# Balancing Authority Power Generation, Demand, and Interchange Forecasting Models using GBRT

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***Abstract*—Today, the power grid facilities are the middle grounds of controlling the balance between demand and supply of the power over their respective geographical regions. With an increase in power demand as industries, businesses and residential areas are rising, it has become more crucial to have a reliable and accurate forecasting system at a balancing authority(BA). A Gradient Boost Regression Tree (GBRT) based accurate and computationally fast predictive forecast models are built on a BA data. In this system, a BA can make a forecast of Net Generation, Demand, Net Interchange, and Interchange between adjacent balancing authorities. The systems ability to make accurate reliable forecasts of demand and interchange can make a BA profitable by avoiding excessive use of resources or reserves than required, avoid blackouts and also have more insightful knowledge about a short-term month ahead future.**

***Index Terms*—Balancing authority, Gradient Boost Regression Tree, Demand, Interchange, Net Generation, Profit**

## I. Introduction

With an increase in businesses, industries, transportation, and other power-consuming sectors, the demand for power is growing exponentially. It is necessary to also increase the power generation entities to match this rise in demand. Today, our entire activities, from work to households, are relied on power supply in one way or another. It is seen that mainly on a higher level, power is distributed to four sectors: transportation, commercial, residential, and industrial [1]. Due to climate change, power generation is now seeing a shift towards more renewable energy plants and a decline in natural gas or coal power generation [2]. It is observed that power generation from renewable sources such as solar, wind, hydro, etc. is not constant and fluctuates depending upon the time. It becomes crucial to try to understand these generation patterns to use them as a cue to generate more power. Thus, with a rise in population, businesses, and technology, in the future, eventually the demand is going to increase exponentially [3]. Also, to shift to renewable energy sources completely in the future, it is necessary to correctly predict the generation patterns ahead of time.

Another aspect of power demand or consumption is that it is not constant, as seen in power generation using renewable sources. Due to various different factors, the power consumption varies on an hourly, weekly, and even monthly basis. Thus, to meet the expectations of these varying power demands, it is necessary to have an entity that keeps checks on the demand and supply. Balance Authorities(BA) are these entities that act as a gateway between power suppliers and end-user consumers. These BAs are associated with their respective geographical region. BAs job is to check on the power demand and let the supplier know when to generate more power and when to generate less as required. Thus, to avoid blackouts or wastage of excess power generation, it crucial for BAs to maintain a fine balance between power generation and demand. Another way these BAs use to meet demand is by borrowing power from another adjacent BA that has more power generated than required for their region. These BAs have an hourly record of the power generated, the power demanded, also the power borrowed or supplied to their adjacent BAs. This data can be used in some predictive analytics way to make these BAs more assured on the future power demand, generation as well as distribution to adjacent BAs to be a month ahead to take any vital actions as required. Also, to make a profit and reduce loss in excessive power generation, or resources in saving more power or blackouts, it is crucial for BAs to make highly accurate reliable forecast predictions. Thus, this predictive analytics has become a viable means for these power grid handlers to be optimal and profitable in the market.

In this project, a predictive analytics approach is utilized on time-series data for a BA to highly accurately predict the power demand, power generation as well as power interchange in-between BAs. Dataset used was downloaded from EIA [1] which had a total of 78 BAs data. A system is developed which, for a single BA, builds predictive models for each forecast prediction based on a few different variables which will be discussed in the next sections. All the models are based on Gradient Boosting Regression Trees(GBRT) machine learning approach. Using this system, a BA can accurately forecast power generation, demand, and interchange so that it can be highly assured of making decisions in balancing power demand and supply, and avoiding blackouts or loss of an excessive generation of power, and make a profit. The aspect of predicting an amount of power that a BA will or may have to interchange with other adjacent BAs adds to the robustness and reliability of meeting the requirements of demand and supply with ease saving time and money.

The rest of the document follows the order given as follows: (1) Literature review and Technique Selection, where we discuss the other techniques which are used for forecasting energy consumption and selection of GBRT algorithm, (2) Implementation, where we discuss the entire implementation of the system and reasons behind any decision taken, (3) Results and Findings, where we interpret all the models built for a BA and also interpret their individual forecasts on an hourly, daily and weekly basis, and finally (4) Conclusion of the study.

## II. Literature Review and Technique Selection

Balancing authorities generally have a "Ramp and Uncertainty prediction tool"(RUT) and a "Day-Ahead Regulation Prediction tool"(DARP) by which currently they are able to manage the power balancing needs. [4] implemented an additional segment as advanced probabilistic information to these tools to which demonstrated a 12-31% reduction in forecast prediction range of regulation. Thus, by being more accurate, BAs are able to utilize fewer resources in balancing the power demand and generation with increased reliability. The inclusion of new probabilistic information consisted of a probabilistic forecast of wind and solar based on weather and a new final load was calculated using the convolution of load forecast, wind forecast, and solar forecast.

Balance authorities also need to maintain adequate reserves of power storage at times to meet the demand. As discussed earlier, that renewable energy generation has uncertain generation times, it is important to also reserve the power generated to an accurate amount only to which the demand will be satisfied and no excess power will be stored. A study proposed by [5] implemented a probabilistic approach that uses probability density function to fit varying net load to predict accurately the number of reserves needed for a BA. This enables power grid operators to utilize fewer resources in saving power thus making it profitable or avoiding loss.

For optimal investments and operations of local energy systems, long-term predictions of load and power consumption are necessary. [6] presented a study where they built a Deep Recurrent Neural Network(DRNN) model of seven different variants along with Gaussian Process(GP) regression to forecast the power loads. They compared the results with other state-of-the-art algorithms like GBRT and Support Vector Regression(SVR). Their results show a little improvement over GBRT and SVMs. And, as multiple hidden layers increase the number of training calculations as well as computational resources and large data, this approach is not entirely feasible on a commercial basis according to me.

Another study by [7] utilized Deep Neural Network(DNN) model to predict heating energy consumption in old houses. The study achieved a Cv(RMSE) of 8.74% which falls under the accepted tolerance limit of errors as an energy forecast standard. For DNNs to fit the data well, the authors used 16,158 old houses data having 11 features in total. Also, the study didn't explain the time taken for the model to converge the results. Thus, our assumption is it'll cost more time as the number of computations is more generally in training a DNN with large data.

A novel forecasting method proposed by [8] is able to make short-term as well as long-term predictions with fast convergence. Their framework utilized three modules: 1) Feature selection, normalization, and filtering, 2) A deep learning factored conditional restricted Boltzmann machine (FCRBM), and 3) A genetic wind-driven optimization (GWDO) technique. This hybrid approach was compared with other hybrid benchmark models where this approach was able to outperform the other models in terms of accuracy by 2-3 Mean absolute percentage deviation (MAPD) but not able to outperform in execution time for all models. The execution time of prediction for day ahead forecast was approximately 40secs, whereas for weak ahead was around 200secs. Further, the time-series dataset used was of PJM BA from 2014-2017, thus again the data needed is large to train this model.

Another study by [9] also proposed a forecasting approach using FCRBM over 1900 household data by integration of price as well as meteorological data with the energy consumption data. It is seen that including these other variables increases the accuracy of the prediction compared to only energy data. Also, FCRBM was able to outperform the SVM model by an average RMSE difference of 90.

[8] also made a critical review on other approaches used for forecasting power consumptions. It is seen that ARIMA and exponential smoothing statistical models can only be utilized for very short-term forecasts with still a compromise in terms of accuracy. Whereas, ARIMAX increases the accuracy but a compromise is made on convergence speed. The long short-term memory approach has notably good accuracy but a slow convergence rate. And, same with SVR where hyperparameter tuning increases the accuracy on the downside of slow convergence.

A study proposed by [10] implemented a novel system where they used an ensemble technique of using five models to predict the forecast and combine the results to increase the accuracy, generalization, and robustness. The models utilized in this stacked approach were K-Nearest Neighbors (KNN), Extreme Gradient Boosting (XGBoost), Gradient Boosted Decision Tree (GBDT), Support Vector Machine (SVM), and Random Forest (RF). Their approach showed an improvement in all the three aspects as compared to these individual approaches with CvRMSE = 10.6% and RMSE = 23.53. It was also seen that the Gradient Boosting Decision Trees method showed second-best results along with K-Nearest Neighbors.

A transfer learning-based DNN approach was also been studied where [11] compared the transfer learned DNN models with traditional multiple linear regression(MLR), RF, XGB, DNN. It is seen that was able to outperform all the other models. But, they only outperformed other models by a mere 2-10% NRMSE and it is seen that NRMSE of XBG only differed by around 3-4% than transferred learned DNN models.

[12] proposed a GB machine (GBM) algorithm to predict energy consumptions of 410 commercial buildings for 6-12months. By using hyperparameter optimization by fine grid search, they were able to outperform the traditional RF and

Time-of-Week-and-Temperature (TOWT) model. The robustness, flexibility, and generalizability provided by this ensemble method give the advantage of using this method. Also, it is seen that by increasing the input parameters, the accuracy and robustness increases of GBM. And, as they are able to fit non-linear time-series graph very well being lightweight computation wise, they are highly reliable.

Another study by [13] proposed a modification to normal GBM where they utilized regression trees using gradient boosting ensemble method. By the inclusion of regression trees having weak learners of fixed size with GB, they were able to outperform SVM, ARIMA, RNN, and ARIMA-RNN models in forecasting consumption with RMSE of 35.56. It also demonstrates high accuracy along with high computational speed.

Thus, in summary, we saw that DRNN and DNN models are not feasible solutions even though they slightly outperform other traditional approaches as they need more data and computational power. Also, statistical models like ARIMA, SES, etc, are only able to make very short-term forecasts and cannot include other variables other than time, seasonality, and trend. Whereas it is clear that regression can perform a very well job in including various different factors to make a robust forecast, linear regression is not suitable for this non-linear time series consumption data. Also, FCRBM outperforms all the models, but the data needed to train the models is generally high. As our dataset is reasonably small of about 6 months training set, we reject deep learning approaches. Also, it is seen that the ensemble approach of GBRT outperforms other approaches like KNN, SVR/SVM, and other discussed models along with high generalizability and low RMSE. Also, GBRT is computationally fast. Thus, for all these reasons, this project utilizes the GBRT machine learning approach to fit the regression model over our power data of a BA. Also, to evaluate our models, we use traditional RMSE statistical metric.

## III. IMPLEMENTATION

As discussed earlier, the dataset used for the forecast system built for individual BA is downloaded from Energy Information Administration(EIA) website. This dataset is an hourly time-series dataset consisting of Power Demand, A-day ahead forecast, Net Generation, Net Interchange, and adjacent BAs Interchange for each individual BA in the U.S. This dataset has the above information for each BA from July 2020 to Feb 2021, i.e. 8months, on an hourly basis, consisting of 7057 rows. A total of 78 BAs data is present in this dataset. And, the proposed system is flexible to create models and forecast predictions for each BA.

The dataset collected was in a horizontal readable CSV file format. Thus, before building a model, the dataset was preprocessed. First, the horizontal time series was changed, to a desired vertical machine-readable format, by transforming the rows into columns. A column is created for each BA where a forecast error is calculated for each reading based on actual demand and predicted day-ahead forecast in the dataset. This column was created to include the errors in the current forecasting algorithm to predict the demand and interchange attributes. The DateTime variable was in "01/12/2020 EDT 1:00" format, meaning 1st January 2020 at 1 am in Eastern Daylight time. This variable was split into sub integer variables where columns like "Date", "Hour", "Day of Week", "Week of Month", "Week of Year", "Month", "Quarter", and "Year". We include the time variables from the single string. Also, as regression needs only integer variables, the decision was made to split the DateTime variable into these sub-parts.

The proposed system is based on a single BA, which can forecast Demand, Net generation, Net Interchange, and power interchange with adjacent BAs. This way, the decisions made by the BA in saving power, generating power, as well as confidence in interchanging with adjacent BA will become more accurate. Ultimately, this system aims to save money, be accurate in forecasting, save resources and time in forecasting, be more profitable with less loss in power.

Since the dataset has 78 BAs, the system first, asks the user for input for which BA does the system should build models. After reading the input, the system then extracts data for that particular BA along with the time and date attributes from the entire dataset. The dataset is then further split into train and test sets. For this project, we had only approximately 8 months of data. Thus, the data is split in 90:10 ratio as train and test respectively. Thus, approximately six and half months of data is used in training the models. And, one and a half months of data is used for testing the models. Since the training data was only of about six months, we only predict for the next one month.

As discussed earlier, the system builds four forecast prediction models to predict Net Generation, Demand, Net Interchange, sub BA Interchange for a given BA. Each prediction model is a Gradient Boosting Regression Tree model, to perform fast accurate forecast prediction. After the model is built and trained on the trainset, we evaluate the model on the remaining 1-month test set. The system checks for weekly prediction as well as a monthly prediction to check hourly, daily, and weekly trends to get insights for immediate future planning for the given BA.

To build each prediction model, intuition-based different independent variables are chosen. For Net Generation, only time and date-based variables were chosen as generation does cause due to the other available variables in the dataset. Whereas, to predict demand, attributes such as DateTime, Net generation, and forecast error are included in the independent variables set. The intuition behind the inclusion of net generation is that demand is fulfilled by net generation. And also, since net generation is based on other aspects like weather, etc., it is assumed that these things indirectly via net generation will also add importance in demand in power. For net interchange prediction, variables considered as independent variables are DateTime variables, net generation, forecast error, and demand. Here we include demand as an intuitive hypothesis that net generation, along with demand, will cause the amount of net interchange so that the actual demand is fulfilled for all

BAs. And finally, to predict individual interchange between adjacent BAs, we use DateTime, Net generation, and Net interchange as our independent causing variables.

### A. Model building and Hyperparameter tuning

As discussed in the previous section, the Gradient Boost Regression Trees algorithm is selected from other options to predict the power demand and interchange for a given BA. The models were built using scikit.learn library using python 3.7. For each regression task, each model was trained on the selected set of variables as discussed above. For these regression tasks, Ordinary Least Square loss was used for model evaluation to understand how well our model is performing based on selected tuned parameters.

All models built were built using the same set of hyperparameters, thus the baseline model is the same for all regression prediction tasks carried out. A naïve approach was taken to select the set of hyperparameters to get the lowest possible error rate. The parameters used to tune the model are “n-estimators”, “max_depth”, “min_samples_split”, and “learning_rate”. The “n-estimators” is the number of trees in regression. Trees ranging from 400 to 800 with a jump of 50 trees were considered as “n-estimators”. For max depth, from 1 depth of tree till 5 depth of the tree was considered. Whereas, for minimum samples required to split the tree values ranged from 2 to 7. And finally, the learning rate steps considered ranged from 0.1 to 0.0075 at a step of 0.025. From these individual lists of values, the best possible parameter values giving the least root mean square error loss value was chosen. The hyperparameters chosen were based on the Demand prediction model. This set of hyperparameters are then used to build all the other regression models.

Finally, 1 month and 1-week forecast prediction is made based on these models to then visualize them using matplotlib. To capture the trend in each target value, a rolling function with a mean is used.

## IV. Results and Findings

In this section, we first discuss the models performance compared to the actual predictions available in the dataset by EIA followed by individual model interpretation.

### A. Model evaluation using RMSE

To predict a timeseries data, along with time cyclicity, seasonality, and trends we used multi-factor regression. And, as decision trees are light weight, and can learn a non-linear relationship better we used GBRT. As, in regression, we predict a value to evaluate the model we use Root Mean Squared Error (RMSE) as our metric. Since, R-squared is invalid for nonlinear regression it is not considered as another evaluation metric [14]. By performing hyper-parameter tuning, we selected a set of hyperparameters which gives least RMSE value for the built models. The final selected set of hyperparameters are: “n-estimator” = 400, “mdepth” = 3, “min_samples_split” = 4, and “learning rate” = 0.0075.

To compare the results from our demand forecast GBRT model to the existing day-ahead demand forecast, we calculate RMSE for each BA and average them out to get a single RMSE value for all the BAs in the dataset. The already existed forecast in the dataset calculation of the average of RMSE values was noted as 10318.48 MegaWatt/hour. Whereas, for our GBRT predicted forecast, calculation of the average of RMSE values was noted as 10081.20 MegaWatt/hour. Thus, with only 6 months of data, our GBRT model is able to predict better on average than the existing forecast approach taken by EIA. This demonstrates the ability of the GBRT algorithm to fit the non-linear data better with less data, and few parameters. Also, the time taken to train and test a single GBRT model is below 1sec with the given data and parameters. In addition, by performing min-max scaling the training and testing performance can further enhanced making it super-fast in prediction.

While performing a train-test with different ratios, it was seen whereby increasing the trainset the GBRT model was able to predict better to give smaller RMSE values. As seen in the table I, for each model with increasing training set size, the RMSE is reducing. As discussed above, our model is performing better on average than the existing approach taken by EIA. Even when our training dataset is just about 6 months long. By this finding, we now know that by increasing the training dataset, our prediction can be even better than the current outcome resulting in a more accurate forecast in demand and interchange. Also, the GBRT model’s performance increases, as the number of features increases, according to [12]. Thus, it is hypothesized that by increasing the number of relevant features such as weather, temperature, region, etc. as well as the number of observations the forecasting ability of the GBRT model can be improved further.

TABLE I: Comparison between RMSE with different train-test split for AEC BA Models

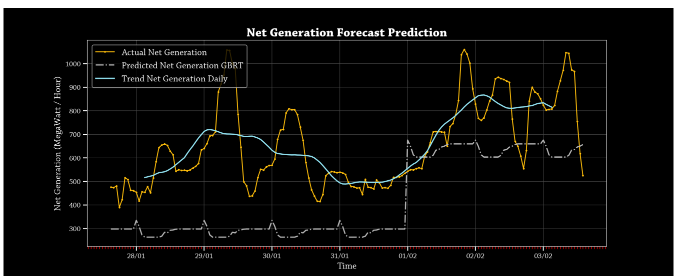
| Train-Test split | RMSE score | | |
|---|---|---|---|
| | Net Generation | Demand | Net Interchange |
| 70:30 | 376.55 | 81.19 | 107.38 |
| 80:20 | 372.12 | 81.58 | 84.51 |
| 90:10 | 218.30 | 59.21 | 44.46 |

Further findings are based on a single BA power forecasting. Simply first BA, PowerSouth Energy Cooperative (AEC), from the BA list was selected for forecast interpretation. Each below method of interpretations for AEC can be extended in a similar fashion for other BA forecast interpretation.

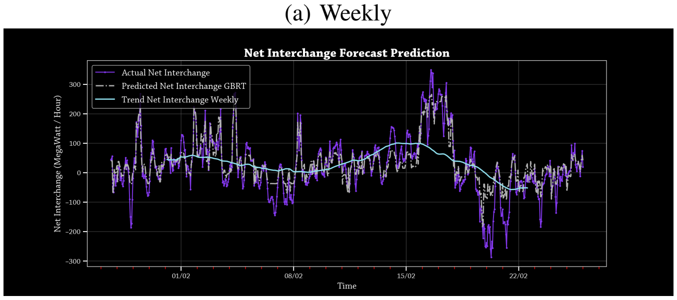
### B. Interpretation of each model

In this sub-section, we interpret each model’s forecast with hourly, daily, and weekly interpretations using seasonality or cyclicity trends over one week as well as a one-month test set. The model’s fit over the actual data as well as feature importance for each model are discussed.

*1) Net Generation Model:* As seen in the fig. 1, our GBRT Net generation model fit the target values poorly for AEC BA. A reason can be fewer factors for prediction as only time and date factors were considered for this prediction. The Net Generation forecast is mainly only for a rough estimate for a BA to be aware of the net power that can be generated at a given time. The RMSE value for this model for AEC was calculated to be approximately 218 Megawatt/hour. This is a reasonable RMSE value compared to the large-scale network of the BA. Thus, AEC can include a confidence interval with this RMSE value to be roughly aware of the net generation. From fig. 1a, we can see that usually, on an hourly basis, power generation peaks during early morning hours at around 6-9 am and stops dropping at noon reaches a minimum in the evening. Also, at night, an increase is noticed every time after a drop in the evening. The daily trend shows that usually on weekends there's a drop in net power generation, whereas at the start of the week from Monday the power generation peaks. And, from fig. 1b it is seen that in a month, here February, at the start of the month the power generation rises and reduces till mid-month from where it again gradually increases to then reach to a very low amount at the end of the month. Thus, AEC can try to generate more and save more power at the above discussed hours, days in weeks, and weeks in a month.




(a) Weekly




(b) Monthly (February)

Fig. 1: Net Generation Forecast Prediction on Test set

Fig. 2 displays feature importance from a scale of 0 to 1 for the Net generation model. As seen, from date-time variables only, "Week of the Year" variable is the highest important feature in decision making or splitting of the trees followed by "Hour" and so on. This means that Net Generation is majorly driven by yearly seasons and then directly daily hours. For example, in the Winter period, less power is generated, whereas, in Summer and Fall, more power is generated. This information, again, can be used to make focused decisions of generating more power at peak times and saving it for future use as per demand.

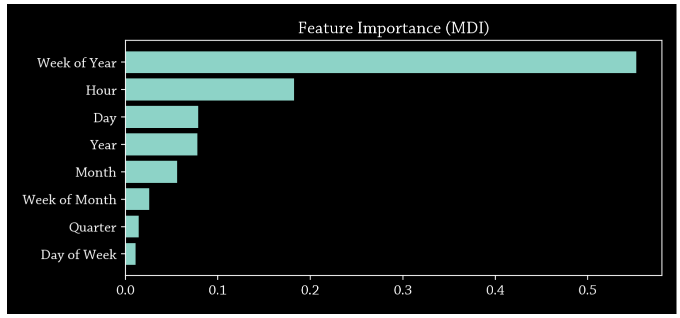
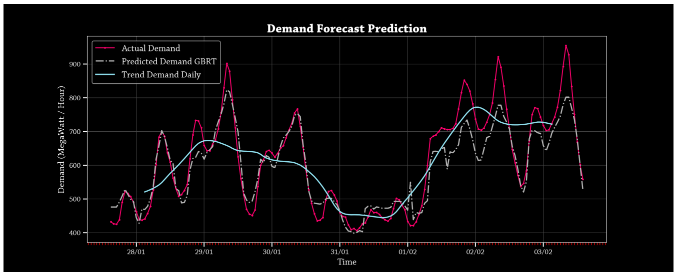



Fig. 2: Feature Importance of Net Generation Model

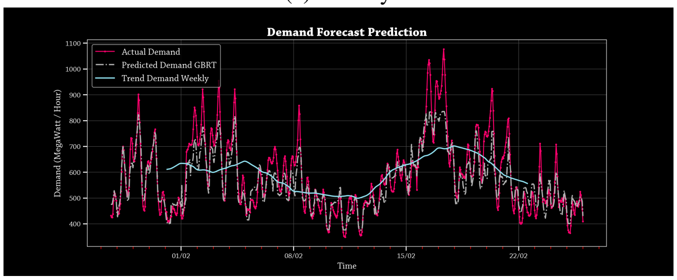
*2) Demand forecasting Model:* The demand forecast model fits the data extremely well as seen in the fig. 3. The RMSE score of this model is approximately 58 Megawatt/hour which shows how reliable this model is to forecast demand. To be more assured, a confidence interval of the RMSE score can be added to the predicted demand value. The demand trend is comparatively similar to that of the trend in a net generation. This shows that net generation is also driven by the demand for power to not generate more power than needed usually. As an hourly trend, from fig. 3a, a general increase in power demand is seen in the morning to peak at around 9-11 am. After that, it drops quickly in the afternoon to be at its lowest point in the evening and again starts rising upwards at night. As normal companies, businesses, industries, factories, etc have major working hours in the day time starting from morning 9 am, this can be interpreted as a reason to rise in demand in the morning and as people end their work starting from afternoon till evening the drop in the demand is obvious. Also, the gradual demand increase at night can be because people use power in their homes at night as well as a few companies and industries also work at night with people in their night shift. On a daily basis, it is seen that from Mondays(01/02) the demand gradually increases till the middle of the week and then gradually drops to being lowest on the weekends. Again, since Saturdays and Sundays are often off for work, we can interpret it as on those days demand is usually less as compared to weekdays. Whereas on weekly basis in February, as seen in fig. 3b, a rise in power demand is noticed at the start of the month then just after the second week the demand falls to the lowest value. At the start of the third week, a steep rise in demand is observed which then gradually drops to lower demand at the end of the month.

Fig. 4 displays feature importance for the demand forecasting model. As seen, Demand is dependent on net generation the most and then forecast error calculated in the dataset and then an hour and so on. Since we didn't have more reliable features, net generation, and previous forecast error is the most significant feature to forecast demand as power is generated based on demand.

Fig. 5 shown below displays model testing on the training data to check overfitting for the GBRT model for selected




(a) Weekly




(b) Monthly (February)

Fig. 3: Demand Forecast Prediction on Test set

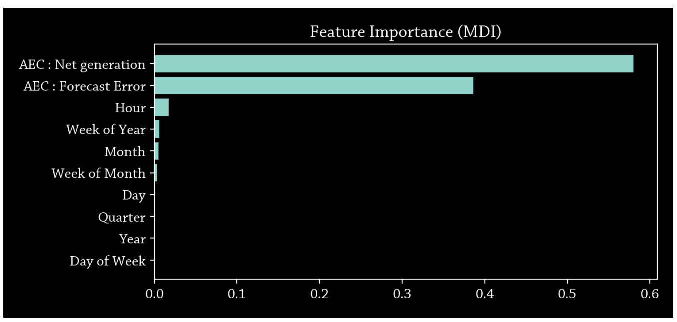



Fig. 4: Feature Importance of Demand Model

hyperparameters. As seen in the figure, the predicted grey line is not entirely overlapping on the actual train values, i.e. pink line. Thus, this gives us confirmation that our models are not overfitting the data on which the model is trained and is a highly generalized model. This conclusion also applies to all other models, as all the other models are also built, trained, and tested in the same fashion and on the same dataset.

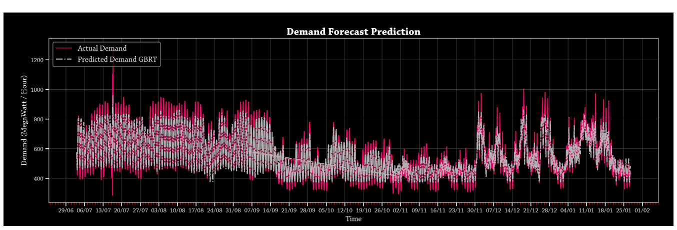
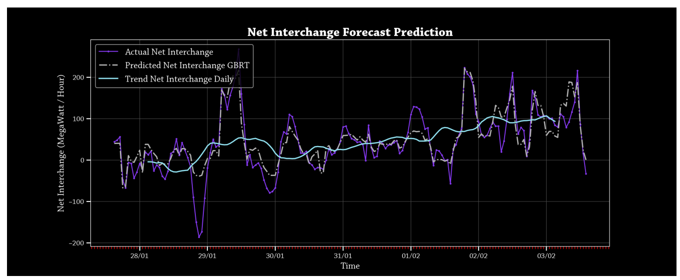
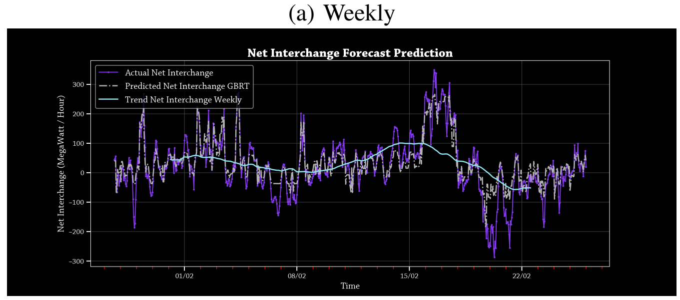



Fig. 5: Generalized Model (No overfitting on Train set)

*3) Net Interchange forecast Model:* Fig. 6 depicts weekly forecast on test data of Net interchange model of AEC BA. As seen, the Net Interchange forecast fits the data extremely well on the test data. The RMSE metric for the Net Generation model is approximately 44Megawatt/hour. Having such a strong prediction of interchange needed to be possibly done is powerful so that a BA can be aware of at what times that BA will be demanding power from other adjacent BAs and thus can also aware other BAs in advance. This way, for every demand a BA will be able to supply power exactly as required and use fewer resources to save more power, or to not able to supply accurately. As seen in fig. 6a, there's no hourly trend as such depicted in the net interchange of AEC but generally, a drop is observed in power demand from other BAs after noon. And, on daily basis, a slight gradual increase in power demand is seen from weekends to the start of the week till mid the week and then drop again. Whereas, on weekly basis, from fig. 6b, the interchange rises to be positive, i.e. demanding power from other BAs, at the first week and gradually drops to become negative, i.e. supplying excess power to other BAs, at the second week. After the second week, again, AEC net interchange spikes to peak at the start of the third week to then plunge over the last week of the month. Thus, at the end of February, AEC majorly supplies its power to other power whereas in its first, second, and third week it usually demands power from its adjacent BAs.




(a) Weekly




(b) Monthly (February)

Fig. 6: Net Interchange Forecast Prediction on Test set

Fig. 7 displays the net interchange model's feature importance. As seen, in net interchange, decision split is majorly dependent on net power generation of the BA and then Demand, Month, and so on. Thus, depending on Net generation the BA tries to interchange the power supply which sounds obvious.

*4) MISO sub-BA Interchange forecast model:* The first adjacent BA with which AEC interchanges power is Midcontinent Independent System Operator, Inc. (MISO). As shown in fig. 8a, this interchange forecast model fits the data well. RMSE metric of this model is approximately 64

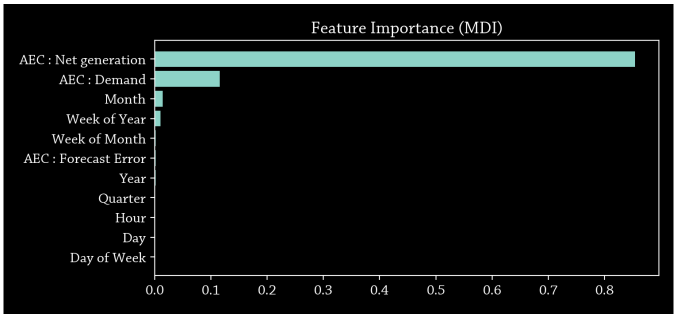



Fig. 7: Feature Importance of Net Interchange Model

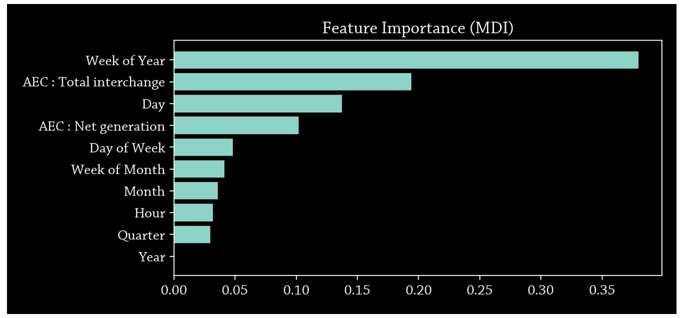
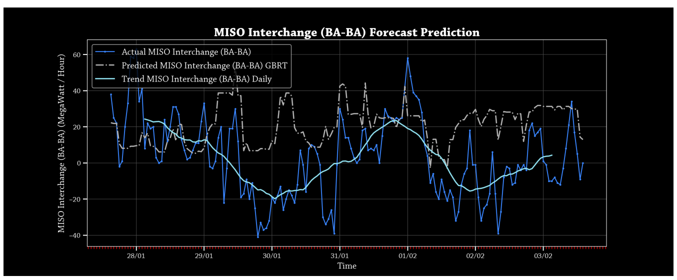
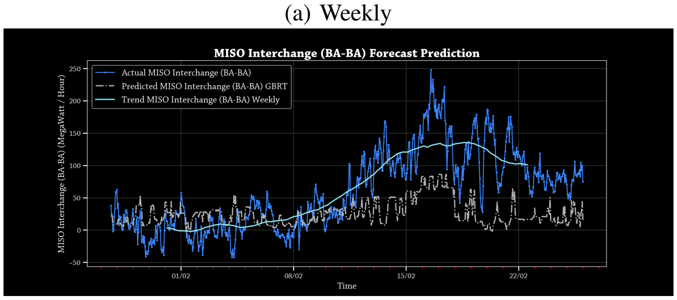



Fig. 9: Feature Importance of MISO Interchange Model

Megawatt/hour which is a reliable score. As a daily trend, it is seen that MISO demands power generally at the weekends. But also on an hourly basis, it generally demands power at night time. Other times AEC demands power from MISO. Whereas on weekly terms, for February, from fig. 8b a gradual rise in positive power interchange between MISO and AEC is observed which peaks at the start of the third week and then starts falling slowly. But, after the first week, mostly AEC demands power from MISO throughout the month.




(a) Weekly

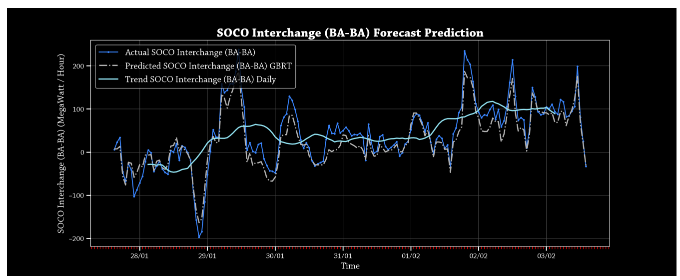



(b) Monthly (February)

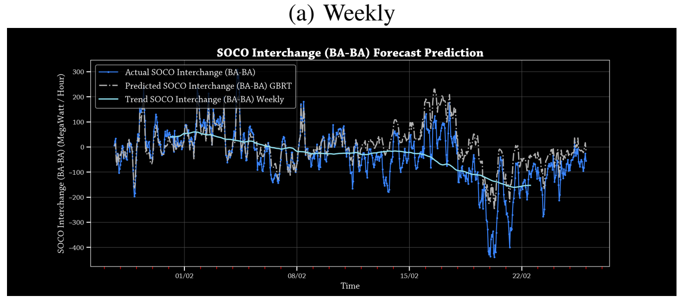
Fig. 8: Interchange with MISO BA Forecast Prediction

From fig. 9, we see that for the MISO interchange forecast model, “Week of Year”, “Total interchange” plays most importance in splitting decision of the regression process followed by “Day” and “Net generation”. This means that for power interchange with MISO, it is important to know which week it is. This can also be interpreted as it might depend on the weather, temperature features too.

*5) SOCO BA Interchange forecast model:* For other adjacent BA, Southern Company Services, Inc. – Trans (SOCO), the interchange forecast model is also built. As seen in fig. 10a, the model fits test data very well with RMSE score of the model approximately 72Megawatt/hours. As an hourly trend, it is seen that the interchange has a drop in the middle of the day whereas high demand in the early morning and a little less over night time. As a daily trend, it is seen that on weekends generally, the interchange is mostly near 0 whereas as the week starts from Monday(01/02) a gradual increase in demand from AEC to SOCO is observed. As seen in fig. 10b, for weekly trend, it is observed that AEC supplies power to SOCO more as the month-end approaches and mostly hovers around 0 with interchange from -200 to 200 generally for the start three weeks of the month.




(a) Weekly




(b) Monthly (February)

Fig. 10: Interchange with SOCO Forecast Prediction

Fig. 11 shows that for the SOCO interchange model the most significant feature is “Total net interchange” of AEC to make regression trees split decisions.

To summarise the observations from findings:

- GBRT model performs better than the current forecast method used by EIA on average.
- GBRT model is able to fit the non-linear nature of power demand, generation, and interchange remarkably well.

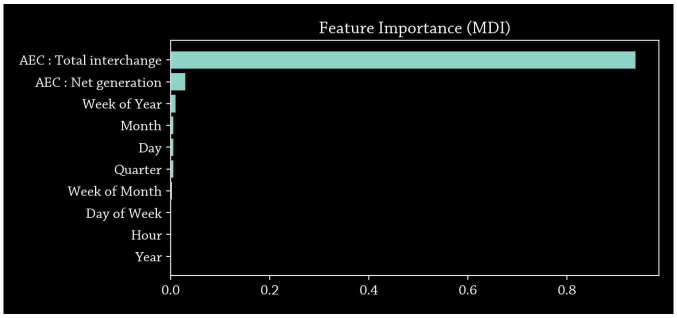



Fig. 11: Feature Importance of SOCO Interchange Model

- GBRT model is able to build, train and predict in very little time, within a few seconds entirely. And, by performing normalization, the model training and testing can become more efficient and optimal.
- GBRT model doesn't overfit the train data and predicts on test data extremely well based on the average RMSE of all the models built for AEC BA.
- By including more features and increasing the training data, the RMSE value reduces and the model fits the data more accurately. Thus, the downside of this experiment of training with only 6months of data can be easily tackled with more data.
- Using this simple lightweight, less time-consuming, system, a BA can predict the demand, interchange needed, and make well accurate decisions saving time, resources, make a profit and avoid power loss.
- By simply utilizing main forecast models of demand and net interchange and power interchange between BAs, a BA can derive insights and make decisions ahead of time to be on the safer side in the power distribution business. Also, by sharing this information with their adjacent BAs, even they can have a heads up on the future supply and demand between BAs and their own region.
- Each BA is also able to get various insights and feature importance from each model forecast as discussed above on an hourly, daily, and weekly basis.
- In this project, the GBRT model shows a better prediction for short-term monthly forecast.

Thus, by using this system, a simple past data of demand, generation and interchange can help a BA to predict demand as well as the amount of interchange that can happen with adjacent BAs on an individual level for both supplying as well as demanding power. This interaction and pre-knowledge can help BAs to be more precise and reliable in maintaining supply and demand accurately, thus making a profit and reducing cost in resources in excess storage of power. In addition, extra knowledge and insights can be gained from each model to make better future decisions.

## V. Conclusion

The balance authorities are the gateways between actual power generation source and end user consumers who maintain the balance between power demand and supply. To avoid any blackouts or loss in excessive power storage than required or use of more resources, it is necessary for them to have an accurate predictive forecast system which is reliable and fast commercially and importantly profitable. In this project, we built a predictive modeling system which utilizes power generation, demand, and interchange between sub-BAs EIA data and make accurate forecasts using GBRT ensemble method.

This systems ability to also forecast interchange that can happen between its adjacent BAs makes it more robust and reliable for a BA to communicate with their adjacent BAs and be ready ahead of time. With accurate demand prediction as well as accurate future knowledge of interchange will make the BA utilize less resources as required and avoid blackouts as well as earn more profits. Additionally, more insights using these predictive models on an hourly, weekly and monthly basis will open more small scale business opportunities for BAs to provide to their customers, for e.g. a discount for not using power at a time when there is a probability of having less power to supply, etc.

This method has shown fast accurate results as well potential to increase its accuracy by increasing the length of the data as well as by including more features. This, can be followed as a future study for this work.

## References

[1] EIA, "Energy consumption by sector," *EIA*, 2019. [Online]. Available: https://www.eia.gov/totalenergy/data/monthly/pdf/sec2.pdf

[2] IEA, "World energy outlook 2020, iea, paris," *IEA*, 2020. [Online]. Available: https://www.iea.org/reports/world-energy-outlook-2020

[3] T. Ahmad and D. Zhang, "A critical review of comparative global historical energy consumption and future demand: The story told so far," *Energy Reports*, vol. 6, pp. 1973–1991, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352484720312385

[4] P. Etingov, L. Miller, Z. Hou, Y. Makarov, K. Pennock, P. Beaucage, C. Loutan, and A. Motley, "Balancing needs assessment using advanced probabilistic forecasts," in *2018 IEEE International Conference on Probabilistic Methods Applied to Power Systems (PMAPS)*, 2018, pp. 1–6.

[5] K. Parker and P. Barooah, "A probabilistic method for reserve sizing in power grids with high renewable penetration," *IEEE Transactions on Power Systems*, vol. 36, no. 3, pp. 2473–2480, 2021.

[6] S. Taheri, M. Jooshaki, and M. Moeini-Aghtaie, "Long-term planning of integrated local energy systems using deep learning algorithms," *International Journal of Electrical Power  Energy Systems*, vol. 129, p. 106855, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0142061521000958

[7] S. Lee, S. Cho, S.-H. Kim, J. Kim, S. Chae, H. Jeong, and T. Kim, "Deep neural network approach

for prediction of heating energy consumption in old houses," *Energies*, vol. 14, no. 1, 2021. [Online]. Available: https://www.mdpi.com/1996-1073/14/1/122

[8] G. Hafeez, K. S. Alimgeer, Z. Wadud, Z. Shafiq, M. U. Ali Khan, I. Khan, F. A. Khan, and A. Derhab, "A novel accurate and fast converging deep learning-based model for electrical energy consumption forecasting in a smart grid," *Energies*, vol. 13, no. 9, 2020. [Online]. Available: https://www.mdpi.com/1996-1073/13/9/2244

[9] E. Mocanu, P. H. Nguyen, M. Gibescu, E. M. Larsen, and P. Pinson, "Demand forecasting at low aggregation levels using factored conditional restricted boltzmann machine," in *2016 Power Systems Computation Conference (PSCC)*, 2016, pp. 1–7.

[10] R. Wang, S. Lu, and W. Feng, "A novel improved model for building energy consumption prediction based on model integration," *Applied Energy*, vol. 262, p. 114561, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261920300738

[11] S.-M. Jung, S. Park, S.-W. Jung, and E. Hwang, "Monthly electric load forecasting using transfer learning for smart cities," *Sustainability*, vol. 12, no. 16, 2020. [Online]. Available: https://www.mdpi.com/2071-1050/12/16/6364

[12] S. Touzani, J. Granderson, and S. Fernandes, "Gradient boosting machine for modeling the energy consumption of commercial buildings," *Energy and Buildings*, vol. 158, pp. 1533–1543, 2018. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0378778817320844

[13] P. Nie, M. Roccotelli, M. P. Fanti, Z. Ming, and Z. Li, "Prediction of home energy consumption based on gradient boosting regression tree," *Energy Reports*, vol. 7, pp. 1246–1255, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352484721001049

[14] Spiess, Andrej-Nikolai, and N. Neumeyer, "An evaluation of r2 as an inadequate measure for nonlinear models in pharmacological and biochemical research: a monte carlo approach," *BMC Pharmacology*, 2010.