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Article

Emerging Trends in Electrical Engineering: Integrating Smart Grid Technologies, Automation, and Artificial Intelligence for Sustainable Power Systems

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Abstract: Smart grids are increasingly important for sustainable power systems because they combine digital communication, automation, renewable energy integration, and intelligent control. However, maintaining grid stability remains challenging due to decentralized producer-consumer interactions, renewable energy variability, and dynamic demand behavior. This study developed an artificial intelligence-based framework for classifying smart grid operating states as stable or unstable using reaction time, power balance, and price elasticity features. The Smart Grid Stability Augmented Dataset was used, containing 60,000 observations and 14 variables. Twelve input features were selected, while the categorical variable stabf was used as the classification target. The continuous stability score stab was excluded to prevent data leakage. Data preprocessing included missing-value checking, duplicate inspection, label encoding, feature scaling, and stratified 80:20 train-test splitting. Several machine learning and deep learning models were evaluated, including Logistic Regression, Decision Tree, Random Forest, Support Vector Machine, Gradient Boosting, XGBoost, and Artificial Neural Network. The results showed that nonlinear and ensemble-based models outperformed baseline classifiers. Tuned XGBoost achieved the best performance, with accuracy of 0.9848, precision of 0.9847, recall of 0.9916, F1-score of 0.9882, and ROC-AUC of 0.9990. Overall, the findings demonstrate that AI-driven stability prediction can support automated monitoring, early instability detection, and sustainable smart grid decision-making.
Keywords: Smart Grid Stability, Artificial Intelligence, Machine Learning, XGBoost, Sustainable Power Systems

1. Introduction

The use of smart grid has been identified as one of the most important areas of direction in modern electrical engineering due to the integration of power grid with digital communication, automation, sensing and intelligent control. Smart gridding differs from traditional power systems in its ability to control bi-directional energy flow, distributed generation, including renewable resources, consumer involvement, and dynamic demand response. With the rising share of renewable energy resources in the grid, the power system is growing more complex with variable, uncertain and intermittent generation from solar and wind energy. Therefore, a good monitoring and stability forecasting is vital to ensure sustainable and resilient power networks. With the advent of recent technological advancements such as artificial intelligence, Big Data, Internet of Things and blockchain, the scope of smart energy management has been further extended, which makes it possible to reduce energy consumption in generation, distribution and consumption by relying on data [1]. Furthermore, anomaly detection and intelligent monitoring are becoming significant factors in relation to energy systems, due to their ability to detect abnormal consumption patterns, inefficient operation and/or risks related to instability at an early stage [2].

Similarly, the use of automation in a micro grid and in a decentralized power system is becoming essential. Today's grids need to be fast to adapt to faults and outages, as well as to demand shifts and change in renewable generation. Microgrid outage management has been studied using multi-agent systems, highlighting the benefits of distributed and intelligent outage control in enhancing microgrid resilience [3]. In recent years, digital twin and machine learning have been adopted in energy systems to optimize the smart grid, manage renewable energy sources, and integrate electric vehicles, indicating the potential of data-driven models for predictive analysis and operational planning in complex energy systems [4]. Meanwhile, consumers have become flexible agents in smart energy systems and control the grid increasingly through their actions and behaviour and decentralized decision making [5]. The developments indicate that an intelligent model that learns from operating data and assists with power system control automation is needed in the future.

AI is making a big impact in solving these problems. Machine learning and deep learning algorithms can be used to assist in grid monitoring, forecasting grid stability, detection of anomalies, load forecasting, and scheduling renewable energy resources. While some difficulties in scalability, reliability and real-time implementation remain, AI-powered renewable integration has been identified as an important route toward carbon neutrality of multi-energy systems [6]. Recent research also highlights the shift from basic machine learning models to more sophisticated technologies like the Digital Twin and the intelligence of large language models in the smart grid sector [7]. Optimization of renewable energy distribution by a combination of machine learning and data analysis has also been used to enable more intelligent and sustainable energy management [8]. Likewise, it is still an important research field for solar power forecasting because it can help to minimize the uncertainties and enhance the stability in the operation of photovoltaic generation systems coupled to the grid [9].

However, accurate and automated prediction of the stability of smart grid is still a significant issue for research. The addition of decentralized energy communities, edge grids, positive buildings and EVs further complicates things as grid stability relies on the interaction between producers, consumers, pricing and control response [10]. AI-enabled digital twins are also gaining traction in the context of smart, green and zero-energy infrastructure [12] and intelligent control is already proving beneficial for ZE and smart buildings [11]. Yet, there is a need for practical classification frameworks, i.e., frameworks based on AI that are able to determine the stability of the operation of a smart grid based on measurable system parameters. Optimization techniques, such as bio-inspired methods, have been investigated for the Smart Grid powered with renewable energy, but predictive classification is also crucial for real-time decision making and automatic control [13].

Hence, in this study, a machine learning and artificial intelligence framework for the stability classification of smart grids is developed and tested. The proposed method is based on two types of variables: reaction time variables and power balance variables, which are combined with price elasticity coefficients and used to determine whether a state of the grid is stable or unstable. Several models such as Logistic regression, Decision Tree, Random Forest, Support Vector Machine, Gradient Boosting, XGBoost and Artificial Neural Network are compared. Hyperparameter tuning is used to enhance model performance and the results conclude that tuned XGBoost is the best model. The key contribution of this study is the development of a comparative AI-based workflow, which incorporates smart grid technologies, automation, and intelligent classification, to aid power system stability prediction for sustainable power systems.

2. Literature Review

Smart grid studies have evolved from traditional grid modernization to a smarter, distributed, secure and sustainable way to operate a power system. An area that is important is the use of autonomous monitoring technology for renewable energy infrastructure. Kumar et al. [14] conducted a review of technologies that can empower the drone to be an intelligent tool for monitoring solar photovoltaic power plant and demonstrated the potential of automated aerial sensing for enhanced fault inspection, maintenance planning and real-time supervision of PV assets. Technologies such as these can be applied to the development of a smart grid as renewable generation units need continuous monitoring to ensure they are efficient and reliable. Complementary, Zafar et al. [15] suggested a hybrid deep learning model based on federated learning for electricity theft detection via smart meters in industry 5.0 smart power grid. They emphasize the need for secure and privacy-protective models in AI-driven power system applications, especially when dealing with the analysis of distributed smart meter data without compromising sensitive consumer information.

IoT and cyber-physical system views have also been adopted in the key aspect of smart energy modelling. Bordin et al. [16] discussed the smart energy and power system modelling in the context of energy informatics, which highlights the smart energy management through the use of IoT-based sensing, cyber-physical integration and data-driven analytics. This confirms the idea of future power systems to rely on digital communication, sensor networks, and computational intelligence as well as on electrical infrastructure. Likewise, Himeur et al. [17] studied and summarized data fusion strategies for constructing energy efficiency and addressed the difficulties and opportunities of fusion heterogeneous data sources to get a more precise energy monitoring and control. While they were developing energy systems, the same concept can be applied to smart grids, where data from smart meters, renewable generators, control devices and the environmental sensors must be combined in order to make sound decisions.

There are multiple studies on smart grid implementation that have focused on the infrastructure and policy aspects. Ibrahim et al. [18] conducted a review of smart grid status in Ghana Power System and listed the requirements for modernization, technical challenges and opportunities for supporting smart grid technologies. Their review shows that the smart grid transformation is not only a modelling issue; it is also an infrastructure and system-planning challenge, as well as a policy challenge. Reynolds et al. [19] introduced the concept of holistic modeling of multi-vector energy systems for their operational optimization, demonstrating that energy systems are becoming more complex and more electric/energy vectors are interacting with each other, including electricity, heating, cooling, storage, and other energy vectors. This view is crucial as smart grid must work in a multi-energy context rather than in an isolated electric grid.

Security is another critical research direction in intelligent power systems. Afrin et al. [20] covered AI-powered cybersecurity for smart grid communication, specifically intrusion detection and threat mitigation systems. They have found that the more connected a smart grid is, the more vulnerable it is to cyberattacks, false data injection, communication disruption, and unauthorized access. So, operational stability and communication security need to be taken into account when using AI-based monitoring. In addition, the problem of electricity forecasting has been thoroughly explored using deep learning. Abdulrahman et al. [21] discussed the use of deep recurrent neural networks for residential electricity forecasting and pointed out that deep learning models are capable of learning temporal patterns in energy consumption. This helps to facilitate wider adoption of neural networks in energy prediction applications, such as load forecasting, anomaly detection, and stability classification.

Planning, advanced analytics and active involvement of distributed resources are key components of future smart distribution grids. Rossi et al. [22] were interested in the future of intelligent distribution grids, and pointed out the requirements for regulatory, technical and operational changes to enable more flexible distribution networks. Their work is relevant to the present study as stability prediction is one of the important analytical needs for intelligent operation of a distribution grid. Based on cost of energy and peak load, Khah et al. [23] investigated optimal sizing of residential PV/battery systems integrated with the power grid. Their research reveals that distributed PV and storage systems will help improve energy management, but these systems also raise the need for intelligent control and stability evaluation as a consequence of the variable generation and bidirectional energy exchange.

Future smart grids have also been considered as an enabling technology by Blockchain. Yapa et al. [24] provided an overview of blockchain applications in the smart grid, technical considerations, integration hurdles, and future research paths. While blockchain's potential applications in energy trading are promising, it is important to consider its scalability, latency, and interoperability aspects in integrating it with the energy grid. Another direction that is related is energy efficiency modelling. In the field of Industry 4.0, Adenuga et al. [25] built an energy efficiency modelling system for manufacturing, which showed the role of digital modelling in enhancing energy management in industry. Smart grids are important in industrial loads because they are important consumers of energy and their efficient operations help in demand side management and sustainable operation of the grid.

3. Materials and Methods

The entire process for the proposed AI-based methodology to predict smart grid stability is given in Figure 1 below. These steps include preparing the dataset, feature selection, target encoding, data splitting, feature scaling, model training, and finally testing the trained model.

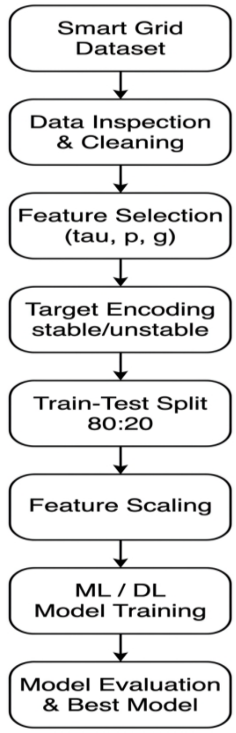


Figure 1. Proposed AI-based smart grid stability prediction workflow

The suggested pipeline involves smart grid data pre-processing activities such as inspection, cleaning, feature selection, and target encoding. After that, data splitting, scaling, and use to develop ML/DL models are carried out, and finally, model evaluation takes place to determine the best performing classifier for automated smart grid stability classification.

3.1 Dataset Description

In this work, artificial intelligence approach to classify Smart Grid stability during prediction was developed using the Smart Grid Stability Augmented Dataset [26]. The data set is a representation of a decentralized smart grid environment and consists of numerical variables that are related to the producer and consumer behavior, power balance, price elasticity, and power grid stability. The feature columns tau1–tau4 and p1–p4, g1–g4 are included in this dataset, as is the continuous stability score stab, and the categorical stability label stabf. From the selected 63 independent variables, 12 independent variables were selected as input features for the implemented workflow and stabf was chosen as the classification target.

There were 60,000 observations and 14 columns. The class variable was either "stable" or "unstable. The class distribution revealed that there were 38,280 unstable samples and 21,720 stable samples, that is, 63.8% unstable and 36.2% stable grid states. This suggests a medium class imbalance which was taken into account when splitting the train and test sets and evaluating the models.

3.2 Feature Description

The input features were organized into three broad groups of smart grid parameter: reaction time parameters, power balance variables and price elasticity coefficients. The dynamic response variables describe the dynamic responses behavior of the producer and consumers of the smart grid system.

They were the reaction time variables tau1, tau2, tau3 and tau4. In this case, tau1 is the reaction time of the energy producer, and tau2, tau3 and tau4 are the reaction times of three consumers. These variables are significant as they can affect the dynamic stability of a decentralized network if not responded in time and consistently by both producers and consumers. The second group was the power balance variables p1, p2, p3 and p4. p1 is the power balance of the energy producer, and p2, p3 and p4 are the power balances of the three consumers. These variables represent the relationship between the power generated and the power consumed in the grid.

The last group were the price elasticity coefficients g1, g2, g3, and g4. The price elasticities of the energy producer and the consumers are represented by the variable g1 and g2, g3 and g4, respectively. These are the sensitivity of producers and consumers to price changes of the smart grid control mechanism.

3.3 Target Variable Selection

The categorical variable stabf was chosen as the target variable for binary classification. It has two class labels: "stable" and "unstable". The aim of the classification problem was to forecast whether a given operating condition of the grid is stable or unstable, given the 12 input features. The dataset also contains the continuous stability score stab, but this was not used as an input feature. The following is a list of the features, along with the type of analysis they represent.The features listed below, and the type of analysis they represent, are directly associated with the final class label stabf, so inclusion as independent features would result in data leakage and artificially boost performance on the model. Only physical smart grid variables tau1–tau4, p1–p4, and g1–g4 were selected as predictors to construct a valid predictive model.

3.4 Data Preprocessing

Preprocessing was performed to prepare the data for developing the machine learning and deep learning models. The data set was checked for missing data first. The missing-value analysis indicated that there were no missing values in all the columns. Hence, there was no need for imputation. A duplicate record check was also carried out to ensure that a model training process would not be biased by duplicate observations. None of the duplicate records were found. This verified the cleanliness and appropriateness of the dataset for direct supervised learning. LabelEncoder was used to encode the categorical target variable stabf. The target values were encoded numerically, with the two classes being labeled as "stable" and "unstable". This change was needed to make the machine learning algorithm work, as it needs numerical target values for classification. The StandardScaler was used for feature scaling. The scaler was applied to the training data only and then applied to both training and testing data. This way, the information leakage problem from the test set to the training process was avoided. For methods like Logistic Regression, Support Vector Machine and Artificial Neural Networks, scaling proved to be significant as in such cases, the amount and distribution of the input features matter a lot.

4.5 Exploratory Data Analysis

To explore the dataset, exploratory data analysis was carried out to check the structure, distribution and class behavior of the dataset before training a model. Class distribution visualization, Feature histogram, Heatmap analysis of correlations, Boxplot inspection and stability score distribution was performed. The class distribution analysis revealed a moderate difference between unstable and stable grid states. The majority class was the unstable class and the minority class was the stable class. This is good enough to use stratified sampling, instead of just using accuracy as an evaluation metric, and as an evaluation metric to use F1-score & ROC-AUC.

To understand the distribution of the selected numerical variables, a feature histogram was used. The reaction time variables, power balance variables and price elasticity coefficients were continuous numerical features, which are suitable for classical machine learning models as well as deep learning models. Correlation heatmap analysis was performed to detect the correlation between the input variables with the continuous stability score. Boxplots were used to check the ranges of features and to compare the behaviour of selected variables among the stable and unstable grid classes. The distribution of the stability score was also explored to gain insight into the separation pattern between the two target classes.

4.6 Train-Test Split

The data set was split into train and test sets with an 80/20 split. There were 48,000 samples in the training set and 12,000 samples in the testing set. The class distribution of both stable and unstable grid conditions was maintained in both subsets by applying stratified sampling when splitting. This was significant as the data was moderately imbalanced.

The model training was done using the training set and the testing set was held back for the final evaluation of the trained models. This separation allowed to test the performance of the models on unseen data.

4.7 Machine Learning Models

A number of supervised machine learning models were implemented to classify the smart grid operating conditions as stable or unstable. The models selected were Logistic Regression, Decision Tree, Random Forest, Support Vector Machine, Gradient Boosting and XGBoost. These models were selected to give a wide range of comparisons between linear, tree-based, margin-based, ensemble and boosting based classification models.

A linear baseline classifier simple logistic regression was used. It served as a baseline to test the ability of the dataset to be separated by a linear decision boundary. A non-linear baseline model was adopted as Decision Tree can capture the relationships between features based on rules.

Random Forest was applied as an ensemble model to increase the classification accuracy and to overcome overfitting effect by using multiple decision trees. SVM with RBF kernel was used to model non-linear class boundaries. Gradient Boosting was considered as a sequential model building weak learners sequentially to enhance prediction performance. Structured tabular data and complex non-linear feature interactions are the reasons why XGBoost was added as an advanced gradient boosting algorithm.

4.8 Deep Learning Model

The deep learning model utilized in the smart grid stability prediction framework consisted of an artificial neural network (ANN). Dense layers were implemented in multiple numbers and sigmoid activation function in the output layers during the formation of the ANN model. Batch normalization was considered useful for enhancing ANN training stability, while the dropout method addressed overfitting issues. In constructing the ANN model, Adam optimizer and binary cross-entropy loss were selected. The use of Adam optimizer was determined based on its adaptability to learning rates. The choice of binary cross-entropy as the loss function was guided by the existence of only two categories in the target variable: stable and unstable.

Early stopping and learning rate reduction approaches were incorporated during ANN training. Early stopping ensured unnecessary training would not continue once validation performance ceased to improve. Conversely, learning rate reduction contributed to improving ANN training convergence by lowering learning rate when validation performance was no longer enhanced. Evaluation of the ANN model was carried out using classification measures similar to those of classical ML models.

4.9 Hyperparameter Tuning

Hyperparameter tuning was done to enhance the generalization of the model and its classification capability. RandomizedSearchCV was carried out for Random Forest, XGBoost, and Support Vector Machine. Randomized Search CV was chosen due to the need to explore multiple hyperparameters in the search space without the need to perform costly grid search.

The hyperparameters that were optimized for Random Forest were the number of estimators, maximum depth, minimum samples for splitting, minimum samples for leaves, and maximum number of features. The hyperparameters for XGBoost were number of estimators, maximum depth, learning rate, subsample ratio, column sampling ratio, gamma, and regularization coefficient. For Support Vector Machines, kernel, penalty C, and gamma were tuned. F1-Score was used as the main criterion for optimizing hyperparameters since the data had moderate imbalance. It is important since in terms of smart grid stability prediction, both Type I and II errors should be avoided.

4.10 Evaluation Metrics

The trained models were assessed by using Accuracy, Precision, Recall, F1 score, ROC-AUC, confusion matrix, ROC curve, and precision-recall curve. Accuracy represented the ratio of all correct classifications. Precision showed the percentage of true cases of instability among all predicted instances. Recall indicated how well the model detected all unstable states of the grid. The F1 score offered a combined indicator of precision and recall, which became crucial in light of the class imbalance problem.

ROC-AUC served as an assessment tool that allowed evaluating the model's capacity to differentiate between stable and unstable grid states at various probability thresholds. The confusion matrix could help analyze the number of true and false predictions made for each target class. ROC and precision-recall curves were utilized to assess visual discrimination capability and predictive accuracy per class. The last step in model comparison was to rely mostly on the F1 score and ROC-AUC values rather than on the accuracy metric. This approach to evaluation was preferred as detecting instability in a smart grid is a vital responsibility, and therefore requires a high recall rate and good separation between classes.

4. Results

4.1 Dataset Characteristics and Target-Class Distribution

The smart grid stability dataset contained 60,000 samples and 14 variables, including 12 predictor variables, one continuous stability score, and one categorical stability class label Figure 2. For the classification task, the 12 physical smart grid variables, namely tau1–tau4, p1–p4, and g1–g4, were used as input features, while stabf was used as the target variable. The continuous variable stab was excluded from the input feature set to avoid data leakage because it is directly associated with the final stability label. The implemented notebook confirms that the selected feature matrix contained 60,000 observations and 12 input features, while the target vector contained 60,000 class labels. The distribution of the classes had a slight bias towards the two states of stability. For instance, the number of samples for the unstable class was 38,280, which accounted for 63.8% of the data set, while those for the stable class was 21,720, accounting for 36.2% of the data set. It implies that unstable states were common compared to stable states in the data set.\

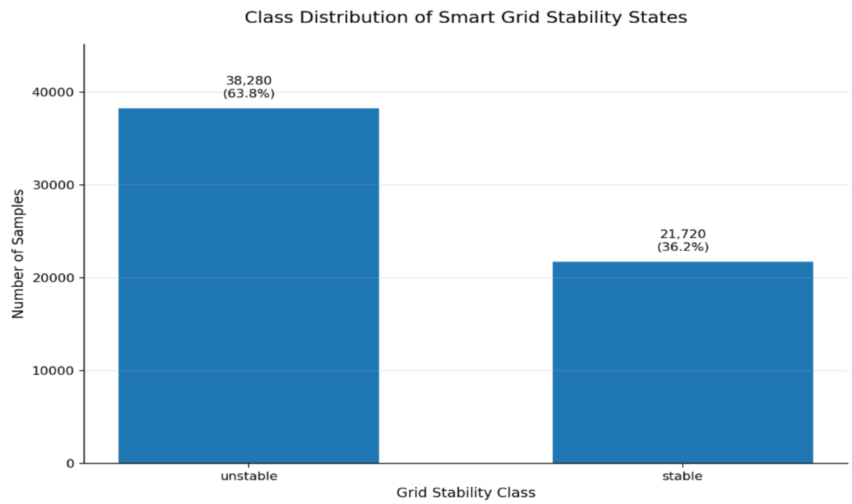


Figure 2. Class distribution of smart grid stability states

Though the disproportion was not massive, it was still considerable and served as a reason to employ stratified sampling when splitting data into training and testing subsets, as well as to consider F1-score and ROC-AUC measures for evaluating algorithm performance. In fact, accuracy would have significantly overestimated results due to class imbalance issue.

4.2 Correlation Analysis of Smart Grid Features

Figure 3 presents a correlation heatmap between the reaction time factors, the power balance factors, the price elasticity factors, and the stability factor. As far as the reaction time factors tau1-tau4 are concerned, they were positively correlated with the stability factor at 0.28. Likewise, the price elasticity factors g1-g4 also had positive correlations with the stability factor at 0.28-0.29. These findings indicate that reaction time and price elasticity factors are positively related to grid stability behaviors.

Unlike the other sets of variables, the relationship between the power balance variables and the stability measure was not as strong as that observed for the other variables. For instance, the power balance variable for producers, p1, had only a very weak positive relationship with stab, whereas the other three power balance variables, which were on the consumer side, p2, p3, and p4, were in very weak negative relationships with stab. The strength of the negative relationship was about -0.58.

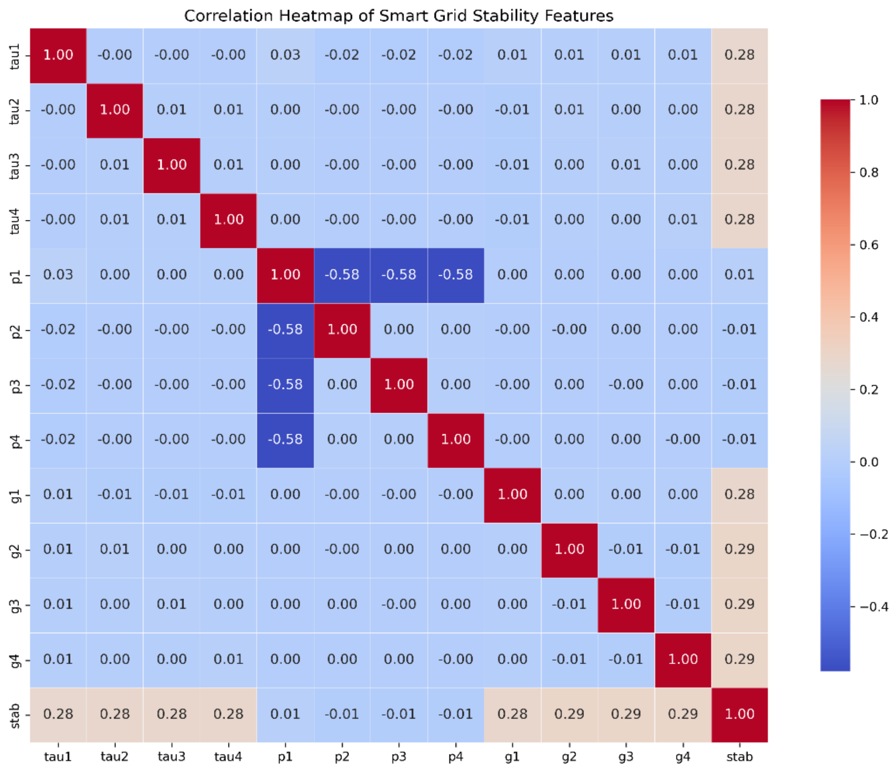


Figure 3. Correlation heatmap of smart grid stability features

In summary, the correlation analysis suggests that the predictive model does not rely on a single major variable. Rather, the performance of the grid seems to be influenced by a complex relationship between reaction time, power ratio, and price elasticity values. Thus, it makes sense to apply a nonlinear model such as Random Forest, SVM, XGBoost, and ANN.

4.3 Feature Distribution by Grid Stability Class

Feature group distribution plots further clarified differences that were present in various smart grid parameters depending on whether or not the state of the grid was either stable or unstable. Feature group reaction time is shown in Figure 4, power balance in Figure 5, and price elasticity in Figure 6.

A clear distinction was observed in the reaction time attributes for both groups. In case of tau1 – tau4, the reaction times of the unstable group were found to be relatively larger than the reaction times of the stable group. This indicates that producers and consumers with larger reaction times tend to exhibit unstable grid performance. The observation has significance from the smart grid control point of view as response delays negatively impact disturbance correction.

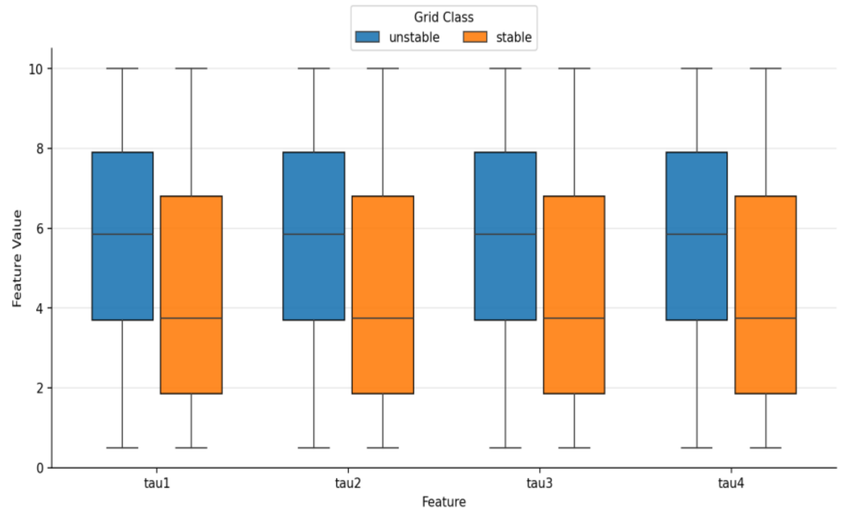


Figure 4. Reaction time features by grid stability class

There was a lack of clear distinction between the stable and unstable groups when it came to power balance variables. This is because the values of p1, p2, p3, and p4 for both groups overlapped in most cases, as illustrated by Figure 4. It can thus be stated that power balance variable alone cannot classify stable and unstable conditions; but it can help when used with reaction time and price elasticity variables.

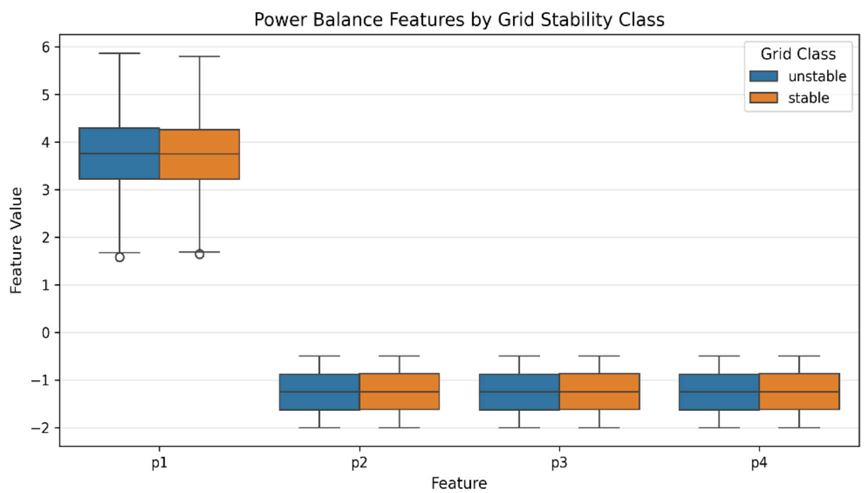


Figure 5. Power balance features by grid stability class

However, the price elasticity coefficient results were more distinguished between the stable and unstable groups. It was observed that for groups g1–g4, the median values of the unstable group were always higher than those of the stable group, as illustrated in Figure 5. This suggests that the price elasticity coefficient plays a significant role in smart grid stability classification.

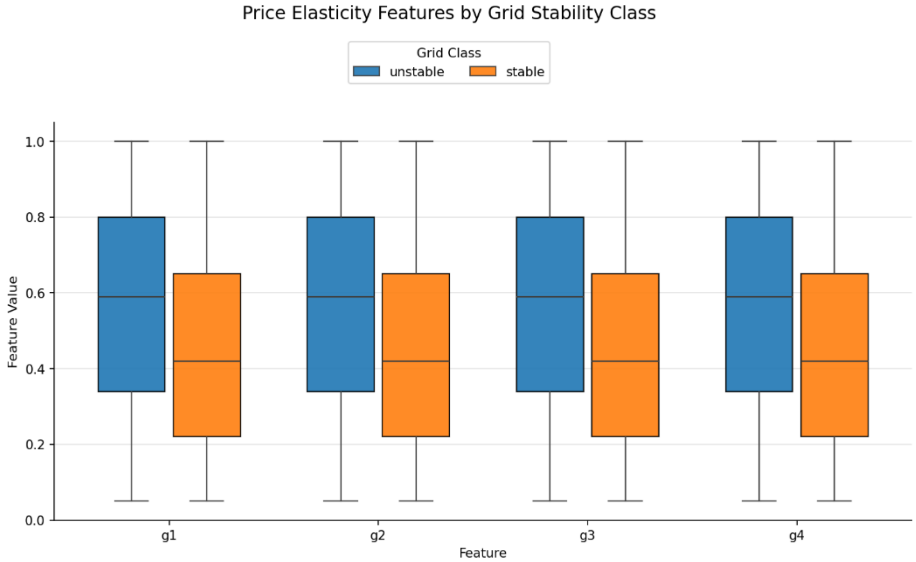


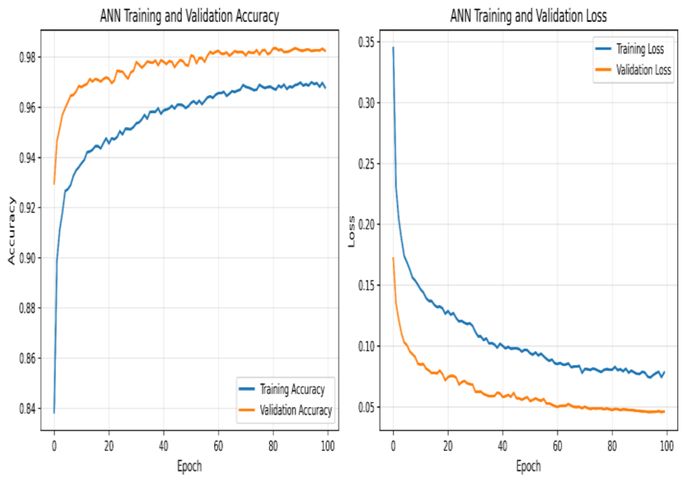
Figure 6. Price elasticity features by grid stability class

4.4 ANN Training and Validation Performance

The ANN model training process included the scaling of the input features, binary cross entropy loss function, Adam optimization, batch normalization, dropout regularization, early stopping, and learning rate reduction techniques. The training process of the ANN model is illustrated in Figure 7.

As illustrated in the training and validation accuracy graphs, there was a consistent rise throughout the training epochs. In particular, the validation accuracy experienced a quick growth at the early stages of training and became relatively stable at around 0.98. Meanwhile, the training accuracy experienced a constant rise and reached 0.97. Moreover, the validation accuracy was always higher than the training accuracy. However, such a condition is acceptable since both batch normalization and dropout techniques were utilized for training.

However, from the loss curves, we can also observe a steady convergence. For instance, there is continuous reduction in training loss starting at about 0.35 and ending at less than 0.08. Similarly, validation loss starts at about 0.17 and ends up below 0.05. This means that the network was not experiencing overfitting. As such, the ANN model successfully learned the non-linear stability relationships.



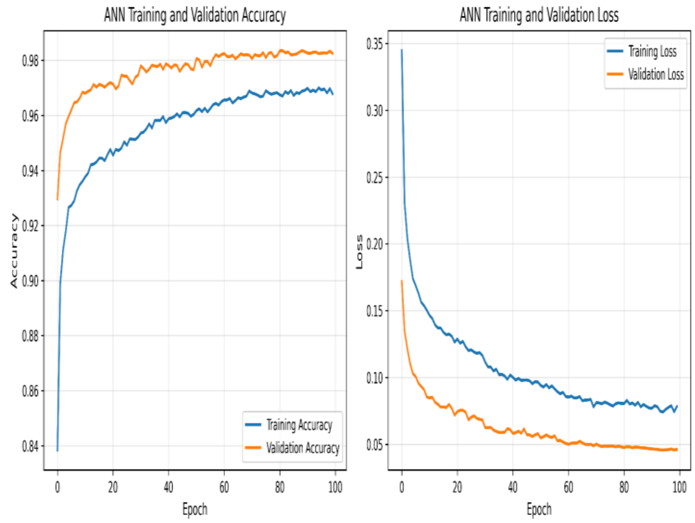


Figure 7. ANN training and validation accuracy/loss curves

It is clear from the above figures that the classification efficiency performed by ANN was very good, with Accuracy=0.9817, Precision=0.9853, Recall=0.9860, F1 score=0.9856, and ROC-AUC=0.9986. It shows that deep learning is a highly efficient tool in classifying smart grids stability if proper pre.

4.5 Final Model Performance Comparison

Performance of all the tested models is presented graphically in Figure 8. These models were Logistic Regression, Decision Tree, Tuned Random Forest, Tuned SVM, Artificial Neural Network, and Tuned XGBoost. Performance comparison was done in terms of Accuracy, Precision, Recall, F1-score, and ROC-AUC.

From the figure, it can be observed that the simplest model that served as the baseline performed worst. This model recorded an accuracy and an F1-score of about 81.95% and about 0.862 respectively. This shows that a linear decision boundary was inadequate for the data used.

On the other hand, the Decision Tree outperformed the Logistic Regression model considerably and scored about 89.53% accuracy and 0.918 F1-score. This indicates the effectiveness of nonlinear decision boundaries in our case.

Finally, after tuning, the ensemble and kernel-based machine learning algorithms yielded much better performance. For instance, after tuning, the Random Forest scored an F1-Score of about 0.9613 and 0.9916 ROC-AUC. Likewise, tuned SVM scored about 0.9790 F1-Score and almost 0.998 ROC-AUC. Finally, ANN had an F1-Score of 0.9856 and 0.998.

Tuned XGBoost was the model that performed best among all, obtaining the best overall results with an accuracy score of 0.9848, precision of 0.9847, recall of 0.9916, F1-score of 0.9882, and AUC of 0.9990. This suggests that XGBoost was the most suitable algorithm for identifying nonlinear patterns related to smart grid stability.

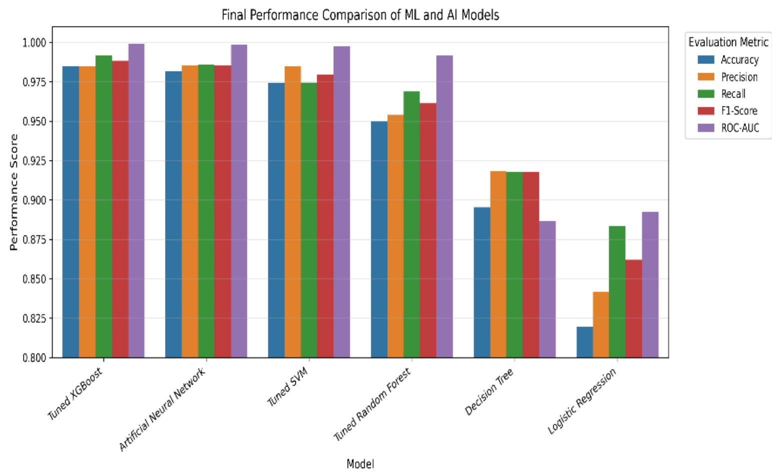


Figure 8. Final performance comparison of ML and AI models

The very high value of recall for Tuned XGBoost is of special significance because the positive class is that of unstable grid state. In practice, the ability to identify the unstable grid states is of particular importance because failures to do so may result in improper control decision making.

4.6 Confusion Matrix Analysis of Tuned XGBoost

A confusion matrix of the top performing model, Tuned XGBoost, is presented in Figure 9. The tuned XGBoost has successfully classified 4,226 stable samples and 7,592 unstable samples; it was unable to classify 118 stable samples and 64 unstable samples accurately.

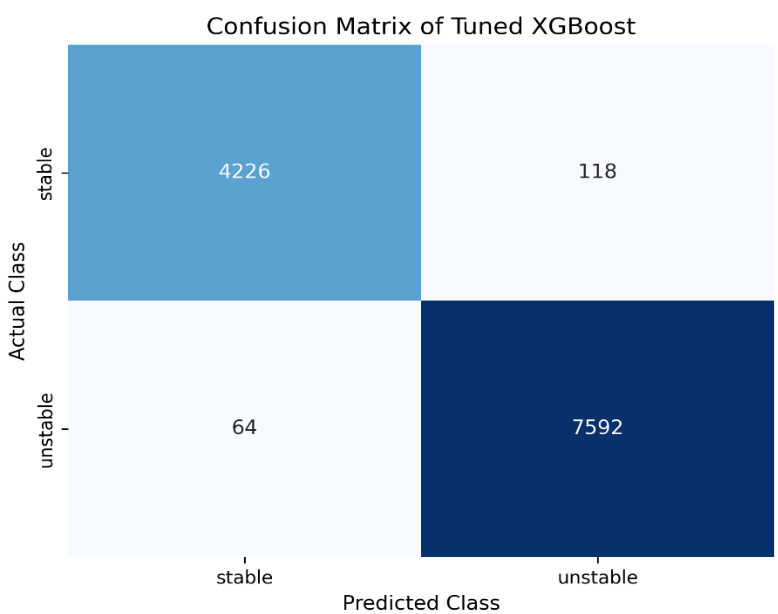


Figure 9. Confusion matrix of Tuned XGBoost

From the confusion matrix results, it is evident that the XGBoost model after tuning showed very low errors for each category. The model classified 64 unstable samples as being stable among 7,656 unstable test samples. This shows sensitivity of the model to unstable grids. This is crucial in ensuring sustainable energy production since unstable grids are critical.

Similarly, the model demonstrated great accuracy for the stable category, correctly identifying 4,226 out of 4,344 stable records. While 118 stable records were incorrectly classified as unstable records, the former mistake is preferable to missing an unstable record in grid monitoring systems. Thus, it is evident from the confusion matrix that the Tuned XGBoost model is suitable for automatic smart grid stability prediction.

5. Discussion

The results confirm that predicting smart grid stability is a nonlinear classification task, which can significantly leverage machine learning and AI algorithms. The tuned XGBoost algorithm had the best performance, attaining accuracy, precision, recall, F1-score, and ROC-AUC values of 0.9848, 0.9847, 0.9916, 0.9882, and 0.9990, respectively. These remarkable results are explained by the modeling of complicated interactions between reaction time, power balance, and price elasticity factors in the XGBoost algorithm. Stability in the case of decentralized smart grids is achieved through several parameters rather than just one. Producer response, consumer behavior, and sensitivity in control are key determinants of stability in such systems. Thus, boost-based ensemble learning techniques are highly appropriate in identifying the complex decision boundaries in these kinds of nonlinear problems. This is in line with the increasing use of AI-scheduling and intelligent controls in smart grid settings [26]. The Artificial Neural Network gave a highly commendable performance too, registering a 0.9817 accuracy, 0.9856 F1-score, and 0.9986 ROC-AUC respectively. From the graphs of training and validation on ANN, we were able to establish that the deep learning technique learned stability trends in the data without overfitting significantly. This is evidence of the application of the neural network model in the smart grid and renewable energy forecast area where hybrid deep learning architectures have proven to be very effective [27]. Regarding the automation process, the developed framework could be applied for grid monitoring, prediction of instability in advance, and automatic decision-making processes. It is important to have a high recall rate for the unstable data as any undetected unstable condition may result in slow control responses and increased risks. In the present research work, the adjusted XGBoost classifier incorrectly labeled 64 examples as being stable when they were actually in the unstable state. Such prediction ability matches the idea of the Energy Internet where intelligent control and digital coordination help achieve sustainable urban development [28]. This finding also has relevance for sustainable power systems due to its potential contribution towards improving the system reliability, supporting renewable energy integration, and avoiding unwanted disruptions. This is in line with future smart cities' power systems that require intelligent transfer learning and data-driven optimization for their sustainable operation [29]. Stability and flexibility in the design of such power grids are also necessary in the context of energy-efficient industries and microgrids, specifically DC-based microgrids used for flexible production [30]. In addition, a more in-depth comparison of simple versus advanced models indicates the necessity of employing advanced models to fulfill the task. Specifically, logistic regression produced the poorest results, whereas decision tree provided slightly better accuracy due to capturing some nonlinearity. In contrast, tuned random forest, tuned SVM, ANN, and tuned XGBoost demonstrated significantly higher effectiveness, showing that intelligent classification of smart grids requires modeling of complex interdependencies among features. This need has been observed for other data-intensive industries implementing automation in the cloud environment [31]. In practical terms, this model can assist utility companies in converting sensing information into operational intelligence as they confront growing demands for monitoring and analysis [32]. However, there are some weaknesses associated with the work. The database used here is simulated and generated, not gathered from smart grid infrastructure. Real life applications can suffer from noise, missing data, cyber-physical attacks, faulty sensors, and varying demand trends. Further areas for future research that must be considered include explainable AI, online learning, deployment at edge through IoT, federated learning, and renewable forecasting. The mentioned areas are in line with the ongoing digitalization towards sustainability [33], data-heavy methods in machine learning applied to renewable energy studies [34], and intelligent systems based on digital twins [35].

6. Conclusion

The current research designed a model for predicting the stability of smart grids using artificial intelligence techniques. The proposed model was implemented by applying the SGSA dataset. The stability of the smart grid was considered as a binary classification problem, where the operating state of the smart grid was categorized into either stable or unstable classes. The process of data preprocessing entailed detecting missing values, target encoding, normalization, and stratified split of training and testing sets. Several models were tested for their performances, which included logistic regression, decision tree, random forest, support vector machine, gradient boosting, XGBoost, and artificial neural network. The analysis indicated that complex models gave better performance compared to baseline classifiers. The performance of Tuned XGBoost outperformed other models with accuracy, F1-score, and ROC-AUC metrics at 0.9848, 0.9882, and 0.9990, respectively. The model performance of ANN also proved satisfactory, proving the efficacy of deep learning in classifying smart grids. The above results show that AI-based stability prediction is capable of enhancing the monitoring process, identification of potential instabilities, and decision-making for sustainable power systems. Future research needs to validate the proposed method through real-time smart grids and AI explainability techniques.

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