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Enhancing Smart Grid Stability: Data-Driven Predictive Modeling in Distribution Systems

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ABSTRACT- The system's ability to retain the equilibrium state during regular and under disturbance decides the power system stability. The power system stability is highly affected by continuous load variation, voltage variation, frequency variation, power flow variation, topology and the work environment. Hence the stability analysis is made to ensure the acceptable equilibrium state throughout the operation of the power system while meeting the demand. As there has been numerous inclusion of renewable energy sources into the electric network, there occurs challenge to maintain the equilibrium level of this decentralized supply with temporary needs. So, to establish this kind of scenario, a Decentralized smart grid control (DSGC) is developed. In DSGC, demand is evaluated with supply through price information and the customers are allowed to decide on usage based on Pricing. The optimal hyperparameter tuning through grid search optimization for DSGC stability prediction is presented in this paper. The local frequency provides the details on equilibrium/power balance, to match supply with demand. Using an ensemble grid search optimization approach, we examine the power grid performance on dynamic stability. Our findings imply that DSGC stability is best predicted by ensemble gradient boost machine grid search with best R2 index performance and accuracy of 93.92%.

Keywords: Hyperparameter Tuning, Grid Search Optimization, Grid Stability Prediction, Ensemble Machine learning, Distribution system.

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1. INTRODUCTION

The integration of renewable energy sources has influenced the demand-supply characteristics of a power grid. The major challenge faced while integrating renewable resources is the fluctuations in power generation that varies with time during a single day [1]. To adapt and regulate the demand for electric power [2] requires a massive shift in the power grid operation paradigm by providing an appropriate demand response [3,4] based on the consumption behaviour of the consumers. The increase in the decentralized generation of power requires a bidirectional flow of power and information between the consumers and producers to balance generation and demand. The smart grid can enhance demand response with bidirectional flow of electricity [5] and information and communication technology (ICT). However smart grid requires advanced cyber security and privacy-preserving mechanisms [6,7] for information security as it is vulnerable to cyber threats and attacks resulting in cascading failures. For an alternative, a decentral smart grid control (DSGC) [8]} has received greater attention recently in grid stability. A DSGC can be applied to maintain grid stability by providing real-time pricing. Stability can be predicted by determining the demand based on local grid frequency. A DSGC offers effective measures to determine the stability of the grid [9,10] by incorporating details about electricity pricing, adapting to the fluctuation and variations in frequency using the demand response characteristics of a particular participant.

Data mining [11,12,13] has been widely applied for predicting load, angular stability, and transient stability [14-24] of a power system [25-27]and so on. We have applied ML algorithms [28] to foresee the grid stability problem using feature selection and seven ML algorithms. The ML algorithm performance depends on the features used for selecting relevant and significant features, improving the performance and reducing the complexity of the model. Hence, the feature selection algorithm [29] helps to select significant, relevant and consistent features for model evaluation. Feature selection methods can be commonly grouped into a filter, wrapper & embedded methods. The various feature selection algorithms are Pearson correlation, rank-based selection, recursive feature elimination, information gain, principal component analysis, etc. In the existing literature, the most widely used Machine learning algorithms are Logistic Regression, Linear Discriminant Analysis, Linear Regression, Classification and Regression Trees (CART) [30], Learning Vector Quantization (LVQ), K-Nearest Neighbors (KNN), Naive Bayes (NB), Support Vector Machines (SVM) [31], RF (Random Forest) [32], Bagging and Boosting for predicting the grid stability. We have developed seven machine-learning algorithms, like Linear regression (LR), K-Nearest Neighbour (KNN), Decision Tree (DT), Ada Boost (AB), Gradient Boosting Machine (GBM), Random Forest (RF), and Extra trees (ET), that utilize the Pearson correlation feature selection algorithm. The dataset is accessed from the University of California Irvine Database Repository using Vadim Arzamasov Electrical Grid Stability Simulated Data to predict the grid stability. The dataset contains three parameters, namely grid participants reaction times under varying grid conditions (tau), each participants electricity generation/consumption volumes(P), and the cost-sensitivity (g). ML algorithms are evaluated based on performance metrics such as MAE (Mean Absolute Error), MSE (Mean Square Error), RMSE (Root Mean Square Error) and R-Squared error. The grid search optimization technique selects the optimal hyperparameters of the model. The experimental evaluation shows that the ensemble Gradient Boosting machine has shown good performance improvement with 93.6% prediction accuracy over the developed algorithms and other unconventional techniques.

The main contributions of this paper can be summarized as follows:

(i) Measures the seven machine learning algorithms performance for the DSGC system through the Z-score normalization technique and compare these algorithms based on the performance metrics.
(ii) Summarize the grid search parameter tuning performance and finalize the machine learning model, which has significantly improved prediction accuracy.

The rest of the paper is presented as follows: *section 2* defines and quantifies the DSGC system and stability issues; *section 3* illustrates the involvement and implementation of ML algorithms in the DSGC stability dataset; *section 4* provides the performance evaluation metrics for measuring the ML algorithms performance; The discussion about the significance of proposed algorithm in the classification of stability in *section 5* and *section 6* summarizes the conclusions.

2. RELATED WORK

Data mining and ML algorithms are applied to analyze and predict demand-side load management, stability, economic dispatch, security, time-series forecasting, etc. In this section, we discuss the literature relevant to electrical grid stability.
The author in [33] studied the electric grid stability using fuzzy rule-based classification (FRBC). A strength Pareto evolutionary optimization algorithm (SPEA) is used to optimize the structure and fuzzy parameters. The FRBC-SPEA obtained a classification accuracy of 91.1% and 85.5% on training and testing data. The study presented in [34] applied SVM, KNN, Logistic regression, NB, Decision tree and neural network for the classification of the grid stability dataset. The authors have pre-processed the data using min-max normalization and used 70% data for training and 30% for algorithm performance testing. The experimental evaluation reveals that the decision tree algorithm achieved a classification accuracy of 99.90% when compared with other models.

The study in [35] applied three feature selection algorithms for selecting the significant features for predicting the result. For stability prediction, the authors developed linear regression, random forest, gradient boost tree and multilayer perceptron (MLP) classifier. The combination of MLP classifier and binary particle swarm optimization achieved a classification accuracy of 93.8% when compared with other models.

The authors in [36] applied a MLP and support vector machine (SVM) model to the Brazilian southeast dataset for predicting the stability problem of the high dimensional power system. The performance result of SVM is better than MLP with the rate of 3.2% and 11.7% as false dismissal and false alarm, respectively.

In [37] studies about the electric grid stability problem with various parameters using an artificial neural network to predict the operation condition within a power system were carried out. The developed model achieved a good performance of result with a 2.5% average absolute error.

The study in [38] analyzed the effect of cyber-physical attacks using the IEC-61850 protocol to identify malicious smart grid devices. The authors applied machine learning algorithms like SVM, RF and CNN (Convolution Neural Network) on 37500 experiments and achieved 95.1% accuracy with a 0.03% false positive rate.

The disturbance of the power system under various faulty conditions is evaluated to find the transient instability in the Iranian national grid. The experiments are conducted on the 9-bus system to predict transient instability using Artificial Neural Network (ANN), SVM and DT models. The DT model achieved better performance with an accuracy of 99.91% than other models. The authors in [39] also used DT techniques for the classification of DSGC stability status using the response from heterogeneous consumers, and the obtained evaluation accuracy was 80%.

An active learning approach is proposed in [40] for predicting voltage stability problems using ML methods like DT, ANN, SVM, RF, and radial basis function networks. The prediction performance of Random Forest is higher with an accuracy of 90% when compared with other ML models.

The stability of the Smart Grid depends on its ability to deliver a constant power supply based on demand. In our study, we have investigated the performance of an ensemble algorithm with a reduced feature subset built with seven machine learning models, namely LR, RF, KNN, DT, ET, AB and GBM for

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prediction of grid stability. Initially, the models are trained, and then their performance is evaluated based on testing data through metrics. A comparison has been made based on prediction accuracy.

Then, the standardization of data has been made for individual algorithms and is integrated to execute the ensemble-based prediction result.

3. PROPOSED WORK

The materials and methods have been described in this section. It contains four subsections: dataset description, Preprocessing, data partitioning/splitting, and the proposed stacked ensemble classifier. For performing the regression task, we follow the steps of data preprocessing, apply K-fold cross-validation to divide the data into training and testing and then test the model after training the model. Then measure the performance metrics and use an ensemble grid search optimization to improve the prediction accuracy when the individual regression algorithm does not produce the best accuracy at the time of deployment.

3.1 Dataset Used

Data Set of Vadim Arzamasov Grid Stability Data accessible since Nov2018 at the University of California Irvine Repository (https://archive.ics.uci.edu/ml) is used as the primary set.

The model shown in the *figure.1(a)* illustrates about the actual elements of power generation along with the utilization of loads. In *figure.1(b)* DSGC structure with boundary conditions for all three input variables.

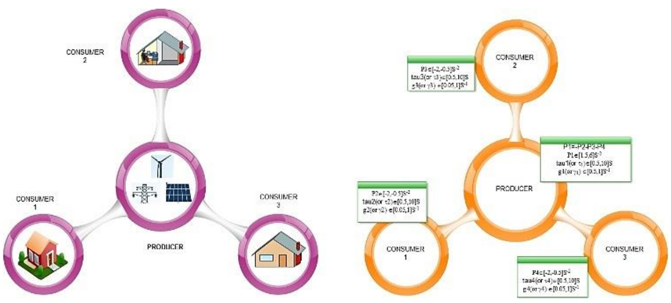

Figure 1. (a)Actual elements of power generation along with the utilization of load. (b) Structure of the DSGC system for all three input variables

The description about the dataset is shown in *Table 1*. The data set consist of 10000 records of DSGC system with 12 input attributes (11 predictable and 1 non-predictable) and 1 output attributes.

The Vadim Arzamasov Grid Stability Data is significant because it provides a comprehensive dataset specifically designed to evaluate and enhance the stability of power grids. This dataset includes various features that are critical for analyzing grid performance and predicting potential stability issues.

Three key factors of the model are:
(i) Pn: Power balance, illustrating the power produced when n=1 or power consumed when n = 2, 3 and 4
(ii) taun: Individual participants reaction time during change in an electricity price, and
(iii) gn: Price elasticity co-efficient.

Table 1: Attribute details

Description of Attribute	Mean	Std Deviation
tau1: Reaction time of electricity producer in sec	5.25	2.742
tau2: Reaction time of electricity consumer 1 in sec	5.25	2.742
tau3: Reaction time of electricity consumer 2 in sec	5.25	2.742
tau4: Reaction time of electricity consumer 3 in sec	5.25	2.742
p1: Nominal power produced	3.75	0.752
p2: Nominal power consumed by consumer 1	-1.25	0.433
p3: Nominal power consumed by consumer 2	-1.25	0.433
p4: Nominal power consumed by consumer 3	-1.25	0.433
g1: Gamma coefficient proportional to price elasticity of Producer	0.525	0.274
g2: Gamma coefficient proportional to price elasticity of consumer 1	0.525	0.274
g3: Gamma coefficient proportional to price elasticity of consumer 2	0.525	0.274
g4: Gamma coefficient proportional to price elasticity of consumer 3	0.525	0.274
stab: Maximal real part of the characteristic equation root (if negative—the system is linearly stable)	0.016	0.037

3.2 Preprocessing

Data preprocessing is transforming the unprocessed data into understandable data. So, data preprocessing is done to improve the quality of data. Two tasks were performed in data preprocessing, namely normalization and feature selection.

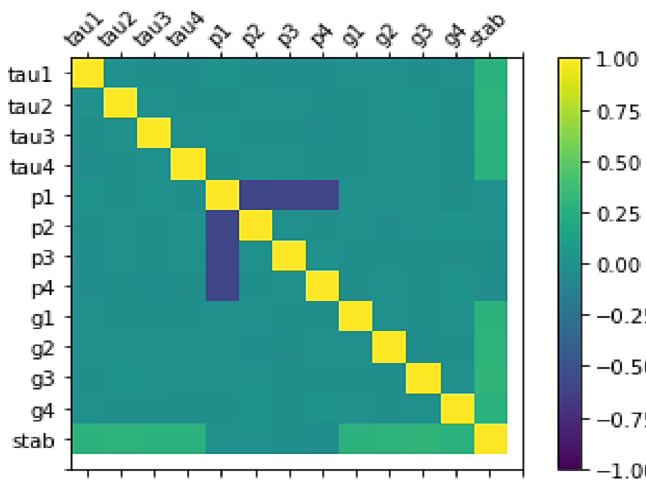

Figure 2. Correlation of Attributes

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Z-score normalization techniques are used to scale the data in attributes to fit within a narrower range. Since all the features of the dataset may not help you build a machine learning model to make the prediction, the Pearson Correlation feature selection technique is used. Pearson correlation is commonly used to measure the relationship between related linear variables, and from the *figure 2* it is clearly understood that the attributes such as nominal power produced, Consumer 1, 2, 3 Nominal power consumption have the least significance for high prediction of result.

3.3 Data Partitioning/Splitting

The data set is split into a training dataset and a testing dataset in this stage. The dataset is partitioned into two parts as 80% for training and 20% for testing. The training dataset is to fit the machine learning model and testing data to evaluate the machine learning model's performance. Thus, the train-test split is used to analyze the behaviour of machine learning algorithms during the prediction process by choosing the test data, which is different from training data. Cross-validation is a simple method primarily used in applied machine learning to measure the performance of machine learning models against invisible data. We used 10-fold cross-validation because the dataset is unbalanced. This approach randomly divides a set of observations into ten equal groups. The first convolution is treated as a test set, and the method fits into the remaining nine groups. Then evaluate your ability to customize machine learning models and use indicators to compare their performance.

3.4 Proposed Stacked Ensemble grid search Optimization

The proposed stacked ensemble grid search optimization architecture is as shown in *figure 3*.

To create a baseline for the performance, spot-check several different algorithms such as LR, Elastic Net, Lasso, KNN, SVM, DT, AB, GBM, RF and Extra trees. All these algorithms' accuracy is compared for mean and standard deviation.

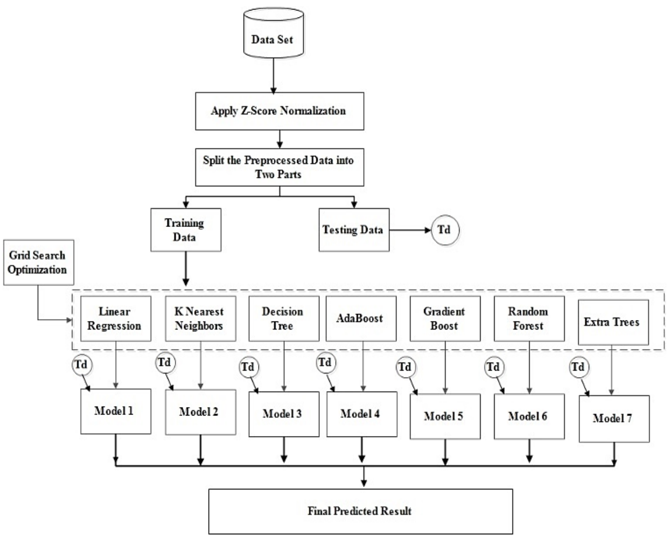

Figure 3. Grid search optimization architecture

We evaluate the model using repeated k-fold cross-validation and report the model's errors.

Graphically through accuracy distribution, the performance of the algorithm is compared using box and whisker plots as illustrated in *figure 4*.

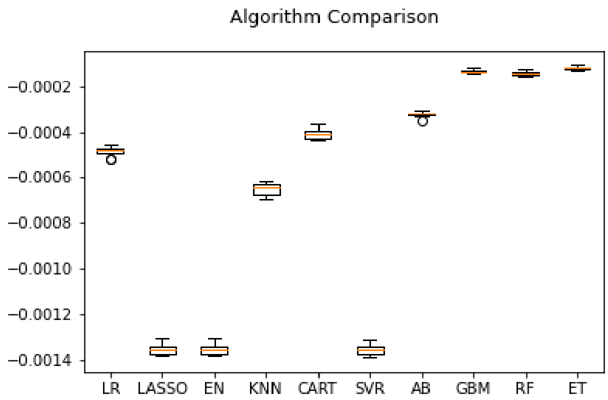

Figure 4. Graphical comparison of algorithm using Box and Whisker plots

From the result generated, an accuracy distribution for ET (Extra Trees) is encouraging with low variance suggestion.

Next, we automate machine learning workflows with pipelines and improve the performance with boosting ensembles techniques (BET) such as Ada Boost and stochastic gradient boosting.

BET generate a sequence of models that attempt to correct the error of the models before them in the sequence. Once built, the models make predictions that can be weighted based on their accuracy, and the results are combined to produce a final prediction of output. To improve performance, two popular ML algorithms have been used by boosting ensembler such as Ada Boost and Stochastic Gradient Boosting.

Algorithm performance is improved through the parameter tuning process, and the best model for the problem is finalized. The grid search parameter optimization approach was used to tune the parameters and evaluate the model for each combination of algorithm parameters specified in a grid R-squared error assessed with other models.

When optimizing machine learning models, several hyperparameter tuning techniques can be considered besides grid search. One popular alternative is random search, which randomly samples hyperparameters from a specified distribution. This method is often more efficient than grid search as it can cover a larger search space with fewer iterations. Another advanced technique is Bayesian optimization, which builds a probabilistic model of the objective function and uses it to select the most promising hyperparameters iteratively. Genetic algorithms and evolutionary strategies are also used for hyperparameter tuning, leveraging concepts from evolutionary biology to evolve the best hyperparameters over successive generations. Finally, Hyperband is a more recent approach that combines random search with early stopping to efficiently allocate resources to the most promising hyperparameter configurations. These techniques offer various trade-offs in terms of efficiency, complexity, and performance, providing multiple options for optimizing machine learning models.

4. PERFORMANCE EVALUATION METRICS

Model evaluation is important for understanding the performance of models. The performance measurement of the stratified K-fold cross validation ensemble grid search algorithm for stability prediction through measure of performance metrics is discussed in here. The prediction accuracy of grid search algorithm is measured in terms of MAE (mean absolute error), MSE (mean square error), RMSE (root mean square error) and R-square error.

MAE: Mean Absolute Error (or MAE) is the sum of the absolute differences between predictions and actual values as represented in *equation 1*. It provides how much wrong the predictions (magnitude of the error) are, but does not provide the idea of the over or under prediction.

$$MAE = \frac{1}{N}\sum_{j=1}^{N}\left|(R_j - P_j)\right| \tag{1}$$

Where N is number of data points; s real output; is predicted output.

MSE: MSE is the sum of square of prediction error which gives an absolute value on how the predicted results are deviated from the actual one. It gives a real value to compare over the result of other models and identifies to select the best regression model.

$$MSE = \frac{1}{N}\sum_{j=1}^{N}(R_j - P_j)^2 \tag{2}$$

RMSE: It is estimated by taking the square root of MSE and is commonly used due to two major reasons.

(i) Big value of MSE
(ii) RMSE generates the error with easy interpretation

$$RMSE = \frac{1}{N}\sum_{j=1}^{n}\sqrt{(R_j - P_j)^2} \tag{3}$$

R- Square Error: R Square is the square of the Correlation Coefficient which measures the level of variability in dependent variable. R squared estimates how much regression line is better than a mean line.

$$R^2 = 1 - \frac{\frac{1}{N}\sum_{j=1}^{N}(R_j - P_j)^2}{\frac{1}{N}\sum_{j=1}^{N}(R_j - M)^2} \tag{4}$$

Where M is mean.

5. RESULT AND DISCUSSION

The experiments were carried out in a Google Collaboratory using an Intel Core i5-11 35G7 windows 10 operating system operating at 2.40GHz, having 16 GB main memory and 512 SSD to evaluate the performance of the proposed ensemble technique using python. The performance of ML ensemble models, namely Random Forest, Extra trees, Ada Boost and Gradient Boosting Machine, are investigated on the original data set. Then Ensemble approach based on a grid search method is implemented by combining the result of the various ML models. To choose the best ML model, it is necessary to compare the performance of different ML algorithms. In this study, ten different ML algorithms were compared.

5.1 Case (i): Unscaled Ensemble Model

The size of the inputs and outputs used to train the model is crucial. Unscaled input variables, in general, can lead to a delayed or unstable learning process, whereas unscaled target variables on regression problems can lead to explosive gradients and failure of the learning process. *Figure 5* shows how well different machine learning models are trained for the inputs and outputs when they are unscaled. It has been noticed that the extra tree model had trained well and generated 92.68% prediction accuracy. Random Forest and Gradient Boosting machines have also shown significant prediction accuracy results with 91% and 90.8% respectively.

Table 2 shows the performance of different algorithm while training and testing the data without scaling.

Table 2: Performance of algorithms while training and testing the data without scaling

Method	Training data				Testing data			
	MAE	MSE	RMSE	R2	MAE	MSE	RMSE	R2
Linear Regression	0.0175	0.0005	0.022	0.6431	0.0173	0.0005	0.0218	0.6603
Lasso	0.0312	0.0014	0.0368	0	0.0317	0.0014	0.0374	-0.0017
Elastic Net	0.0312	0.0014	0.0368	0	0.0317	0.0014	0.0374	-0.0017
K Neighbors	0.0169	0.0004	0.0212	0.6696	0.0193	0.0006	0.0241	0.776
Decision Tree	0	0	0.0001	1	0.0144	0.0004	0.0188	0.7464
Support Vector	0.0312	0.0014	0.0368	-0.0009	0.0318	0.0014	0.0375	-0.005
Ada Boost	0.015	0.0003	0.0178	0.7652	0.0154	0.0003	0.0183	0.7607
Gradient Boost	0.0078	0.0001	0.0101	0.924	0.0087	0.0001	0.0113	0.9082
Random Forest	0.0032	0	0.0043	0.9866	0.0086	0.0001	0.0112	0.9107
Extra Trees	0	0	0	1	0.0076	0.0001	0.01	0.9284

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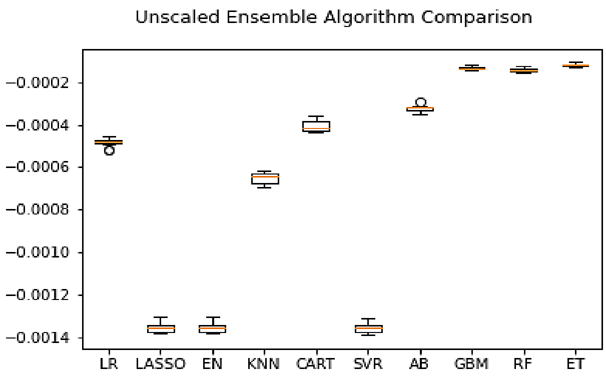

Figure 5. Unscaled Ensemble Algorithm Comparison

5.2 Case(ii): Scaled Ensemble Model

For each variable, the scale and distribution of data gathered from the domain may differ. Differences in scales between input variables may make the problem more complex to model. A target variable with a wide range of values might lead to significant error gradient values, which can cause weight values to fluctuate dramatically, making the learning process insecure. Scaling, or normalization, significantly impacts the performance of different machine learning models by adjusting the range of features to ensure equal contribution. For linear models like linear and logistic regression, scaling is crucial because these models are sensitive to the range of input features, and without scaling, features with larger ranges can dominate the objective function, leading to suboptimal coefficients and poorer performance. In distance-based models such as K-Nearest Neighbors and Support Vector Machines, scaling is essential as these models rely on distance calculations, and unscaled features with larger ranges can disproportionately affect these calculations, skewing results and reducing accuracy. Gradient-based models, including neural networks, benefit from scaling as it ensures faster convergence of gradient descent algorithms by making sure all features contribute proportionately to the gradients, thus improving training efficiency and preventing the optimization process from becoming inefficient. While tree-based models like decision trees and random forests are generally insensitive to feature scales, scaling can still be beneficial in ensemble or hybrid models involving both tree-based and other types of algorithms. Overall, standardizing feature ranges enhances the performance and training efficiency of most machine learning models.

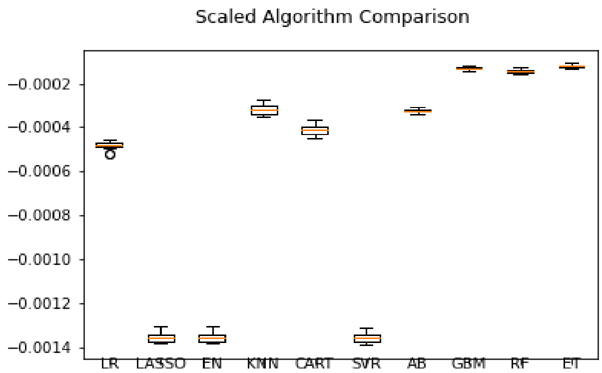

Figure 6. Scaled Ensemble Algorithm Comparison

Figure 6 shows how well different machine learning models are trained for the inputs and outputs when the dataset is standardized. It has been noticed that the extra tree model had trained well and generated 92.8% prediction accuracy. We have used the data standardization technique for scaling the input variable and target variable. Rescaling the distribution of values so that the mean of observed values is 0 and the standard deviation is 1 is the process of standardizing a dataset. Standardization necessitates knowing or being able to determine the mean and standard deviation of observable quantities with accuracy. From the training data, these values are predicted. *Table 3* shows the performance of the different algorithms when datasets are standardized.

Table 3: Algorithms Performance while training and testing the data with scaling

Method	Training data				Testing data			
	MAE	**MSE**	**RMSE**	**R2**	**MAE**	**MSE**	**RMSE**	**R2**
Linear Regression	0.0175	0.0005	0.022	0.6431	0.0173	0.0005	0.0218	0.6603
Lasso	0.0312	0.0014	0.0368	0	0.0317	0.0014	0.0374	-0.0017
Elastic Net	0.0312	0.0014	0.0368	0	0.0317	0.0014	0.0374	-0.0017
K Neighbors	0.0085	0.0001	0.0113	0.9063	0.0093	0.0002	0.0127	0.8845
Decision Tree	0	0	0.0001	1	0.0144	0.0004	0.0188	0.7464
Support Vector	0.0312	0.0014	0.0368	-0.0009	0.0318	0.0014	0.0375	-0.005
Ada Boost	0.0141	0.0003	0.0166	0.7956	0.0145	0.0003	0.0172	0.7882
Gradient Boost	0.005	0	0.0067	0.9672	0.0068	0.0001	0.0092	0.9392
Random Forest	0.0031	0	0.0041	0.9873	0.0085	0.0001	0.011	0.9135
Extra Trees	0	0	0	1	0.0076	0.0001	0.0099	0.9295

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5.3 Case(iii): Ensemble Grid Search Model

Hyperparameter optimization is necessary to get the most out of ML models. Hyperparameters are configurable points in a ML model that allow them to be tailored to a specific job or dataset. Finding a set of hyperparameters that result in the optimal model performance on a dataset is frequently necessary. A search space is defined as part of an optimization technique, an n-dimensional volume, with each hyperparameter representing a separate dimension and the scale of the dimension representing the possible values for the hyperparameter, such as real-valued, integer-valued, or categorical. Here we have used a grid search optimization algorithm by defining a search space as a grid of hyperparameter values and evaluating every position in the grid. Grid search is ideal for spot-checking combinations that have previously performed well. Among different machine learning modes, it was found that Gradient Boosting Machine grid search (GBMGS) had produced a 93.9% prediction accuracy result. The performance of various grid search machine learning algorithms is recorded as in *table 4.*

Table 4: Performance of Ensemble algorithms while training and testing the data with scaling

Method	Training data				Testing data			
	MAE	MSE	RMSE	R2	MAE	MSE	RMSE	R2
Linear Regression	0.0175	0.0005	0.022	0.6431	0.0173	0.0005	0.0218	0.6603
Lasso	0.0312	0.0014	0.0368	0	0.0317	0.0014	0.0374	-0.0017
Elastic Net	0.0312	0.0014	0.0368	0	0.0317	0.0014	0.0374	-0.0017
K Neighbors	0.0085	0.0001	0.0113	0.9063	0.0093	0.0002	0.0127	0.8845
Decision Tree	0	0	0.0001	1	0.0144	0.0004	0.0188	0.7464
Support Vector	0.0312	0.0014	0.0368	-0.0009	0.0318	0.0014	0.0375	-0.005
Ada Boost	0.0141	0.0003	0.0166	0.7956	0.0145	0.0003	0.0172	0.7882
Gradient Boost	0.005	0	0.0067	0.9672	0.0068	0.0001	0.0092	0.9392
Random Forest	0.0031	0	0.0041	0.9873	0.0085	0.0001	0.011	0.9135
Extra Trees	0	0	0	1	0.0076	0.0001	0.0099	0.9295

5.4 Comparison of Proposed work with Previous work

In this subsection, the proposed CS-SEM is compared with other models developed in previous studies. The proposed study and the previous literature work used the same dataset publicly available in the UCI machine learning repository. The comparison is made in terms of a number of features selected for model evaluation and accuracy of the classifiers. The proposed method produced the better result than the previous other methods.

The comparison of proposed work with the previous work is shown in *table 5.*

Table 5: Comparison of previous work with Proposed work

Method	Features	Accuracy
Strength Pareto evolutionary algorithm [33]	12	91.1%
Multilayer Perceptron Classifier [35]	12	93.8%
Random forest [41]	12	88.5%
Proposed Ensemble Gradient Boosting Machine Grid Search	12	93.92%

The *table 5* provides a comparison of four different machine learning methods based on their accuracy using 12 features each. The Strength Pareto Evolutionary Algorithm achieved an accuracy of 91.1%, while the Multilayer Perceptron Classifier performed slightly better with an accuracy of 93.8%. The Random Forest method had the lowest accuracy among the four, at 88.5%. The highest accuracy, 93.92%, was achieved by the Proposed Ensemble Gradient Boosting Machine with Grid Search. This indicates that the Proposed Ensemble Gradient Boosting Machine with Grid Search outperformed the other methods in terms of accuracy for the given task.

6. CONCLUSION

The DSGC has been demonstrated as a cost-effective technique in meeting out the demand. The control approach was developed in light of the assumptions, allowing for a better understanding of the relationship between the grid's properties and its stability. The data utilized in the analysis is the reaction of heterogeneous users' numerous value fluctuations supported the grid power balance. ML is used to identify a correlation between the input value, the eigenvalue and system stability criteria. The focus of future research will be on more sophisticated statistics. An ensemble grid search method is provided in this paper to make grid stability prediction easier. Using the Vadim Arzamasov Electrical Grid Stability dataset, we examined the performance of the suggested ensemble technique to analyze the model's predictive performance. We used a feature selection method and chose eight features based on their importance in prediction. The algorithm's performance is then independently assessed on unseen test data by 10-fold cross-validation on the training data. When compared to all other models, the ensemble Gradient Boosting Machine grid search algorithm outperforms them all, accurately predicting grid stability 93.92% of the time. The proposed ensemble gradient boosting machine with grid search method offers a novel and robust solution for smart grid stability prediction. By combining comprehensive hyperparameter tuning with the strengths of ensemble learning, it addresses the limitations of existing approaches.

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