Energy Sources Driven Electricity Production: A Global Tactical and Strategical Paradigm

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Abstract: Energy forecasting for electricity productivity is the process of applying statistics with possible Quantum or Classical Computing with help from new innovative techniques offered by artificial intelligence to make predictions about consumption levels. This kind of computation presents corresponding utility costs in both the tactical and strategical or short term and long term. Energy forecasting models take into account historical data, trends, weather inputs, tariff structures, and occupancy schedules in the urban city due to population growth, etc. to make predictions. Additionally, energy forecasting as future paradigm is driven by electricity production demand and it is a cost-effective technique to predict future energy needs, which is a paradigm to achieve demand and supply chain equilibrium based on available energy both renewable and non-renewable sources.

Key words: Quantum computing and computer, classical computing and computer, artificial intelligence, machine learning, deep learning, fuzzy logic, resilience system, forecasting and related paradigm, big data, commercial and urban demand for electricity.

1. Introduction

“When it comes to energy, there is one matter everyone agrees on. For the near future, at least, the world will need more of it—and how it is produced and used will be a critical factor in the future of the global economy, geopolitics, and the environment”.” Scott Nyquist—McKinsey & Company

Energy has always been a central factor in the formation, transformation, and development of human societies. Availability, the form, and technology to utilize energy are the driving force in the creation and advancements of civilizations from the very beginning of human settlements. It is impossible to overstate the importance of energy. Just thinking where humanity would be without it is enough to demonstrate this point. In the creation and transformation of human societies, a constant and pivotal factor has always been the form and technology related to energy.

In 1955, Fred Cottrell published his classic book, *Energy and Society*. This book was among the first interpretive treatments of the connection between a society’s energy conditions and the evolution of its culture. The book begins with an initial discussion of the earliest forms of energy uses and evolves through a discussion of how the evolution of alternative energy converters has impacted the growth of civilization. Dr. Cottrell takes us from food gathering societies up through the beginning of the industrial revolution into the age of nuclear power. With each step of change, he discusses how society has changed and the impact these changes have had on economic, moral, and social issues. Today, more than any time in history, the questions of energy sources, energy conversion, energy uses, and energy distribution are among the most significant challenges faced by civilization. In this book, Dr. Cottrell does not give you answers or predictions but takes you through the thought processes necessary to overcome the multiple barriers we face in moving into the future.

Like the past, energy plays a vital role in shaping the future in any industries, cities, nations, and the world. If the forecast about the growth in the human population is accurate, then the economic role of
energy would be more significant than before. That is why we include energy as one of the critical factors that shape future paradigms in any target entity or world.

Our approach to studying energy, therefore, is not technical. In other words, we plan to provide data about the energy that can be used in forecasting the future paradigms in the targeted areas. That is why, in this volume, we define energy, factors that affect the supply and demand for it, and study a different type of it. Our focus is mainly on understanding the historical and future trends of each type of energies. We also present data about the impact of energy on economic development, the environment, and climate change. All data are gathered from either government sources or other reliable ones [1].

Energy can be generated from different sources. Based on their long-term availabilities, these sources can be divided into two categories of renewable and nonrenewable. Presently more than eighty percent of the world’s energy consumption generated from nonrenewable or fossil fuels like petroleum, coal, and natural gas. However, by advance in technology and significant investments in renewable sources of energy, more renewable energy becomes available that can substitute fossil fuels.

Solar energy, for example, we know that radiation from the sun is capable of producing heat, causing chemical reactions, or generating electricity. According to the Encyclopedia of Britannica, “the total amount of solar energy incident on earth is vastly more than the world’s current and anticipated energy requirements. If suitably harnessed, this highly diffused source has the potential to satisfy all future energy needs. In the 21st century, solar energy is expected to become increasingly attractive as a renewable energy source because of its inexhaustible supply and its nonpolluting character, in stark contrast to the finite fossil fuels coal, petroleum, and natural gas”.

The role of technology in producing energy is also significant enough that needs to be considered. For example, artificial leaf, which is a silicon-based device that uses solar energy to split hydrogen and oxygen in water, thereby producing hydrogen energy in a clean way, leaving virtually no pollutants. The technology, which was designed to simulate the natural energy-generating process of photosynthesis used by plants, was first successfully developed by American chemist Daniel G. Nocera and colleagues in 2011. Further work was needed to improve its efficiency and cost-effectiveness for practical use.

The essential component of an artificial leaf is a silicon chip that is coated in chemical catalysts, which speed up the water-splitting reaction. In an open vessel of water, when solar energy hits the chip, a chemical reaction similar to photosynthesis occurs—the hydrogen and oxygen molecules of water are split apart, resulting in the separation of protons and electrons. The protons and electrons are captured on the chip and are recombined to form hydrogen gas, which can be used for the immediate generation of electricity or stored for later use (same source).

In the bottom line, seven billion people shape the world’s energy system and have a direct impact on the fundamental drivers of energy demand. Energy impacts the economy as well as security and environmental goals. Energy solutions can vary over time and circumstances. Think about how access to energy affects your own life, and how that translates to billions of other people around the world. Global energy demand will continue to rise through 2040, reflecting its fundamental link to growing prosperity and better living standards for an increasing population worldwide. “Energy security and environmental security are two of the most important issues the world will face in the coming decades. These are often extremely complex topics. They are also sometimes emotionally laden. There are many different perspectives on many problems involved.” [2].

One noticeable definition that we are using in this article and short communication is the word of Electrical Load or simply “Load”, which by definition, is:
The load is the amount of electricity on the grid at any given time, as it makes its journey from the power source to all the homes, businesses, and industries within a utility’s territory. They monitor both demands and load around the clock to make sure it is the right amount to meet the real-time needs of the customer, either private or commercial.

2. Energy Forecasting Classification according to Time Period

According to the time period, energy forecasting can be classified as shown in Fig. 1. Very short-term electrical energy consumption forecasting (VSTCF) or ultra-short-term electrical energy consumption forecasting (USTCF) includes between 1-minute and 1-hour ahead of forecasts, while short-term electrical energy consumption forecasting (STCF) contains among 1-hour and 2 weeks ahead of forecasts.

Medium-term (or mid-term) electrical energy consumption forecasting (MTCF) refers to future predictions from 2 weeks to 3 years, and finally, long-term electrical energy consumption forecasting (LTCF) is performed for forecasts from 3 years up to 50 years [3].

Moreover, several forecasting techniques have been employed for STCF; however, there can be found literature around VSTCF as well [4]. That is commonly employed and used for smart grid and automated demand response applications under normal condition and usage of electricity by consumers either commercially or privately owned electric meters at a location.

However, none of these techniques and methods was not incorporating unexpected scenarios such as CORONA VIROUS pandemic of a few months ago that took place globally, which is a thermidors shock load to the grid and rise to electricity consumption commercially, in particular in hospital industry fighting as front line and industry supporting manufacturing of personal protection equipments (PPEs).

There are unprecedented load forecasting effects due to the COVID-19 pandemic. On March 26, companies like Itron’s forecasting team discussed how to best model the sudden load shifts due to the various COVID-19 mandates [5].

This company and its teams are modeling their forecasting based on the three following categories and time period classifications as:

1. Maximize Operations (Short Term)
   With short-term forecasting (5 minutes-10 days), you can improve grid and retail operations, and enhance energy trading.

2. Improve Financial Performance (Medium Term)
   With medium-term forecasting (1-3 years), you can gain insights into sales forecasts, revenue forecasts and variance analysis.

3. Enhance Planning
   With long-term forecasting (5-20 years), you can enhance visibility and planning for a variety of energy, peak and hourly load forecasting activities.

In summary, one can use “Forecast As A Service”, where from short-term operations and power procurement to long-term capacity planning, rely on the forecasting techniques and models that work with system operators and utilities around the world to deliver accurate and reliable forecasts scalable to your needs.

Furthermore, bear in your mind that, deep penetration of non-grid connected renewable generation and storage, electric vehicle charging, smart load control, and time-of-use rates create greater load volatility, which in turn leads to eroding operational load forecast performance.

To improve the system operator’s confidence with the load forecasting process, there has been a
movement toward developing and presenting an ensemble of load forecasts. The ensemble could include forecasts designed to handle the impact of rooftop solar photovoltaic (PV) and electric vehicle charging, forecasts that incorporate the impact of time of use (TOU) pricing and smart load control, and load forecasts produced under alternative weather forecasts.

If the alternative load forecasts are clustered closely around each other, then system operations may have greater confidence in the system conditions predicted by the ensemble. On the other, a forecast ensemble with a wide range could raise doubts about the forecasted system conditions leading to system operators taking actions to hedge against the worst-case scenario.

In effect, the forecast ensemble quantifies the plausible range of loads given uncertainty around future meteorological conditions such as temperatures, wind, and solar conditions, as well as uncertainty around price sensitive loads and load control actions.

3. Forecasting Methods and Background

Historically, in the past few decades, different methods and techniques were utilized to forecast energy production from two different energies, either renewable or non-renewable sources, thus driving electricity from these forms for distribution and consumption, which were implemented.

The traditional forecasting techniques and methods such as Regression, Time Series (i.e., Linear Trend, Polynomial Trend, and Logarithmic Trend), and statistical methods were used, when energy consumption to produce electricity was considered. However, in recent years, with the rush to augment artificial intelligence (AI) the above statistical methods were integrated with AI and its soft computing techniques such as Artificial Neural Network (ANN) [2], Support Vector Machine (SVM), Fuzzy Logic (FL), and Grey prediction as parts of the paradigm of forecasting are integrated. A good overall review of these techniques can be found in Ref. [6].

Note that an artificial neuron (AN) is the simplest unit of an ANN which can handle and manage complex behaviors by the connections and interoperability between the processing neurons and weight parameters [7]. In Fig. 2, one hidden layer that is known as Multi-Layer Perceptrons (MLPs) has been demonstrated MLPs are nonlinear functions to approximate a sufficiently regular function to an arbitrary degree of accuracy [8].

It is known that ANNs with excessive numbers of neurons and weights are easy to train. Besides, this may cause overtraining [9].

Lately, conventional feed-forward MLP ANNs have been replaced by Radial Basis Function (RBF) networks [10-14]. In comparison with traditional sigmoidal ANNs, the RBF networks have minimal interaction between RBF units, because each RBF unit is frequently affected by smaller portions of input patterns.

Typically, we need a large amount of data, when we augment AI as a tool to perform any forecasting and achieving a prediction. This comes along with Machine Learning (ML) and Deep Learning (DL) which are becoming a common denominator for Artificial Intelligence (AI) as depicted in Fig. 3.

Thus, the question is that Machine Learning (ML) and Deep Learning (DL) components of Artificial Intelligence (AI) are the Holy Grail of forecasting
giving the recent technical progresses we have had in this science.

The answer for it is “YES” and “No”.

Since regression and neural networks both fall within the domain of machine learning and they happen to be the work horses of operational forecasting the answer is yes. Further, there are opportunities in the load forecasting arena for K Means Clustering, Decision Tree Regression and Support Vector Machine. Do we expect these approaches to supplant regression and neural networks? Ultimately, the marketplace will determine this. These techniques will need to prove themselves in an operational world where the quality of the forecasts is judged every hour.

Note that: DL is repository of historical data that compare it with incoming present data in omni-direction format and passes the proper information to ML to learn for it so AI can process and achieve the paradigm of forecasting as a model.

Furthermore, combination of ANN and AI along with ML and DL as a tool for energy load forecasting may implement additional technique that is known as Long Short Term Memory (LSTM) [2].

Note that: long short-term memory (LSTM) is an Artificial Recurrent Neural Network (RNN) architecture used in the field of deep learning. Unlike standard feed forward neural networks, LSTM has feedback connections.

A common LSTM unit is composed of a cell, an input gate, an output gate and a forget gate as depicted in Fig. 4.

The LSTM cell can process data sequentially and keep its hidden state through time.

Furthermore, two variants of LSTM have been studied for this purpose and they are standard LSTM and the LSTM-based Sequence-to-Sequence (S2S) architecture. Both variants are tested with one hour and one minute time step resolution data, the results indicate S2S worked well in both datasets [3].

With the new revolutionary and innovative technique of Quantum Computing [15] utilization of method such as LSTM makes life easy when we deal with the sheer volume of data at the level of Big Data along with next generation of AI such as Super Artificial Intelligence (SAI) in particular with a supervised form of SAI [7].

As the market of artificial intelligence implementation in the industry is on the rise in recent several years, the energy industry and owner of power plants producing electricity are at least constantly looking for a way to be able to forecast their electric load into the smart grid so they can be ahead of the marketplace.

According to the privatization and deregulation of the power system, accurate electric load forecasting has come into prominence recently. The new energy
market and the smart grid paradigm ask for both better demand-side management policies and for more reliable forecasts from single end-users, up to system scale [3].

Such forecasting of electric load into the smart grid applies a state-of-art review of the artificial intelligence technique, at least for short-term electric load forecasting, as it is described in Section 2 of this article.

However, it is complex to predict the electric demand owing to the influencing factors such as climate factors, social activities, and seasonal factors. The methods developed for load forecasting are broadly analyzed in two categories, namely analytical techniques and artificial intelligence techniques [3].

Commonly used analytic methods in the most published literature that can be found are the Linear Regression method, Box-Jenkins method, and finally Nonparametric Regression method. The analytical methods work well under normal daily circumstances, but they can not give contenting results while dealing with meteorological, sociological, or economic changes; hence they are not updated depending on time. Therefore, artificial intelligence techniques have gained importance in reducing estimation errors. Artificial neural networks, support vector machine, and adaptive neuro-fuzzy inference systems are among these artificial intelligence techniques. In this paper, a state-of-the-art review of three artificial intelligence techniques for short-term electric load forecasting is comprehensively presented [3].

In a nutshell, we can state that “Using the Past to Predict the Future”.

4. Conclusion

At the end of the day, any model, no matter how complex, is only as good as the explanatory variables that are included in the model specification. It is the knowledge and skills of your forecasting team that drives what explanatory variables to include. If you are going to invest in improving the accuracy of your load forecasts, do not overlook the importance of investing in the knowledge and skills of your forecasting team. However, one thing is obvious as we said and that is “Using the Past to Predict the Future”.

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