ANALYSIS OF LOAD FORECASTINGERRORIN SMART GRID USING ML ALGORITHMS FOR (STLF)

Alekya Pammi[1], Arunkumar Beyyala[2]
[1]M.Tech Student, [2]Associate Professor
[12]Dept. of CSE in Srinivasa Institute Of Engineering And Technology,(Autonomous), NH-216, Cheyyeru(V), KrapaChintalapudi (post), Katrenikona(M), Amalapuram, Dr.B.R.Ambedkar Konaseema.Dist-533216.

ABSTRACT

Smart Grid is the environment where electricity will be generated and due to growing population demand of electricity will also be increased and at current there is no accurate system to forecast electricity demand and to overcome from this problem author is evaluating performance of various machine learning algorithms such as SVM, Naïve Bayes, KNN, Decision Tree and Neural Network. These algorithms can be used for Short Term Load (electricity) Forecast. Among all algorithms Decision Tree classifier is giving best accuracy and author further improving this algorithm by adding LOSS and BOOSTING function to decision tree classifier and this algorithm is called as EDTC (enhance decision tree classifier). After enhancing EDTC, Extension XGBOOST algorithms giving 100% accuracy

KEYWORDS: ML, Smart grids, Load

1] INTRODUCTION:

As our population grows and progresses, the demand for electricity rises, prompting the need for increased energy production. The essential concerns in energy management (EM) are electricity generation, transmission, and distribution. The electric grid (EG) is a well-known interconnected network that connects customers to energy providers and transports energy from producer to consumer. It consists of power plants that generate electricity, substations that regulate electrical voltage based on usage, transmission lines (the transporter of electricity), and distribution lines that link customers.

As described above, classical EGs use a centralized network with thousands of units. Enhancing the EG load introduces the potential for generating overhead, resulting in power quality issues. As a result, the installation of new plants becomes necessary. On the other hand, these grids lack a reliable forecast system for predicting intermittent power failures, their reasons, reaction latency, memory space, and resource utilization.

2] LITERATURE SURVEY:

2.1]L. Hernandez, C. Baladron***et al***

In the `70s, the usage of non-linear techniques was generally not popular among scientists and engineers. However, in the last two decades they have become very important techniques in solving complex problems which would be very difficult to tackle otherwise. With the recent emergence of smart grids, new environments have appeared capable of integrating demand, generation, and storage. These employ intelligent and adaptive elements that require more advanced techniques for accurate and precise demand and generation forecasting in order to work optimally.

2.2]M. Alazab, S. Khan, S. S. R. Krishnan

A smart grid system follows the Cyber-Physical Systems (CPS) model, in which Information Technology (IT) infrastructure is integrated with physical systems. In the scenario of the smart grid embedded with CPS, the Machine Learning (ML) module is the IT aspect and the power dissipation units are the physical entities. In this research, a novel Multidirectional Long Short-Term Memory (MLSTM) technique is being proposed to predict the stability of the smart grid network.

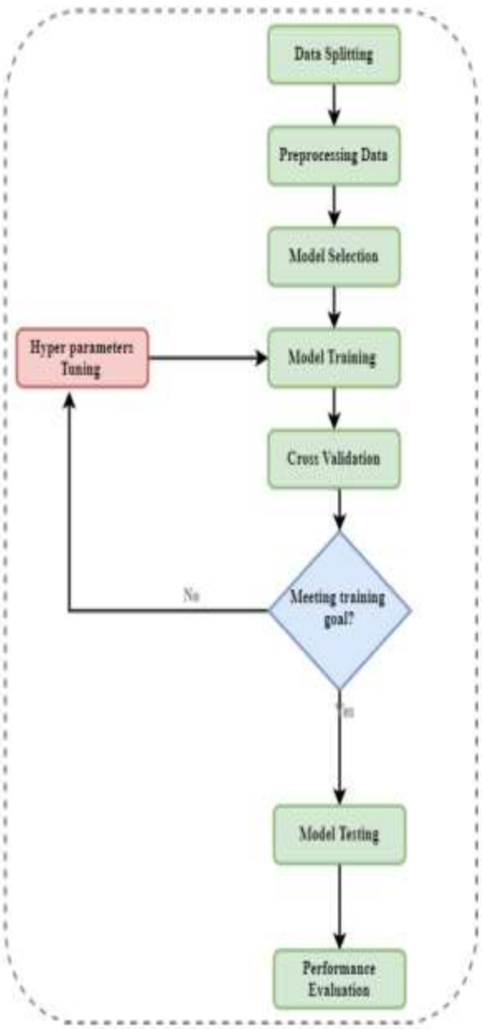
3] PROBLEM DEFINTION:

Classical EGs use a centralized network with thousands of units. Enhancing the EG load introduces the potential for generating overhead, resulting in power quality issues. As a result, the installation of new plants becomes necessary. On the other hand, these grids lack a reliable forecast system for predicting intermittent power failures, their reasons, reaction latency, memory space, and resource utilization.Scientists determined that the current electrical power system (PS) has remained unchanged for several decades.

4] PROPOSED APPROACH:

The main objective of this paper is to present a comparative analysis of ML algorithms for short-term load forecasting (STLF) regarding accuracy and forecast error. Based on the implementation and analysis, we have identified that, among other algorithms, the DTC provides comparatively better results. Therefore, we devised the enhanced DTC (EDTC) by integrating fitting function, loss function, and gradient boosting in DTC mathematical model for fine-tuning the control variables. The implementation results show that the proposed EDTC algorithm provides better forecast results

5] FLOW CHART OF ML FRAMEWORKS:



6] PROPOSED METHODOLOGY:

Dataset Collection:

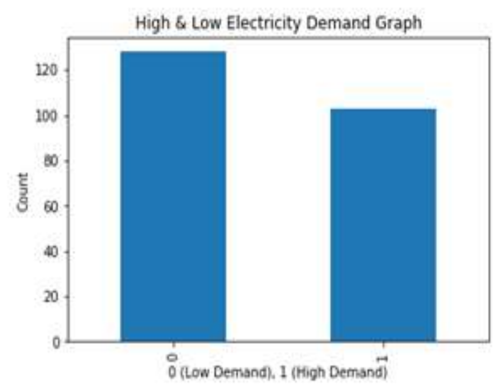
To implement this dataset we has used New York electricity dataset (NYISO) .In dataset we have Time, area name, load and label as 0 (low load require) and 1 (high demand) columns in dataset and other rows contains dataset values.

Datset can be downloaded from below link

http://mis.nyiso.com/public/P-58Clist.htm

Preprocessing:

We are reading dataset with total records require LOW and HIGH electricity demand and we are encoding non-numeric columns to numeric columns and then shuffling and normalizing dataset and after normalizing will get all data between 0 and 1.



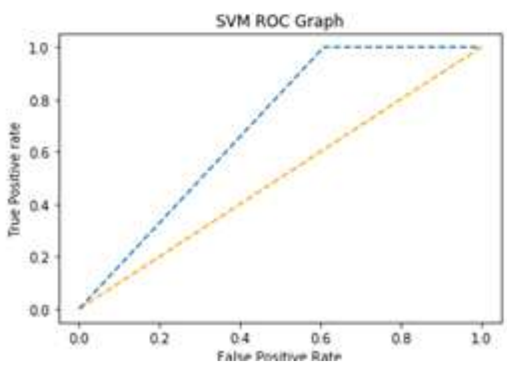
We are showing graph with total records require LOW and HIGH electricity demand. In above graph x-axis represents demand type and y-axis represents counts of the available records

Training and Testing

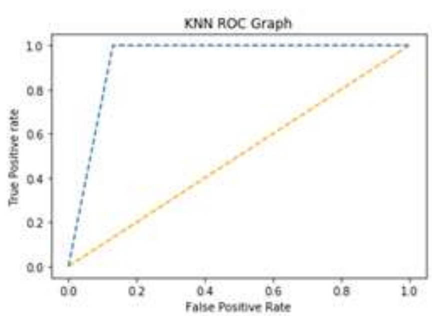
In this work we are applying RFE (recursive features dimension reduction algorithm) to select relevant features and reduce irrelevant features. Entire dataset is split into train and test where 80% dataset is using for training and 20% for testing.

Define function to calculate accuracy, precision, RoC graph:

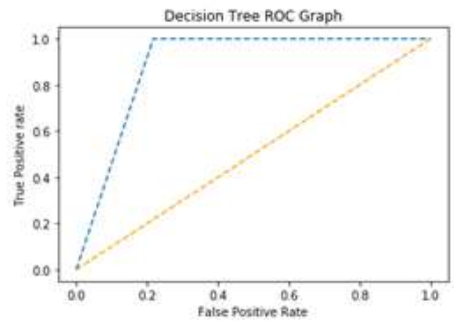
We are Defining function to train existing SVM, KNN, Decision Tree, Neural network, Naive Bayes, enhance decision tree, Extension XGBOOST algorithms to calculate accuracy, precision, Recall, FMeasure.And in ROC graph if blue line comes on top of orange line then prediction is accurate and true positive and comes below means prediction is false positive.



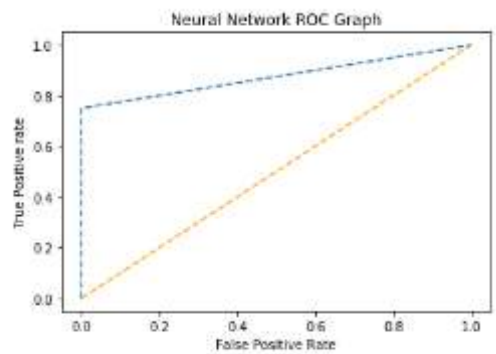
Training SVM we got it accuracy as 70%



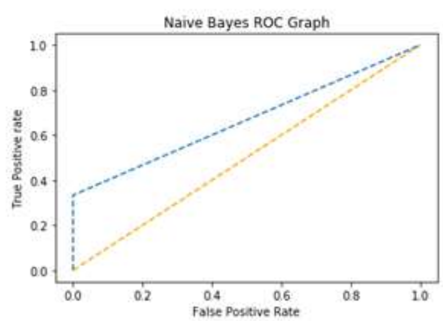
Training KNN we got 93% as accuracy



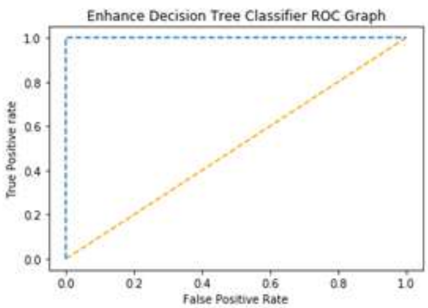
Training with decision tree we got 89% as accuracy



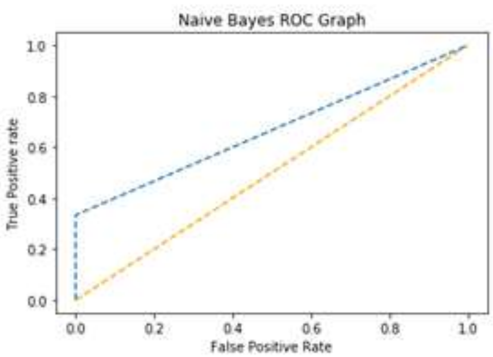
Training with neural network we got 87% accuracy

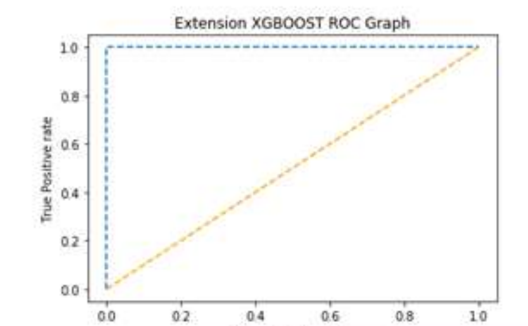


Training with Naive Bayes we got 65% accuracy



Training with propose enhance decision tree we got 100% accuracy

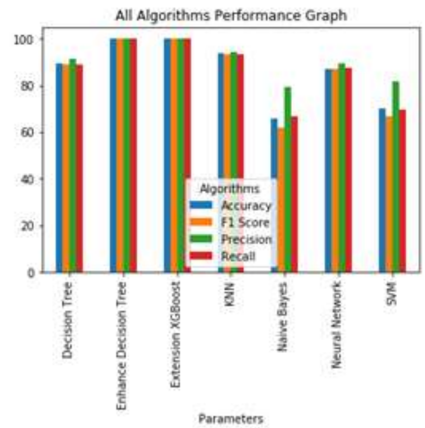




Training with extension XGBOOST also we got 100% accuracy

7] RESULTS:

All algorithms evaluation metrics



In above graph x-axis represents algorithm names with different colour bar for different metrics and y-axis represents accuracy and precision %. In above graph extension XGBOOST and propose EDTC got 100% accuracy.

	Algorithm Name	Precison	Recall	FScore	Accuracy
0	SVM	81.578947	69.565217	66.834677	70.212766
1	KNN	94.444444	93.478261	93.570451	93.617021
2	Decision Tree	91.379310	89.130435	89.185458	89.361702
3	Neural Network	89.655172	87.500000	87.087912	87.234043
4	Naive Bayes	79.487179	66.666667	62.096774	65.957447
5	Enhance Decision Tree	100.000000	100.000000	100.000000	100.000000
6	Extension XGBoost	100.000000	100.000000	100.000000	100.000000

```
Test Data : ['10/19/2022 00:40:00' 'EDT' 'DUNWOD' 61760 489.017] =====> LOW Electricity Demand Forcasted
Test Data : ['10/19/2022 00:40:00' 'EDT' 'GENESE' 61753 904.7061] =====> HIGH Electricity Demand Forcasted
Test Data : ['10/19/2022 00:40:00' 'EDT' 'HUD VL' 61758 823.3002] =====> LOW Electricity Demand Forcasted
Test Data : ['10/19/2022 00:40:00' 'EDT' 'LONGIL' 61762 1594.1459] =====> HIGH Electricity Demand Forcasted
Test Data : ['10/19/2022 00:40:00' 'EDT' 'MHK VL' 61756 658.1436] =====> LOW Electricity Demand Forcasted
Test Data : ['10/19/2022 00:40:00' 'EDT' 'MILLWD' 61759 246.4697] =====> LOW Electricity Demand Forcasted
Test Data : ['10/19/2022 00:40:00' 'EDT' 'N.Y.C.' 61761 4139.5527] =====> HIGH Electricity Demand Forcasted
Test Data : ['10/19/2022 00:40:00' 'EDT' 'NORTH' 61755 597.6095] =====> LOW Electricity Demand Forcasted
Test Data : ['10/19/2022 00:40:00' 'EDT' 'WEST' 61752 1508.6824] =====> HIGH Electricity Demand Forcasted
Test Data : ['10/19/2022 00:45:00' 'EDT' 'CAPITL' 61757 1114.5566] =====> HIGH Electricity Demand Forcasted
```

In above screens XGBOOST classifier algorithm giving 100% accuracy and this algorithm is applied on test data to predict HIGH or LOW demand. We are loading test data and then forecasting demand as HIGH or LOW based on test data.

8] CONCLUSION:

With the emergence of different Ml algorithms, the foremost challenge is to find the most appropriate algorithm to predict the stability of the Smart Grid. A comprehensive survey of the state-of-the-art ML algorithms has been performed to predict the stability of Smart Grid. We train existing SVM, KNN, Decision Tree, Neural network, Naive Bayes, enhance decision tree, algorithms and we have used XGBOOST classifier and this algorithm also giving 100% accuracy and this algorithm is applied on test data to predict HIGH or LOW demand.

9] EXTENSION:

As extension of this project we used XGBOOST classifier and this algorithm also giving 100% accuracy and this algorithm is applied on test data to predict HIGH or LOW demand. In propose EDTC algorithm we are adding tuning performance as Boosting and loss which may take more execution time but in extension we are not supposed to add any tuning parameters so its executing time will be less and LITE compare to propose EDTC algorithm.

10] REFERENCES:

[1] B. Zhao, L. Zeng, B. Li, Y. Sun, Z. Wang, M. Shahzad, and P. Xi, ‘‘Collaborative control of thermostatically controlled appliances for balancing renewable generation in smart grid,’’ IEEJ Trans. Electr. Electron. Eng., vol. 15, no. 3, pp. 460–468, Mar. 2020.

[2] K. Berk, A. Hoffmann, and A. Müller, ‘‘Probabilistic forecasting of industrial electricity load with regime switching behavior,’’ Int. J. Forecasting, vol. 34, no. 2, pp. 147–162, Apr. 2018.

[3] J. R. Cancelo, A. Espasa, and R. Grafe, ‘‘Forecasting the electricity load from one day to one week ahead for the Spanish system operator,’’ Int. J. Forecasting, vol. 24, no. 4, pp. 588–602, 2008.

[4] M. Djukanovic, S. Ruzic, B. Babic, D. J. Sobajic, and Y. H. Pao, ‘‘A neuralnet based short term load forecasting using moving window procedure,’’ Int. J. Electr. Power Energy Syst., vol. 17, no. 6, pp. 391–397, Dec. 1995.

[5] L. J. Soares and M. C. Medeiros, ‘‘Modeling and forecasting short-term electricity load: A comparison of methods with an application to Brazilian data,’’ Int. J. Forecasting, vol. 24, no. 4, pp. 630–644, Oct. 2008.

[6] R. Hu, S. Wen, Z. Zeng, and T. Huang, ‘‘A short-term power load forecasting model based on the generalized regression neural network with decreasing step fruit fly optimization algorithm,’’ Neurocomputing, vol. 221, pp. 24–31, Jan. 2017.

[7] A. Kavousi-Fard, H. Samet, and F. Marzbani, ‘‘A new hybrid modified firefly algorithm and support vector regression model for accurate short term load forecasting,’’ Expert Syst. Appl., vol. 41, no. 13, pp. 6047–6056, 2014.

[8] Z. H. Osman, M. L. Awad, and T. K. Mahmoud, ‘‘Neural network based approach for short-term load forecasting,’’ in Proc. IEEE/PES Power Syst. Conf. Expo., Mar. 2009, pp. 1–8.

[9] N. Zeng, H. Zhang, W. Liu, J. Liang, and F. E. Alsaadi, ‘‘A switching delayed PSO optimized extreme learning machine for short-term load forecasting,’’ Neurocomputing, vol. 240, pp. 175–182, May 2017.

[10] V. C. Gungor, D. Sahin, T. Kocak, S. Ergut, C. Buccella, C. Cecati, and G. P. Hancke, ‘‘Smart grid technologies: Communication technologies and standards,’’ IEEE Trans. Ind. Informat., vol. 7, no. 4, pp. 529–539, Nov. 2011.

[11] S. K. Desai, A. Dua, N. Kumar, A. K. Das, and J. J. P. C. Rodrigues, ‘‘Demand response management using lattice-based cryptography in smart grids,’’ in Proc. IEEE Global Commun. Conf. (GLOBECOM), Dec. 2018, pp. 1–6.

[12] M. Alazab and R. Broadhurst, Cyber-Physical Security: Protecting Critical Infrastructure at the State and Local level, 1st ed, M. C. Robert and H. Simon Eds. Cham, Switzerland: Springer, 2017, pp. 251–266.

[13] L. Hernandez, C. Baladron, J. M. Aguiar, B. Carro, A. J. Sanchez-Esguevillas, J. Lloret, and J. Massana, ‘‘A survey on electric power demand forecasting: Future trends in smart grids, microgrids and smart buildings,’’ IEEE Commun. Surveys Tuts., vol. 16, no. 3, pp. 1460–1495, 3rd Quart., 2014.

[14] A. Rahman, V. Srikumar, and A. D. Smith, ‘‘Predicting electricity consumption for

commercial and residential buildings using deep recurrent neural networks,'' Appl. Energy, vol. 212, pp. 372–385, Feb. 2018.

[15] L. Xiao, W. Shao, C. Wang, K. Zhang, and H. Lu, ''Research and application of a hybrid model based on multi-objective optimization for electrical load forecasting,'' Energy, vol. 180, pp. 213–233, Oct. 2017.

[16] N. Deepa, B. Prabadevi, P. K. Maddikunta, T. R. Gadekallu, T. Baker, M. A. Khan, and U. Tariq, ''An ai-based intelligent system for healthcare analysis using Ridge–Adaline stochastic gradient descent classifier,'' J. Supercomput., vol. 77, no. 2, pp. 1998–2017, 2021.

[17] Anamika and N. Kumar, ''Market clearing price prediction using ANN in Indian electricity markets,'' in Proc. Int. Conf. Energy Efficient Technol. Sustain. (ICEETS), 2016, pp. 454–458, doi: 10.1109/ICEETS.2016.7583797.

[18] T. R. Gadekallu, N. Khare, S. Bhattacharya, S. Singh, P. K. R. Maddikunta, and G. Srivastava, ''Deep neural networks to predict diabetic retinopathy,'' J. Ambient Intell. Hum. Comput., pp. 1–14, Apr. 2020, doi:10.1007/s12652-020-01963-7.

[19] H. Patel, D. S. Rajput, G. T. Reddy, C. Iwendi, A. K. Bashir, and O. Jo, ''A review on classification of imbalanced data for wireless sensor networks,'' Int. J. Distrib. Sensor Netw., vol. 16, no. 4, 2020, Art. no. 1550147720916404.

[20] W. Tian, ''A review of smart grids and their future challenges,'' in Proc. MATEC Web Conf., vol. 173. Les Ulis, France: EDP Sciences, 2018, p. 02025.