Power Grid Demand and Generation Forecasting

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***Abstract*—Today, with growing industrial, residential areas, businesses and commercial areas, it has become difficult to keep up with the power consumption demand. It is seen that the power demand will exponentially rise in upcoming years. Thus it is necessary for power grid operators to have efficient use and manage of energy for maintaining balance between power demand and supply. The grid operaters generates continuous data which can be used for power demand forecasting and predictions to then have cost effective power supply**

***Index Terms*—Predictive analysis, Power demand and generation**

I. Background and Scope

With the advent of power generation using natural gas, coal, and now focus on renewable energy resources, and as the increase in different technologies, industries and growing cities and businesses, the demand for electricity and power has increased exponentially today. Electricity drives enormous amount of day to day practices and instruments we use for living, work, and other sources. According to Energy Information Administration(EIA), power is supplied to four different sectors, mainly, residential, industrial, commercial, and transportation [1]. According to the study, in 2020, world electricity consumption prediction was 22.536 kTWh. As new businesses and population grows, the electricity and power demand is projected to grow till 35.407 kTWh by the year 2040 [2]. Thus, with this constant increase in demand year by year, it is important for increase in power generation and efficiently supply as per the demand.

As rise in climate change and global warming, power production using sources which emits greenhouse gases, like coal and natural gas, are seen to be gradually reduced by the year 2040 [3]. And, a shift to attainable renewable energy sources like solar, wind, bioenergy, and hydro is currently happening, which by 2040 will account for most of our global energy production source. But, the problem with renewable energy generation is it is dependent on weather. For solar, the power generation is at peak at hours around noon and then drops at night. Similarly, with wind, wind turbines are only efficient to produce enough energy in highly windy regions and thus are geographic specific as well. Thus, energy production using the renewable sources is not constant and varies with the weather and climate. Also, the power demand for different sectors varies throughout the day. For residential and commercial sector, at night less power is consumed, whereas for industrial sector, the power requirements remains almost same throughout the day [1]. Thus, the demand for power also depends on different sectors as well as rise in new businesses, companies, properties, and industries. Some portion of demand for power always varies due to unknown factors and reasons, thus it becomes necessary for energy suppliers to be ready with appropriate demand for power in a given region.

Power demand and generation is not constant always and varies as discussed above, it becomes critical for power suppliers to keep track of power consumption, optimally manage and distribute it among geographical regions. Power grid operators are the balancing authorities which acts as the gate between power suppliers and end user consumers. These balancing authorities are entities in the power systems to ensure correct supply to the consumers according to their demand. Each region has a grid operator for supply of power to that region. The grid operators need to maintain a fine balance between the demand and supply of the power so that no excess power generated is wasted or no blackouts happen in a given region. The net power generated for a given region cannot always meet the requirements due to changing factors on daily power generation at source and consumption fluctuations. Also due to transmission of power over different regions and to end customers, it is also lost in some amount in a form of heat energy, dissipated in air. It is thus important for a grid operator to manage and distribute the excess generated power to the adjacent authorities to fulfill the demand to use the power effectively and optimally. According to the demand being fulfilled or not, these power grid operators are in constant contact with the suppliers to reduce the supply or to increase it.

These authorities keep track of hourly based data of power generated and supplied at their given region and also distributed among the other regions. It is important for the power grid operators to predict and forecast the demand based on the past data to be ready and equipped to have the required supply. Effectively mining this generated data may produce patterns in power demand, supply and distribution, which can be used to improve the power management and meet the supply-demand balance. This need for meeting the balance is costly with risks of wastage of excess power or blackouts and can be made achievable cost-effectively by the use of predictive analytics for forecasting values to be ready for unknown scenarios. With the advances in data mining algorithms, such time-based forecasting have become viable options for such businesses to thrive and use them for optimal management of their business as well as to become profitable.

The dataset used in this research is downloaded from an open source web-site, "Energy Information Administration (EIA)", which has global energy related data [4]. In this research, only the US related data is used which is hourly data for 6 months from July to December 2020. This data is in tabular format and consists of 4418 hours of a total of 63 Balancing authorities(BA) across the US. The data is hourly based time-series data and consists of columns such as Demand, day-ahead demand forecast, Net generation(for their respective region), total interchange and individual BA interchange.

II. Goals

The aim of this project is to unveil patterns to make a prediction model based on hourly based past historic data generated by a power grid to forecast the demand for a particular region, and predict if it can meet the demand finely or not. If not, then do they have sufficient power to distribute or are they in need to meet the demand. Other goal is to check patterns in forecast error. If yes, then how can we leverage that information to predict better about the demand and supply. With a predictive model tool in hand, the power grid operators can tap into the knowledge and intelligence by which the power supply and distribution can be optimally managed, thus creating an opportunity to save money.

III. Ethical Concerns

As a company or an organisation, it is always necessary and crucial to follow ethics in performing any tasks with the data collected from the end customers. Ethical concerns are thus moral principals the business must follow for any practice performed by a company to be legally accepted. For a company to use any data about their customers, they must have their consent first and provide details about what purpose the data is going to be used for and that not for anything else [5].

A. Data Privacy and Security

In Energy industry, data can be collected from the end user using smart meters and be used to have targeted marketing and cross-selling of other services. A general practice any company follow today is to have profiling of their customers for their own purpose. According to General Data Protection(GDPR), an organisation is not authorised to have liberty to get private data from their customers without their consent. Thus, to avoid having bad practice of using personal data of customers, businesses can simply inform customers about data collection and purpose of its use by giving any disclaimers as well as a choice if the customer wants to participate or not. It is also important to have all the data collected to be secured and assured to the end users.

B. Integrity and no discrimination

Integrity is another ethical concern when it comes to predictive analytics using any particular algorithm or methods. The moral obligations must be followed in such practices to have integrity for practices in the business. For e.g., a company might use data and create a model with the data to then have a certain discriminating profiling, which is socially unacceptable. Thus, a company when designing or modeling any predictive algorithm should also adhere to this norm.

C. Transparency

The company must be able to be transparent about any practices they follow within the company with the data they collect, and not hide anything. With power managing companies, it is necessary for them to be transparent about the metering and how the power cost for a particular house for a month was that if raise a question by the customer. There should not be any unclear things when a customer asks a question about any complaint or its service.

IV. Business Value

With the slow transition of many power managers or grids to smart meters and data collection, energy companies are searching for ways for cost reduction and make energy savings to prevent excess generation loss. And, as the new emerging energy players in renewable energy producers, the focus on efficient energy management along with maintaining balance between power generation and consumption is becoming crucial than ever. With smart metering, energy business can tap into customer-based statistics on their energy consumption behavior, region wise energy demands, improve outage detection in real time, energy theft detection, better billing and cost can be offered to retain customers, etc.

As discussed in the previous section, the goal is to identify patterns in power demand, generation at regional power grid level and interchange between regions to make correct forecasts to improve energy management, distribution and balance between demand and supply.

Null Hypothesis: "For net power generation, demand, and total interchange, there is no pattern found to forecast and predict leaving the time-series stationary or with random fluctuations."

Alternative Hypothesis: "For net power generation, demand, and total interchange, there is a seasonal or cyclic pattern found to make predictions and forecast."

Based on the data collected from EIA, if the alternative hypothesis turns to be true, then accurate predictions can be made about power demand for a particular region at a given hour along with net power generation by which power grid utility can effectively balance the demand and supply as well as distribute to other regions based on interchange predictions efficiently. With this grid data and predictions, many value outcomes are possible for power suppliers and grid operators as well as to end customers.

A. Efficient Energy Management

The main aim for the power utility in the first place is to effectively manage the power throughout the regions. Timely gathered data by power grids can help them achieve this objective with minimum cost and efficiently. Using predictive forecasting, they can monitor real-time demand and forecast to effectively supply power. On the other hand, by understanding consumer behavior, they can also run targeted energy management campaigns to meet global national target goals. Also, predicting how much the grid will be in power positive or negative in terms of demand and generation, other adjacent power grids can also come into picture to interchange the supply accordingly. This is a huge deal for energy utilities when it comes to balancing demand and supply very finely and to predict outage situations beforehand or not generate more power than demand to then have loss.

B. Cost reductions at Utility grid plants

For power grids to make sure no outage occurs or backup supply is ready, they need to have lots of resources and reserves ready for such situations. This not only increase in extra cost for unknown situations, but also having backup with not often use makes it less efficient for a business. The power grid can reduce their costs in scheduling and reserving lots of requirements for unknown demand or outage situation by having a predictive model which can have forecasting values very close to actual demand values. This will also make use of the resources at power grid efficiently with less loss in business.

C. Regional classification based on power consumption behavior

Based on consumer behavior, different characteristics of combinations of sectors in a given region can have different demands. This information can be useful for power operators to have better consumer oriented targeted rebates or campaigns to have customer retention.

D. Cheaper power cost

Grid operators when are able to achieve a correct balance between supply and demand and can distribute the power efficiently, the cost for the power can be reduced for the end consumer. As discussed earlier, with having almost error free forecasting of demands can help in achieving this target. Also, in the other scenario, where net generation is less than the demand, power managers can also ask customers to reduce down the demand with certain incentives to prevent outages.

V. Visualization

Visualisation is a very important tool to perform descriptive analysis for a prior understanding of data before performing any modeling to the data. In this section, we look at certain visuals to get a grasp of the dataset and make an understanding out of it. As discussed earliear, the EIA dataset is an hourly timeseries data from July to December 2020 of 63 BA across the US and for each BA for each hour, the values for demand, net generation and interchange of power is noted. To keep the visuals simple, we only select 12 major BA's out of all BA's across the U.S..

A. Correlation Matrix

It is expected that Power demand is correlated with net power generation as grid utilities try to manage the balance between the two. As shown in the fig. 1, it is clear that the correlation between Demand and Generation for all 12 BA's is strongly linear, meaning power demand and generation moves in the same direction, which has to be. For power interchange between BA's, it is seen that when Demand is higher than the Generation, the interchange is in negative, meaning it has borrowed from neighboring BA's and when Demand is lower than the Generation, the interchange is in positive, meaning it has supplied the excess generated power to its neighboring BA's.

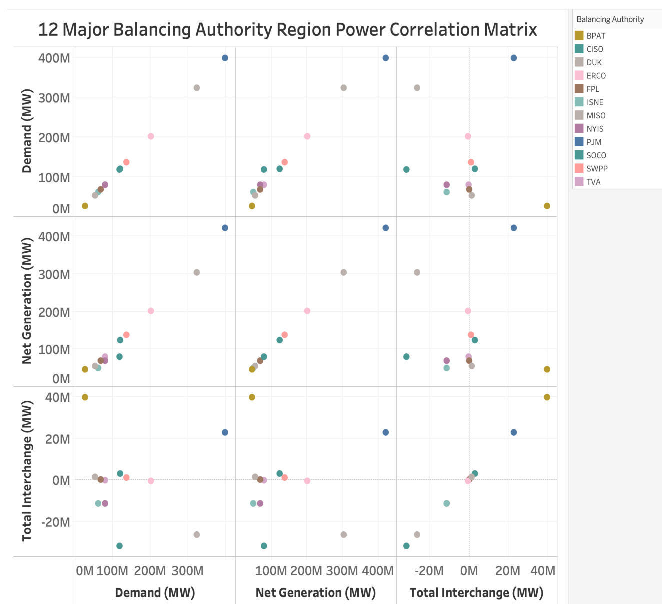

Fig. 1. Correlation between Power Demand, Generation and Interchange

B. Demand vs Generation for 12 Balancing Authorities

Fig. 2 displays Power demand, in bars, and Power generated, in line, for each of the 12 BA's over 6 months along with correlation between the demand and generation for those individual BA. It is seen that for some BA, net power generation is slightly higher than the demand whereas for other the demand is higher than the net power generated in the region. We can also see that among all the 12 BA's, ”ERCO”, ”MISO”, and ”PJM” BAs actually have higher demand and power generation, above 200M MW. ”CISO”, and ”MISO” are two regions where power demand is a lot higher than the power generation.

C. Interchange of power among the BAs

Below fig. 3 depicts the amount of power interchanged by a given BA or region, i.e. supplied to or borrowed from

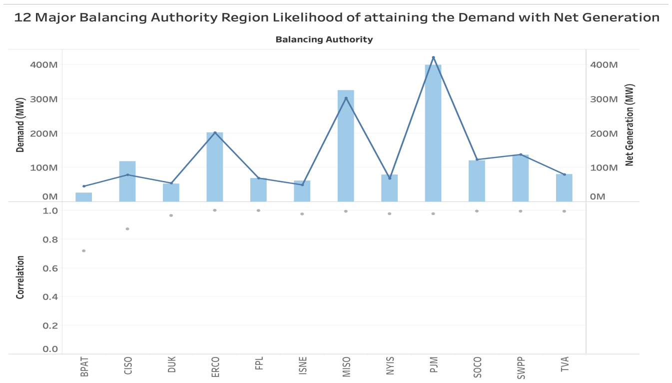

Fig. 2. Power Demand vs Power Generation in 12 BA's and its correlation

another BA to fulfill the balance between demand and supply overall. From the below figure, we can see that most of the BA shows a particular characteristic of either borrowing or supplying of power. BAs "BPAT", "PJM", "SOCO", and "SWPP", have values above the 0MW axis, meaning they have constantly generated more energy than required and thus supplied to neighboring BA's. Whereas, for BAs "CISO", "ISNE", "MISO" and "NYIS" has shown constant borrowing of power from other BAs. It is also clear that BA "BPAT", at the top, is the highest supplier and "CISO", at the bottom, is the highest borrower of power over these 6 months amongst all 12 BAs.

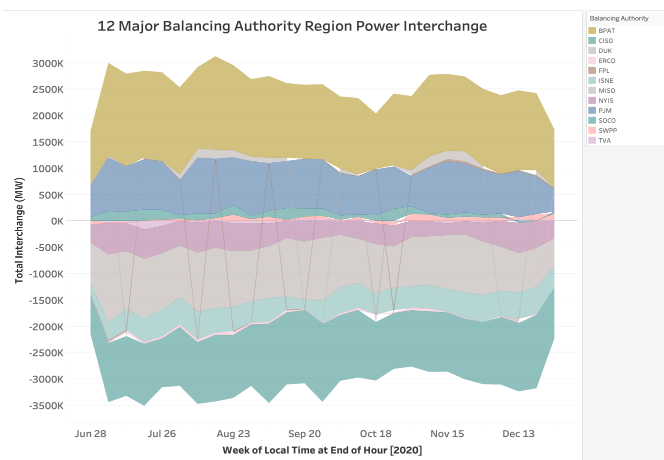

Fig. 3. Overall Interchange over the 6 month period for 12 BAs

D. Total U.S. Visualization of Power attributes

Below fig. 4 displays overall power demand, generation and interchange in the U.S. over the given 6 months. We can see that, for the most of the time, net total power generation has been slightly above the actual demand by a couple of million MW. There are certain point times where power demand has dropped significantly. And, at those time points the interchange of power has be significantly higher than usual.

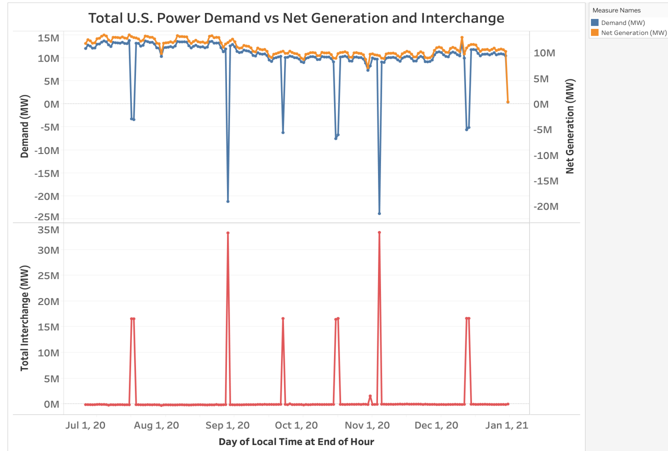

Fig. 4. Total U.S. Power Demand, Generation and Interchange

VI. Applicable techniques

For performing predictive analytics on a time-series data, there are several machine learning as well as statistical modelling methods.

Mel K. et. al, performed a critical study on forecasting building energy consumption demand. The study discusses cloud-based predictive model development and compares use of three machine learning models namely SVM, K-NN, and ANN. It concluded that SVM outperformed the other two and had accurate forecast for actual demand of electricity [6].

Another study performed by Tianyi Z. et. al, performed predictive analytics on campus energy consumption prediction to have an accurate forecast to the demand. They found out that for their given data, using bottom up modelling approach using Bayesian analysis improves accuracy for accurate forecasting [7].

For time-series forecasting, there are statistical models like ARIMA models, SARIMA models, SES models which can be also used for prediction.

VII. References

[1] "Energy Consumption by Sector", 2019, https://www.eia.gov/totalenergy/data/monthly/pdf/sec2.pdf

[2] Tanveer Ahmad, Dongdong Zhang, "A critical review of comparative global historical energy consumption and future demand: The story told so far", 2020, doi: https://doi.org/10.1016/j.egyr.2020.07.020., url: https://www.sciencedirect.com/science/article/pii/S2352484720312385

[3] IEA (2020), "World Energy Outlook" 2020, IEA, Paris, url: https://www.iea.org/reports/world-energy-outlook-2020

[4] "HOURLY ELECTRIC GRID MONITOR", Energy Information Association (EIA), 2021, url: https://www.eia.gov/beta/electricity/gridmonitor/dashboard/electric_overview/US48/US48

[5] X. Deng, "Big data technology and ethics considerations in customer behavior and customer feedback mining," 2017,doi: 10.1109/BigData.2017.8258399.

[6] Mel Keytingan M. Shapi, Nor Azuana Ramli, Lilik J. Awalin, Energy consumption prediction by using machine learning for smart building: Case study in Malaysia, 2021, doi: https://doi.org/10.1016/j.dibe.2020.100037., url: https://www.sciencedirect.com/science/article/pii/S266616592030034X

[7] Tianyi Zhao, Jingwen Xu, Chengyu Zhang, Peng Wang, ”A monitoring data based bottom-up modeling method and its application for energy consumption prediction of campus building”, 2021, doi: https://doi.org/10.1016/j.jobe.2020.101962., url: https://www.sciencedirect.com/science/article/pii/S2352710220335944