Artificial intelligence Based Analysis of Smart Grid by Using MachineLearning Techniques in an Electrical power system

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Abstract—

The idea of a "smart grid" is crucial to transforming the power industry into an intelligent, digitalized energy network that can provide the best possible energy to consumers. Information, communications, and sophisticated power technologies are integrated with the current electrical systems to create smart grids, which are self-sufficient systems. In smart grids, artificial intelligence (AI) is a key technical driver. Because traditional modelling optimization and control approaches have their own limits, the employment of AI techniques in smart grid is becoming increasingly obvious. Being a subset of AI, machine learning (ML) enables intelligent decision-making and response to unexpected changes in consumer energy needs, power supply disruptions, rapid variations in renewable energy output, or any other catastrophic occurrences in the environment. This study compares many cutting-edge ML algorithms for forecasting the stability of smart grids. The dataset that has been chosen comprises the outcomes of simulations on the stability of the smart grid. To predict the stability of the smart grid, improved ML algorithms have been implemented, including the Support Vector Machine (SVM), Logistic Regression, K-Nearest Neighbor (KNN), Naive Bayes (NB), Decision Tree (DT), Random Forest (RF), Stochastic Gradient Descent (SGD) classifier, XGBoost, and Gradient Boosting classifiers. Based on the following assessment measures, including accuracy, a comparison of the various ML models has been conducted.

Key Words **—artificial intelligence, comparative analysis, machine learning, smart grid, stability prediction**

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1. INTRODUCTION

Global energy demand is growing rapidly. Therefore, it is necessary to develop and modernize energy systems to make them more efficient, flexible and sustainable. The integration of information and digital communication technologies with conventional energy grid systems is known as a smart grid. A smart grid can be defined as a network of self-sustaining systems that enable the integration of power generation sources (both conventional and non-conventional) into the electricity grid, leading to a reduction in labor and offering safe, reliable, high-quality and sustainable electricity. to consumers [1], [2]. Smart grids enable the two-way flow of electricity and data using digital communication systems that include smart meters, smart appliances, renewable energy sources, and energy-efficient sources. Two-way communication between producers and consumers of electricity and two-way flow of energy increases the safety, reliability and efficiency of energy systems [3], [4]. Smart grids are interconnected and integrated with advanced measurement infrastructure, control and communication technologies, resulting in the generation of vast amounts of high-dimensional and multi-species data. Such a huge amount of data requires collection, storage and management. Existing technologies have many limitations in data processing. Therefore, it is necessary to implement artificial intelligence (AI) techniques in smart grid applications. Artificial intelligence techniques provide a powerful way to analyze data, learn from it, and then make appropriate decisions to ensure network performance meets intended purpose. Artificial intelligence has the potential to revolutionize the energy industry. Artificial intelligence can act as the brain of a smart grid by continuously collecting and synthesizing massive amounts of data from a large number of smart sensors and making timely decisions to increase the stability and reliability of the smart grid. Artificial intelligence plays an important role in harnessing large amounts of potentially useful data and generating useful insights from it. Conventional techniques involve huge and complex data, thus increasing computational time and in some cases also reducing accuracy, a problem that can be easily solved by AI and machine learning (ML) [5], [6]. AI and ML can help better understand consumer behavior and allow suppliers to access their exact electricity requirements. This will also enable the generation of the correct type of billing data. Integrating AI and ML with smart grids will help consumers access energy consumption and pricing data to proactively respond to requests to reduce energy consumption during peak energy demand. This in turn will lead to increased operational efficiency of smart grids. The incorporation of information and communication technologies (ICT) into smart grids enables both consumers and producers to become active agents in maintaining the intended operation of the smart grid.In order to make the grid smart, a communication between the customers and the utility generating the electricity is needed to be established. The major objectives for the implementation of smart grids are

- improving demand side management
- increasing energy efficiency
- promoting a self-healing grid, thus improved reliability and resiliency

With the advancement of technology, the smart grids have been further modernized through the development of a concept known as demand response (DR). DR allows an increase in consumer control and cost savings. The consumers are provided an opportunity to reduce or shift their usage of electricity voluntarily during the peak hours with various forms of compensation like incentivizing with lower rates. Theutilities and the operators are using DR programs to balance supply and demand of electricity in an evolving market. The main aims of DR analysis are

- minimization of the total electricity consumption
- reduction of the total required power generation
- promoting the idea of green and clean energy

elimination of line overloading DR is one of the most important concepts in smart grids.

DR enables end customers to play a significant role in the operation of the smart grid by changing their electricity consumption in response to changes in the price of electricity over time [7], [8], [9]. If the consumption rate or tariff is constantly changing, the consumption pattern of consumers is expected to change. Also in the DR, incentives are paid to consumers to induce reductions in electricity consumption at times when market prices are high or when the reliability of the smart grid is at risk. DR is performed both at the grid level and at the consumer level to achieve a low peak load curve and reduced electricity costs [10], [11], [12].

By integrating newer advanced technologies such as AI and ML with smart grids, it is possible to predict consumer electricity demand and automate DR [13], [14], [15]. Since the smart grid involves a huge amount of data, ML models can be improved over time and new predictive models can be deployed. So everything depends on data and data is the key to unlocking ML. Thus, AI and ML can be used to enhance the performance of smart grids.

2.LITERATURE REVIEW

Artificial intelligence is gaining momentum and has a huge impact in today's world. The transition of the traditional power grid system to a smart grid can be achieved by integrating AI and ML techniques with existing conventional methods. With the emergence of AI and ML, the reliability and resilience of smart grids can be improved. Artificial intelligence techniques can be used to predict load, assess power grid stability, detect faults and security issues in smart grids and energy systems.

Azad et al. [16] reviewed the application of different money laundering approaches aimed at increasing the stability, reliability, security, efficiency and responsiveness of smart grids. They also discussed some of the challenges in implementing ML solutions for smart grids.

Zheng et al. [17] proposed ML models based on historical data to investigate the effect of customer schedulable loads and predicted daily electricity price profile on aggregator profits. They chose K-Nearest Neighbor (KNN) and Gaussian progress regression in their study because these algorithms performed consistently and provided accurate results compared to other ML classification and regression algorithms.

Bomfim [18] investigated the development of ML application in the field of smart grids. He presented an overview of research that used ML in the field of smart grids through a quantitative descriptive analysis of periodical articles and newspapers registered in the IEEE Xplore Library database. He conducted a survey that concluded that the main topics related to smart grids that have been researched are power grid security and reliability and energy management/forecasting.

You and co. [19] presented how compared to conventional simulation-based approaches, AI can potentially save time for model development and numerical calculations of stability assessment in smart grids. They also presented the development of an ML-based tool for assessing electrical network transient stability, frequency stability, and small-signal stability. The test results from their proposed model were quite encouraging.

Hossain et al. [6] conducted a comprehensive study on the application of big data and machine learning in the electrical distribution network introduced as a result of the emergence of a new generation energy system – the smart grid. They stated that IoT integrated Smart Grid system can provide effective load forecasting and data collection technique along with cost efficiency. Smart grids generate huge amounts of data, and such a massive volume of data requires techniques much better than conventional methods for proper analysis and decision-making.

Günel and Ekti [20] presented the advantages of ML methods in extracting and analyzing features for designing modern industrial systems such as smart grids. They discussed ML algorithms and provided a short study on smart grid applications.

Verma et al. [21] presented how the scope of smart grid planning and operation has expanded with the introduction of forecasting methods such as artificial neural networks (ANN), deep learning methods, etc. Their work provided an overview of works related to some smart grid components and classified the works based on tools computational intelligence used in solving a planning or operational problem.

Shi et al. [22] provided a comprehensive and clear picture of recent advances in artificial intelligence techniques for stability analysis and control in smart grids. They presented a general overview of AI, including definitions, history and state-of-the-art methodologies. And then they conducted a comprehensive review of artificial intelligence applications for security assessment, stability assessment, fault diagnosis and stability management in smart grids. The implementation of artificial intelligence-based techniques has produced impressive results. In addition, they also discussed the main challenges that arise during the implementation of AI-based solutions in terms of high data requirements, unbalanced learning, AI interpretability, learning transfer difficulties, AI resistance to communication quality, and robustness. against attacks or hostile examples. They also provided potential solutions to overcome these obstacles to bridge the gap between research and practice, and thus promote AI applications for stability management and analysis in smart grids. with smart grids, artificial intelligence techniques can be used for the future development and success of smart grids. In their work [23] Zhang et al. summarized the potential of deep learning (DL), reinforcement learning (RL) and their combined deep reinforcement learning (DRL) for application in smart grids. They also provided an overview of recent advances in research work on their applications in smart grid technology. AI 2.0 is expanding exponentially due to the decreasing cost of computing power, the amount of data and the availability of better algorithms in AI. Smart grids are the development trend of energy systems, and the integration of artificial intelligence with existing technologies is likely to increase the performance of smart grids.

The emergence of smart grids promises more efficient and effective generation, transmission and consumption of energy in contrast to conventional electrical systems. DR, an important concept in the smart grid, promotes customer participation in energy savings. In order to maintain a balance between electricity supply and demand, an accurate forecast of electricity consumption is essential. ML-based predictive models can be used to achieve this forecast. Smart meters embedded in smart grids send user statistics to a server. ML techniques can be used to design predictive models for smart meter data processing. Ali and Choi [24] provided a comprehensive review of state-of-the-art artificial intelligence techniques to support rapid real-time demand response. Thanks to the rapid progress of AI in recent years, ANN expert systems and fuzzy logic have been used in the energy sector for energy management in residential areas, within smart homes using the DR program and overall demand side management (DSM).

DR is a key aspect of a smart grid to improve its reliability in a cost-effective manner. Over the years, interest in DR research has increased. DR involves high complexity, the use of large-scale data, and real-time decision-making. AI and ML play a critical role in enabling demand-side response. In their research paper [25] Antonopoulos et al. provided an overview of artificial intelligence methods used for DR applications. Their work is based on a systematic review of more than 160 articles, 40 companies and commercial initiatives, and 21 large-scale projects. They illustrate the growing interest in AI-based solutions in the DR sector. Artificial intelligence methods have provided tools for prediction, efficient real-time control of distributed systems, and decision-making for applications in DR. Load prediction and estimation is an integral part of power system operation; AI and ML techniques have been used in DR load forecasting. Artificial intelligence methods have also been used to predict electricity prices. Thus, AI applications in DR allow network operators to maintain the balance of network traffic.

The installation of many smart meters generates a huge amount of data about the customer's electricity consumption for analysis. To build energy-efficient and reliable smart grids, it is essential to develop probabilistic load forecasting (PLF). Yang et al. [26] used a technique called Bayesian deep learning to solve this challenging problem. They proposed the development of a novel Bayesian deep learning-based multi-objective PLF framework to quantify shared uncertainties across different customer groups while accounting for their differences. They proposed a clustering-based clustering method to increase the variety and volume of the data, thereby reducing overfitting and improving the performance of the model for prediction. The test results that were obtained proved that their proposed model showed better performance compared to conventional methods.

Energy load forecasting is an important aspect in the development of future smart grids. Using traditional statistical and ML approaches involves prediction errors and a high degree of overfitting. In their paper [27], Mohammad and Kim proposed an energy load forecasting (ELF) model based on deep neural network architecture for energy consumption management in smart grids. The applicability and performance of deep feedforward neural network (deep-FNN) and deep recurrent neural network (deep-RNN) were investigated. Both architectures were simulated using a multi-size training set. The performances of architectures using different activation functions and different hidden layer combinations were also tested and the simulation results were compared in terms of mean absolute percentage error. From the experimental results, they were able to infer that their proposed model outperformed existing load forecasting models.

Kuo and Huang [28] introduced an accurate deep neural network algorithm for short-term load forecasting (STLF). The performance of the proposed load forecasting model was compared with five other commonly used artificial intelligence algorithms, namely Random Forest (RF), Support Vector Machine (SVM), Decision Tree (DT), Multi-layer Perceptron (MLP), and Long Short Term Memory Network (LSTM). Their model produced a mean absolute percentage error (MAPE) and cumulative variation root mean square error (CV-RMSE) of 9.77% and 11.66%, respectively, a very high prediction accuracy.

Effective and accurate price forecasts are essential in smart grids to avoid serious consequences of price dynamics. Atef and Eltawil [29] proposed two intelligent techniques to solve the electricity price forecasting (EPF) problem using ML. They first implemented a Support Vector Regression (SVR) model to predict the hourly price and then compared the results with a deep learning model. The deep learning approach outperformed the SVR model with an average root mean square error of 1.1165 and 0.416, respectively.

Lu et al. [30] proposed a reinforcement learning-based decision system to assist in the selection of electricity pricing plans to minimize dissatisfaction with electricity payments and consumption of individual smart grid end-users. They modeled the decision problem as a transition-free Markov decision process (MDP) with an enhanced state framework and solved it using a batch Q-learning algorithm integrated into the core, improving computational and predictive performance. Their proposed algorithm has the ability to extract hidden functions behind time-varying pricing plans from a continuous high-dimensional state space. The test results were quite promising. In this way, an accurate predictive policy can be created for individual users, which will reduce their costs and dissatisfaction with energy consumption

3.PROPOSED METHODOLOGY

The proposed methodology has been described in this section.

A. Dataset used

The dataset that has been used corresponds to an augmented version of the ―Electrical Grid Stability Simulated Dataset‖, created by Vadim Arzamasov (Germany) and donated to the University of California (UCI) Machine LearningRepository.

The dataset contains the simulation results of grid stability for a reference 4-node star network as shown in Fig.1.

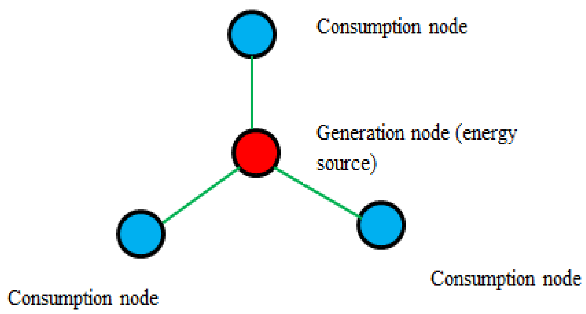


Fig. 1. Reference 4-node star network

The model has taken into consideration input features related to

- the total power balance (nominal power produced or consumed at each grid node)
- the response time of the participants to adjust consumption and/or production in response to the price changes, referred to as the reaction time
- energy price elasticity, which is a measure of the percentage change in the energy consumption relative to the percentage changes in the prices, all the other factors being equal

The dataset consists of 60,000 observations and 12 predictive features. The predictive features are

- Reaction time- Energy producer
- Reaction time- Consumer 1
- Reaction time- Consumer 2
- Reaction time- Consumer 3
- Power balance- Energy producer
- Power balance- Consumer 1
- Power balance- Consumer 2
- Power balance- Consumer 3
- Price elasticity co-efficient (gamma)- Energyproducer
- Price elasticity co-efficient (gamma)- Consumer 1
- Price elasticity co-efficient (gamma)- Consumer 2

4.RESULTS AND DISCUSSION

A performance comparative analysis of the different ML models has been performed based on the following evaluation metrics such as

1. Accuracy
2. Precision
3. Recall
4. F1-score
5. Area Under Curve- Receiver Operating

TABLE I

ATTRIBUTES FOR CALCULATING THE PERFORMANCE METRICS OF THE DIFFERENT MODELS

Model	TP	FP	FN	TN
SVM	8407	1633	1218	3742
Logistic Regression	8408	1611	1217	3764
KNN	9094	1102	531	4273
NB	8855	1743	770	3632
DT	8840	818	785	4557
RF	9312	508	313	4867
SGD	8209	1555	1416	3820
XGBoost	9471	225	154	5150
Gradient Boosting	9290	742	335	4633

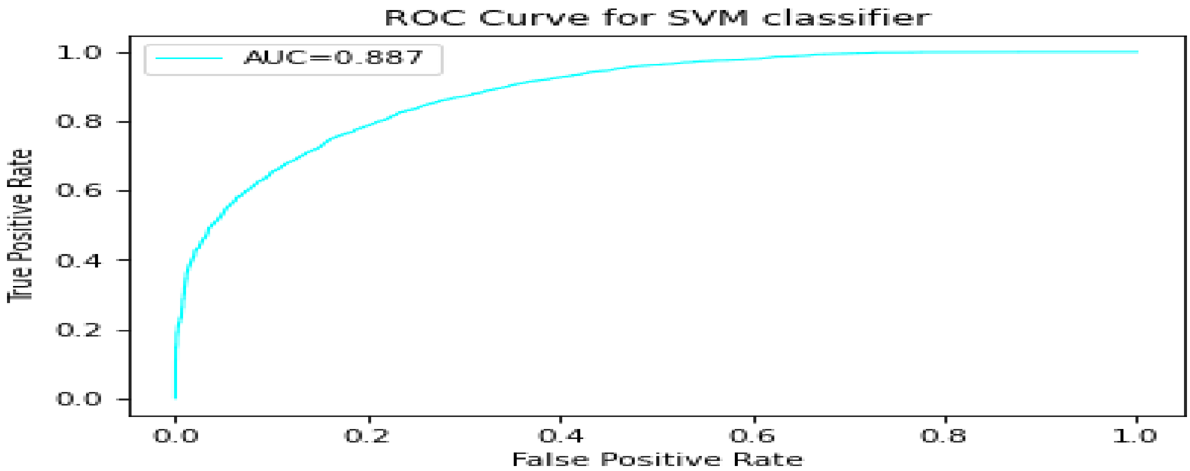
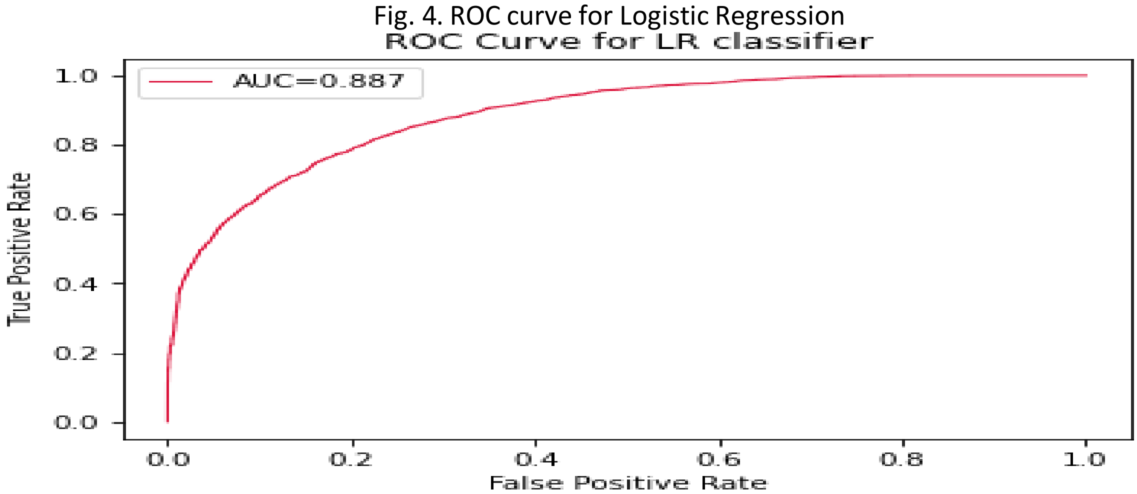


Fig. 3. ROC curve for SVM

Fig. 4. ROC curve for Logistic Regression



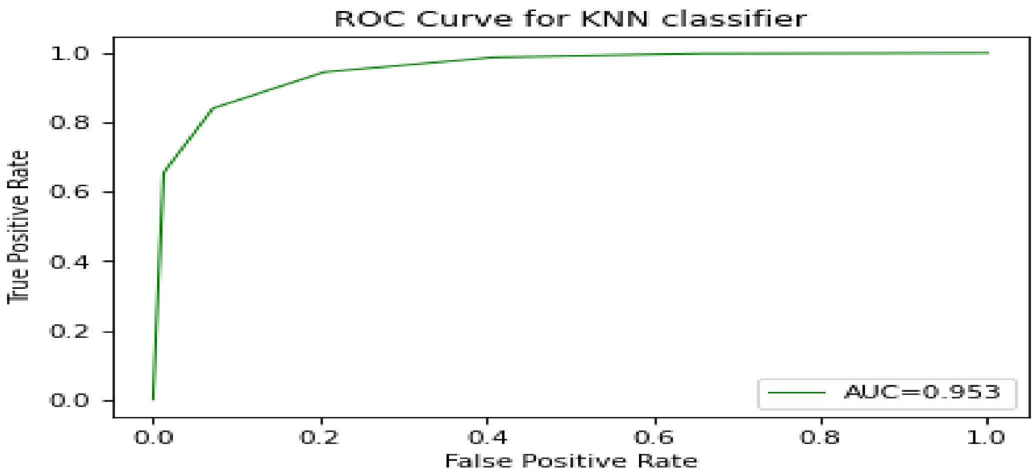


Fig. 5. ROC curve for KNN

5.CONCLUSION

The application of AI and ML techniques in smart grids provides powerful technical support for digital energy systems. In this paper, a comparative analysis of nine ML classification algorithms namely SVM, Logistic Regression, KNN, NB, DT, RF, SGD, XGBoost and Gradient Boosting was performed based on six evaluation metrics namely Precision, Recall, Accuracy, F1-score, AUC -ROC and

AUC-PR for predicting smart grid stability from a dataset that was obtained from the UCI Machine Learning Repository. The XGBoost classifier achieved 97.5% precision, 98.4% recall, 97.6% precision, 97.9% F1 score, 99.8% AUC-ROC, and 99.9% AUC-PR, outperforming all other implemented classifiers algorithms. The training and prediction times of each ML model were also analyzed. Logistic regression showed the least training and prediction time among other models. It takes 0.043 s to train and 0.001 s to predict the result. The training time and prediction time for the XGBoost classifier are 11.135 s and 0.047 s, respectively. In general, the experimental results that were obtained for each of the nine ML algorithms were quite encouraging. The stability of the smart grid is essential to enable efficient energy distribution. ML plays a vital role in predicting the stability of a smart grid. In future work, additional ML models can be deployed to predict the stability of smart grids and increase their reliability. Also, hardware implementation of ML models can be achieved using Field Programmable Gate Array (FPGA) for real-time analysis.

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