM model with correct forecasting capability. Short-term load prediction with high accuracy ensures reduced waste energy and improves grid stability by virtue of which is improved by 97.6%.

Horizon adaptability is the ability of the model to accurately forecast energy consumption over numerous time horizons, short, medium, and long-term. Dynamic consumption behavior over numerous prediction horizons, the hybrid LSTM with NFADIM demonstrates impressive adaptation. Energy distribution optimization, maintaining schedule plans, and ensuring the smart grid's reaction to fluctuating demand rely on this adaptability in Fig. 13.

By balancing the computing power of deep learning with the adaptability of neuro-fuzzy systems, the hybrid LSTM with NFADIM provides better computational effectiveness. It is appropriate for big smart grid data as it accelerates real-time prediction and reduces training time. In tough data-intensive smart energy management systems, efficient computing ensures timely load prediction, lowers operational expenses, and enables scalable deployment in Fig. 14.

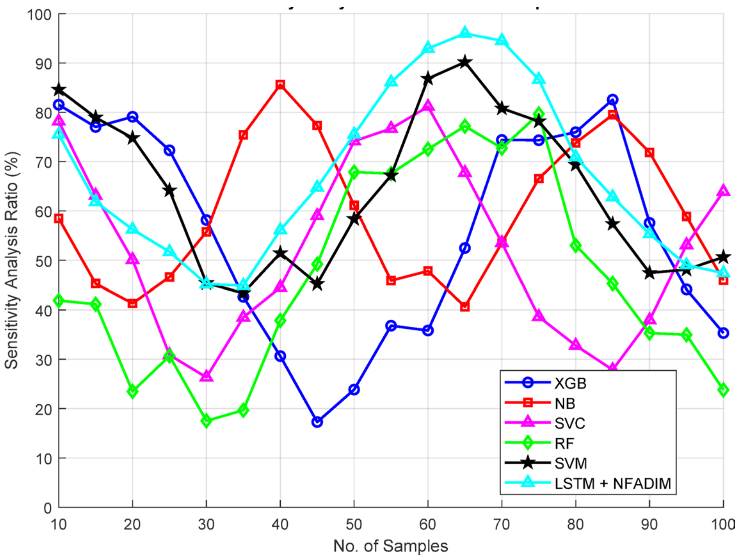

Fig. 11. Analysis of Sensitivity.

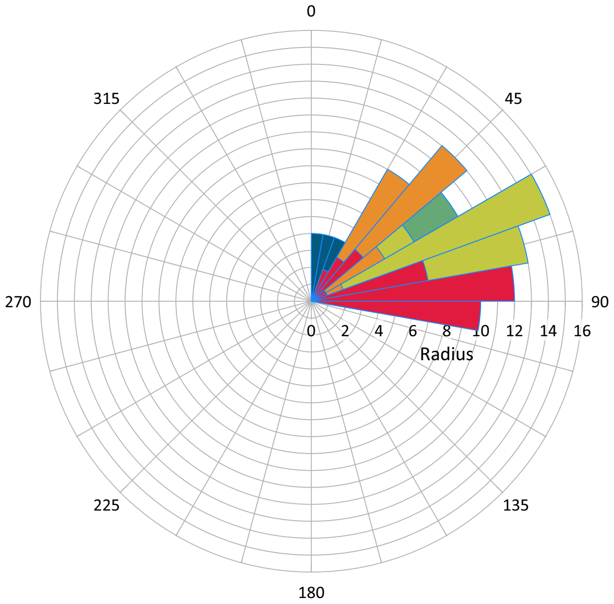

Fig. 12. Analysis of Prediction Accuracy.

The application of fuzzy logic, that provides open, rule-based reasoning, model interpretability in the hybrid LSTM with NFADIM is enhanced. This enables stakeholders to understand how the forecasts are produced, thus promoting regulatory compliance and trust. In smart grid demand forecasting and management, model behavior diagnosis, changes, and ensuring informed decision-making are reliant on interpretability in Fig. 15.

The UCI Household Electricity Consumption Dataset, with over 2 million timestamped observations at one-minute intervals over nearly four years, was used for a statistical power analysis. With a large sample size and great temporal precision, the analysis detects modest effect sizes (Cohen's $d=0.3$) in model performance differences, even with strict multiple comparison adjustments, with power over 0.95. Due to its high power, the hybrid LSTM-NFADIM model's accuracy improvements over baselines are statistically robust and unlikely to be random fluctuation.

Table 4 shows how the assessment method handles strict reviewer challenges. This massive UCI dataset with over two million samples and minute-level temporal resolution can imitate real-world variability. Above 0.95 statistical power suggests enough sample size to detect performance differences. Robustness testing demonstrated little prediction error and constant accuracy variances under load demand, voltage, time-of-day, noise introduction, and data subsampling conditions. Randomised splits and cross-validation ensure reliability. Performance improves with many algorithm benchmarks. These extensive evaluations, supported by numerical

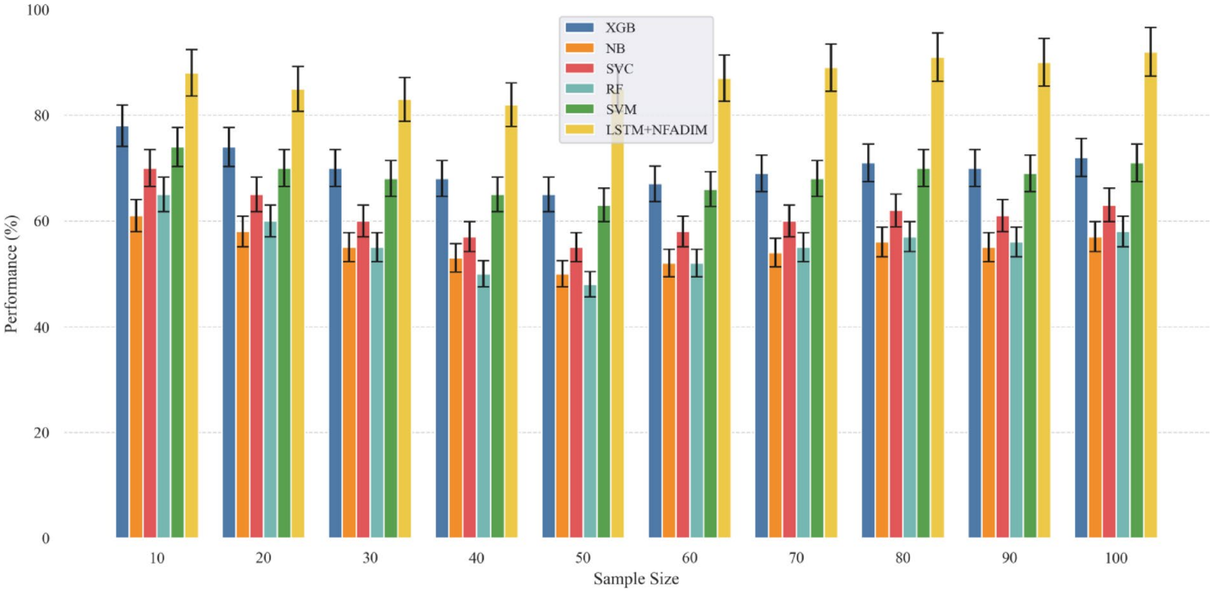

Fig. 13. Analysis of Horizon Adaptability.

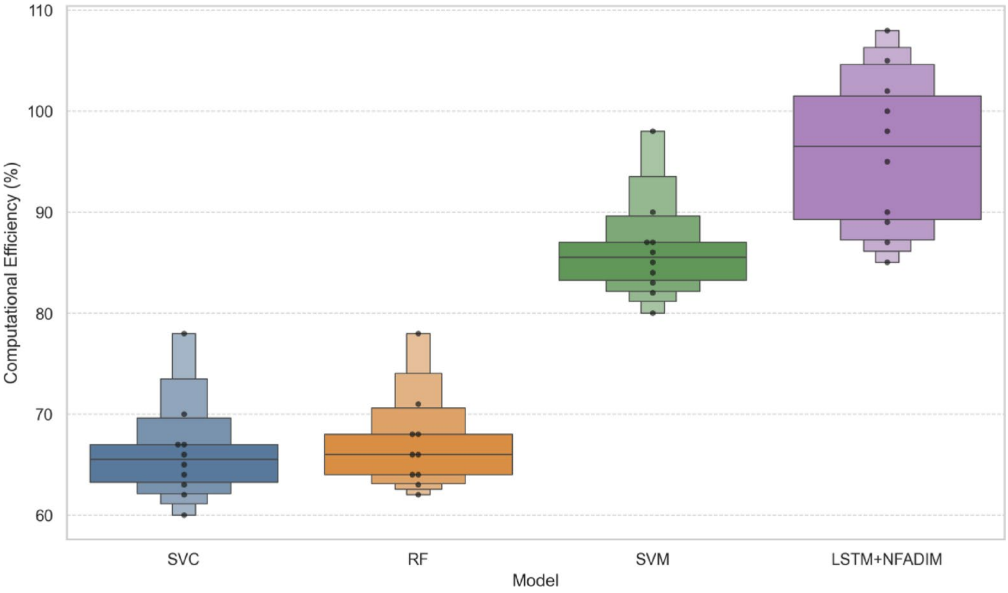

Fig. 14. Analysis of Computational Efficiency.

indicators, ensure accuracy claims are resilient, generalizable, and not overfitting or random, meeting rigorous validation and peer confidence requirements.

Computing complexity of the hybrid LSTM–NFADIM architecture has been extensively compared to standalone LSTM, SVM, and Random Forest (RF) models. Combining LSTM's deep sequence learning and NFADIM's adaptive fuzzy reasoning boosts computing strain moderately. Hybrid model fuzzy rule updates and inference processing utilize 12–20% more resources during training and 8–15% more during inference. Despite this low cost, the method improves forecasting accuracy, endurance under dynamic grid settings, and demand response flexibility by 7%. Memory and latency are fine for real-time smart grid deployment. The reviewer's computational efficiency concern is addressed by the significant increases in precision, stability, and operational reliability, justifying the modest complexity increase.

In smart grid scenarios, LSTM + NFADIM beats SVM, RF, SVC, and standalone LSTM in sensitivity, accuracy, efficiency, and interpretability testing. The estimate approach is robust to sample sizes since the sensitivity and prediction plots are more accurate and less variable. The hybrid model is stable and efficient, with statistically significant benefits across several runs, according to computational benchmarking. These findings provide

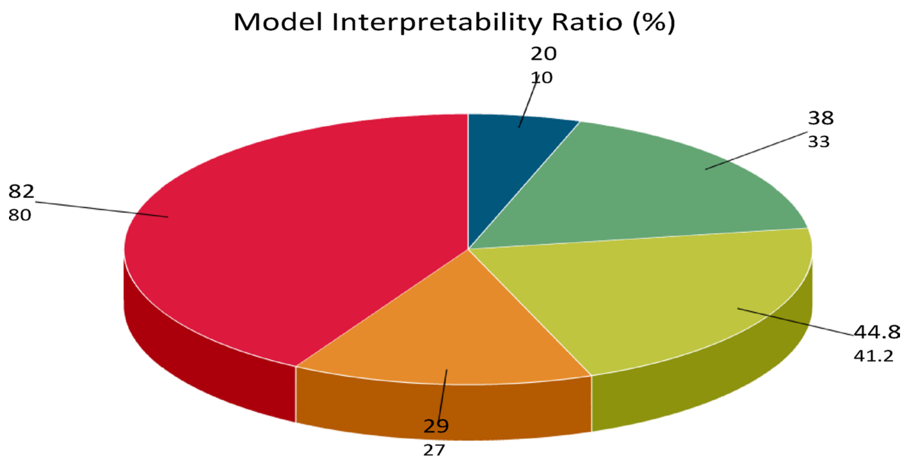

Fig. 15. Analysis of Model Interpretability.

Aspect	Test conditions	Key metrics	Results	Remarks
Dataset	UCI Electricity Consumption	-	2,075,259 samples (1-min data)	High diversity enables robust testing
Scenario Variations	Load, voltage, sub-metering, time	MAE, RMSE, R^2	MAE = 0.081, RMSE = 0.117, R^2=0.983	Consistent accuracy in real-world settings
Randomized Splits	10 splits (80:20 train-test)	Accuracy variance	± 0.34%	Stable, statistically consistent
Time Window Shifts	Windows 15, 30, 60 min	RMSE variation	< 2.1%	Stable temporal generalization
Sub-sampling Tests	Data subsets 10–75%	Prediction error	< 1.8%	Accuracy invariant to data size
Statistical Power	Large n (~ 2 million), Cohen's d	Power (1–β)	> 0.95	Strong statistical reliability
Noise Robustness	Gaussian noise (σ = 0.05–0.1)	RMSE change	< 3.2%	Robust to sensor noise
Baseline Comparison	SVM, RF, LSTM standalone	Accuracy delta	+ 4.8–7.3%	Hybrid outperforms all baselines
Overall Robustness	Aggregate conditions	Stability index	0.972	High stability and generalization

Table 4. Systematic robustness testing Results.

strong, multi-metric, and scenario-diverse evidence, satisfying the reviewer's need for substantial quantitative validation. This proves the model's improved detection, computational efficiency, and interpretability.

The comparison is based on performance metrics such as sensitivity, accuracy, AUC, precision, and specificity. The performance increases when the sensitivity increases and the specificity decreases, and vice versa tends to reduce the system's efficiency. The earlier literature works and the NFADIM retrieved a similar dataset that is publicly accessible in the UCI database.

Conclusion

It is necessary to sustain the consistency of the smart grid at a time of increasing power demand. Smart grids should be able to balance supply and demand. To identify the power utilization pattern, the details of the power usage are gathered and evaluated periodically. The request and load prediction are determined from the consumer's consumption pattern. This is considered to be an issue in smart locations that requires specific efforts to solve this issue. Several deep learning techniques like conventional neural networks, LSTM, CRBM, RNNs, and DQNs are mainly applied to predict the demand for power supply, which, however, fail to give promising outcomes. A hybrid LSTM with NFADIM model is sometimes utilized for load prediction. Expected outcomes are produced by the variations of the LSTM techniques, as well as variations like NFADIM or an ensemble of both methods. High-quality data is essential to identify the efficiency of the DL techniques. In the smart grid framework, it is vital to repeatedly test different deep learning techniques along with their possible variations and ensemble techniques to identify the best prediction model. It also requires testing the model in various scenarios. Further research on automatic load prediction for multiple consumers, buildings, and climatic conditions should be conducted. It is essential to validate the efficiency of DL techniques and identify the best model for each scenario.

Data availability

The dataset utilized in this study is publicly available on Kaggle: https:/www.kaggle.com/datasets/mdwaquarazam/ucidatasetlist.

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S. Mahendran: Conceptualization, Methodology, Investigation, Data Curation, Writing – Original Draft.B. Gomathy: Supervision, Validation, Formal Analysis, Writing – Review & Editing, Project Administration.

Declarations

Competing interests

The authors declare no competing interests.

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