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ORIGINAL ARTICLE

A novel approach to predicting the stability of the smart grid utilizing MLP-ELM technique

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Availability

Abstract Evaluating and forecasting stability across different conditions is essential since smart grid stabilization is among the most significant characteristics that could be employed to assess the functionality of smart grid design. Some intelligent methods to foresee stability are required to mitigate unintended instability in a smart grid design. This is due to the rise in domestic and commercial constructions and the incorporation of green energy into smart grids. It is currently hard to forecast the stability of the smart grid. In this framework, a smart grid with reliable mechanisms is being implemented to meet the fluctuating energy demands as well as providing more availability. The involvement of consumers and producers is one of the many factors influencing the grid's stability. This study suggested a novel approach for locating stability statistics in smart grid systems utilizing machine learning frameworks was presented. This paper outlined the multi-layer perceptron-Extreme Learning Machine (MLP-ELM) methodology to predict the sustainability of the smart grid. Additionally, this utilized the principal component analysis (PCA) approach for extracting features. In addition to an empirical assessment and a comparison to various approaches, this article presents an implementation result for smart grid stability. Simulation findings demonstrate that the suggested MLP-ELM approach outperforms traditional machine learning techniques, with accuracy reaching up to 95.8%, precision at 90%, recall at 88%, and F-measure at 89%.

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1. Introduction

The rapid development in industrialization and the enormous growth in the world's population and economic activity can substantially raise the demand for energy utilized in the coming decades. Electricity can be produced from various means, including thermal energy, solar energy, water, nuclear power plants, wind, and fossil fuel extraction, making it a significant energy source [1]. A further factor is that when the population grows and develops, there is a corresponding rise in power demand, which raises the bar for energy production. Managing electricity's production, transmission, and distribution are its three most crucial components. Electric utilities are understood to be interconnected networks that connect power producers to consumers and transfer power from generators to consumers. It includes the energy plants that generate the power, the sub-stations that adjust voltages by consumer demand, and the distribution and transmission lines that link the users [2]. Conventional electrical systems incorporate millions of the following specifications. A rise in electricity consumption could lead to a rise in overhead, which could cause poor power quality. Therefore, the new plant must be installed. These grids do not, however, have a sufficient forecasting method that would enable them to anticipate regular power outages, their effects, response time, resource consumption, and storage requirements [3].

According to researchers, the present electrical power grid has hardly changed during the previous 100 years. There is undoubtedly a significant need for power because of the growing population. The shortcomings of the conventional electrical system include a shortage of transparency, mechanical switching devices that slow response times, supervision, and an inability to regulate energy. Unilateral communications, changing climate, the requirement for fossil fuels, the requirement for power, population growth, component failure, a shortage of power storages, a decline in electricity production, and several other issues are extra elements that necessitate a new grid advanced technologies [4]. Hence, new grid infrastructures are needed to address these difficulties. The existing electric power grid will be converted into a network with electronic control as part of the smart grid idea. To connect various electric operations, the smart grid technologies comprise data control and management innovations, technologically oriented monitoring, technologies for communication, and field-based equipment, according to the US Ministry of Energy's Smart Grid System Assessment [5]. The conventional grid organization and maintenance issues have altered in a minimum of three key ways because of these smart grid innovations, most notably in their increased capacity to: analyze or determine processes, communicate information back to functioning centers, and frequently react effortlessly to modify a procedure; transmit information among equipment and infrastructure; and procedure, analyze, and assist operators in accessing and applying the data generated by digital technology throughout the grid [6]. Forecasting loads, power grid stability evaluation, detection of faults, and smart grid security are some of the linked issue areas in smart grids. An enormous amount of multidimensional and high-dimensional information regarding the operation of the electric power grid is being gathered because of these crucial components. The Smart Grid (SG), the next-generation electrical energy architecture, stands out as a notable technique to meet these highly prioritized requirements and improve the standard of modern human existence [7]. The latest technological electric power grid technique, called Smart Grid, enables two-way communication to enhance the electrical power system's safety, effectiveness, and dependability for more electrical energy production utilizing modern communications technology. It is a two-way energy distribution and transportation process that encourages its consumers to make energy-related selections [8]. In effect, Smart Grid reduces the price consumers must pay for power. The security measures put in place in the event of natural catastrophes and other types of attacks are also strengthened, therefore. As a substitute, it ensures a significant decrease in risks that could result in the loss of life and other tangible assets crucial to the normal operations of the grid. Smart Grids promote the incorporation of electric mobility and the upgrading of the transportation industry in terms of implementation. With the difficulties of global warming and the need for efficient power consumption, smart grids help to reduce energy waste as well as the harm caused by greenhouse gas emissions [9].

The conventional grid system has a far slower reaction time as well as being more susceptible to catastrophic events and cyber-attacks. Consumers are significantly less affected by the SG, which offers automated problem identification and resolution. In SG, numerous components are combined with communication channels and sensor nodes to allow interoperability in residential, commercial, and industrial applications. By offering an interactive smart electricity generation control and surveillance system, the goal is to prevent power turbulence brought on by natural catastrophes, capacity restrictions, and component failures [10]. The SG provides cutting-edge services with automatic monitoring, two different communications, self-remedial skills, and an intelligent system. By forecasting energy consumption, SG helps in management control as well. By changing their consumption patterns, customers can get profitability determinants on how much power they use, enhancing efficiency. The abovementioned can be done by providing energy to consumers with better dependability and security characteristics. The necessity for communications is crucial in SG infrastructures since a vast collection of information from several applications must be processed and regulated. Finding the greatest communications network is therefore essential if the overall structure is to receive affordable, dependable, and protected services. Several advancements have been made in the situation of SG communications utilizing two mediums, namely wireless and wired networks, which may be employed for data transmission between smart meters as well as other electronic systems. Technologies for wireless communication are inexpensive, and even in difficult-to-reach places, connections may be established without difficulty [11]. Yet, because of the characteristics of the transmission channel, where wireless systems rely on batteries, the signals may get degraded. Contrarily, since wired technologies are not battery-dependent, they do not require any supervision. There are two different information flow types at present in the SG architecture. Smart meters get the initial flow of information from electrical sensors and applications. The secondary flow originates from the SG power data centers and smart meters. For the initial category of data flow, wireless communication technology may be employed, and for the second category, cellular or internet technologies. Different applications might not be compatible with identical communications technologies. So, the selection of communication technology should be dependent on the applications domain [12].

Nearly all fields and operations involving energy can benefit from smart grid technologies. It provides the following advantages: real-time analysis of energy consumption according to the kind of applications; dynamic prices; quicker and more efficient electricity regeneration following a power loss; in-house electrical presentations; adjusting the electrical consumption throughout the day according to cost signals and levels of demand; and shifting from customer to generator [13]. Most of the industrialized nations have used SGs in size varying from tiny to huge. The wide range of uses for cloud computing technology in SGs must be mentioned. Communication and information technologies are employed by the smart grid to allow resource interaction. Throughout the production, distribution, and transmission of electricity, SG generates tremendous amounts of data. Hence, cloud computing can be implemented in SGs for energy management, data management and security services. An SG could use the Zigbee protocol for information control and surveillance, transmission line monitoring and fault finding. The implementation of energy meters benefits greatly from the Internet of Things (IoT). The automation of smart homes, smart buildings, smart cities, smart substations, and feeders may all be accomplished with SGs in this regard. Although SG uses a number of different technologies to overcome the difficulties with traditional power networks, it also has concerns that require attention and must be resolved [14]. Generally, there are two broad categories: socioeconomic concerns and technological challenges. Storage issues, lack of policies, cyber security flaws when integrating the grids to cyber-physical mechanisms, insufficient grid infrastructures to meet the future demands and requirements for storing infrequent energy production, voluminous data management from various grid components, grid stabilities with energy-sharing, power oscillation, system complacency, and power reservations are just a few of the technical hurdles. On the other hand, technical difficulties in utilizing electric vehicles include power efficiency including power transfer from vehicles to grids, grids to vehicles, and vehicles to vehicles. Stakeholder management, a lack of knowledge, a lack of regulations, and significant capital expenditures are a few of the socioeconomic issues [15]. Moreover, that raises problems about electricity prices, new tariffs, medical conditions from RF consumption, privacy concerns, concerns of expiration, and power stealing. Security is still one of the biggest worries because both wireless and wired communication networks might compromise SG. Machine learning algorithms, a form of artificial intelligence, can be implemented to anticipate issues in SG and help with preventative measures.

The connection between electricity-producing facilities, distribution hubs, and other businesses, including industrial plants, electrical motors, smart buildings, and homes, is shown in Fig. 1. The effective distribution of the proper quantity of energy to these many entities is greatly aided by the smart grid. The smart grid uses a variety of AI algorithms to gain flexibility in the electricity distribution process. A more intelligent grid that can anticipate energy consumption is urgently required. Using the data produced by the grid, Machine Learning (ML) methods may be applied to achieve this. Smart grids can lower the cost of power and contribute to a reduction in pollution. The main contribution of the study proposes a novel MLP-ELM method to categorize the smart grid datasets obtained from the machine learning repository at UCI and evaluate the stability of SG. It demonstrated a unique method for identifying stability data in smart grid networks using machine learning techniques. In order to forecast the long-range viability of the smart grid, the present research described the multi-layer perceptron-Extreme Learning Machine (MLP-ELM) technique. Furthermore, this employed the principal component analysis (PCA) strategy for feature extraction. Precision, recall, accuracy, and F1-Score are used as productivity evaluation indicators to compare and evaluate the produced methods. The paper gives an implementation result for smart grid stability along with an experimental evaluation and comparison to other methodologies. The experiment's results are then compared using a range of machine learning methods. The following are the measures taken in the present work:

- The datasets for the Electricity Grid were obtained from the machine learning repository at UCI.
- The datasets are normalized utilizing the min–max normalization.

2. Related works

A Multi-directional LSTM Framework for Forecasting the Stability of Smart Grids was suggested by Mamoun Alazab et al. [16]. The term "grid" refers to the electrical grid, which is made up of lines of communication, command centers, distributors and transformers is utilized to refer to the system for distributing electricity from an electrical plant to customers. Nowadays, the electric system is made up of enormous power generation facilities that produce millions of megawatts of electrical energy that are dispersed over demographical zones. Effective management of the power provided to the many customer domains, including businesses, smart buildings, homes, and organizations, is vital. To meet the fluctuating power needs, a smart grid with advanced technologies is being implemented. A smart grid system corresponds to the Cyber-Physical Systems concept, which integrates physical processes with information technology infrastructures. The machine learning module constitutes the information technology component, and the power dissipations entities are the passive components in the concept of the smart grid integrated with CPS. In the study, a brand-new method called Multidirectional Long Short-Term Memory is put forth to forecast the stabilities of the smart grid network. The acquired findings are contrasted to those of various well-known Deep Learning techniques, including standard LSTM, GRU and RNN. The findings from the studies show that the MLSTM technique performs better than the other ML algorithms. Nevertheless, smart grids are not more dependable and are not installed to meet the dynamic power demand.

Smart Grid Stability was predicted by Paulo Breviglieri et al. utilizing an optimized deep learning technique [17]. With a smart grid, data on customer demands is gathered, centralized availability and demand analysis are performed, and the resultant recommended pricing information is then forwarded to consumers so they may select how much to use. Dynamically calculating the stability of the grid becomes not just a

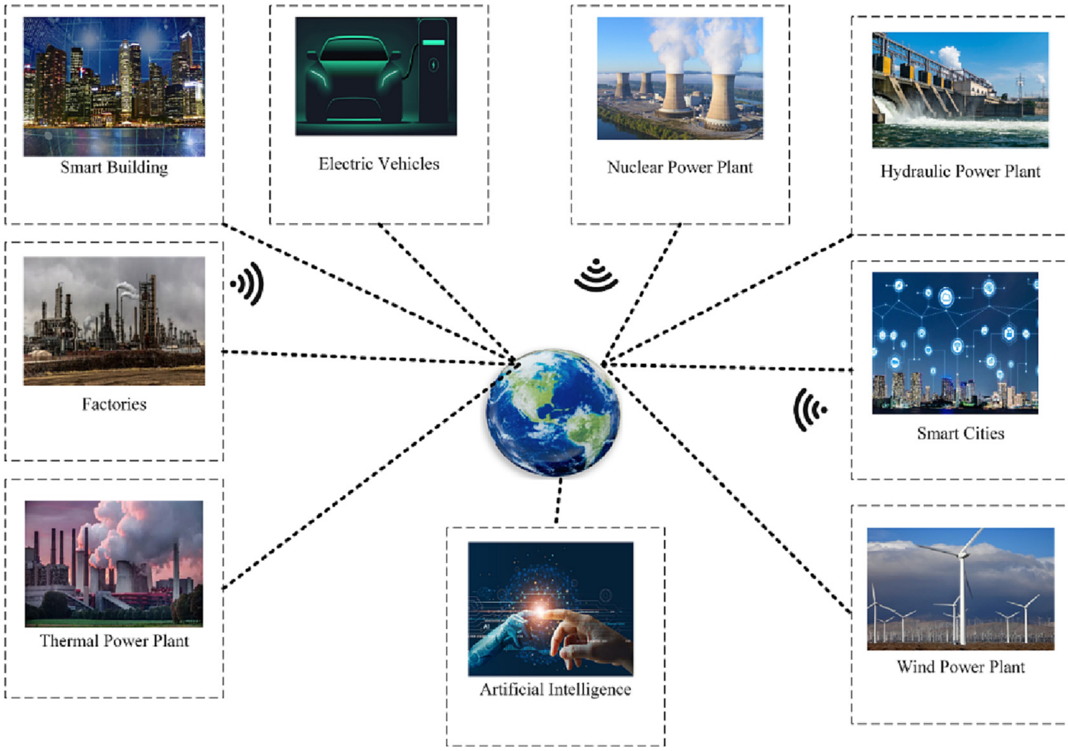

Fig. 1 Smart Grid Components.

problem but also a crucial need because the overall process is time-dependent. Decentralized Smart Grid Control systems are constantly monitoring the frequencies of the grid, which is one specific attribute. As a result, it links the price of power to the frequencies of the grid to make it accessible to all consumers, including all energy manufacturers and consumers. The DSGC makes various assumptions about user behavior. Differential equations are used to explain the DSGC system. To address the equality and fixed inputs difficulties in the DSGC system, researchers investigate optimal deep learning approaches in the research. The system administrators may thus rate its energy offering and advise users appropriately by monitoring the grid frequencies at the location of each customer. This would be sufficient to give the system administrators all the necessary information about the present network balance of power. Researchers investigate the DSGC system over a wide range of input values using several optimized DL simulations to forecast the stability of the smart grid, doing away with such constrictive input value assumptions. Researchers show that DL algorithms do, in fact, lead to fresh perceptions of the simulation model. Researchers now know that rapid adaptation enhances the stability of the system. Yet, the datasets from DSGC simulation with alternate input parameter ranges are not utilized.

For smart grids, Raghavendra et al. developed an artificial hummingbird with a data-driven stability prediction algorithm. New developments in renewable power offer a sustainable substitute for fossil fuels [18]. Smart grids operate by gathering information on client demand, contrasting them with information on available stock, calculating power bills, etc. As the processes depend on time, dynamic estimation of SG stabilization is essential for the system. The proper operation of the SGs depends on dynamically analyzing variations and disruptions. Latest developments in data science, DL, and ML algorithms have made it easier to build a practical stabilization prediction approach for the SGs context. The research presents a feature selection approach for the SG environments that is dependent on the Artificial Hummingbird algorithm and has the best stabilization predictions for DL-empowered systems. AHB-based feature selection approach design constitutes the primary focus of the AHBFS-ODLSP model. Also, a prediction system for the stability level dependent on Multiheaded-Self Attention LSTM is currently being developed. Subsequently, utilizing the symbiotic organism search optimization approach, the MHSA-LSTM models' hyperparameters were changed. The MHSA-LSTM model's capacity to forecast stability is significantly influenced by the SOS and AHBFS algorithm designs. Improvements to the AHBFS-ODLSP models are illustrated throughout a variety of simulations, and the results are evaluated in several approaches. The AHBFS-ODLSP technique has operated at its peak efficiency. A comprehensive examination of comparisons revealed that the AHBFS-ODLSP approach performed significantly better than other prediction techniques.

According to the increasing need for electricity in smart microgrids, this is anticipated that peer-to-peer electricity trade will account for a sizeable portion of the study in the next production electrical network. To obtain the best price for homes, on-demand power consumption is thought to be a significant difficulty. To offer real-time assistance, day-ahead managing, and production planning of distributed power resources, this article suggests a blockchain-based prediction power trading system. The suggested blockchain-based system has two components: one for smart contracts-enabled advanced analysis and the other for blockchain-based energy markets. Contemporaries are provided with real-time monitoring of energy usage, simple electricity market management, a compensation system, and unalterable electricity market transaction logs thanks to the blockchain technology modules. The predicting and prescriptive modules for smart contracts intend to create a forecasting model depending upon previous information on electricity consumption to forecast near-term power usage. This study makes use of actual power usage information from the Republic of Korea's Jeju Provincial Power Administration. This project intends to enhance energy exchange between consumers and prosumers by achieving optimum energy flows and resource crowdsourced. To fulfill the load requirements of the smart grid, power trade is focused on the day, actual authority, and planning of distributed generation units. Additionally, they do time-series analysis using data mining techniques to uncover and examine hidden trends in the overall energy utilization information. The time-series analysis will help power consumption improve judgments in the future to successfully manage and plan sources of energy. Researchers used a variety of quantifiable metrics, including the mean square error and root mean square error on numerous machine-learning designs, including recurrent neural networks and similar models, to assess the effectiveness of the suggested statistical model. Additionally, researchers assess the blockchain technology system's performance in regard to delay, bandwidth, and resource consumption using hyper ledger tape measure. The developed framework is successfully used only for energy crowdfunding between the utility and customer to achieve the quality of service, according to the test findings. To render it more reliable, this technology has to perform much better by including a mixed machine-learning approach [19].

According to the latest advancement, automated technology that improves decision-making and power transmission processes may ultimately be able to regulate power, both availability and demand. To improve decision-making in power transmission infrastructure and processes, new cutting-edge machine learning technologies are crucial. The goal of this investigation would have been to demonstrate the importance of this field of inquiry by examining data-driven probability ML approaches and their real-time applications to smart energy systems and networks. 2 main regions were the focus of this investigation. Utilization of machine learning in enhanced electricity components, power generation and storage devices, fuel efficiency, production of smart electrical components in the context of smart grids, organizational electricity-making plans, incorporation of sustainable power, and big data predictive analysis in the context of smart grids are among the fundamental power generation. Electricity demand and pricing, the quality ordering of power price prediction, and customer retention rates are all included in the explored ML field in power distribution networks. Electricity distribution and transmitting networks, grid edge processes, distributed energy resources, and cyber protection flaws also are extensively covered. The main objective of this effort was to pinpoint frequent problems that would be beneficial in further ML research for efficient power transmission activities. Numerous economic views on important opportunities and problems were presented at the study's conclusion. It has been observed that the utility industry and the power sector may possibly save $237 billion to $813 billion if smart ML mechanization is implemented in its targeted power systems. Unfortunately, the utility appears hesitant to utilize these resources because of unknowable concerns [20].

The combination of numerous distribution elements, such as smart metering, communications infrastructural facilities, distributed sources of energy, and electric cars, is undergoing a significant change in the global electricity network to enhance its administration, privacy, administration, and dependability. These parts are integrating with the Internet - of - things more and more. To serve several smart grid activities, including decentralized power control, production prediction, network health maintenance, defect identification, residential power control, etcetera. These are anticipated to produce a sizable amount of information. Methods of artificial intelligence could be utilized to manage and enhance the functioning of the smart grid using these new parts and data. In this study, researchers present a thorough analysis of the cutting-edge artificial intelligence approaches used to enable different uses in a dispersed power grid. More particularly, they cover the use of synthetic approaches to promote the penetration of sustainable power resources, the incorporation of power storing technologies, load management, network and residential energy control, and security. Researchers further address whether artificial intelligence and economic liberalization may be able to contribute to enhancing the entire welfare programs of the network since the microgrid involves a wide range of players, including energy producers, marketplaces, and customers. To develop a truly smart grid, researchers present extensive study objectives for the extensive incorporation and coordination of autonomous distributed servers. In conclusion, the use of AI approaches could be used to improve energy reliability by lowering leakage current in the distribution model. Additionally, AI technologies can enhance and simplify the administration of distributed energy resources, expanding the range of smart energy services to developing an even wiser network [21].

In the twenty-first decade, the Smart grid, sometimes described as the next electricity network, replaced outdated power infrastructure. It is merged with cutting-edge communications and processing capability; therefore, it is anticipated to improve the reliability and effectiveness of the electricity network with little consequences. It brought a significant number of data that necessitates different methodologies for thorough assessment and making decisions due to the massive architecture it contains and the underpinning communications system in the system. Big data analysis, machine learning, and deep learning are critical for assessing this massive volume of information and creating relevant insights. This article examines and surveys the critical elements of the Smart grid and deep learning-based approaches. This report also addresses the shortcomings of the present work and prospective approaches in regard to machine learning-based data analysis. The only way to find important data and find solutions to several difficult situations that can't be addressed using traditional techniques is through the study of the original data. However, these Machine Learning and DL-based systems might encounter issues including learning from unbalanced data, challenges with comprehension, and challenges with learning algorithms due to the intensive aspect and the huge architecture. Although privacy should be taken into consideration with the electrical energy networks and it needs to be substantially integrated while constructing a smart grid, it is currently in progress and a much additional study is being done. Since the smart grid is a crucial asset, it needs the greatest level of security; as a result, a thorough design with security incorporated right from the beginning is required [22].

The power system is rapidly shifting away from petroleum and coal and towards renewable energy, which gives the urban smart grid structure a cleaner power source. Since renewable sources are uncertain and inconsistent, it is challenging to establish a realistic and efficient short-term load forecasting model. Lately, Machine Learning-based prediction techniques have been employed to predict short-term demand, yet most of them overlook the value of characterizing data, fine-tuning characteristics, and predicting consistency. To address the abovementioned issues, a short-term demand prediction technique that incorporates substantial information collection and multi-step rolling predictions is presented. An approach to de-noising that relies on deconstruction and reconstruction is utilized to reduce the instability caused by the short-term load. The train-test ratios and neuron parameters of the artificial neural network are then dynamically determined using the phase space reconstruction technique. Also, a multi-objective grasshopper optimization procedure is utilized to optimize the ANNs' characteristics. In Australia's metropolitan smart grid networks in Victoria and New South Wales, research is conducted. The suggested framework could precisely anticipate short-term load utilizing a variety of measuring indicators according to simulation outcomes. The suggested prediction model performs well in terms of reliability and precision, as demonstrated by many criteria and statistical analysis. In conclusion, the suggested framework exhibits high precision and resilience, which will also serve as references for RE transitions and smart grid optimization as well as provide direction for the growth of urban sustainability. Nevertheless, the prediction method suggested by this research is solely based on the comprehensive historical short-term load data and doesn't take other pertinent elements into account [23].

To make strategic decisions in the smart grid, real-time, precise, and reliable prediction is essential. This guarantees financial savings, efficient planning, and dependable and secure functioning of the electricity systems. Unfortunately, owing to the erratic and irregular behavior of the power load, precise and consistent prediction is difficult. In this situation, a strict prediction algorithm with strong unpredictable and non-linear behavior apprehending capabilities is required. As a result, an SVR model was developed to accommodate the projections from non-linear time series. Unfortunately, it has an issue with hard-to-tune proper characteristics and computational difficulty. These issues make it difficult for support vector regression predicting findings to be as precise as needed. By integrating feature engineering, the modified firefly optimization technique, and Support vector regression, or the feature engineering-SVR-mFFO prediction architecture, a new hybrid strategy for solving these challenges is created. To achieve great computing performance, feature engineering removes unnecessary and redundant elements. The SVR model's significant aspects are acquired and fine-tuned using the modified firefly optimization algorithm to successfully prevent trapping into local optimums and to produce a reliable predicting outcome. In addition, most literature studies concentrate on increasing prediction performance. Nonetheless, the prediction model's reliability and converging ratio are equally important in determining its efficacy and productivity. Since it is insufficient to focus on just one aim, the suggested FE-SVR-mFFO prediction model accomplishes these three seemingly unrelated goals at once. Utilizing actual half-hourly demand statistics from 5 Australian states—Queensland, Tasmania, New South Wales, Victoria, and South Australia—as a research study, the efficiency and feasibility of the suggested methodology are assessed. The suggested system outperforms better than benchmark systems like FS-TSFE-CBSSO, EMD-SVR-PSO, VMD-DCP-SVM-WO and FFT-IOSVR regarding precision, durability, and convergence ratio, according to experimental data. However, because of its slow searching speed, early convergence, and poor memory function, this approach is not generally used [1].

Creating safe, dependable, completely automated power smart grid systems necessitates the utilization of a reliable electricity load prediction model. Current research has demonstrated the effectiveness of LSTM in anticipating power demand. Nevertheless, such estimates do not include an assessment of uncertainties, which might be harmful when crucial choices in power generation and transmission are taken independently. Researchers describe techniques to assess uncertainty in short-term electricity load estimates utilizing gradient tree boosting and deep learning in this research. Using actual power demand statistics, they train Bayesian supervised learning and gradient boosting algorithms and demonstrate that an uncertainties assessment could be provided alongside the forecast with minimum precision degradation. Furthermore, unpredictability is a significant statistic for electricity generation and transmission since it enables utility firms to analyze the reliability of projections before making choices. Utilizing the EUNITE power requirements statistics, researchers show the usefulness of the learning approaches, long short-term memory and gradient boosting, as well as the uncertainty assessment processes. Both strategies have been proven to generate reliable estimates. Researchers discover that the generated uncertainty estimations are resistant to modifications to the input attributes. This outcome is a significant step towards developing efficient automated smart grids notwithstanding the fact that they only provided strategies for estimating uncertainties for 2 techniques. There's still a lot to learn about uncertainty assessment as well as its relevance to energy prediction [24].

3. Proposed mechanism

This study suggested a novel approach for locating stability statistics in smart grid systems utilizing machine learning frameworks was presented. This paper outlined the multi-layer perceptron-Extreme Learning Machine (MLP-ELM) methodology to predict the sustainability of the smart grid. Additionally, this utilized the principal component analysis (PCA) approach for extracting features. The developed algorithms are examined and contrasted in terms of Efficiency assessment metrics like accuracy, precision, recall, and F1-Score. In addition to an empirical assessment and a comparison to various approaches, this article additionally presents an implementation result for smart grid stability. Python software was utilized to carry out the simulation approach for this research. The outcomes show that the suggested technique is more effective than existing approaches. The suggested technique work process is depicted in Fig. 2.

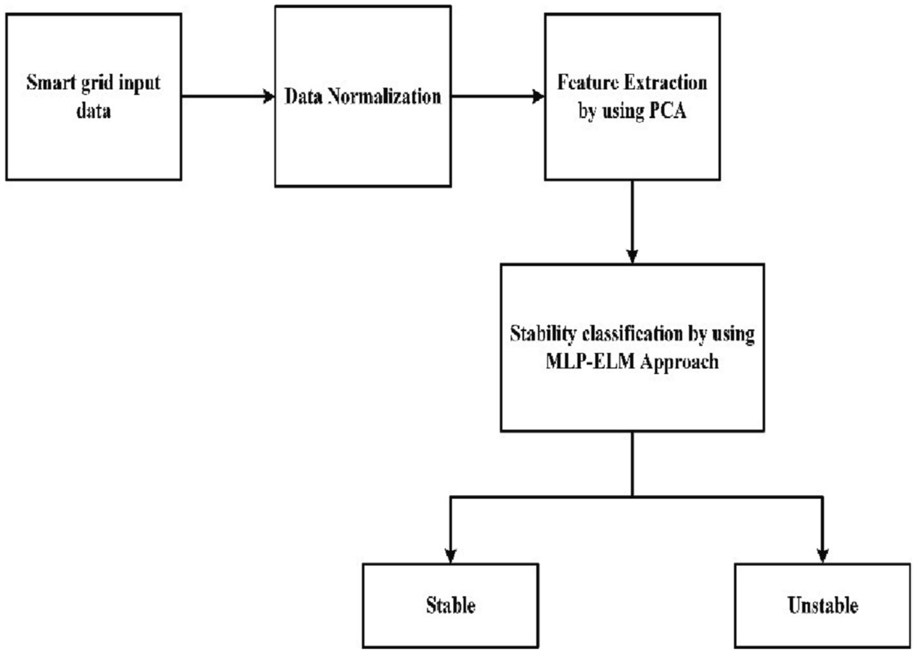

Fig. 2 Schematic of proposed system workflow.

3.1. Data collection

This research employed the utilization of the Kaggle Grid Simulated Database. 10,000 occurrences and Fourteen characteristics are included in the information, of which 3450 were stable and 5780 are unstable. Because there are many more unstable than stable cases, the database has additionally experienced concerns with class imbalance. The statistics comprise the participants' response time (tau1, tau2, tau3, tau4), nominal power produced and consumed (p1, p2, p3, p4), and gamma coefficients, or aspects of cost elasticity [25]. The mathematical equation for pricing elasticity, which measures how much power is consumed in reaction to cost changes, was:

$$Determiningcostelasticityutilizingamathematicalformula = \frac{Changeinpowerquantitydemand(inpercent)}{ChangeinCost(inpercent)} \quad (1)$$

The corresponding target rating is determined by a mathematical optimization problem called the features roots equation. Whereas negative actual numbers demonstrated the grid's resilience, positive actual values suggested instability.

3.2. Data normalization

The primary difficulty with numerous characteristics is the inconsistent representation of every statistical characteristic or attribute. Hence, data normalization is a useful statistic preparation method for tabular data to facilitate correlations among observations when developing a system. To generate novel inputs, it rescales attribute values to face the conventional normality test. Like the response times of distinct participants, power ratings of providers, power values of customers, and gamma quantities. By optimizing characteristic root equations, the goal variable quantities were produced. All these characteristics have been normalized utilizing the w-score method to fall within a predetermined limit. The range-specific scaling has been applied to all quantitative data. Equation (2) contains the formula for the Z-score approach.

$$w = \frac{u - \widehat{u}}{r} \quad (2)$$

where w is the average rating, r is a standard error, each element in the collection is represented by u, and $\widehat{u}$ is the database's average amount across all entries. Z-score normalization has been discovered to be more effective than some other dataset normalization methods [26].

3.3. Feature extraction process

In empirical investigations, a variety of influencing elements should be assessed to conduct a thorough and methodical examination of the issues. Yet as information evaluation becomes more involved, it becomes substantially more difficult. The significant data of the original information could be represented with fewer parameters to minimize the characteristic space's degree of dimensionality since the data supplied by certain inter-correlated elements may overlap. Karl Pearson created Principal component analysis in 1901 based on this concept, and Harold Hotelling separately coined and modified it in the 1930 s [27]. Principal component analysis transforms the potentially associated characteristic elements into a distinct collection of linearly uncorrelated data, known as principal components, depending on the orthogonal transformation. In contrast to the initial characteristic parameters, the number of main elements is either equal or reduced. Prior to starting our SVM procedure, it utilizes Principal component analysis to minimize the quantity of the information and generate a baseline for quickly creating a classification. The following definition applies to Principal component analysis execution:

Presented a statistical model $u \in S^q$ with q characteristic parameters and N instances, it changes into an entirely distinct collection of data $v \in S^r$:

$$v_{j,1} = \left(c_{11}u_{j,1} + c_{12}u_{j,2} + \cdots + c_{1q}u_{j,q}\right),$$

$$\left(v_{j,2} = c_{21}u_{j,1} + c_{22}u_{j,2} + \cdots + c_{2q}u_{j,q}\right) \cdots\cdots$$
$$\left(v_{j,r} = c_{r1}u_{j,1} + c_{r2}u_{j,2} + \cdots + c_{rq}u_{j,q}\right)$$

$$Here, \forall u_j = \left(u_{j,1}, u_{j,2}, \cdots\cdots, u_{j,q}\right)^t \in u, j = 1, 2, \cdots\cdots, N \tag{3}$$

For the first primary element $P_1 = v_{1,1}, v_{2,1}, \cdots\cdots, v_{N,1}$ has the maximum variance feasible within the restriction that makes it orthogonal to the following elements, and every subsequent element has the maximum variance feasible within its own set of constraints. The principal component analysis characteristics are indicated by:

$$Variance(P_1) \geq Variance(P_2) \geq \cdots \geq Variance(P_r)$$

$$Covar(P_a, P_b) = 0, a \neq b, a, b = 1, 2, \cdots\cdots, r$$

Where the $r \times q$ matrix k specifies the $j - th$ rows and a distinct coordinate structure and $k_j = k_{j1}, k_{j2}, \cdots\cdots, k_{jq}$ makes up element $j - th$ of the information covariance matrix M.

$$M = \frac{1}{N}\sum_{u=1}^{N} u_j u_j^t \tag{4}$$

As a result, Principal component analysis first calculates the covariance matrix M before solving the characteristic expression:

$$Mk_j = \gamma_j k_j, j = 1, 2, \cdots, r \tag{5}$$

Obtaining the eigenvalues $\gamma_j (j = 1, 2, \cdots, r)$ and related eigenvectors of the eigenvalues. The initial element P_1 is made up of the eigenvector with the biggest eigenvalue, which represents the most variation within the information collection u, followed by the eigenvector with the 2nd biggest eigenvalue P_2, continuing in this manner. To reduce the quantity of the dataset while retaining as much as possible, it could sort the eigenvalues in decreasing order and then select the initial r principal component to describe the actual information.

4. Proposed MAP-ELM method

4.1. Multi-layer perceptron

Utilization of Neural network models includes forecasting, filtering, signal identification, process identification, and efficiency optimization of conventional mathematical programming. Weights refer to a network of linked neurons with connections that could be either weak or powerful. By comprehending the database and employing a mathematical technique like backpropagation, the parameters could be changed. It may be utilized as a task after training to produce whatever outcome is required. A supervised learning technique called the Multilayer Perceptron (MLP) generates a function $f(.) : S_a \rightarrow S_c$ that trains on a dataset to learn a function with and as input and outcome parameters, respectively [28]. Assuming a collection of characteristics $U = u_1, u_2, \cdots\cdots u_a$ and a target v, It can approximate a non-linear characteristic for both regressions as well as classification. In contrast to logistic regression, it allows for the possibility of one or more non-linear layers—known as hidden layers—between the input and output layers. A basic representation of MLP is shown in Fig. 3. The leftmost layer, termed the input nodes, is made up of a collection of neurons reflecting the input characteristics $\{u_j | u_1, u_2, \cdots\cdots u_a\}$. The variables from the preceding layer are transformed by every neuron in the hidden layer utilizing a weighted linear aggregation $h_1a_1, h_2a_2, \cdots\cdots + h_a u_a$, then a nonlinear activation parameter follows $k(.) : S \rightarrow S-$ comparable to the hyperbolic *tan* functions. The final hidden layer sends its values to the output nodes, which turn them into output values. Multi-Layer Perceptron's benefits include its capacity to acquire non-linear structures and its ability to learn patterns in real-time.

4.2. Extreme learning Machine (ELM) technique

The conventional Extreme learning machine (ELM) is a forecasting approach. The idea of the Extreme learning machine network in response to the drawbacks of the backpropagation neural network; the ELM network does not have the output unit bias that the backpropagation neural network does. A restriction of the backpropagation neural network's manual modification of every layer's variable could be overcome by the ELM network's input load and hidden state bias, which are produced at random and only needs to be utilized to calculate the final load. This increases predictive performance. The Extreme Learning Machine is a tool for handling both regression and classification issues that has a single hidden layer and a neural feed-forward network [29].

Fig. 4 illustrates the input, hidden, and output unit elements that constitute the Extreme Learning Machine's fundamental architecture. In the ELM, the correlation among the testing phase (N), the hidden neurons (L) and the activation function $A_f(u)$ is stated as:

$$E_i = \sum_{j=1}^{h} A_f\left(p_j, q_j, r_j\right) i = 1, 2, \cdots\cdots n \tag{6}$$

where p_j is a weight matrix for the hidden input nodes, δ_j measures the weighted sum of the concealed output units, r_j is the input value, q_j reflects the $j - th$ concealed neuron's biased rating and E_i is the ELM outcome for the initial statistic j. Weights for inputs that are created randomly are provided via a continuous distribution of probabilities [30]. The following is a quick and easy way to determine the output weights:

$$\gamma = D^+ V \tag{7}$$

where D denotes the output matrix of the hidden units in Equation (11), D^+ is determined by the Moore-Penrose method, and it is a generalized reversal of D and V indicates the ELM's goal parameters. Equation (10) could be expressed more concisely as $D = V$, where V denotes the output of variable vectors, while D denotes the neural network's hidden state output matrices [27]. The following is a concise representation of the 3 matrices:

$$D = \begin{bmatrix} l(u_1) \\ \vdots \\ \vdots \\ l(u_n) \end{bmatrix} = \begin{bmatrix} A_f(p_1, q_1, r_1) \cdots\cdots A_f(p_L, q_L, u_1) \\ A_f(p_1, q_1, r_1) \cdots\cdots A_f(p_L, q_L, u_b) \end{bmatrix} \tag{8}$$

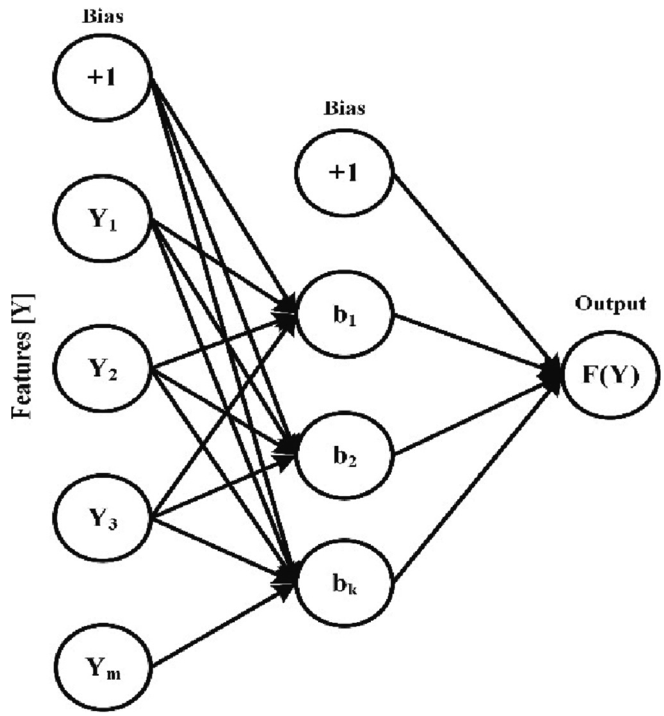

Fig. 3 Basic Schematic of MLP Method.

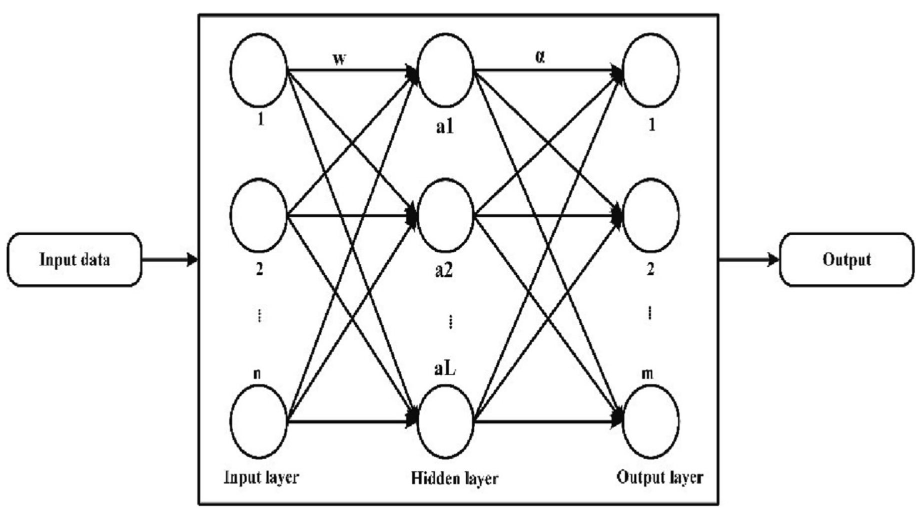

Fig. 4 Basic Structure of ELM approach.

$$\delta = \begin{bmatrix} \delta_1^t \\ \vdots \\ \vdots \\ \delta_L^t \end{bmatrix} and V = \begin{bmatrix} v_1^t \\ \vdots \\ \vdots \\ v_L^t \end{bmatrix} \tag{9}$$

where $l(u)$ is a representation of the hidden layer's feature mappings. The Extreme Learning Machine system's outcome is built around Matrix D. The kernel operation is employed to resolve the ELM (g, u_a, u_b). In such a circumstance, the characteristic mapping is performed utilizing the kernel matrix computation provided as:

$$g(u_a, u_b) = l(u_a).l(u_b) \tag{10}$$

The Extreme Learning Machine forecasts seem to be more precise since it possesses a higher learning efficiency at greater speeds than many traditional models of neural networks as well as a better generalization capability [28].

5. Result and discussion

Several classifiers have been used to assess the efficiency of a Kaggle Grid Simulated Dataset. The effectiveness of algorithms has been evaluated using the train-test split method. The dataset was divided into two subsets, with 30% used for testing and 70% for training. The training dataset utilized to determine the model's fit is the first subset. The algorithm is supplied the dataset's input component rather than the second subset, which is used to simulate data. The outcomes are then contrasted with the projections which have been produced. The test dataset is the second dataset in question. The effectiveness of the MLP-ELM technique has also been evaluated in comparison to other algorithms. The SG data that have been gathered are split into 8:2 ratios for training and testing, accordingly. The study outcome is displayed utilizing the confusion matrix. Fig. 5 depicts the MLP-ELM confusion matrix and the suggested model for categorizing the Smart Grid stability database.

The assessment of the models is a significant stage in each computational activity. In predicting ensemble modeling, where variability and varying levels of performance should be carefully assessed, it becomes much more crucial. One of four classes serves as the foundation for each assessment statistic. True Positives (T_P), True Negatives (T_N), False Positives (F_P), and False Negatives would be categories (F_N).

Accuracy is often used to evaluate a model's effectiveness using the confusion matrix. The model's precision has been calculated using Equation (11).

$$Accuracy = \frac{T_P + T_N}{T_P + T_N + F_P + F_N} \tag{11}$$

Precision is the percentage of genuine positives among all anticipated positives. In other words, precision counts the number of occurrences that the classifier identified as affirmative. Equation (12) has been used to assess the model's accuracy.

$$Precision = \frac{T_P}{T_P + F_P} \tag{12}$$

A recall concerns the percentage of genuine positives among all real positives. The recall of the model has been calculated using Equation (13).

$$Recall = \frac{T_P}{T_P + F_N} \tag{13}$$

The geometric median of recall and accuracy is known as the F-measure. Precision (P) and Recall (R) were incompatible; generally speaking, low recall is correlated with increased precision. The model's F-measure has been calculated using Equation (14).

$$F - measure = \frac{2 * P * R}{P + R} \tag{14}$$

Efficient predictive control management and control in decentralized power networks are challenging. Key factors affecting the reliability of the grid are the amounts of electricity usage generated by every grid participant (p), as well as their cost-sensitivity (g), also known as relative prices as well as response time (tau), to pricing. It is because the production and consumption behaviors of grid participants are impacted by price signals that are approved and responded to on a second scale. A model of a decentralized grid applied on a four-node star grid. According to Tables 1, 2, 3 and 4, the dataset includes the participants' response time $(tau1, tau2, tau3, tau4)$, actual energy generated $(p1, p2, p3, p4)$, aspects of relative prices $(g1, g2, g3, g4)$ and grid stability or un-stability.

For various candidate threshold levels between 0.0 and 1.0, it shows the false positive rate (-axis) vs the genuine positive rate (-axis). It is utilized to evaluate possibilities that are predicted for binary classification challenges. Table 5 shows the performance effectiveness of the proposed and existing approaches.

The MLP-ELM exceeded many other algorithms, with the highest accuracy of 92%. In comparison to the F-measure, which revealed 90% and 89%, respectively, the precision and recall executed at 84.3% and 84.1%, were additionally superior. Fig. 6 depicts the graphical representation of performance efficiency.

MLP-ELM fared better on an unbalanced dataset than other models. The findings are shown in Table 5, with the MLP-ELM model predicting the dataset for an unbalanced electricity grid with the highest accuracy at 92%. Any other algorithm may be made more effective by tuning its parameters. The process is creating a grid with every potential parameter and comparing them to determine which values maximize the performance of the classifier. If variables whose values are not defined, then the input variables are utilized.

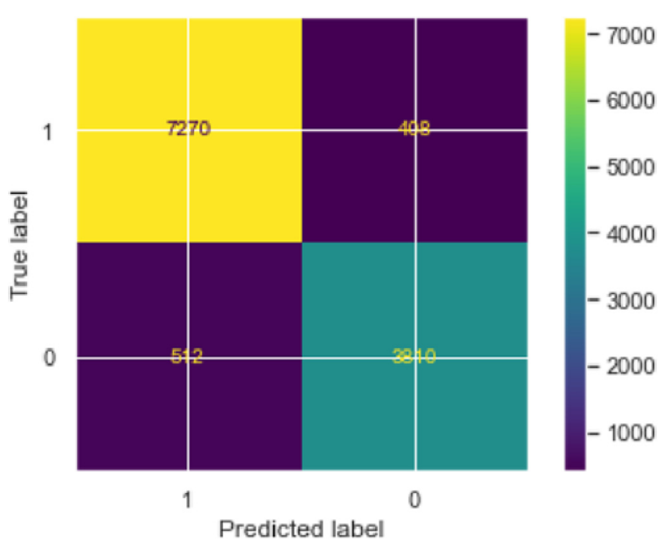

Fig. 5 Confusion Matrix.

Table 1 Response time of the participants.

Range	tau1	tau2	tau3	tau4
0	2.959060	3.079885	8.381025	9.780754
1	9.304097	4.902524	3.047541	1.369357
2	8.971707	8.848428	3.046479	1.214518

Table 2 Power generated by grid participant.

Range	p1	p2	p3	p4
0	3.763085	−0.782604	−1.257395	−1.723086
1	5.067812	−1.940058	−1.872742	−1.255012
2	3.405158	−1.207456	−1.277210	−0.920492

Table 3 Cost Sensitivity.

Range	g1	g2	g3	g4
0	0.650456	0.859578	0.887445	0.958034
1	0.413441	0.862414	0.562139	0.781760
2	0.163041	0.766689	0.839444	0.109853

Table 4 Stability level of grids.

Range	Stability rate	Stable or Unstable
0	0.055347	unstable
1	−0.005957	stable
2	0.003471unstable	0.003471unstable

Throughout the research, the existing approaches were combined with resizing methods to enhance the prediction of decentralized grid stability. The study's simulation network depicts straightforward decentralized grid architecture. Maximum and minimum values were established on the twelve independent variables, and a simulation was done using the absolute values of power output and consumption. As planned, the approach effectively explores the possible solution space with an assessment of examples. Nonetheless, there are probably larger relationships between the grid participants in decentralized grids. It has been shown that class balancing affects the classifier's performance. When there are more minority samples in the dataset, accuracy improves. The classification has a better probability of discovering the features that distinguish binary classes as the sample size rises. The MLP-ELM model had the greatest prediction accuracy (92%), such as LR yielded 80.4%, and SVM produced 80.8% accuracy predictions. The study fared better than previous studies, as demonstrated in Table 5. It can assist in preventing power outages and dramatically enhance grid functioning.

Objective factors like deteriorating power lines, restricted power supply, dynamic and irregular demands, volatile RES behavior, etc. have a significant impact on the stability of the SG. The study implements, analyses, and evaluates an effective detection algorithm that is suggested to anticipate the smart grid stability margin according to predetermined computational characteristics. The following could be drawn from the findings: The main threat to contemporary power systems' stability, security, and dependability is the voltage instability phenomena. Off-line voltage quality monitoring could no longer guarantee the secure functioning of the electricity system because of load fluctuations and unexpected circumstances. So, to reduce the possibility of severe blackouts, experts and enterprises place a high priority on developing quick and effective ways to evaluate power system voltage stability. It is crucial to concentrate on intervals and point prediction to reduce uncertainty as well as maintain the grid stability-based SG concept. An effective computational framework was built throughout the study to address the Smart Grid Stability Predictions. To validate the suggested technique, a dataset simulating electrical grid stability was considered. To the extent possible, the research study has been the first to identify the

Table 5 Performance efficiency of existing and proposed approach.

Methods	Precision	Recall	F-Measure	Accuracy
Logistic Regression	84.3%	81.2%	85%	80.4%
Support Vector Machine	84.1%	86.2%	84.3%	80.8%
Proposed MLP-ELM	90%	88%	89%	95.8%

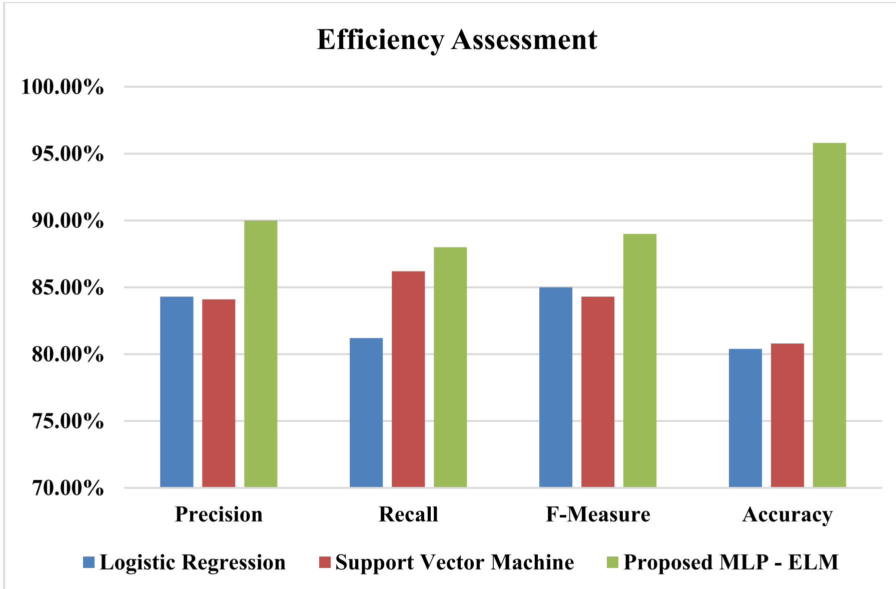

Fig. 6 Graphical representation of Performance efficiency.

stability status forecasting for the powered smart grid network utilizing conventional machine learning approaches. Nonetheless, the study can contrast it to other cutting-edge methods that use the same dataset and deep learning methods. The study trained the network for 20 epochs with a batch size of 10. The accuracy and loss of 1–5 epochs are given in Table 6.

Table 6 Accuracy and loss of 1–5 epochs.

Epochs	Accuracy	Loss
1	0.8160	0.1300
2	0.8560	0.1023
3	0.8640	0.0959
4	0.8690	0.0899
5	0.8886	0.0812

Fig. 7 shows the accuracy and loss range of 1–5 epochs with a batch size of 10. Although the suggested forecasting algorithm is less complicated and has a smaller forecast cost than the other deep learning algorithms shown in the table, it is obvious from the material that it is equivalent to and better in numerous assessment criteria. Also, the study included an overall measurement (overall score) in the last column that combines the metrics readings for the same modeling to get a single score that reflects the overall effectiveness of the prediction model.

Although all methods have achieved a high overall rating, the suggested predictive model has achieved the highest overall score across all approaches where the model obtained a rise in the overall measure. Future research might further enhance the performance of the suggested approach for applications with high-dimension datasets by integrating the suggested method

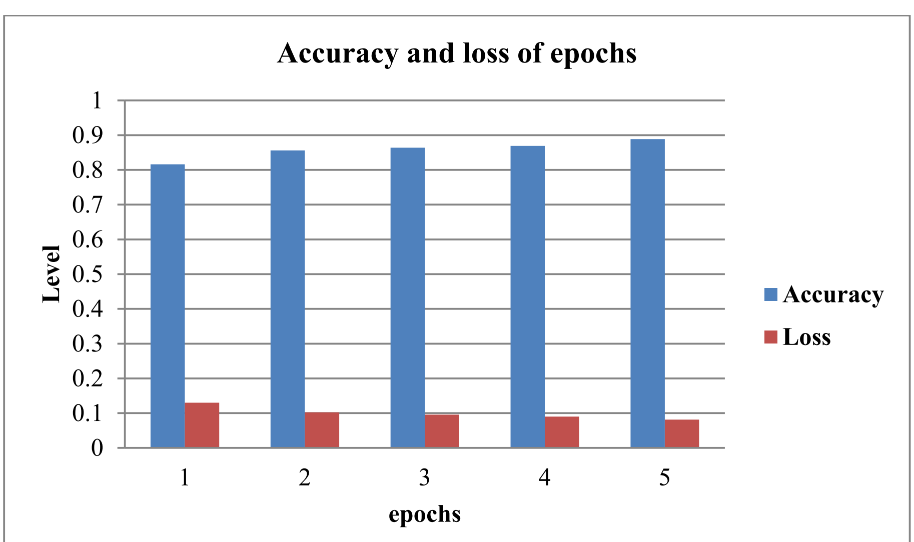

Fig. 7 Accuracy and loss.

with big data structures to increase the efficiency and productivity of the estimation method over longer prediction horizons. Additionally, the technology may be utilized for various purposes in smart grids, such as energy and load management, to improve energy efficiency.

6. Conclusion

This study uses a unique multi-layer perceptron-Extreme Learning Machine approach to forecast the stability of the smart grid network (MLP-ELM). The pre-processing techniques that are most often used are normalization and data transformation. The distributed form of the data in a Smart Grid dataset frequently produces a bias towards values with bigger weights, undermining the usefulness of the proposed model. To avoid this in the study, the SG dataset is normalized using $Z-score$ normalization. The $Z-score$ normalization improves the classifiers' performance by converting the data to a common scale. Most of the dataset contains numerical and category variables; hence data pre-processing involves converting the non-numeric values into numeric ones. Data exploration is the first phase of data gathering, throughout which users examine a sizable dataset haphazardly in search of the first patterns, focus points, and distinctive characteristics. The stability of the smart grid network is finally predicted using a brand-new multi-layer perceptron-Extreme Learning Machine (MLP-ELM), and therefore the availably of SG is achieved. Experiment results show that the proposed MLP-ELM methodology works better than conventional machine learning methods, with accuracy attaining 95.8%, precision at 90%, recall at 88%, and F-measure at 89%. Context-aware models may be used in the future to support dynamic power needs and improve the dependability of smart grids.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] G. Hafeez, I. Khan, S. Jan, I.A. Shah, F.A. Khan, A. Derhab, A novel hybrid load forecasting framework with intelligent feature engineering and optimization algorithm in smart grid, Appl. Energy 299 (2021) 117178.

[2] J. Li et al, A novel hybrid short-term load forecasting method of the smart grid using MLR and LSTM neural network, IEEE Trans. Ind. Inf. 17 (4) (2020) 2443–2452.

[3] Z. Shi et al, Artificial intelligence techniques for stability analysis and control in smart grids: methodologies, applications, challenges and future directions, Appl. Energy 278 (2020) 115733.

[4] S. Azad, F. Sabrina, S. Wasimi, Transformation of the smart grid using machine learning, in: 2019 29th Australasian Universities Power Engineering Conference (AUPEC), IEEE, 2019, pp. 1–6.

[5] D. Syed, A. Zainab, A. Ghrayeb, S.S. Refaat, H. Abu-Rub, O. Bouhali, Smart Grid Big Data Analytics: Survey of Technologies, Techniques, and Applications, IEEE Access 9 (2021) 59564–59585, https://doi.org/10.1109/ACCESS.2020.3041178.

[6] I. Colak, R. Bayindir, S. Sagiroglu, The Effects of the Smart Grid System on the National Grids, in: in *2020 8th International Conference on Smart Grid (icSmartGrid)*, IEEE, Paris, France, Jun. 2020, pp. 122–126, https://doi.org/10.1109/icSmartGrid49881.2020.9144891.

[7] T. Kotsiopoulos, P. Sarigiannidis, D. Ioannidis, D. Tzovaras, Machine Learning and Deep Learning in smart manufacturing: The Smart Grid paradigm, Computer Science Review 40 (May 2021), https://doi.org/10.1016/j.cosrev.2020.100341 100341.

[8] B.S. England, A.T. Alouani, Real time voltage stability prediction of smart grid areas using smart meters data and improved Thevenin estimates, Int. J. Electr. Power Energy Syst. 122 (2020) 106189.

[9] M.B. Rasheed, M.A. Qureshi, N. Javaid, T. Alquthami, Dynamic pricing mechanism with the integration of renewable energy source in smart grid, IEEE Access 8 (2020) 16876–16892.

[10] I. Worighi, A. Maach, A. Hafid, O. Hegazy, J. Van Mierlo, Integrating renewable energy in smart grid system: Architecture, virtualization and analysis, Sustainable Energy Grids Networks 18 (2019) 100226.

[11] M.Z. Gunduz, R. Das, Cyber-security on smart grid: Threats and potential solutions, Comput. Netw. 169 (2020) 107094.

[12] K. Kimani, V. Oduol, K. Langat, Cyber security challenges for IoT-based smart grid networks, Int. J. Crit. Infrastruct. Prot. 25 (2019) 36–49.

[13] T.N. Nguyen, B.-H. Liu, N.P. Nguyen, J.-T. Chou, Cyber security of smart grid: attacks and defenses, in: ICC 2020–2020 IEEE International Conference on Communications (ICC), IEEE, 2020, pp. 1–6.

[14] C. Lamnatou, D. Chemisana, C. Cristofari, Smart grids and smart technologies in relation to photovoltaics, storage systems, buildings and the environment, Renew. Energy 185 (2022) 1376–1391.

[15] T. Kotsiopoulos, P. Sarigiannidis, D. Ioannidis, D. Tzovaras, Machine learning and deep learning in smart manufacturing: The smart grid paradigm, Computer Science Review 40 (2021) 100341.

[16] M. Alazab, S. Khan, S.S.R. Krishnan, Q.-V. Pham, M.P.K. Reddy, T.R. Gadekallu, A Multidirectional LSTM Model for Predicting the Stability of a Smart Grid, IEEE Access 8 (2020) 85454–85463, https://doi.org/10.1109/ACCESS.2020.2991067.

[17] A.A. Sewisy, M.H. Marghny, R.M. Abd, ElAziz and Ahmed I. Taloba, Fast Efficient Clustering Algorithm for Balanced Data, International Journal of Advanced Computer Science and Applications (IJACSA) 5 (6) (2014). https://doi.org/10.14569/IJACSA.2014.050619.

[18] R. S, S. Neelakandan, M. Prakash, B. T. Geetha, S. Mary Rexcy Asha, and M. K. Roberts, "Artificial humming bird with data science enabled stability prediction model for smart grids," *Sustainable Computing: Informatics and Systems*, vol. 36, p. 100821, Dec. 2022, doi: 10.1016/j.suscom.2022.100821.

[19] A.I. Taloba, A.A. Sewisy, Y.A. Dawood, Accuracy enhancement scaling factor of Viola-Jones using genetic algorithms, in: In 2018 14th International Computer Engineering Conference (ICENCO), IEEE, 2018, pp. 209–212.
[20] T. Ahmad, R. Madonski, D. Zhang, C. Huang, A. Mujeeb, Data-driven probabilistic machine learning in sustainable smart energy/smart energy systems: Key developments, challenges, and future research opportunities in the context of smart grid paradigm, Renew. Sustain. Energy Rev. 160 (May 2022), https://doi.org/10.1016/j.rser.2022.112128 112128.
[21] R.M. Abd, A.I. El-Aziz, Taloba, and Fahad A. Alghamdi., Quantum Computing Optimization Technique for IoT Platform using Modified Deep Residual Approach, Alex. Eng. J. 61 (12) (2022) 12497–12509.
[22] K.C. Ravikumar, N. Pandi Chiranjeevi, M. Devarajan, C. Kaur, A.I. Taloba, Challenges in internet of things towards the security using deep learning techniques, Measurement: Sensors 24 (2022) 100473.
[23] C. Li, Designing a short-term load forecasting model in the urban smart grid system, Appl. Energy 266 (2020) 114850.
[24] M. Selim, R. Zhou, W. Feng, P. Quinsey, Estimating Energy Forecasting Uncertainty for Reliable AI Autonomous Smart Grid Design, Energies 14 (1) (2021) 247.
[25] ‘‘Predicting Smart Grid Stability with Deep Learning.” [Online]. Available: https://www.kaggle.com/code/pcbreviglieri/predicting-smart-grid-stability-with-deep-learning/notebook.
[26] T.M. Alam, M. Mushtaq, K. Shaukat, I.A. Hameed, M. Umer Sarwar, S. Luo, A novel method for performance measurement of public educational institutions using machine learning models, Appl. Sci. 11 (19) (2021) 9296.
[27] H. Hotelling, Analysis of a complex of statistical variables into principal components, J. Educ. Psychol. 24 (6) (1933) 417.
[28] M. Koopialipoor, P.G. Asteris, A.S. Mohammed, D.E. Alexakis, A. Mamou, D.J. Armaghani, Introducing stacking machine learning approaches for predicting rock deformation, Transp. Geotech. 34 (2022) 100756.
[29] A.I. Taloba, A. Elhadad, A. Rayan, R.M. Abd, M.S. El-Aziz, A.A. Alzahrani, F.h.S. Alharithi, C. Park, A blockchain-based hybrid platform for multimedia data processing in IoT-Healthcare, Alex. Eng. J. 65 (2023) 263–274.
[30] M. Pal, S. Deswal, Extreme learning machine-based modeling of resilient modulus of subgrade soils, Geotech. Geol. Eng. 32 (2014) 287–296.