Machine Learning-Based Model for Prediction of Power Consumption in Smart Grid

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Abstract: *An electric grid consists of transformers, generation centers, communication links, control stations, and distributors. Collectively these components help in moving power from one electricity station to commercial and domestic consumers. Traditional grid stations can't predict the dynamic need of consumers' electricity. Furthermore, these traditional grids are not sufficiently strong and adaptable. This is the driving force for the transition towards a smart grid. A modern smart grid is a self-healing, long-lasting electrical system that can adapt to changing client needs. Machine learning has aided in grid stability calculation in the face of dynamically shifting consumer demands. By avoiding a breakdown, the smart grid has been transformed into a reliable smart grid. The authors of this study used a variety of machine learning-based algorithms to estimate grid stability to avoid a breakdown situation. An open-access dataset lying on Kaggle repository has been used for experimental work. Experiments are conducted in a simulation environment generated through Python. Using the Bagging classifier algorithm, the suggested model has attained an accuracy level of 97.9% while predicting the load. A precise prediction of power demand will aid in the avoidance of grid failure, hence improving grid stability and robustness.*

Keywords: *Smart grid, grid stability, machine learning, load balancing, prediction model.*

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1. Introduction

Power companies are transforming traditional electrical grids into non-traditional grids called smart grids. Traditional power grids are unidirectional as power can be transmitted only in one direction. Also, a significant amount of power gets lost during distribution and transmission. To address these issues associated with the conventional grid, the smart grid comes into existence [17]. Two-way transmission is possible in a smart grid. Control systems, two-way communication tools, and information systems are used to design smart grids. Cutting-edge phasor networks are included in these advanced tools. Supervisory Control and Data Acquisition (SCADA) systems, Phasor Data Concentrators (PDCs), and Phasor Measurement Units (PMUs) are part of these phasor networks. Operators can use these advanced sensors to analyze the stability of the grid. The smart grid utilizes smart digital meters to get instant customer feedback, to sense the fault in the system, and to get updated customer information in the event of a grid outage, feeder switches are utilized to reroute power. It also uses batteries for the storage of surplus energy. This will help to satisfy the electricity demand in a shortage situation. While advancing the present grid capabilities, fascinating smart grid evolution from the traditional grid has put some challenges and opportunities in front of us. To save operational costs and improve power management tasks, the smart grid relies heavily on forecasting electricity demand. Future trends can be predicted using load and pricing predictions [18]. The availability of large volumes of diverse data in power grids, as well as contemporary advances in information technology, are paving the way for intelligent algorithms to be employed. Machine learning approaches have benefited from their core generalization competency when compared to traditional computational methods. The key issue in the adoption of the smart grid is its capability to manage communication and electric networks in dynamically changing demand, cost, and quality of power. As a result, the focus is on designing intelligent systems that make decisions based on machine learning algorithms, even in changing settings [3]. The stability of the grid can be achieved by making a balance between customer demand and power generation. With the rise of decentralized power generation, the power flow has become bidirectional. To maintain an equilibrium between output and energy requirement, these changes will necessitate the use of a smart control center. Intelligent algorithms are utilised to ensure the stability [7]. Smart grid stability prediction is an attractive study topic because it may help identify the components that cause smart grid volatility and, as a result, it is critical in creating configurations that keep the grid stable even when some members display anomalies. The major contribution of this research work are as follows:

- Designed multiple machine learning-based models to predict the grid stability in a dynamically changing environment.
- Use the prediction of the proposed model to avoid the grid failure situation by managing the power in advance.

The remaining sections of the paper are separated into four groups. The literature on machine learning applications for smart grids is reviewed in section 2. Sections 3 and 4 detail methodology and results analysis, respectively. Section 5 reflects conclusive remarks.

2. Review of Literature

The present use of smart grids is opening up new research avenues for the real-time use of artificial intelligence in the prediction of the stability of smart grids. Many researchers have looked into using machine learning approaches to overcome a range of difficulties related to smart grid implementation. In subsection 2.1, we go over a number of them in detail.

2.1. Related Work

Alazab *et al*. [2] propose the Multidirectional Long Short-Term Memory (MLSTM) approach for forecasting the firmness of smart grid networks. Traditional machine learning models viz. Long Short-Term Memory, Recurrent Networks, and Gated Recurrent Units are compared to the results of MLSTM. The comparison analysis indicates the predicted model's advantage over other models.

Hafeez *et al*. [11] have highlighted the significance of precise energy consumption forecasting in a smart grid system. But due to the non-linear nature of energy consumption patterns, a highly accurate model is required for its prediction. For this study, the scientists used a deep learning-based model. As an activation function, they employed ReLU. The authors used power grid data from a site in the United States to train the network. The performance of the model was analyzed on the scale of variance, average deviation, correlation, and rate of convergence. Through simulation results, the authors have concluded that the proposed model is fast and accurate for short-term load forecasting. Gorzaczany *et al*. [10] suggested a fuzzy inference-based prediction system for apparent and flawless forecasting of smart grid control stability in decentralized smart grids. It is defined by a trade-off between interpretability and accuracy. Furthermore, from the perspective of grid stability, the authors proposed a hierarchy of input properties. Yu *et al*. [28] have addressed the issue of estimating the level of uncertainty due to the varying demand for energy. Statistical modeling analysis was used to get an idea of energy usage distribution. Using this analysis, the authors have used a support vector machine algorithm for the forecasting of energy usage. For this purpose, they have used the real-world data collected through the reading of electricity meters at Stanford University. Further, they have utilized Gaussian distribution for data approximation. Ma *et al*. [15] propose a software-based Grid Stability Awareness System for monitoring and analyzing real-time smart grid stability. The system includes five modules that can help with small-signal firmness, voltage steadiness, and transient constancy in power systems. Ahmed *et al*. [1] have mentioned the grouping of smart grid and renewable energy as the future solution of exponentially increasing energy demand. They have discussed the different challenges in proposing an integrated model of a smart grid with renewable energy. The authors have also highlighted the significance of machine learning models relative to the statistical model while dealing with non-linear data. By integrating machine learning with Gaussian Process Regression, they have proposed a machine learning-based energy management model in a smart grid. They have compared the result of the proposed model with particle swarm optimization and genetic algorithm-based energy management model and found that the proposed model has outshined the later two. When working with bulky and high-dimensional data, one of the most difficult issues is assuring learning speed and rapid reaction for the optimum components of the used technique. Wang *et al*. [27] present a grid steadiness assessment strategy based on the Bayesian optimized Light GBM optimization technique. Rai and De [22] have proposed a load forecasting model which was based on real-time data acquired from smart meters from the campus of NIT Patna, India. To remove the outliers and transform raw data in a suitable format, they have done data pre-processing. They have found that the best performance in terms of Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) is achieved through the support vector regression model. Researchers used a simulated model to evaluate the impact of local wind farm power fluctuation and upgrading operations on grid voltage stability, as well as the upgrading implications of grid voltage stability with various reactive power compensation approaches [21]. Krc *et al*. [13] have mentioned load flexibility as the key factor behind the success of the smart grid. The authors have contributed towards the achievement of load flexibility by proposing a node characterization model. The proposed model is based on a machine learning-based artificial neural networks classification technique. Parameter space and clustering analysis are used to judge the performance of the proposed model for node characterization. Panda and Das in [19] have used regression analysis and feature ranking to investigate the relationship between decentralized control system parameters. It is based on computer-generated data that incorporates various characteristics of heterogeneous customers. Ghosh and Kole [9] and Bashir *et al*. [5] have compared the different machine learning algorithms for the prediction of grid stability. Authors have utilized the smart grid stability dataset [4]. In [9], XGboost classifier has predicted the stability of the grid with an accuracy of 97.5% while in [5], the Decision tree classifier has displayed the maximum accuracy. Malbasa *et al*. [16] have proposed a machine learning-based model for the prediction of the stability of voltage in a transmission system. The authors have utilized a pool-based active learning approach to enhance the dataset. They have identified random forest as the best classifier for prediction of the voltage stability.

2.2. Gap

Traditional resources used in power generation are limited and the power demand is increasing day by day. This has created the need for a system that not only minimizes the loss of power during transmission and distribution but is also able to cope up with the changing power demand. This has shifted the gear from conventional grid to smart grid. High-speed communication networks, sensor-based technologies, and artificial intelligence can play a key role in this paradigm shift towards the smart grid. Through the related work discussed in section 2.1, it has been found that most of the research in the smart grid domain has been carried out in the hardware domain or communication domain. Very little work has been found in the literature about the usage of AI for smart grid implementation. Moreover, prediction of customer's power demand will help not only in achieving the stability of the grid but also improve the customer satisfaction index.

2.3. Motivation

The gaps discussed in section 2.2 have motivated the authors to propose a machine learning-based model for the load estimation of the grid. Moreover, very few researchers have contributed to the area of usage of artificial intelligence in smart grids. The authors in this manuscript have utilized machine learning algorithms (subdomain of artificial intelligence) to predict the load on the grid so that peak load situations can be handled efficiently. Details of the methodology are described in section 3.

3. Methodology

3.1. Dataset Details

The smart grid stability dataset [4] produced by Vadim Arzamasov, which is freely available at Kaggle for research purposes is used for the designing of the model. There are 60000 rows with 14 features in the dataset. The grid's stability value is calculated using the first 12 features, and based on this value, the grid is categorized as stable or unstable. Their details are given below:

- The reaction times of all network participants are represented by the first 4 features Their value varies between 5 and 10.
- The next four variables describe how much power each network participant produces and consumes. Production is shown by a positive value, whereas consumption is indicated by a negative amount. Their values vary from -2.0 to -.5.
- The following four variables reflect the price elasticity coefficient for each network participant: gama1, gama2, gama3, and gama4. The range of their value is .05 to 1.00.
- The last two features stab and stabf are dependent on the first 12. Using the first 12 features, grid stability value stab is calculated, and accordingly, the label is assigned to stabf.

A heatmap depiction of attribute relationships is shown in Figure 1. A correlation matrix is a table that displays the 'correlations' between two variables in a dataset. The heat map shows that the features are highly connected and thus suitable for predicting smart grid stability.

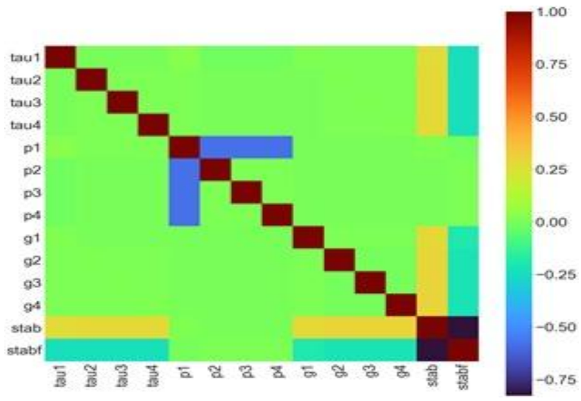
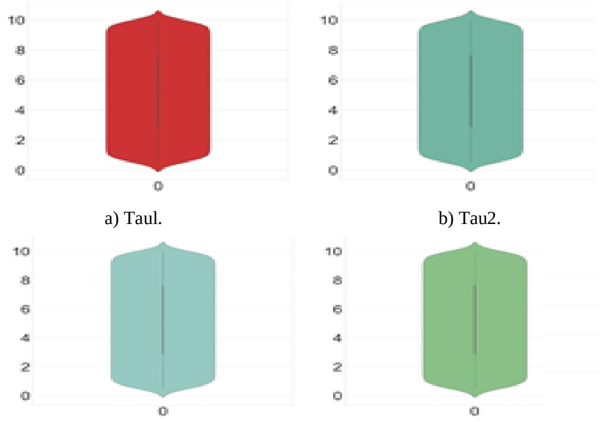


Figure 1. correlation heatmap of smart grid dataset features.

3.2. Dataset Pre-Processing

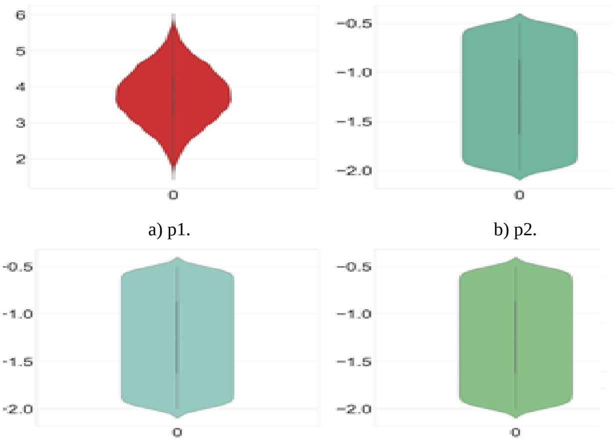
The dataset used in this work was developed artificially, so there is no scope of missing values. Furthermore, because all of the dataset's characteristics are used, there is no need to use the feature selection technique. Feature coding is required due to the numerical component of feature value. It is clear from Figures 2 (a-d), 3 (a-d), and 4 (a-d) respectively that there is no outlier value in the dataset. Dataset is divided into two parts of size 70% and 30% for training and testing purposes respectively. Details of classifiers used for the model training are given in the next subsection 3.3.



a) Taul. b) Tau2.

c) Tau3. d) Tau4.

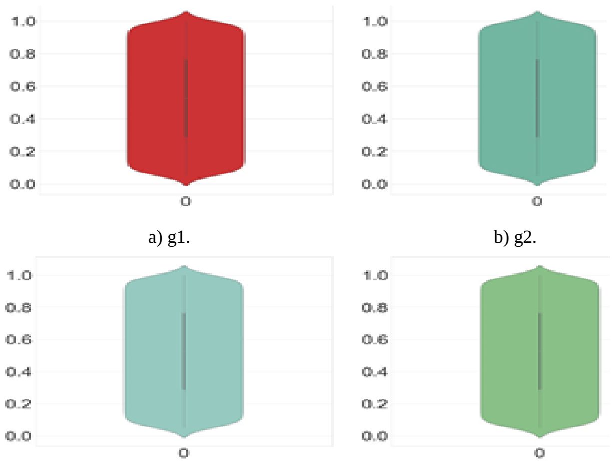
Figure 2. Violin plots showing the distribution of quantitative data for the reaction time of electricity producer and consumer shown for first 4 features in part (a), (b), (c) and (d) respectively.



a) p1. b) p2.

c) p3. d) p4.

Figure 3. Violin plots showing the distribution of quantitative data for nominal power produced and consumed shown for features (5-8) in part (a), (b), (c) and (d) respectively.



a) g1. b) g2.

c) g3. d) g4.

Figure 4. Violin plots showing the distribution of quantitative data for gamma coefficient for producer and consumers for features (8-12) in part (a), (b), (c) and (d) respectively.

3.3. Classifier Details

Detail of different classifiers used for the model training and testing are given below:

- Gradient Boosting It's an incremental functional gradient approach for minimizing a loss function by repeatedly finding a function that flows in the negative gradient's direction. It can be used as a regressor as well as a classifier for prediction. The cost function when used as a regressor is mean square error, while when used as a classifier, the cost function is log loss. Each predictor in Gradient Boosting aims to improve on the previous one by lowering the errors [23, 25].
- Logistic Regression: this classification technique is used to determine the likelihood of one feature depending on another. A value of 0 or 1 is assigned based on the probability dependant feature [12].
- Extra Tree Classifier: Extra Trees Classifier also referred to as Extremely Randomized Trees Classifier is a type of ensemble learning method that performs categorization by combining the results of multiple de-correlated decision trees composed in a “forest”. This algorithm generates a large number of unpruned decision trees using the training dataset. Predictions are created in regression by averaging the forecasts of the decision trees, whereas, in categorization, majority voting is employed [6].
- Quadratic discriminant analysis: It's a non-linear data partitioning method based on linear discriminant analysis. Using a quadratic decision surface, it isolates two or more classes of the classification issue [8].
- Decision Tree: it is a tree-structured, supervised learning-based machine learning classifier technique that consists of decision nodes and leaf nodes. Decision nodes are applied to select one feature out of multiple features and leaf nodes are utilized to specify the predicted value [14].
- Bagging classifiers: bootstrap aggregating also referred to as Bagging classifier is an ensemble meta-estimator that fits the base classifier on random subsets of the original data and then aggregates their predictions by average or voting to generate a final decision. Here, Bagging is a technique that can be used to solve both regression classification. The final predictions for regression problems will be an average of the predictions from the basic estimators. The majority vote will determine the final forecasts for categorization difficulties. Support Vector Classification (SVC) is used as a base classifier in the bagging strategy of classification [20].
- Random Forest: it is a meta heuristic-based supervised learning classifier that consists of numerous independent decision trees that work together to classify data. As an output, each decision tree creates a class, and the random forest class is the most prevalent among all decision tree outputs. When to stop and which attributes to split are two factors that can affect decision tree categorization effectiveness [24].

4. Result and Analysis

As discussed in subsection 3.3, seven machine learning models namely Logistic Regression, decision tree, extra tree classifier, quadratic discriminant analysis, random forest, gradient boosting, and bagging classifier are implemented for grid stability prediction. The proposed models are tested in an environment constructed using Python 3.7 on a machine running Windows 10 with 8 GB RAM and an i3 processor. The most significant performance metrics are computed to assess the effectiveness of any classifier model are accuracy, precision, recall, F-score, accuracy, and Area Under Curve (AUC) [26]. These metrics are calculated to compare the performance of machine learning models that have been used. Precision calculates the number of positive class predictions that are true positive class predictions. The number of positive classes predicted from all positive cases in the database is computed using sensitivity. The F-score is a single figure that takes into account both precision and recall factors. The accuracy of a classifier refers to its ability to correctly anticipate the correct class. When True Positives and True Negatives are more significant, accuracy is employed, while F-score is used when false negatives and false positives are critical. Because there is an uneven class distribution in most real-world classification situations, F-score is a better metric to use to evaluate our model. The AUC score is a measure of how well a classification task performs at different thresholds. The AUC is a separability metric, whereas the Receiver Operating Characteristic (ROC) is a probability curve. The AUC indicates how well the model distinguishes between stable and unstable smart grids. The greater the AUC, the better.

Table 1. Results in terms of performance metrics for each machine learning model

Classifier / Metrics	Precision (Positive predictive value)	Sensitivity (Recall)	F-score	Accuracy	Area Under Curve (AUC)
Logistic Regression	0.802	0.789	0.812	0.814	0.890
Decision Tree	0.897	0.896	0.904	0.905	0.896
Extra Tree Classifier	0.966	0.952	0.962	0.953	0.995
Quadratic Discriminant Analysis	0.870	0.860	0.875	0.860	0.951
Random Forest	0.950	0.942	0.951	0.950	0.992
Gradient Boosting	0.849	0.842	0.858	0.858	0.939
Bagging Classifier	0.978	0.978	0.979	0.979	0.998

Table 1 shows these statistics. It can be observed from these statistics that the Logistic Regression model provides the least accuracy among all the models i.e., 89%. The Extra Tree classifier provides adequate performance with 96.6, 95.2, 96.2, 95.3, and 99.5 percentages for precision, recall, F-score, accuracy, and AUC respectively. However, the Bagging classifier has offered the best performance. The precision, sensitivity, F-score, accuracy, and AUC metrics are 97.89, 97.8, 97.9, 97.9, and 99.8 percentage respectively for the Bagging classifier. A performance comparison plot is provided in Figure 5 that illustrates the superiority of the Bagging classifier on other models. It also compares the accuracy of different classifiers. The Bagging classifier has the highest accuracy.

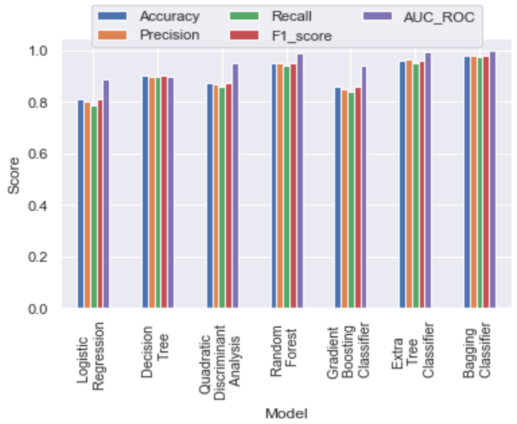
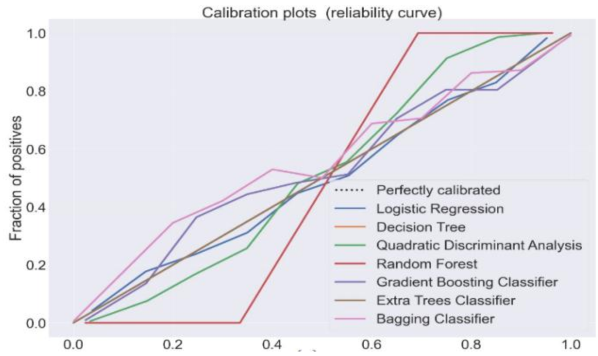
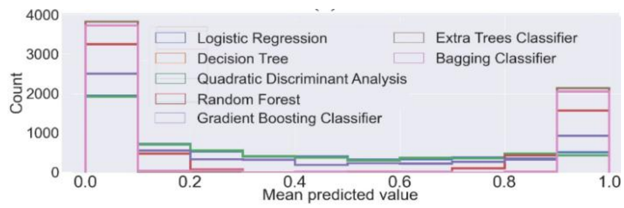


Figure 5. Comparison of machine learning techniques for predicting smart grid stability.



a) Calibration plots (reliability curves) of machine learning models.



b) Mean predicted vale plot for smart grid stability prediction.

Figure 6. Performance analysis of different machine learning models.

The performance of models is also assessed using reliability diagrams. These plots are essentially graphs of an event's observed frequency compared against its predicted probability. This effectively informs the user of the frequency with which a forecast likelihood was realized. The curve in a reliability diagram should be as close to the diagonal/identity as possible for fully calibrated predictions. The bagging classifier returns well-calibrated probabilities close to the diagonal line in comparison to other models. This is shown in Figure 6 (a) and (b) respectively.

5. Conclusions

The smart grid is a concept that involves converting an electromechanically managed electric power infrastructure to an electronically controlled network. With the rapid growth of the world's population and economy, the worldwide power demand has skyrocketed. As a result, to prevent power loss, it is required to properly distribute electricity to families and companies. Smart grids can eliminate such power losses in the delivery of electricity. On smart grids, machine learning and computational intelligence are effectively deployed to improve consumer demand prediction accuracy. There is a critical necessity to assess and evaluate the various algorithms to define which one is most appropriate for practice in smart grids stability prediction. In this work widely standard machine learning algorithms are implemented for smart grid stability prediction. From simulation results, it can be determined that a model developed with a Bagging classifier predicted the load at the grid with the maximum accuracy of 97.9%. The outcome of the AUC score has further confirmed it. In the future, further study is required to establish the efficacy of the proposed model; additionally, we will go even further by incorporating other approaches and technologies to strengthen the resilience characteristic in smart grids.

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