IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received March 3, 2020, accepted March 25, 2020, date of publication April 7, 2020, date of current version April 23, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2986317

A Qualitative Study on the United States Internet of Energy: A Step Towards Computational Sustainability

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This work was supported in part by the multiple grants of Oregon Renewable Energy Center (OREC).

ABSTRACT The burgeoning growth of Big Data not only matures and improves the data management efficiency and useful information extraction techniques, but also motivates the computational science researchers to come up with a new method or solution that can be repurposed for problems across the domain. Computational Sustainability joins this movement for a transferrable computational technique for sustainable development and a better future. Internet-of-energy (IoE)– leveraging IoT to smart grids associated with advanced analytics– is one of the prominent efforts in this regard. This paper presents a qualitative analysis on the elements of the energy and power management ecosystem in the United States. This qualitative study includes the Grid Overview of the United States; Weather and Climate and its impact on the entire energy generation and consumption dynamics; Peak Load Forecasting and its techniques and burgeoning challenges; Variable Renewable Energy, its reliability challenges and how we can take advantage of this variability; Commodity Prices and its criticality; Energy Disaggregation and its impact on consumption-awareness; and Generation Expansion and Decision Analysis. Besides, IoE integration, associated trade-offs, challenges, research opportunities and transferable computational techniques are addressed in this communication. Furthermore, schematics and quantitative analysis are presented in support of this study.

INDEX TERMS Computational sustainability, Internet of Things, smart grid, Internet of Energy, big data, transferable computational techniques.

I. INTRODUCTION

Computational Sustainability, a massively interdisciplinary field of study, lies in the intersection of the multiple domains, such as applied mathematics, statistics, computer and information science, electrical and electronic engineering, economics, environmental science, operational research, and policymaking [1], [2]. The overarching goal of this field of study is leveraging the knowledge of these multiple domains to meet the essentials and demands of the current generation without compromising the future generation's potentiality to confront their known needs and prosper [3]–[5]. Computational Sustainability joins the movement of sustainable development through developing data-driven and robust computational models and adopting scientific methods to optimize decisions regarding resource allocation and management with the motivation to solve the most challenging sustainability problems [6]–[9]. The rise of Big Data and advanced analytics have contributed to the recent surge in this effort [10], [11].

The advent of the Big Data era brings scopes and opportunities for computational sustainability research regarding multi-dimensional challenges, complexities of the problems, scalability issues, computational efficacy, and impact towards overarching motivation [12]–[14]. This abundance of data not only comes with ample information and potential knowledge but also offers a scientific approach driven by multi-source data and enhances the efficiency and accuracy of problem-solving. That is why the growth of extensive multi-dimensional data and computational sustainability are crucial

The associate editor coordinating the review of this manuscript and approving it for publication was Muhammad Maaz Rehan.

to meet the sustainability challenges [12], [15]. They contribute to addressing tradeoffs in scientific decision making, understanding complicated systems, and explaining uncertainties with complex reasoning [16], [17]. CompSustNet, a unique virtual network led by Carla Gomez at Cornell University and supported by the National Science Foundation (NSF) of the United States, establishes on the research, results, and achievements of the ICS (Institute of Computational Sustainability) [1], [2], [18]. It unites and helps more and more scholars, across the domain, use data mining techniques to solve the most complex and pressing problems of this time, such as efficient and reliable energy management [19], [20], healthcare [21]–[23], biodiversity loss protection, addressing issues regarding climate change and environmental collapse [24], [25], poverty eradication [26], [27], meteorology [28]–[30], disaster management [31], [32], and material discovery for renewables sources [33]–[36]. The most compelling aspect of this virtual network– besides making a platform for computational science researchers to put their muscle towards making the world a more sustainable and livable place– is that a new method or solution created to solve one particular problem can be repurposed for another distinct problem.

One of the major attention of computational sustainability research is centered around the question of how we can leverage Big Data accumulated from the smart grid components and raise collective awareness and proactive demeanor towards smart and sustainable energy management [37], [38]. Besides Big Data, the recent advancement of information and communication technologies allows the regime switch from a traditional ''predict (forecast) and provide'' approach to a more flexible and responsive demand-based approach of power system management. The purpose of this approach is to reach several policy targets regarding sustainability, such as reducing carbon emissions, generating power from renewable resources to a certain percentage, smoothing peak demand, assuring a better rate of return on investments, and preventing network overprovisioning [15], [39], [40].

Smart Grid technology facilitates more accurate energy-loss monitoring and more precise control and adaptive techniques by escalating the intelligence and capacity of the energy distribution, as well as the control system, from the central cores to numerous peripheral nodes [13], [41], [42]. On a different note, recent studies showed that IoT is looming as a significant trendsetter in realizing the advancement of information and communication technologies, and analytics at a considerable dimension. IoT enables connecting, monitoring, and controlling the physical objects used in our day-to-day life by extending the web paradigm. It engenders more frequent and impactful human-to-machine and machine-to-machine interactions in everyday life. Smart Grid is one of the recent inclusions in this avenue, realizing the concept of the Internet of Energy (IoE) [43]–[46].

The overarching motivation behind the Internet of Energy (IoE) is assuring a flexible but highly reliable and resilient, cost-effective, and efficient power supply network in the combination of large-scale centralized generators and small-scale renewable sources. IoE can convincingly be defined as a network infrastructure that enables a real-time balance between the local and global generation and storage capability based on the energy demand of the consumer [47]. It allows for a high level of consumer awareness and involvement with the help of advanced analytics. From the functional point of view, IoE, de facto, integrates power distribution, energy storage, grid monitoring, and synchronous and asynchronous communication, as illustrated in Figure 1. This network infrastructure is built on the standard and interoperable communication transceivers, gateways, and protocols. Besides, by taking advantage of widely accepted security and privacy frameworks, it can assure seamless interoperability and broad connectivity. And, by leveraging the power of cloud computing systems, it can promote service virtualization and distribution [48].

To benefit the new entrants and scientists in the domain of smart grid and IoE around the world, the authors of this article decided to take a step back and take a more in-depth look at specific research issues before delving into the IoE integration, challenges, and possible solutions to address these. These research issues are not only studied for long to understand the entire dynamics of energy production, transmission, distribution, and consumptions system but also anticipated to be addressed by IoE in the large scale deployment. In this paper, we primarily discuss the Grid Overview of the United States; Weather and Climate and its impact on the entire energy generation and consumption dynamics; Peak Load Forecasting and its techniques and burgeoning challenges; Variable Renewable Energy, its reliability challenges and how we can take advantage of this variability; Commodity Prices and its criticality; Energy Disaggregation and its impact in consumption awareness; and Generation Expansion and Decision Analysis and trade-offs before addressing IoE integration, and challenges. The article manifests how these research issues are correlated with each other in the energy internet. This qualitative study pursues a process of scientific inquiry that seeks an in-depth understanding of scientific phenomena and its cause and effect in respective contextual settings. It primarily concentrates on answering ''why'' rather than ''what'' of the scientific phenomena and entrusts on the evidence manifested in the literature, in addition to comments and suggestions by the domain experts at Oregon Renewable Energy Center (OREC) at Oregon, United States.

The organization of this article is as follows. Section II presents an overview of the United States energy grid. Load forecasting is outlined in Section III, highlighting the impact of weather and climate and state-of-the-arts forecasting techniques. Section IV features the penetration of renewable energy, investigating the variability of renewables and the effect of commodity prices. Section V delves into understanding energy consumption and explores energy disaggregation techniques and generation expansion decision analysis. In section VI, we dissect our discussion on IoE into IoE architecture, broader impact, challenges, computational

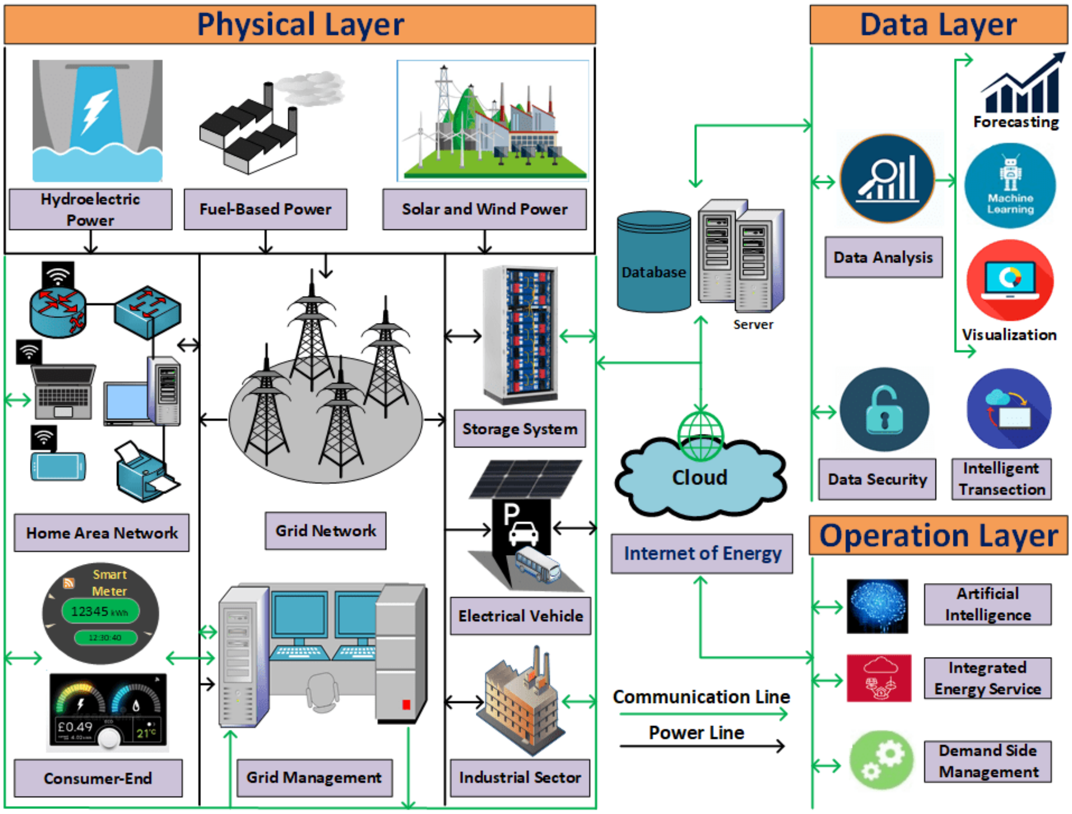

FIGURE 1. Functional layers of IoT application, accumulating physical, data and operational layers with communication and power lines.

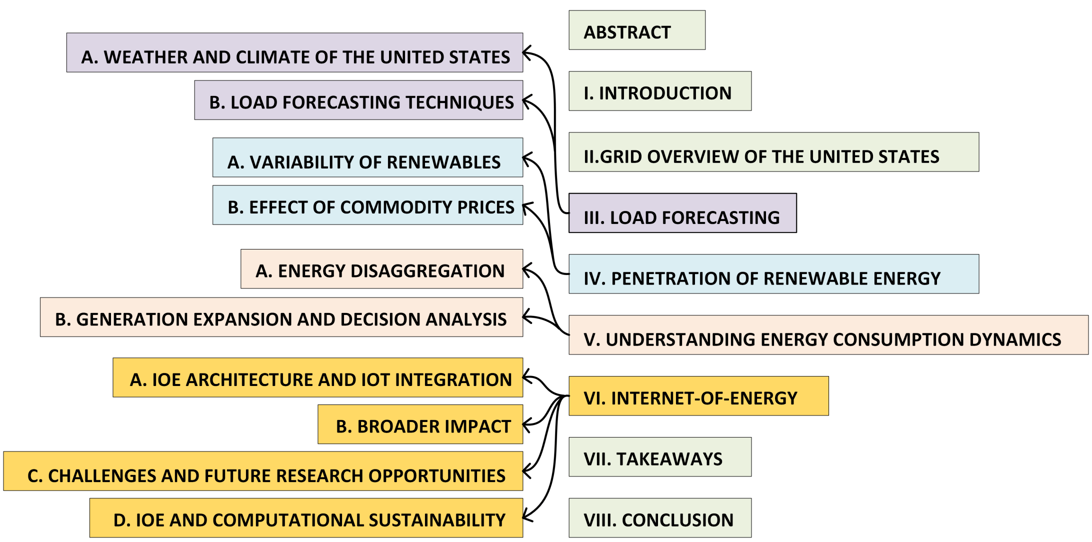

FIGURE 2. Information flow of each of the aspects in this paper.

sustainability and IoE, future works, and opportunities. Considering the breadth of the article, Figure 2 summarizes each of the sections and subsections to help the reader navigating concepts and research issues discussed in this paper.

II. GRID OVERVIEW OF THE UNITED STATES

With the evolution of the energy industry, utility companies- for the very first time in the United States- adopted the joint operations in order to share the peak coverage and backup power in the 1920s after a more-than-fifty-years-adherence

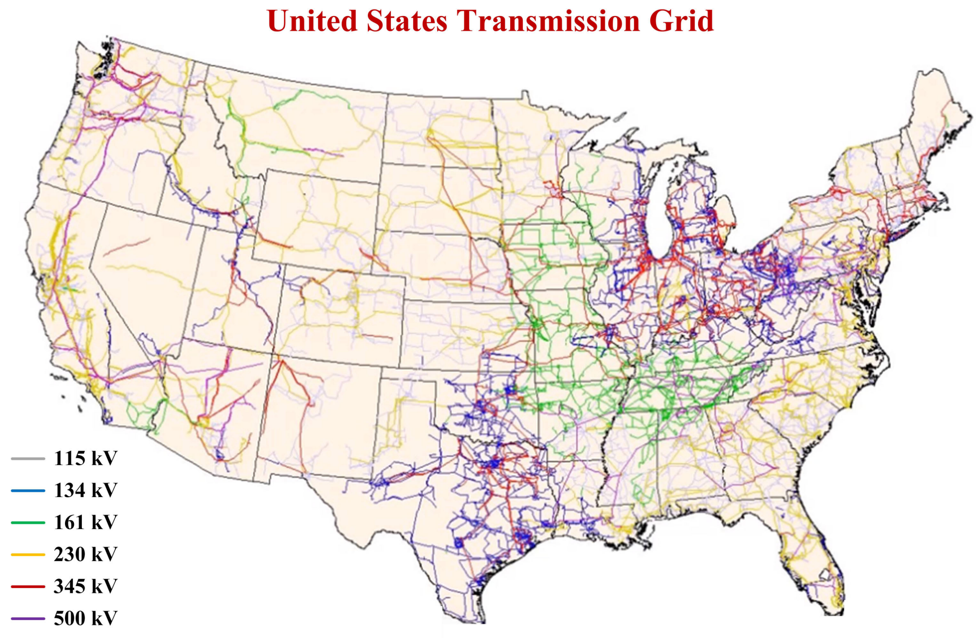

FIGURE 3. United States synchronous grid of 186, 411 miles.

to the conception electric energy needs to be produced near the device or service requiring that particular energy. Then, in this regard, the Public Utility Holding Company Act was passed in 1934, realizing the electric grid of the United States with outlined restrictions and regulatory oversight of operations. Later on, to date, the Energy Policy Act of 1992 and the Energy Policy Act of 2005 are considered as the stepping stone of the modern electric grid of the United States [49]–[51]. The first one granted the electric generation companies open access to the transmission line network and initiated competition in power generation as opposed to vertical monopolies, where generation, transmission, and distribution were administered by a single authority [52]. The later one promoted the alternative energy production and greenhouse emission free cutting-edge technologies with incentives and loan guarantees [53], [54].

United States interconnects are synchronized at 60 Hz, unlike those of Asia and Europe operate at 50 Hz. The interconnects in the United States are tied to each other either via DC ties (HVDC power transmission lines) or with VFTs (variable frequency transformer), allowing a controlled flow of energy, and at the same time, isolating the each side's independent AC frequencies functionally. The advantages of having synchronous zones consolidated by the utility grid include pooling of generation, pooling of load, common provisioning of reserves, opening of the markets, and collective assistance in the event of interruptions [55]. On the contrary, the possibility of repercussions (like a chain reaction) across the entire grid, if any problem happens in one part, is a certain threat in the case of synchronous grid [56]. The United States synchronous grid is presented in Figure 3, consisting of about 186,411 mi operated by more than 500 companies [56].

The United States utility electric grid is expected to confront certain challenges in the years to come posed by the modern power generation and distribution systems. Reference [57] identified the challenges and the reasons behind it, and contemplated the possible solutions of them in a comprehensive fashion. In a nutshell, the challenges- categorized there based on the severity and impact- are cyber threats and attacks in utility, challenges in transmission system, from aging infrastructure, regulatory challenges, challenges in workforce, challenges from distributed generation and mixed sources of generation, challenges from the intermittent nature of renewable energy sources, challenges from microgrid and smart grid, challenges from communication, challenges from energy storage systems and evolving technologies, and challenges from system complexity and cost issues. Here, their feasible solutions- with detailed explanation and depiction- include cyber security measures, upgrading the system infrastructure, new business strategies, compensating for the intermittency of renewables (concentrated on the law of large number, power of prediction, incentivizing energy production at the right time and place), and the proper use of energy storages. Later, they presented the severity and frequency analysis for each of the challenges in the United States context.

Super Grid, commonly known as Mega Grid, aims to considerably advance the transmission capacity with a particular policy that include effectively enabling the renewable energy industry to sell electricity to distant markets, increasing intermittent energy source usage by distributing them across

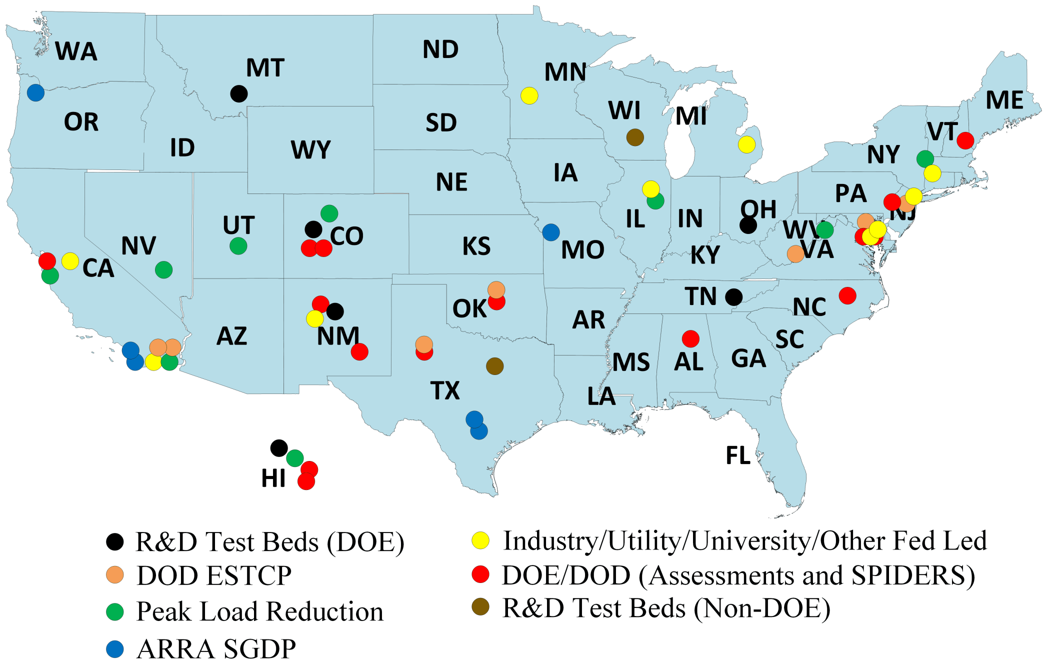

FIGURE 4. Geographical distribution of Federal MG assessment and demonstration projects in the United States.

the extensive geological region, and trimming the congestion that averts the electricity markets from succeeding. Then, to promote the concept of integrating localized generation into the centralized generation-based distribution, microgrid technology has been introduced. In 2010, Office of Electricity Delivery and Energy Reliability of the US Department of Energy (DOE)– incorporating the final amendment made in 2017– proposed the definition of Microgrid (MG) as it is a group of interconnected loads and distributed energy resources within clearly defined electrical boundaries that acts as a single controllable entity with respect to the grid, can connect and disconnect from the grid to enable it to operate in both grid-connected or island-mode, considering that a remote MG is a variation of an MG that operates in islanded condition [58]. DOE started their major MG program in 2008, initiating with nine RDSIs (Renewable and Distributed Systems Integration) depicted as green points in Figure 4. These projects– with $100M budget equally financed by the DOE and co-funders– aimed to achieve a minimum 15 peak load reductions. The red points illustrate the projects under SPIDERS program (Smart Power Infrastructure Demonstration for Energy Reliability and Security) launched in 2010. The SPIDER program was introduced to meet the fact that almost all the military bases are located in the resource-limited setups inadequately served by the utility grid where highly reliable power is often required. The first three among this effort are Hickam Air Force Base and Camp Smith in Hawaii, and Fort Carson in Colorado. Though the federal programs are the cardinal efforts to the United States MG research in the early stage, private sector activities in the recent years are noteworthy. The large commercial organizations, such as educational campus, medical institutes, and industrial sites, focused on building self-generation projects. In a dramatic fashion, these efforts made 2011-2012 a pivotal year in MG development for the United States. DOE defined the next-generation MG system with certain specific goals expected to achieve by 2020. The goals are to establish MG systems of a capacity<10 MW in commercial-scale capable of curtailing outage time of required loads by more than 98% at a cost comparable to the nonintegrated-baseline solutions, while offering more than 20% improvement both in emission reduction and energy efficiency. Research shows control and protection are the significant challenges to meet this goal [58].

According to North Carolina Clean Energy Technology Center, in 2017, 37 states– well-reflected by 82 relevant bills introduced in the different regions of the United States– endeavored to modernize electric grid to make it more interactive and resilient. These endeavors include deploying advanced metering infrastructure, smart grid, and offering time-varying rates for the residential consumers. Recently, in August 2018, a policy paper has been published with five major recommendations to modernize the United States electric power grid. It points out making the federal permit process more efficient and effective for advanced energy projects, inspiring grid planners look at the alternatives to making investment in transmission, promoting energy efficiency and allowing energy storage to compete with the additional generation, allowing big consumers to adopt their own source for electricity, and letting both the consumers and

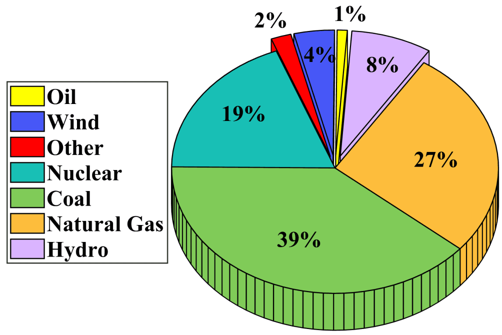

FIGURE 5. Distribution of generation from different sources in the United States in 2017.

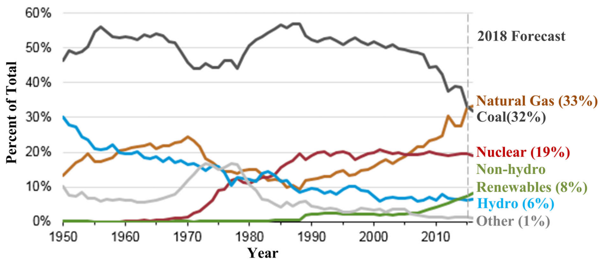

FIGURE 6. Annual share trend in United States for electricity generation by source from 1950 to date.

utilities to take advantage leveraging the cloud computing facilities [59], [60].

21st Century's electrical grid in the United States is blessed with smart grid technology that leverages the power of two-way communication and distributed-intelligent devices, assuring improved delivery network. With the objective to enable utilities predict their demand efficiently and involve customers in smart-time-of-use-tariff, smart grid development was facilitated in the United States by Energy Policy Act of 2005 and Energy Independence and Security Act of 2007. A recent surge has been observed in the literature regarding different systems and aspects of smart grid. We can categorize these research into three clusters: infrastructure system research, research on the management system, and research on the protection system. The infrastructure system research are aiming to meet advanced electricity generation, uninterrupted delivery, and intelligent consumption; smart information metering, monitoring, and management; and last but not the least, advanced interactive communication technology. Research on the management system- leveraging advanced machine learning, optimization, game-theoretical approaches- include improving energy efficiency, demand profile, cost, utility, and carbon emission. Most of the research on protection systems focus on grid reliability, failure, and privacy protection, security services [61], [62].

In 2017, Utility-scale facilities generated about 4.03 trillion KWh of electricity in the United States. Among them, majority (about 67%) of this generation was from fossil fuel, 19% was from nuclear energy, and roughly 14% was from renewable energy sources. Apart from that, United States Energy Information Administration reckoned an additional generation of 24 billion kWh from the small-scale solar photovoltaic systems, such as small-scale solar photovoltaic systems that are installed on building rooftops, in 2017 calendar year [63]. Figure 5 illustrates the distribution of generation from different sources. Then, Figure 6 shows the annual share trend in United States for electricity generation by source from 1950 to date and Figure 7 depicts the evolution of the generation mix contributing to the United States electricity generation over the time. The generation mix is highly affected by the resource availability of the particular state. The following figure (Figure 8) illustrates the net generation distribution of electricity by type and states [63].

This varying-nature of resources with time and region, along with other commercial factors, have a predominant influence on the tariff. In 2006-2007, average electricity tariff in the united states- though it varies state to state- was higher than Canada, Australia, France, and Sweden, but relatively lower than that of the United Kingdom, Germany, and Italy among the developed countries, and the average residential bill was noted \$100 per month. A statistics of 2008 shows the United States average electricity tariff was 9.82 Cents/kWh, varying from 6.7 Cents/kWh (in West Virginia) to 24.1 Cents/kWh (in Hawaii). Compared to that, data of October 2018 reveals that the average electricity tariff is 12.87 Cents/kWh, varying from 9.11 Cents/kWh (in Louisiana) to 32.46 Cents/kWh (in Hawaii). It demonstrates a 0.5% rise in price compared to 2017 [64].

United States grid is organized administratively in the following order: Reliability organizations; Balancing authorities that include independent system operators, regional transmission organizations, and vertically integrated utilities; Generators comprised of utilities and independent power providers; and Load Serving Entities [65]. NERC (North American Electricity Reliability Corporation) is the not-for-profit organization to assure reliability of the north american bulk power system. They are in charge of monitoring and enforcing compliance with standards, besides being the authority of the data source for system reliability and system failure. Since the United States power system is interconnected physically, any problem occured in one area may influence other interconnected systems, and NERC is centrally responsible to take care of it and assure reliability. Besides, NERC's major responsibilities include working with all the stakeholders to develop well-defined standards for power system operation, monitoring; and enforcing compliance with those standards, assessing resource adequacy, and providing educational and training resources as a part of accreditation program to ensure power system operators remained qualified and proficient in operation. NERC oversees eight regional reliability entities. The sub-parts of NERC are WECC (Western Electricity Coordinating Council), MRO (Midwest Reliability Organization), NPCC (Northeast Power Coordinating Council), SPP (Southwest Power Pool), RFC (Reliability First Corporation), SERC (SERC Reliability Corporation), FRCC (Florida

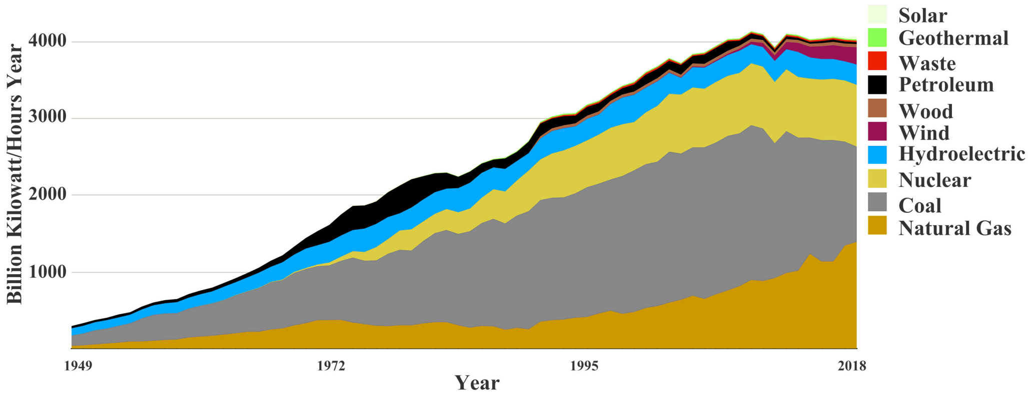

FIGURE 7. Evolution of the generation mix contributing to the United States electricity generation over the time.

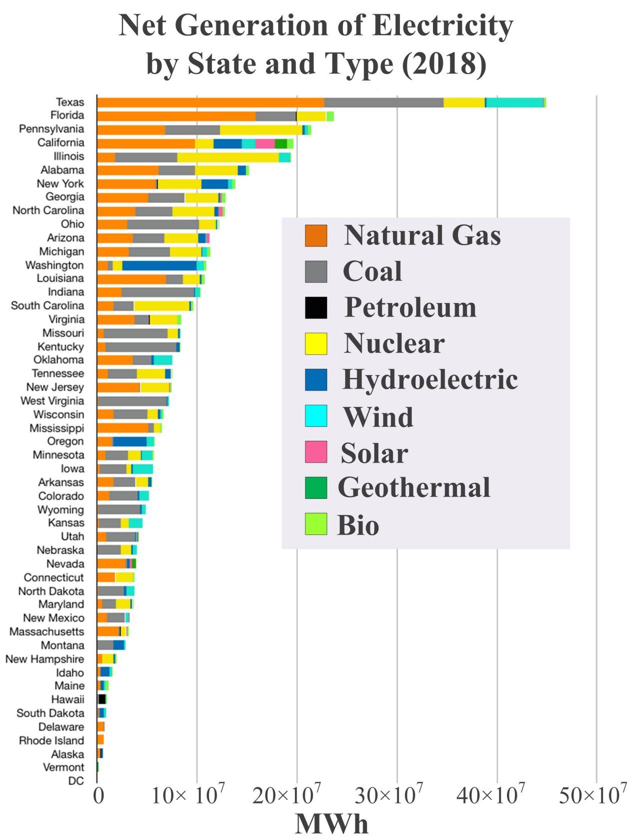

FIGURE 8. Net generation distribution of electricity by type and states in the United States.

Reliability Coordinating Council), TRE (Texas Reliability Entity). Traditional wholesale electricity market, which are vertically integrated so that they own and are responsible for the generation, transmission and distribution systems to serve the electricity consumers, exists in the south east, south west, and north west. In other part of the United States, the power systems are managed by Independent System Operators (ISO) and Regional Transmission Organizations (RTO), facilitating open access to transmission. In particular, ISO operates the transmission system independently, and foster competition for electricity generation among the wholesale market participants [66], [67]. The extent of ISOs are visualized by Figure 9.

Each of the ISOs and RTOs have energy and ancillary services markets in which buyers and sellers can bid for or offer generation. These ancillary services include reserves, frequency regulation (grid needs to be operated at 60Hz in the United States), and demand response. Though the vital sections of the United States operate under more traditional market structures, two-thirds of the nation's electricity load is served in RTO regions [66]–[68].

III. LOAD FORECASTING

A. WEATHER AND CLIMATE OF THE UNITED STATES

Weather and climate have an impact on both sides of the electricity industry- it drives the energy consumption demand, affects most of the noncombustible generation, and has an effect on electricity transmission and distribution. Before the expository narratives on the impacts, challenges, and state-of-the-art solutions, we need a proper understanding of three factors and its interpretation: weather, climate, and extreme weather. Here, temperature change, precipitation, humidity, and wind speed are interpreted and interchangeably used as the weather. Climate refers to the average seasonal conditions for a particular geographical area. In our study, extreme weather will include droughts, floods, hurricanes, heat waves, and cold snaps; statistically rare weather events that have cataclysmic impacts. The weather elements that directly affect the demand are as follows: temperature, wind speed, cloud, visibility, and precipitation. For example, the temperature, being allied to wind speed, regulate heating or cooling demand. Besides, cloud, visibility, and precipitation are considered to estimate the level of daylight illumination, therefore affecting the lighting demand. Research shows that each of the attributes of these meteorological elements has weighted sensitivity to demand and the sensitivity weight

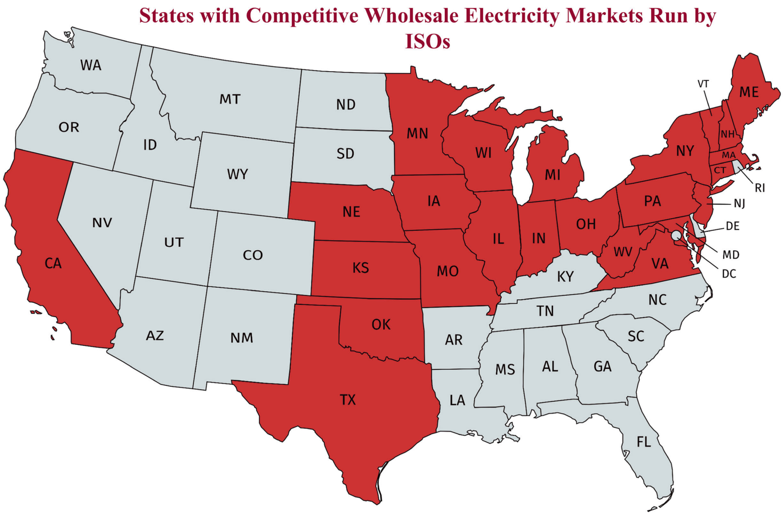

FIGURE 9. Extent of ISOs in the United States.

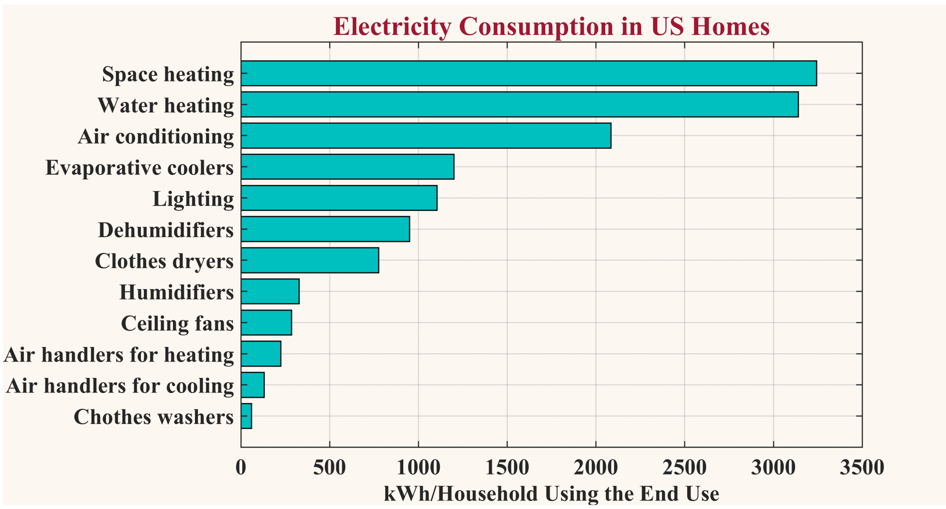

FIGURE 10. Electricity consumption in US homes during 2018 (kWh/year).

varies with the geographical location of the representative region. To compare the impact of weather elements, the meteorological elements are scaled down to three specific factors: effective temperature, cooling power of the wind, and rate of precipitation [69]–[71].

Figure 10 shows why the demand side of the energy system is related to the weather and climate which is well-reflected by the electricity consumption in US homes during 2018 (kWh/year). As has been observed from this figure, the cardinal electricity consumption in US homes is for space heating in wintertime and air conditioning in the summertime. Furthermore, the average length of wintertime in the US even intensifies the case. Besides, lighting and space heating engender a considerable amount of electricity consumption. Though lighting over the year is correlated with the weather and can be influenced by other factors, space heating in the wintertime and air conditioning in the summertime primarily depend on weather and climate. The relationship of Demand and Temperature is parabolically nonlinear, and the rationale behind that is when the temperature is low, it requires heating demand, and with the temperature rise the heating demand decreases, and there is a sweet temperature zone, in between 65F to 70F, when we do not need any heating and cooling. Again, after that point, we need cooling demand, and it increases with the rise of the temperature. Such parabolic nonlinearity encouraged us to study the impact of weather parameters on electricity demand separately: heating and cooling demand; in particular, using the concept of heating degree days and cooling degree days.

A degree day compares the ambient temperature to a standard temperature of 65F. The more severe the temperature, the higher the number of degree days. A higher number of degree days will require more energy for space heating or cooling. Figure 11 classifies the United States based on heating degree days [72], [73]. Here, the darker the red, the more the heating is required in the winter time. As has

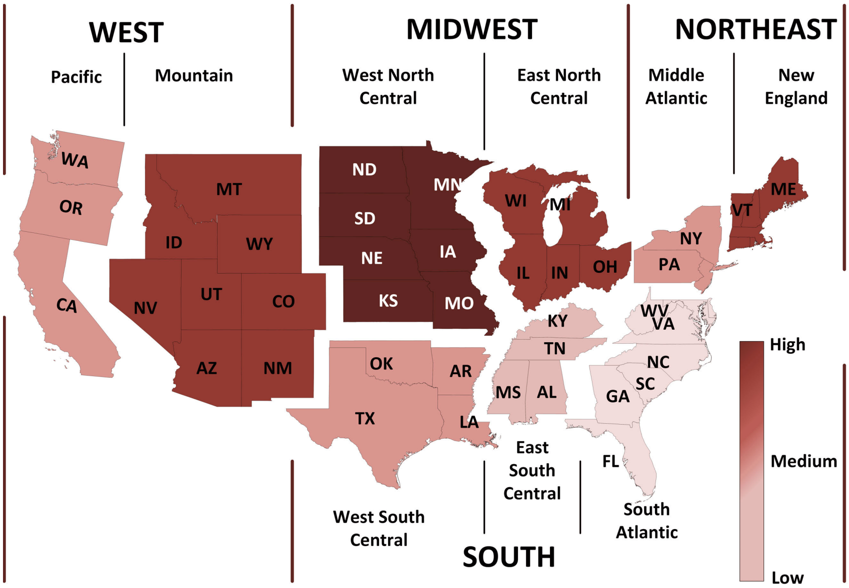

FIGURE 11. Region classification of the United States based on heating degree days.

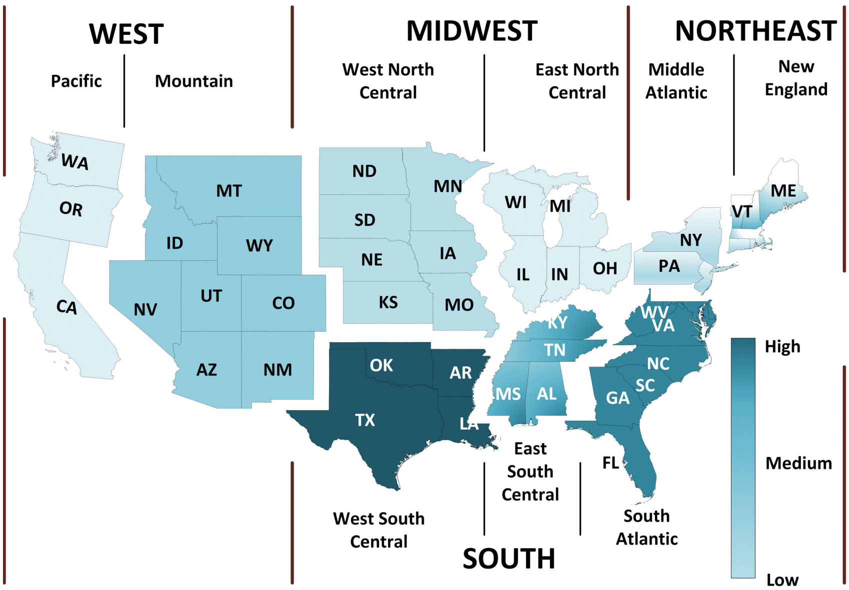

FIGURE 12. Region classification of the United States based on cooling degree days.

been observed from the Figure 11, the west north central region of the United States, which includes North Dakota, South Dakota, Minnesota, Nebraska, Kansas, Iowa, and Missouri, requires most of the heating degree day demand. Figure 12 depicts the cooling degree day demand distribution over the United States [72]. Here, the darker the blue, the more the cooling is required in the summertime. It is evident from the figure that west south central region, which includes Oklahoma, Arkansas, Texas, and Louisiana, requires most of the cooling degree day demand in the summertime, and conversely, east north central and west north central region exhibit the lowest cooling degree day requirement in summer.

There has been experiencing a continual net temperature increase in the United States over the years, so the electricity demand has been. The annual average temperature over the contiguous US (48 states excluding Alaska and Hawaii) has increased by 1.2F for the period 1986–2016 comparative to 1901–1960 and by 1.8F based on linear regression for the period 1895–2016. Both surface and satellite data consistently support the fact of rapid warming since 1979. Furthermore, Paleo-temperature evidence reveals that recent decades

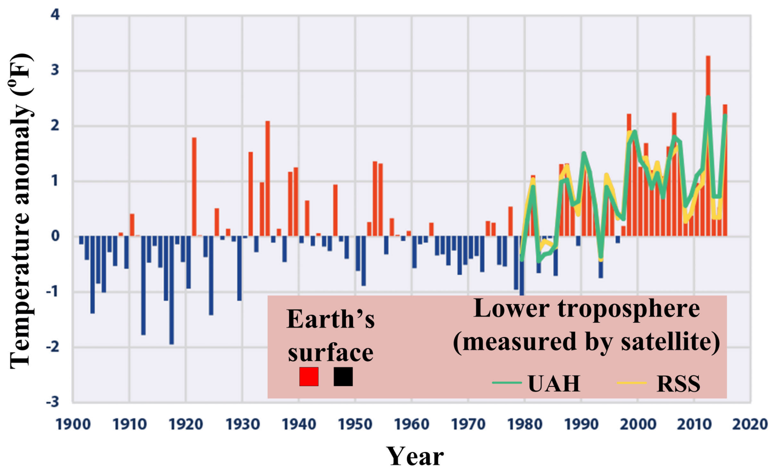

FIGURE 13. Temperature anomaly from 1901 to 2015 in the contiguous 48 states.

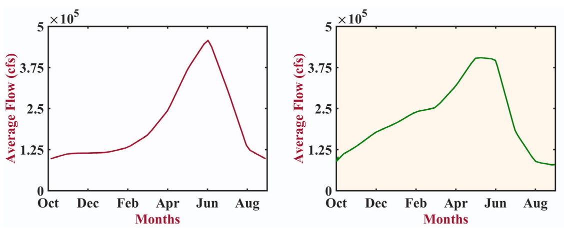

FIGURE 14. Anomaly between a normal atmospheric condition and forecasted catastrophic condition in the dynamics of hydropower-based system.

are the warmest of the preceding 1,500 years. As a result, the number of high-temperature records placed in the previous two decades considerably outstrips the number of low-temperature records. However, the Dust Bowl era of the 1930s remains the peak period for the extreme heat. Moreover, the annual average temperature over the contiguous US is projected to ascend about 2.5F for the period 2021–2050 corresponding to 1976–2005 in all RCP scenarios. In particular, much higher rises are expected by late century (2071–2100): 2.8–7.3F in a better case and 5.8–11.9F in the exacerbated scenario [74]. Figure 13 illustrates the temperature anomaly from 1901 to 2015.

Since population distribution is not uniform over the entire United States and population density has a strong impact on energy consumption, the US EIA (Energy Information Administration) use population-weighted degree days to model and project energy consumption. Mathematical modelings are involved in incorporating the impact of weather and climate on national electricity consumption. Reference [75] contributed to model the effect of summer temperature on electricity demand and consumption. This model includes three aspects: estimate the impacts of unusual weather (such as heat wave), consider the effects of governmental policies, assess the impacts of projected climate change on energy demand and supply. This model can be described as (1):

$$E = a_0 + a_1 CDD + a_2 CDD_{(-1)} + a_3 Y_1 + a_4 Y_2 - a_5 H \tag{1}$$

Here, E, CDD, $CDD_{(-1)}$, H, Y_1, and Y_2 stand for weekly national electric output in billions of kWh, weekly national cooling degree day total, previous week's national cooling degree day total, holiday factor, penultimate year growth factor, and last year growth factor. This is one of the earliest mathematical modeling that considers weather and climate change into account shows R^2 of 0.96 and RMSE of 0.544. The recent models investigate the additional explanatory content of the weather and climate [75], [76]. Reference [77] incorporates residual temperature, along with specific humidity, in forecasting weather-dependent warm-season electricity demand. Apart from that, A hierarchical Bayesian regression model is presented in [77], [78] to predict summer residential electricity demand across the United States.

The change of weather and climate directly impacts the variable renewable energy productions (hydropower, wind, and solar-based generation) besides that of conventional fossil fuel. A study shows that the north-west region of the United States confronts most of this challenge since Washington, Oregon, and Idaho essentially depends on renewable energy sources, particularly on hydropower. Though the blessings of immense hydropower resources assure extremely low carbon generation in these states, they experience a significant cut in their generation during drought time. Federal Columbia River Power System operated by Bonneville Power Administration, which extends through Canada, Montana, Idaho, Washington, and Oregon, is an excellent example to study the impact of weather and climate in a hydropower-based generation. Collectively, it is about 23GW of hydropower capacity and meets 60% of the regional demand. Unlike the hydropower systems in the east coast, this system is snowmelt-dominated where most of the precipitation occurs as snow is stored throughout the winter time. Then, in the summertime, when the snow starts melting as water, and coincidently the demand of the electricity generation gets high, it helps in gearing up the generation. In recent years, the dynamics of this hydropower-based system, such as the amount of precipitation, the amount of melted water,

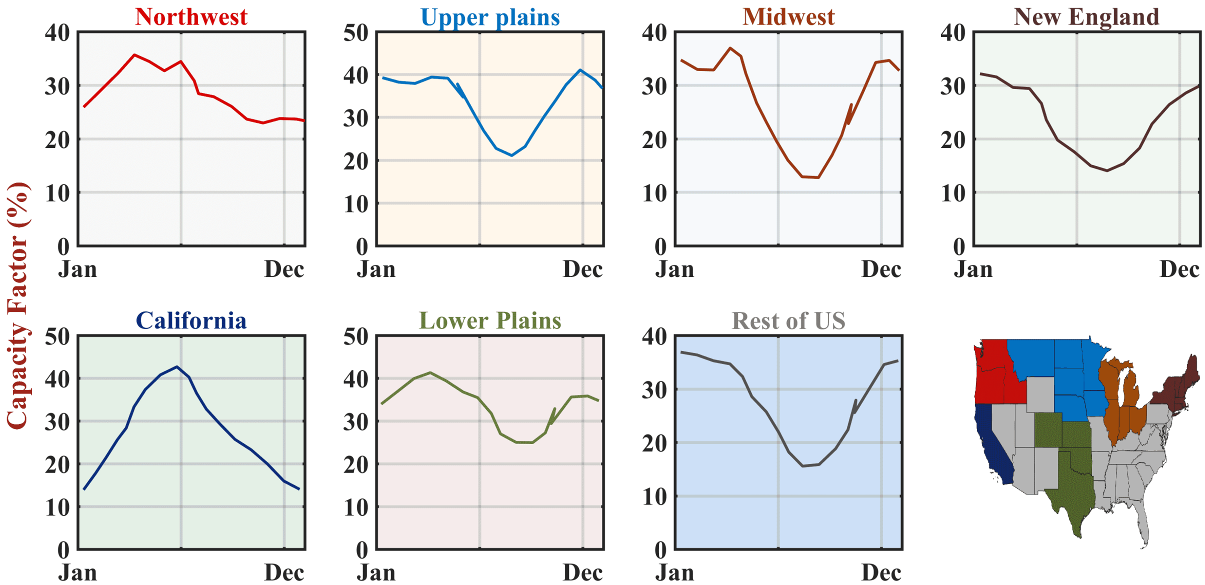

FIGURE 15. Patterns of seasonal wind variability in different regions of the United States.

and the timing of water melting, has been affected by climate change.

Figure 14 shows the anomaly between a normal atmospheric condition and the forecasted catastrophic condition (due to climate change) in the dynamics of this hydropower-based system. As has been seen for the normal condition, a snowmelt-dominated system naturally boosts up the resource flow to generate electricity when the demand is maximum [79]–[82]. Here, we observe when the electricity demand is relatively low in the wintertime, the flow is low as the snow precipitation is getting stored in the mountains and not contributing in the streams. Then, in the early summer, when the snow is melting down, we experience a sharp increase in the flow. In the middle of the summer, when the electricity demand is maximum, the melt rate is maximum, we experience the peak flow. Then, again with the decrease in the melting rate, the flow gradually decreases in the fall, coincidentally with the drop in the demand. In the catastrophic condition, we expect to experience higher temperature, which will result in less snow storage and more melting water in the flow during wintertime. Consequently, we will experience higher stream-flow in the winter, resulting in more generation in the time when the demand is not high. Whereas in the early summer, it will undergo a less sharp increase in the flow, and the peak flow in the middle summer is significantly dropped down, and eventually, we will not get the necessary flow for power generation when the demand is maximum. In short, climate change will result in less precipitation falls as snow, more falls as rain (no winter storage) because higher temperatures initiate spring snowmelt earlier [83].

The weather and climate engender variability in wind energy. Research shows regional climate is crucial in terms of resource development because, in the United States, there are some parts of the country which are significantly more wind-rich than the others. A considerable change has been observed in year-to-year wind power generation due to the climate and weather variability, resulting in difficulty to plan around. The historical wind speed distribution for a particular region can help to plan the energy generation mix of that specific region; however, inadequate historical wind data to figure out the distribution and the prospective computational complexity are the major challenges. Figure 15 depicts the pattern of seasonal wind variability in different regions of the United States. Here, the dotted straight line illustrates the yearly median of the wind-energy generation capacity factor for each of the geographical regions. It is evident that the upper plains (dark blue) and the lower plains (brown) have the high average capacity factor; hence they can be considered the perfect area for the wind energy generation. Besides, this figure implies how the geographic wind-generation capacity factor pattern overlaps with the electricity demand patterns. On top of that, like the localized heating and cooling requirement, the wind flow and volume follows a diurnal pattern for a particular geographical locality [84].

Most of the assessment and planning regarding solar energy systems assume that the amount of solar radiation on the Earth's surface is more-or-less constant over the years. However, due to change in climate, along with air pollution as a factor, solar resources will inexorably experience substantial decadal changes. Several research confirms long-term changes in dimming and brightening quantity. The prospective aberrant changes in the surface solar radiation projected by the available climate models may unfavorably affect solar power production, including both PV and CSP (Concentrated Solar Power). Apart from the renewables, conventional fossil fuels- besides experiencing the inevitable

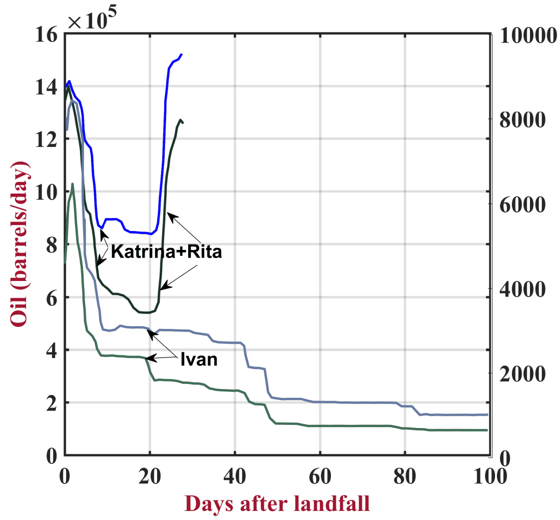

FIGURE 16. Impact of Hurricanes on oil and natural gas production in the United States.

TABLE 1. Statistically Significant Blackouts' Cause Categories in the United States.

	Mean size in MW	Mean size in Customer	% of events
Earthquake	1,408	375,900	0.8
Hurricane/ Tropical Storm	1,309	782,695	4.2
Ice Storm	1,152	343,448	5
Wind/Rain	793	185,199	14.8
Other External Causes	710	246,071	4.8
Other Cold Weather	542	150,255	5.5
Operator Error	489	105,322	10.1
Fire	431	111,244	5.2
Equipment Failure	379	57,140	29.7
Tornado	367	115,439	2.8
Supply Shortage	341	138,957	5.3

impact of weather and climate change- exhibit strong seasonality in availability and cost, resulting in relatively less expensive in the winter time and more expensive in the summertime [85].

Extreme weather condition has a severely adverse effect on fossil fuel production. Figure 16 illustrates the impact of extreme weather condition, in particular, Hurricanes on oil and natural gas production. It shows how the production in those regions experienced a sharp decline just after the incidents. It is indeed notable how Hurricane Frances made a significant loss in oil refinery, and Hurricane Katrina came with an unprecedented loss in the natural gas refinery. The loss due to the strike of Hurricane Dennis in the natural gas refinery is also striking. Table 1 summarizes the crucial events that caused power outages in the United States from 1984 to 2006 [85]. We observe significant research in effort to reduce storm-related outages in the literature. These mostly suggest tree-trimming schedules, undergrounding distribution and transmission, implementing smart grid improvements, distributed generation, reliability-centered maintenance regulations, and mutual assistance agreements to mitigate the impact of extreme weather condition.

TABLE 2. Impact of Weather Elements in Electricity Demand and Generation.

Weather Elements	Demand	Generation
Temperature	***	**
Wind Speed	**	***
Cloud	*	***
Visibility	*	*
Precipitation	**	**

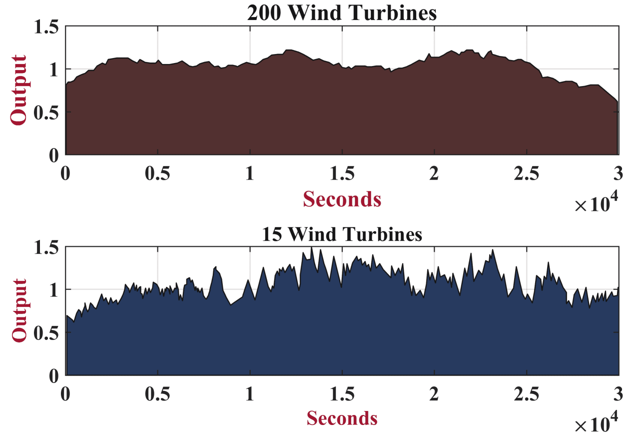

FIGURE 17. Variation in wind energy generation output for 200 and 15 wind turbines placed in dispersed positions.

Table 2 summarizes the impact of weather elements in electricity demand and generation. Here, the number of asterisks indicates the degree of impact in the corresponding domain of concern: three asterisks symbolize profound impact, two asterisks express moderate impact, and a single asterisk implies it somehow has an impact.

One interesting challenge in power system planning, particularly in a step towards replacing baseload (coal generation) with the variable renewable energy like wind and solar, is how to combine different variable renewable energy sources in such ways so that it is possible to complement each other and reduce the inherent uncertainty comes from the renewable energy sources. Specifically, how can we place renewable energy projects to take advantage of less covariance when they are producing energy? The implementation of statistical law of large number can be helpful. Figure 17 depicts the scenario of wind energy generation output normalized to mean for 200 and 15 wind turbines placed in dispersed positions [85].

As can be seen, the bottom one shows more zigzag (which means more variability and uncertainty) along with the lesser mean value (though the mean value is self-evident) compared to the top one. This analysis provides an insight that the curve can even be smoother with high output mean value if we place 500 wind turbine in different places. The insight from the law of large number also applies for the solar power generation aggregation, implying the more it integrates with the solar plants located in different places, the more predictable the generation curve becomes. One immediate

TABLE 3. Applications of Different Load Forecasting in Energy Workflow.

Operations	VSTLF	STLF	MTLF	LTLF	VLTLF
Producing, purchasing and selling electric power	✓	✓	✓	✓	✓
Transmitting and distributing electric power	✓	✓	✓	✓	✓
Fuel Allocation		✓			
Inrush current stabilizer	✓				
Security assessment and analysis	✓	✓			
Maintenance scheduling			✓		
Searching for renewable resources					✓
Environmental policies planning					✓
System planning				✓	
Economic dispatching	✓				
Load dispatching coordination			✓		
Staff recruitment				✓	✓
Optimal generator unit commitment		✓			
Price deciding to meet demand with fixed capacity			✓		
Sensitivity analysis of electrical equipment	✓				
Load flow estimations		✓			
Scheduling construction of new generating capacity					✓

question, in this regard, can be how far apart solar plants need to be placed to gain the advantage in predictability from the law of large numbers because only building a number of wind turbines or solar panels (right next to each other) cannot guarantee optimal generation. Research shows we experience more covariance with the lesser distance between each plant-site. And after a certain range, we experience more-or-less constant covariance. This insight can be helpful in deciding the minimal distance to get the optimal output.

B. LOAD FORECASTING TECHNIQUES

Load forecasting is a technique used by the electricity providing companies to predict the required energy to attain a dynamic demand-supply equilibrium. The predictive accuracy of load forecasting is of profound importance for the operational, as well as managerial loading, of a utility organization. Load forecasting, precisely peak load forecasting, is an integral and indispensable process in strategic planning and efficient operation of electric utilities. Primarily, reliability and low cost are the two significant motivation behind load forecasting since electric utility is expected to operate without having a failure in continually balancing supply and demand, and within as low as possible cost. In recent years, to mitigate the environmental challenges and promote renewable resources in the generation infrastructure, lowest possible emission is considered as one of the crucial factors in predicting both the load magnitude and geographical location of the load in a certain planning horizon. Assuring reliability is a multi-scale challenge that involves balancing between supply and demand on a second-to-second, minute-to-minute, hour-to-hour, daily, seasonal, and all the way up to years and decade. Frequency regulation is one of the most obvious reliability issues that require active dynamic management. It is known that different power systems may have different frequencies, and in the United States, all the power systems operate at 60 Hz, unlike in Europe and Asia at 50 Hz. If we do not stably balance between demand and supply, the frequency will increase or decrease: If the demand is greater than the supply, the frequency increases, and if the supply is greater than the demand, the frequency decreases. If it deviates considerably away from 60 Hz, we may have a grid-scale failure. Hence, to assure reliability, it requires to continually adjust the availability of supply to match it to demand within a certain range and keep frequency close to 60 Hz [86], [87].

From the aspect of the duration of the planning horizon, load forecasting can broadly be classified into five categories: VSTLF(very short-term load forecasting that ranges from few minutes to an hour ahead), STLF (short-term load forecasting that concentrates on hourly forecasts for one day to one week ahead), MTLF (medium-term load forecasting that ranges from few months to one year), LTLF (long-term load forecasting that includes from one year to five years), and VLTLF (very long-term load forecasting that includes ten years ahead) [88]. In short, VSTLF and STLF are mostly required for balancing operation of the grid system. Besides, they help in trading strategies for the day-ahead electricity market. MLTF is essential for planning major tests, commissioning different events, determining outage time for plants and key parts of equipments, besides the trading strategy. On the other hand, LTLF and LTLF are crucial for resource planning for the power system, and the subsequent price evaluation of the energy contracts. Table 3 points out the possible applications of different forecasting based on time horizon.

Long term load forecasting conveys design implication in system planning. One of the critical elements of system planning in most power systems is the diversity of the resources. It requires different levels of flexibility with different types of generations so that it can meet the electricity demands that continually changes on an hour to hour, week-to-week, and seasonal basis that entails some resources which are flexible. It won't be wise to have all the resources flexible since they are considerably costly compared to the other options. That's why we need an optimal balance between the resources that are inexpensive but not flexible (such as coal and nuclear), and flexible but more expensive (such as natural gas and oil). Another key element in system planning is redundancy. It is

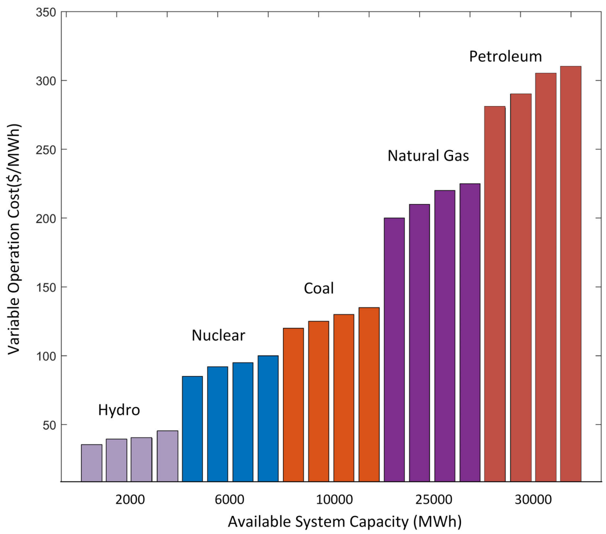

FIGURE 18. **Trade-off in flexibility of resources, though we need flexibility in resources to address variability in demand, flexible resources are costly.**

a very pronounced trade-off in the infrastructural planning and engineering that increase in redundancy comes with an increase in reliability, but also increases the cost. Therefore, it is an optimization challenge to investigate up to how much redundancy it is worth investing to secure a balance between the cost and reliability. Figure 18 explains the scenario of flexible and not flexible resources where the horizontal-axis represents cumulative quantity supplied in MWh, and the vertical-axis means the marginal cost in $/MWh. As has been seen, oil, in general, is costly and suggested not to use until it is of absolute necessity [89], [90].

Thermal power plants can typically be categorized into three levels: baseload, shoulder load, and peaking. Shoulder power plants lie in an intermediate category that can ramp up a bit but not enough to consider it a peaking power plant. Thermal power plants can be classified in another way: by its fuel type such as coal, natural gas, nuclear, and oil. Fuel type is pertinent to the capacity of the plant. Capacity factor, the fraction of installed capacity and of getting used throughout the year, is another parameter to distinguish thermal power plants. Capacity factor ranges between one and zero, and the higher value indicates more usage throughout the year. The value close to one implies that they are online almost every hour of every day throughout the year except some days when the plants are shut off for maintenance purpose. On the flip side, the peaking power plants, such as oil and natural gas power plants, shows capacity factors close to zero, indicating seldom usage in generation-flow [91].

Addressing the reliability and redundancy trade-off mentioned before, system planners optimize it by building enough plants to cover future peak demand plus a 15% reserve margin. Reserve margin is the ratio between the difference of total available capacity and peak annual load to the peak annual load as shown in (2).

$$ReserveMargin = \frac{AvailableCapacity - PeakAnnualLoad}{PeakAnnualLoad} \tag{2}$$

The load forecasting techniques can broadly be clustered into nine categories as far as the mathematical approaches are concerned: Multiple Regression; Exponential Smoothing; Iteratively reweighted least-squares; adaptive load forecasting; stochastic time series such as Auto-Regressive (AR) model, Auto-Regressive Moving Average (ARMA) model, and Auto-Regressive Integrated Moving Average (ARIMA) model; Auto-Regressive Moving Average with eXogenous terms (ARMAX) models based on genetic algorithms; fuzzy logic; neural networks; and knowledge-based expert systems.

Multiple regression analysis, leveraging the weighted least-squares estimation for each of the factor variables based on the statistical relationship between total load and factors' influence, is the most common technique for load forecasting. References [92]–[94] suggested the fundamental model for the multiple regression analysis as shown in (3).

$$Y_t = v_t a_t + e_t \tag{3}$$

Here, t is sampling time, Y_t is measured total load, v_t is vector of adapted variables, a_t is transposed vector of regression coefficients, and e_t is model error at t. In multiple regression, v_t can be expanded based on the different insights regarding historical metered load, expected distributed generation, calendar effects (day of the workdays, weekends, month of the year, etc), weather data (degree days, wind speed, humidity, light intensity, etc), and economic and demographic drivers. On top of that, though linear dependency demonstrates best results in most of the cases, multiple regression offers select the polynomial degree of influence ranged from 1 to 5.

Then, exponential smoothing, one of the classical techniques used in load forecasting, with a fitting function is used for load forecasting as presented in (4) [93], [94].

$$y(t) = \beta(t)^T f(t) + e_t \tag{4}$$

Here, $f(t)$ is fitting function vector of a process, $\beta(t)$ is coefficient vector, and e_t is white noise. Exponential smoothing can be augmented with power spectrum analysis, as well as adaptive autoregressive modeling, to address the challenges induced by a unique pattern of energy and demand in fast-growing regions.

Iterative reweighted least-squares– through an operator that controls each variable at a time– is used to identify the order, including parameters as well, of the model. It initiates with an optimal starting point determined by the operator, and then, uses the autocorrelation, as well as partial autocorrelation, of the resulting differenced preceding load data to identify a suboptimal model for the load dynamics. In the case of iterative reweighted least-squares techniques, the weighting function, along with the tuning constants and the weighted sum of the squared residuals, form a three-way decision variable to determine an optimal model and the subsequent parameter estimates [93], [94].

Adaptive load forecasting is one of the commonly used techniques in recent days. In this technique, to keep track of the continually changing load conditions, the model parameters are automatically corrected. Here, regression analysis is implemented based on the Kalman filter theory that incorporates the current prediction error and present weather data acquisition programs to estimate the next state vector. To determine the state vector, it not only analyses the most recent measured load and weather data, but also takes the historical data into account, and the mode of operation is facilitated switching in multiple and adaptive regression analysis [93], [94].

Though time series modeling is not a suitable forecasting approach for long term load forecasting because of the frequent unique change in demand pattern in the developed and fast-developing regions, it is one of the most popular methods in short term load forecasting. In simple, time series modeling is initially generated based on the previous data, and then, the future load is predicted based on the model.

The autoregressive model can be adapted to model load profile as follows if the load is considered as the linear combination of previous loads as presented in (5).

$$\hat{L}_k = -\sum_{i=1}^{m} \alpha_{ik} L_{k_{-1}} + w_k \tag{5}$$

Here, m is the order of the model, w_k is random load disturbance, a_{ik} are coefficients tuned from least mean squares algorithm. $\hat{L}_k$ represents predicted load at time k.

In addition, the ARMA (Auto-Regressive Moving-Average) model considers the current value of the time series linearly regarding values from previous periods and previous white noise values. A p and q ordered ARMA model can be represented as (6).

$$\begin{aligned} y(t) = \phi_1 y(t-1) + \ldots + \phi_p y(t-p) + a(t) \\ -\theta_1 a(t-1) - \ldots - \theta_q a(t-q) \end{aligned} \tag{6}$$

In addition, the ARMA model considers the current value of the time series linearly regarding values from previous periods and previous white noise values. A maximum-likelihood approach or a recursive scheme is generally used for parameter identification in ARMA model.

If the process is not stationary, it requires to transform the series to a stationary form first by a differencing operator. An ARIMA (autoregressive integrated moving average) model of order p, q, d can be presented in (7) where the series of p and q ordered autoregressive and moving average component is required to be differenced d times.

$$\phi(B)\nabla^d y(t) = \theta(B)a(t) \tag{7}$$

ARIMA model, using the trend component, is deployed to forecast the growth of the system load.

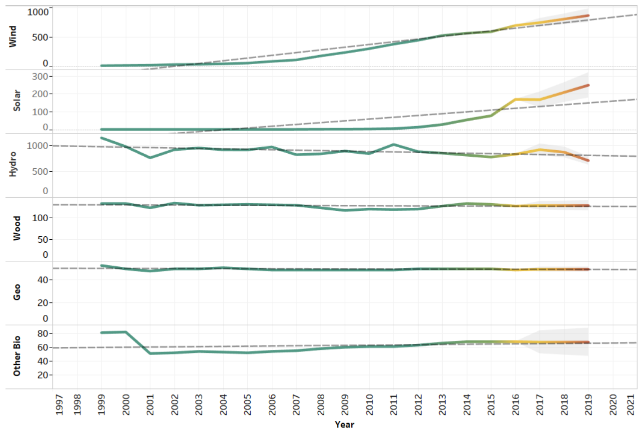

FIGURE 19. Yearly US per capita consumption in kWh by renewable sources from 1999-2016 with trendlines and five year-forecast.

Apart from the time-series-based short-term forecasting, ARMAX, leveraging genetic algorithm, is a popular technique for the long term load demand forecast. Through simulating the natural evolutionary process, it allows the ability to converge towards the global extremum of a complex error surface [93], [94].

Apart from that, leveraging the idea that the fuzzy logic system with a centroid defuzzification can successfully identify and sufficiently approximate an unknown dynamic system on the compact set to arbitrary accuracy, fuzzy logic can be implemented in the case of load forecasting. The fuzzy logic-based forecasting method follows two stages: Training, and then, On-line Forecasting. In its training stage, a $2m$-input and $2n$-output fuzzy-logic based forecaster are trained using the metered historical load data to generate patterns database and fuzzy rule base patterns database and a fuzzy rule base from first-order and second-order differences of the data. After the training stage, it will be connected with a controller to forecast the load change online. An output pattern is generated through a centroid defuzzifier if it attains a most probably matching pattern with the highest possibility [94].

Neural networks, such as multilayer perceptron network and self-organizing network, have a strong potential to overcome the sole reliance on a functional form of the predictive model. It makes the neural network-based forecasting a very active area of research. It facilitates improving the accuracy of load forecasting by neural networks integrated with several other techniques such as stochastic time series methods, weighted least squares procedure, a combination of fuzzy logic and expert systems, etc. Table 4 grouped the commonly used load forecasting techniques based on the duration of the planning horizon [93].

Different forecasting horizons, such as STLF, MTLF, and LTLF, have different challenges in forecasting. The peril of long term load forecasting is profound since uncertainty is rampant regarding climate, technology, population growth, and economic conditions. Overestimating demand might seem like the prudent modeling choice from the reliability

TABLE 4. Available forecasting methods grouped by forecasting horizon.

Methods for VSTLF and STLF	Methods for MTLF and LTLF	Methods for VLTLF	General Usage
Similar-day Approach	Trend Analysis	Trend Analysis	Bayesian Hierarchical Model
Regression Methods	End-use Models	Econometric Models	Fuzzy Inference Systems
ANN	Econometric Models		PCA
Expert Systems	Statistical Model-based learning		LLE
Fuzzy Logic			Isomap
Genetic Algorithms			
Stochastic Time Series			
✓AR			
✓ARMA			
✓ARIMA			
✓Seasonal ARIMA			
SVM			

aspect, but it can be costly, and hence unwise. In addition, it has been observed the usage behavior differs between the consumers using different types of meters, in particular between the consumers using smart and traditional meters along with different tariffs. The utility must take this into account and develop separate forecasting model for each of the metering systems and then plug-in them up for the final forecast value. Otherwise, they may come up with an inaccurate forecasting. In the case of STLF and MTLF, it is sometimes overly complicated to precisely fit various complex factors affecting demands for electricity into the forecasting models. In addition, it may not be easy to obtain an accurate demand forecast based on parameters such as change in temperature, humidity, and other factors that influence consumption. The utility may suffer losses if they do not understand and decide on an acceptable margin of error in load forecasting [95], [96].

IV. PENETRATION OF RENEWABLE ENERGY

A. VARIABILITY OF RENEWABLES

Electricity demand frequently fluctuates throughout the day, week, and year. Albeit having noise and uncertainty, how we are going to use electricity uniquely shows a tremendous amount of predictability. This predictability lets the generation planning and integration in a prudent manner, such as meeting the baseload with not-flexible and not-able-to-ramp-up resources, intermediate and peak load with must-take (like renewables), flexible and able-to-ramp-up resources. With the recent surge of the renewable energy-based generation in generation mix of the United States, variability in the renewable resources, particularly solar and wind, has been developing into a critical challenge in generation planning and integration. In this section, the discussion will be limited to the variability of solar and wind for two reasons [97]. First, apart from the fact that wind and solar are emission-free, compared to rest of other types of resources wind and solar are not dispatchable and controllable. So, we cannot consider them as baseload: turn them on and leave them on, and they cannot provide a steady amount of electricity. We cannot consider them as peaking resources: leaving them off most of the time and only turn them on when the electricity demand is highest. We consider them as must-take resources: when they are available, we will use them, when they are not, we won't use them. So, from the grid operators' point of view, wind and solar are considered for demand reduction since they have negligible operational costs, their capital cost is all about building those projects. Second, as has been noticed from the yearly US per capita consumption in kWh by renewable sources from 1999-2016 with trendlines and forecast depicted in Figure 19, only solar and wind exhibit incrementing trends with an exciting prospect to be the renewables of choice in generation planning [98].

When we model the solar PV production, we take the following variables into the account: size of the panel array, solar insolation (determined by hour of day, day of year, latitude, aspect, and tilt), efficiency (conversion of solar energy to electricity), and performance losses (temperature and inverter). Among these variables, solar insolation is not dispatchable, and hence a key driver in solar PV production. It has an immediate impact on the amount of generation from a particular project and distinctively varies throughout the United States. For example, the further south and south-east we go, the higher the availability of solar insolation is reported. Therefore, it is intuitive if we assume the solar installation cost in Wisconsin or New York is as same as that of Arizona and Florida, we would prefer to install the solar panels in the region from where we can get the most energy out. However, it is not the only parameter to analyze its financial viability and economic competitiveness [99], [100].

On a different perspective from the solar insolation, solar irradiation, in particular, is very predictable, at least theoretically. We– more or less– can perfectly model the solar irradiation as it changes throughout the day. However, cloud dynamics regards as the most stochastic element of solar power production, and in several instances, adds a tremendous amount of uncertainty in the case of incorporating large amounts of solar into power systems. Figure 20 portrays the impact of sky condition, in particular, cloud, on the solar generation. It is evident how the heavy dark clouds add noise in the electricity generation streams. Consideration of the cloud factor in generation makes the forecasting a way more stochastic and uncertain process, and in practice, exhibits a significant difference between the day-ahead-forecast, hour-ahead-forecast, and the actual generation. Even more, it is

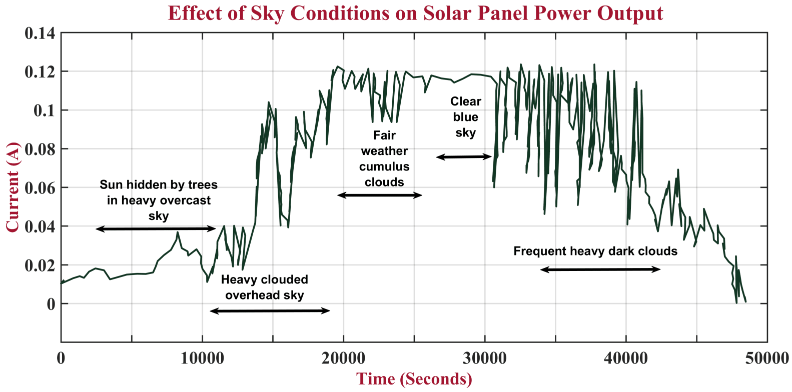

FIGURE 20. The effect of sky conditions on solar panel power output.

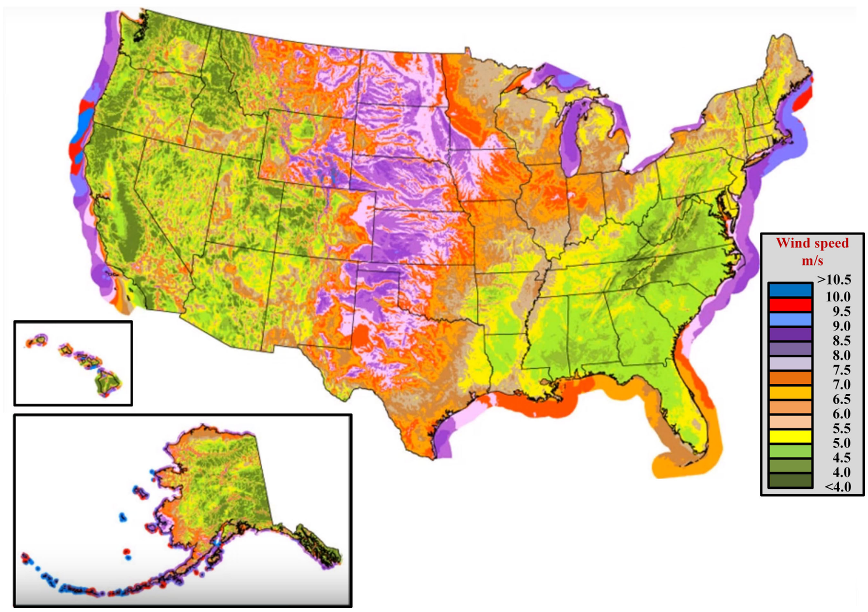

FIGURE 21. The wind velocity distribution over the United States.

critical to predicting solar power even just an hour before its generation because of the cloud factor albeit efficient prediction of solar irradiation [101].

Now, delving into the wind-based power, power generation depends on three cardinal variables: the amount of air (volume), the speed of air (velocity), and the mass of air (density) flowing through the area of interest (flux). The generated power from the wind turbine follows the equation as presented in (8):

$$P = \frac{1}{2} * \rho * A * v^3 \tag{8}$$

From this equation, it is apparent that power production from the wind turbine is very sensitive to the wind speed or the velocity (v), and algorithmically, if the wind velocity increases by a small amount, power generation goes up by the function of this cubic relationship. However, according to the Betz limit, the power coefficient is the quotient of the power extracted by the turbine to the total energy contained in the wind resource [102]. This coefficient helps us to estimate the generated wind power in the real case scenario. Betz limit is of the maximal possible $Cp = 16/27$ which indicates 59% of efficiency for the conventional wind turbine in extracting power from the wind. Since it is identified from the equation that wind velocity is the most impactful parameter in wind power generation dynamics, Figure 21 delineates the wind velocity distribution over the United States.

Figure 21 implies where installing wind turbines is more advantageous. Since, like other renewable energy resources, wind energy-based power generation only requires the capital cost for installation- requiring no cost for fuel- and we can presume the installation cost of wind turbine is– more or less– same across the entire United States, we can infer from this figure that US midwest, west-offshore, and east-offshore are the most convenient places to install the wind power

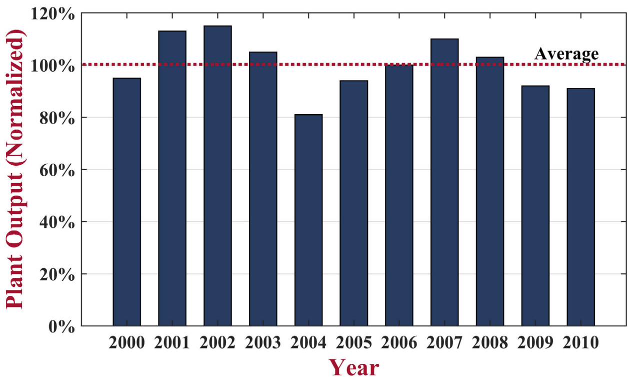

FIGURE 22. Year to year changes in wind power production.

generators [103], [104]. However, there are some additional confounding variables. First, financial viability of the project can be crucial since there is a notable population dearth in the US midwest region and it necessitates significant added cost for high voltage transmission to deliver the wind power to load centers or to the communities of high electricity consumption. Second, as can be seen from the year-to-year changes in wind power production for a single wind project depicted in Figure 22, the more uncertain variability and less predictable generation compared to solar energy are imperative in this dynamics. Though the generation variability in the case of a single plant is considerable, this evidence is not sufficient to have a conclusive idea regarding the impact of unpredictable variability and integrating the portfolio of several wind plants may come up with a different insight. On top of that, it may seem more uncertain in a smaller time scale, and considering a larger time scale may address a different view on this point.

Third, the variation in wind power generation on an hourly basis makes it confounding to incorporating into electric power systems. In particular, with the rising share of wind energy in the United States' electricity generation mix, having the possibility that a big chunk of it goes away unexpectedly during the day is a significant concern, and it is intricate for utilities since it impacts the maintenance of the power system operations in more than one way.

Next, to understand the grid integration challenges in variable renewables, Figure 23 – besides introducing the concept of duck diagram– illustrates the hourly distribution of the net demand with increasing PV penetration considering overall demand remains unchanged [105], [106]. As can be observed from Figure 23 and 24, with the increase of PV penetration, the non-PV supported portion of the net demand curve gets dropped down (consider the drastic drop down in case of 58% penetration) from 9 am to 5 pm when the sun is available). It- putting the net load in the context of increasing PV penetration- implies a trend that anticipates two major issues: over-generation risk and ramp requirement.

As can be interpreted from Figure 23, it requires a moderate amount of generation online to meet demand in the early morning and the late afternoon (when the sun goes down), and in the middle part of the day, it does not need much because of having greater PV penetration. In many cases, it has been observed it may be less costly to leave generation on around 9 am compared to achieve high ramp up, and kind of waste it throughout the day in order to have that generation online later on the day. This problem is called overgeneration. Since we have been experiencing greater penetration of PV (in general, renewables) in the conventional systems, the risk of overgeneration becomes greater, makes physical issues of safety and reliability. Another trade-off of having greater renewable-penetration is if significant changes in wind and solar availability take place very quickly– without warning– that can pose a challenge to system reliability. In the case of operations, it can be minute-to-minute, hour-to-hour, and day-to-day. For minute-to-minute, frequency regulation is needed, since it requires to maintain 60 Hz of frequency for AC system in the United States, and undersupply of generation can cause that frequency to deviate from 60 Hz, and if it goes too far, then it may experience a significant instability on the grid. It has to be actively managed through automatic generation control at generators. To address the hour to hour variability, load following and reserves are crucial. It requires certain power plants to increase or decrease their production to follow the net electricity demand patterns. Reserves are online sometimes, and offline sometimes, they are not primarily producing electricity, but they can quickly ramp up and produce electricity at the right frequency in order to account for any unexpected change in the availability of wind and solar. For day-to-day, unit commitment is critical to make decision to turn a plant on and off. It is crucial as it is exorbitantly costly to turn a plant on and off.

In the case of planning, it is about a year-to-year basis: capacity planning based on the pick load forecasting, considering the likelihood that given uncertainty in electricity demand because of the weather and given the uncertainty in renewable energy production on year-to-year basis, and the reserve margin being below a certain point of inability to meet electricity demand. Another interesting point to discuss is that there has been observed a steady downward trend in wind speed globally over the last fifty years. The trade-off in considering the historical data over the recent trend in generation forecasting can pose a critical challenge in planning because of the third order relation of wind speed in wind energy generation, and eventually, end in a serious failure [107].

B. EFFECT OF COMMODITY PRICES

Commodity prices are one of the key drivers in the dynamics of United States Internet of Energy, and hence, is imperative to be discussed explicitly in an individual section. Previously, energy commodities were essentially conceptualized as including natural gas, petroleum products, and coal. With the recent surge of renewable-based generation, the raw materials used in the fabrication (along with cutting, bending, and assembling) of renewable energy and storage

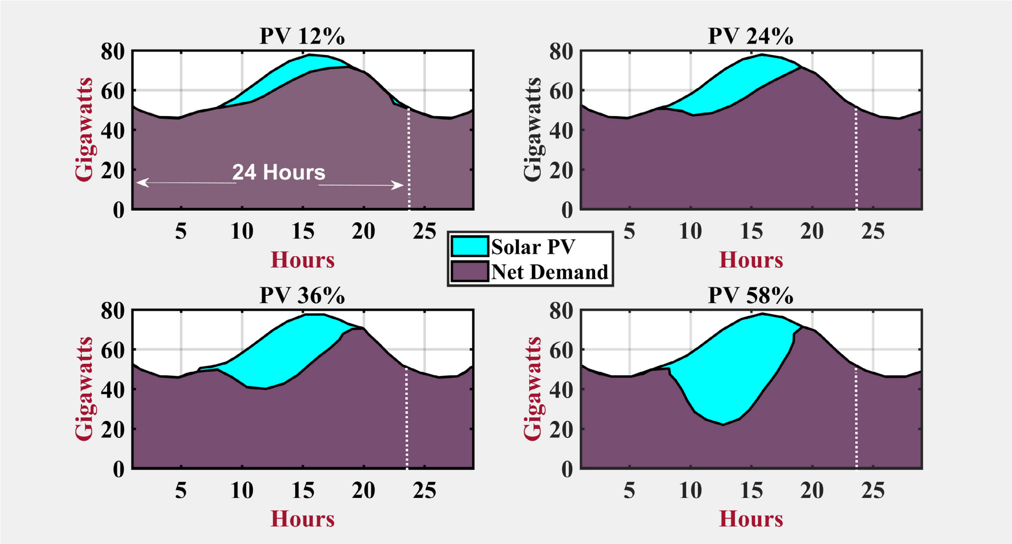

FIGURE 23. Impact of increasing PV penetration and duck diagram interpretation of over-generation risk and ramp requirement.

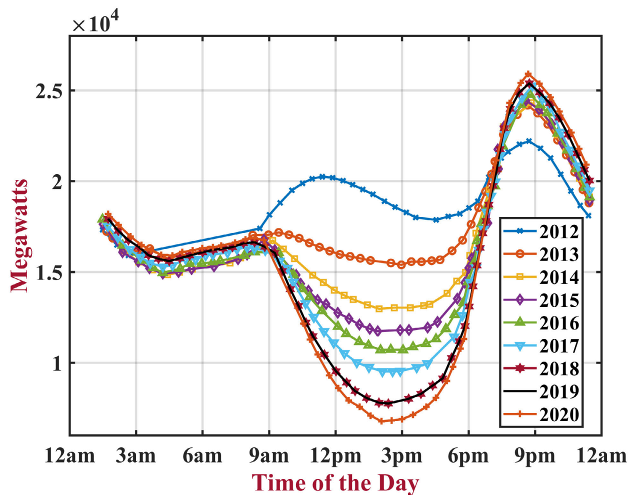

FIGURE 24. Duck diagram interpretation of over-generation risk and ramp requirement.

technologies are considered as energy commodities. In this section, we will briefly discuss the factors that influence commodity prices and how these propagate to electricity prices. The direct impact of the commodity market on electricity prices is observed in the fossil fuel power plant that ultimately gets incorporated into the wholesale prices, and eventually, retail prices for customers. Unlike this, renewable energy-based generation is considered as immune to year-to-year changes in fuel cost. The reason is though it is uncertain how much energy we will get from the renewable energy plant, such as solar and wind, we know exactly how much we will cost for it. However, it is required to factor in the availability of the renewable resource across the year, since it ends up impacting in the levelized cost of electricity.

Nevertheless, commodity prices do matter– albeit in an indirect fashion– for renewable energy, since the majority cost (compared to the fixed operation and maintenance cost) of the renewable energy is drawn from compensating the annualized capital cost. If commodity prices fluctuate the capital cost of renewable energy projects, this capital cost aggregate into the cost of renewable energy over the entire project lifetime. So, if the solar plant or wind turbine is developed in a year when steel and copper prices are high, the long term electricity selling price to adjust this cost will be significantly high; and there is no chance for the commodity prices to go back and lower the price of electricity from solar or wind firm. For example, Figure 25 depicts the instances of how the copper and steel price reflects the levelized Power Purchase Agreement (PPA) from 1990 to 2010 across the different regions in the United States. As can be noticed from this figure, the price of copper and steel experienced a significant increase in 2006-2008, so the different regions in the United States did in their levelized PPA. Typically, these agreements are of twenty-five to thirty years which implies the plant developed in 2006-2008 reflects into the higher price of electricity for the next thirty years, not just in the year it was developed.

The United States Critical Materials Institute (CMI), an entity associated with the DOE, concentrates on technologies that make better use of materials indispensable for the United States' competitiveness in clean energy; and identify and eliminate the demand for materials that are crucial to supply disruptions. They have four principal objectives. First, diversifying supplies: if on geographical source goes offline or out-of-function, a different source can take its place in operation. Second, developing substitute materials that can functionally serve the same purpose compared to the materials currently used. Third, using the available materials more efficiently by reducing waste and adopting recycle in manufacturing. Finally, last but not least, forecasting which materials might become critical in the future. Table 5 reports

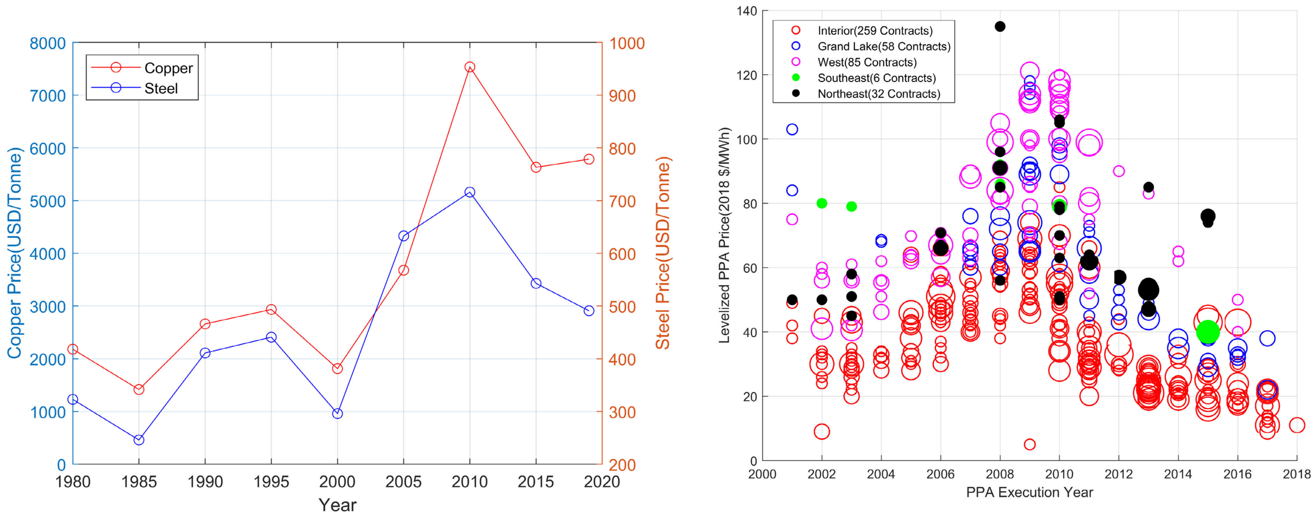

FIGURE 25. Commodity prices drive wind energy prices.

TABLE 5. Materials for clean energy technologies and components.

	Photovoltaic Films	Wind Turbines	Vehicles		Lighting
Materials	Coatings	Magnets	Magnets	Batteries	Phosphors
Cerium				✓	✓
Cobalt				✓	
Dysprosium		✓	✓		
Europium					✓
Gallium	✓				
Indium	✓				
Lanthanum				✓	✓
Lithium				✓	
Manganese				✓	
Neodymium		✓	✓	✓	
Nickel				✓	
Praseodymium		✓	✓	✓	
Tellurium	✓				
Terbium					✓
Yttrium					✓

the CMI's investigation on materials used in clean energy technologies and components. It incorporates the materials including rare earth elements, and their applications in photovoltaic films, wind turbines, vehicles, and lighting. Red rows in Table 5 indicate the rare earth elements.

Besides, the CMI classified the materials used in clean energy (mostly in photovoltaic cell and energy storage systems) into three categories based on two evaluation metrics: supply risk and how important it is in clean energy. Both are considered on a scale of 4, indicating low as 1 and high as 4. The materials which are of high (4) or high-medium (3) in both metrics are identified as critical materials, the materials which are of high-medium (3) or medium (2) in both metrics are considered as near-critical materials, and the materials which are of medium (2) or low (1) in both metrics are studied as not critical materials. The third parameter is essentially the time-frame of the supply availability that reflects on the categorization, and eventually, necessitates forecasting of resource availability. Figure 26 illustrates the criticality matrix of materials used in clean energy for the short-term and medium-term.

Unlike the materials used in clean energy, commodity prices have a direct short-term influence in the case of conventional fossil fuel-based generation. Similarly, in the case of conventional fossil fuel-based generation, commodity prices vary with a number of reasons such as energy crisis, natural calamities, inexplicable tracking, global financial crisis, polar vortex, and excess supply from fracking.

V. UNDERSTANDING ENERGY CONSUMPTION DYNAMICS

A. ENERGY DISAGGREGATION

To meet the environmental challenges and continually depleting energy resource dilemma, energy demand reduction, along with improving energy efficiency, is considered as the safest and most sustainable approach. It has been reported that the residential sector occupies approximately 22% of total energy in the United States which reflects in 37.8% of total electricity consumption in the US (electricity consumption by different sectors and household-electricity consumption distribution of the United States depicted in Figure 27). Consequently, household energy usage shares about 38% of the

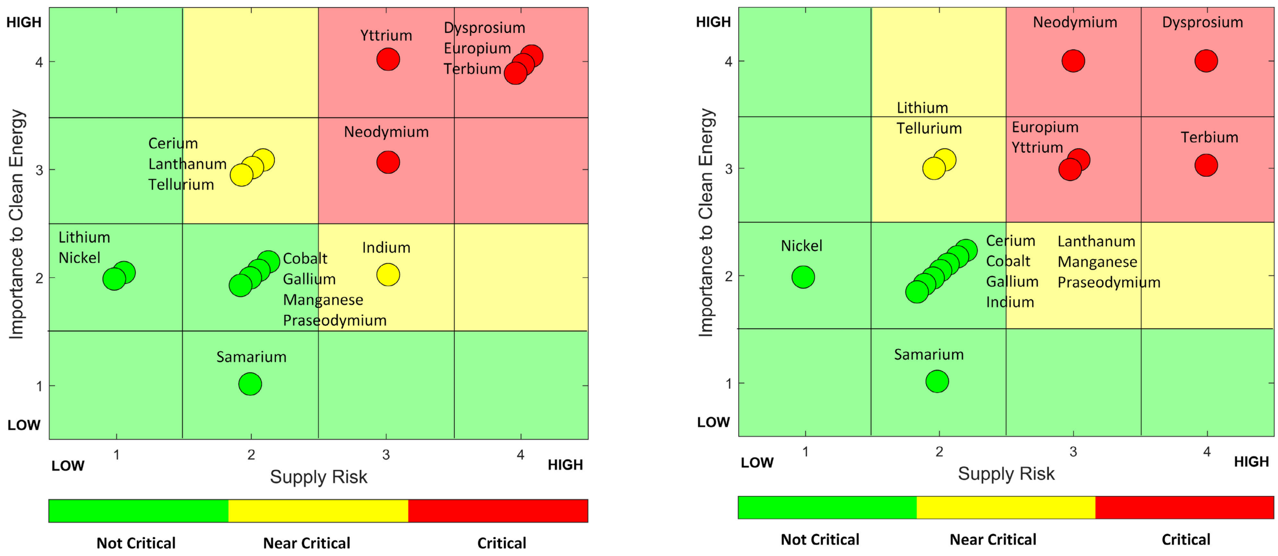

FIGURE 26. **Criticality matrix of materials used in clean energy for short-term and medium-term.**

total yearly carbon emissions in the US. Research shows approximately 27% of the current households' energy, so as the electricity, can be saved through efficient demand-side energy management. Household-demand-side management majorly concentrates on six objectives, namely, peak clipping, load shifting, valley filling, strategic load growth, strategic conservation, and flexible load shape [108]. These require to classify the factors that affect household energy usage into different categories, such as demographics and socio-economics, location, temperature, energy prices, and building characteristics, and eventually, understand the household energy consumption behavior. Electricity consumption patterns of different users in different time granularity, which is affected by both objective and subjective factors, can be discovered through effective analysis of electricity consumption data accumulated by different data acquisition terminals, such as smart meters. Therefore, energy disaggregation is essentially being an integral part of the Advanced Metering Infrastructure (AMI) in this effort [109], [110].

The benefits of energy disaggregation are manifold. It ranges from raising awareness regarding energy usage to empower consumers across different dimensions in making better decisions, offering sophisticated options for automated commissioning, diagnosis, and fault detection of residential buildings to providing simplified and improved load studies leading to the identification of specific end-use equipment and facilities. Thus, it encourages considerably more efficient, relatively cost-effective, and comprehensive quality assurance programs in order to achieve substantial savings from energy efficiency measures and demand response [108], [111].

In simple, energy disaggregation can be defined as an approach that allows taking a whole building (aggregated) energy signal into consideration, and then classifies it into appliance-specific data, such as a plug or end-usage data, by a set of IOT-based computational techniques. It is an effort motivated to delve into understanding energy usage behavior and modeling. In general, energy modeling involves iterative approaches for finding variables and parameters using more nuanced information and features as depicted in Figure 28 which eventually minimize the model error. It necessarily starts out with an extensive set of training data. Then, the training data set is employed to come up with models for energy consumption for individual activity based on a number of features across different dimensions. After that, it gradually eliminates any kind of statistically insignificant variable. After a certain iteration, a model is finalized which is as accurate and, at the same time, as parsimonious as possible [112].

Different energy models of different dimensions unpack different energy usage behaviors. Among them, behavior that incorporates different time granularity and sectors are regarded as crucial for knowledge extraction for resource planners. For example, the consumption patterns of different sectors, such as industrial, residential, and commercial, are illustrated in Figure 29 for both monthly and sub-daily basis. It is evident from Figure 29 that the consumption patterns of the various sectors are strikingly different, and the residential electricity consumption is the critical driver, as well as the most reactive sector with changes of weather and climate, in total demand [113].

From this stage, it requires special techniques to acquire insights on the household level, helping individual consumers make a smart decision about their electricity consumptions based on multiple parameters, such as price and availability of renewable energies, and therefore AMI is deployed into operation. It collects information about electricity consumption at the household level on a minute-to-minute basis, and then, transmits this information back to the central console

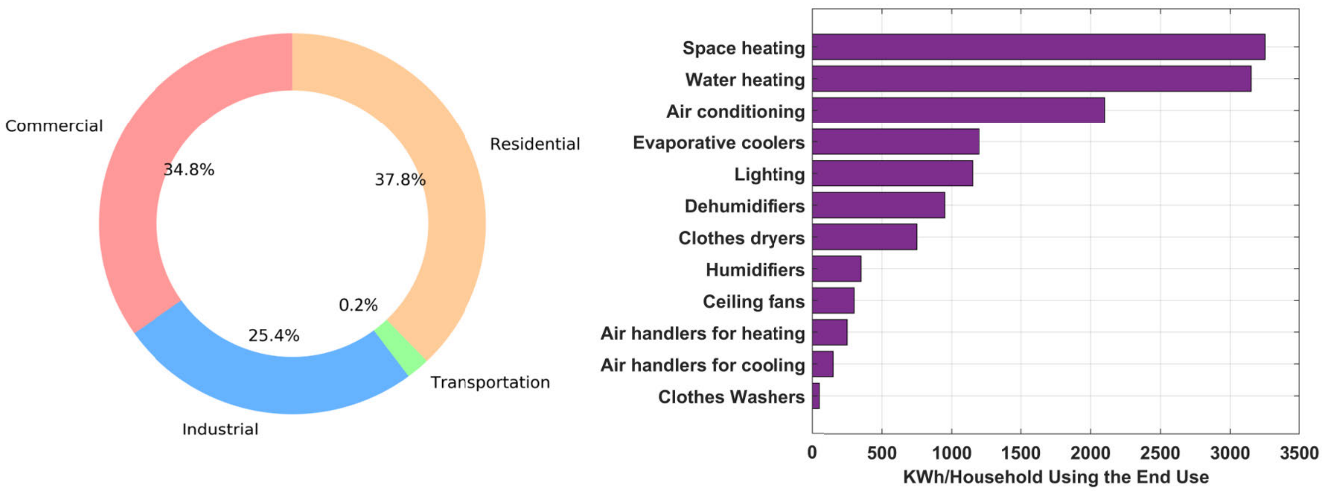

FIGURE 27. Electricity consumption by different sectors and household electricity consumption distribution in the United States.

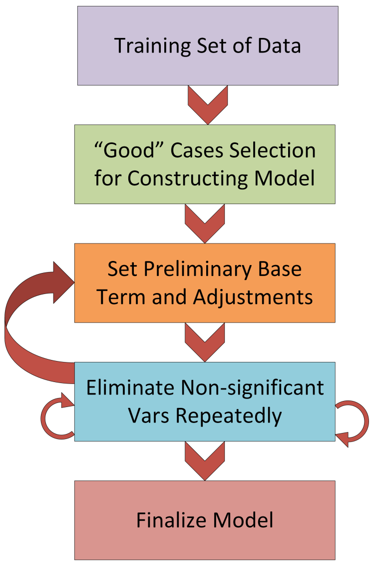

FIGURE 28. Iterative process for developing models to understand energy usage behavior.

system, facilitating two-way communication and almost real-time sampling. However, the information that comes from the advanced meter is not apparently comprehensive and it requires advanced analytics to leverage the advantages of this information. Figure 30 explains what we receive from the advanced meter (total power) and what we desire to know for the smart decision (disaggregated power) [114].

The initial approach to obtaining disaggregated power was sub-metering, installing the separate individual smart plug in each major appliance in residents. It worked and met the fundamental objectives that we want, however, the cost for integrating a number of smart plugs in each house and implementing it in residential level in the entire United States challenges the overall purpose of efficiency and cost-effectiveness. Table 6 compares the hardware-based and software-based disaggregation techniques from the consumer-level costs, installation effort, and adoption aspects. Table 6 lets us conclude that the smart meter can be the most efficient and cost-effective option if advanced analytics can be incorporated to obtain appliance-level information [114], [115].

NILM (Non-Intrusive Load Monitoring) or NIALM (Non-Intrusive Appliance Load Monitoring) is an analytic approach employed to disaggregate the building loads primarily based on a single metering point. This advanced load monitoring and disaggregation technique have the potential to come up with an alternative solution to high-priced sub-metering and facilitate innovative approaches for energy conservation, energy efficiency, and demand response. From the functional point of view, NILM can be explained as a three sequential operation, namely, signal acquisition, feature extraction, and finally appliance classification. The state-of-the-art NILM and NIALM techniques for energy disaggregation are briefly discussed below. Reference [111] proposed a cluster splitting approach to disaggregate the overlapping home appliances' consumptions. It addresses the challenges in disaggregating energy consumption by each of the appliances when several home-appliances have power consumption-levels that overlap (loosely or tightly) with each other. This approach initiates with analyzing the cohesion between devices' clusters to determine whether a cluster is required to be split into two or multiple clusters. This proposed technique– using REDD public data sets– was tested on overlapping devices' clusters of six residences, and it was evident from results that the degree of overlapping in devices' clusters and the sizes of individual clusters are crucial in its performance.

After that, for energy disaggregation, committee decision mechanisms (CDMs) have been introduced by [112] to disaggregate load at the metering level. Their investigation shows load signatures inherently embedded in the patterns of typical electricity consumptions are able to provide crit-

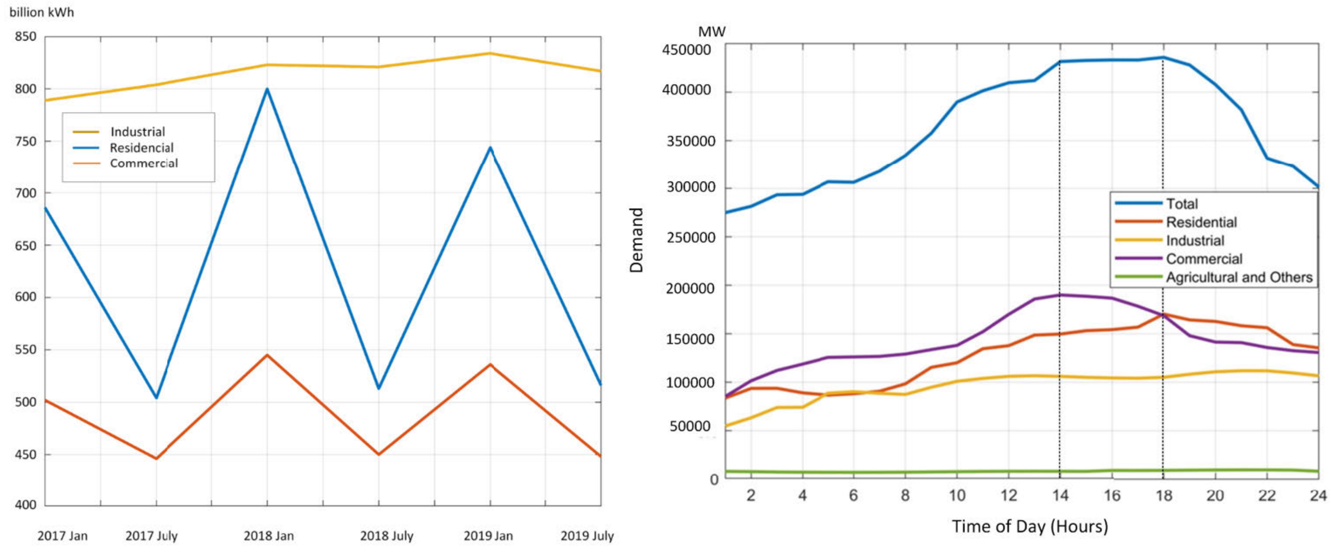

FIGURE 29. Energy consumption patterns of different sectors for both monthly and sub-daily basis.

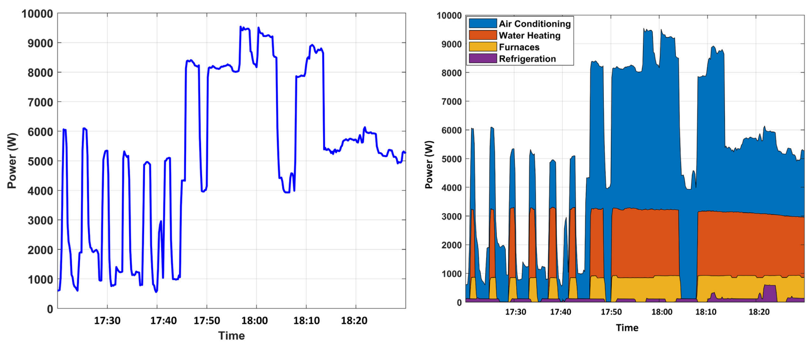

FIGURE 30. Almost real-time household level total power provided by the advanced meter and the desired disaggregated power.

TABLE 6. Comparison between Hardware-based and Software-based Disaggregation Techniques.

	Hardware Disaggregation		Software Disaggregation	
Sensing Technology	Plug Level Hardware Monitors	Smart Appliances	House Level Current Sensor	Smart Meter
Cost	$30 - 50/plug$ $300 - 600/home$	\$100+ additional for other non-smart appliances	\$200+/home	None
Installation Effort	Most plugs– Moderate 240V plugs– Hard	Easy	Very Hard	Not Required
Adoption	Low	Moderate	Low	Very High and Fast

ical information about the characteristics of the appliances as well as their usage patterns. Multiple evidence bolstered that all CDMs- through Monte Carlo simulations- outperform any single-feature and single-algorithm-based energy disaggregation methods, and are considerably less sensitive to any load dynamics and noise. They reported some case studies using this technology in appliance usage tracking and energy consumption estimation. In [116], Misbah *et al.* proposed sparse optimization for end-use disaggregation, a novel nonintrusive appliance load monitoring (NIALM) algorithm, that can characterize the appliance power consumption profiles accurately over time. The primary assumption of this algorithm is that power consumption profiles of the unknown appliances are piecewise constant over time, and it leverages the knowledge on the time-of-day probability in which a particular device might be used. Here, it formulates the energy disaggregation problem as a least-square-error minimization problem, including an additional penalty term to enforce the disaggregate signals to be piecewise constant over time. Testing this algorithm on the household electricity data is reported in [116] with satisfactory accuracy.

Next, in [117], the authors proposed a dictionary learning-based approach in addressing energy disaggregation problem. This technique is usually a synthesis formulation, involving in learning a dictionary for each device and then applying the learned dictionaries as evidence for the blind-source separation during energy disaggregation. It facilitates disaggregation as drastically reduces the sensing cost. In [118], Singh *et al.* presented a distributed and scalable method for semi-intrusive large-scale appliance load monitoring. They–with sufficient conditions considered for unambiguous state recovery– incorporate an SSER model (sparse switching event recovering) for retrieving appliances' states from the aggregated load data stream. This approach demonstrates satisfactory results in improving the accuracy of load disaggregation for large-scale appliances with a small number of meters. Then, in [119], Xia *et al.* proposed a deep dilated convolution residual network- based non-intrusive sequence to sequence energy disaggregation approach in an effort to reduce the network optimization intricacy and explain the vanishing gradient problem. They, initially, normalized the primary data, and then, applied the sliding window to formulate the input for the residual network. Here, they met the challenges of learning long time series data by increasing receptive fields and capturing further data through the dilated convolution. Several case studies bolstered the improved efficacy of this proposed deep dilated convolution residual network- based sequence to sequence disaggregation method in energy disaggregation.

On a different note, [120] presented a GSP-based approach (graph signal processing) to disaggregate the entire energy consumption down to individual appliances' level. The authors addressed the complexity of general graph-based methods associated with large training overhead employing event-based graph approach. This paper showed two approaches leveraging the piecewise smoothness of the power load signal. The first one searches for a smooth graph signal under known label constraints following the principle of total graph variation minimization under some known label constraints. The second one initiates with the total graph variation minimizer and delves into further refinement through simulated annealing. The paper reported a competitive performance using the proposed approach compared to the decision tree and hidden Markov model-based approaches. After that, considering the fact that the aggregated or smart meter signal can be expressed as a linear combination of the basis vectors in a framework for matrix factorization, Alireza *et al.* presented a technique to disaggregate energy data using non-negative matrix factorization with sum-to-k constraint [121]. This technique– through imposing non-negative constraint as well as sum-to-k constraint– can extract perceptually meaningful sources efficiently from the complex mixtures. They compared its performance with the state-of-the-art decomposition-based disaggregation algorithms and reported superior results. In general, all the state-of-the-art nonintrusive energy disaggregation techniques can be broadly classified into two categories: optimization-based approaches and machine learning-based approaches.

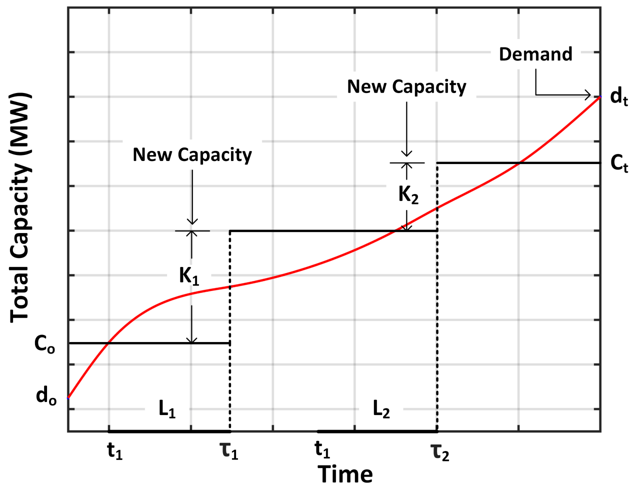

FIGURE 31. Capacity expansion over time.

B. GENERATION EXPANSION AND DECISION ANALYSIS

Capacity expansion, in broad generation expansion, is an indispensable part of the infrastructural planning of the power industry, and subsequently, the internet of energy; and hence to be highlighted in this sub-section. In simple, capacity expansion is the process adopted by the utilities to increase their capacity of the generating-resources gradually to meet either of the following objectives: primarily, meeting electricity demand growth, then, making replacement of the existing generation that comes offline or retires because of aging infrastructure, and confronting relatively more stringent circumstances or regulations. In other words, mostly from the aspect of the electric power industry, it is the process of adding additional facilities of a similar type over time in order to meet the rising demand. Capacity expansion is a multi-faceted decision that concerns the timing, scale, and location of the major projects in the face of uncertain- often with the considerable unpredictability- demand forecasts, costs, and completion times [122]–[124]. The simple pictorial depiction of capacity expansion is shown in Figure 31.

In literature, it has been documented that the highly unpredictable uncertainty often resulted in surprise or shock to the system planners either as a critical shortage or provision of gross amounts of unwanted capacity. Both of them are highly undesirable. Figure 32 illustrates the impact of the critical shortage (building not enough capacity) challenges in the case of the Pacific Northwest of the United States. It shows the causal relation of unpredictable growth of electricity demand, having not enough capacity, and market deregulation to market manipulation; and shows how market manipulation and hot summer and drought can lead to increase in natural gas prices [125].

A popular example of the impact of building too much capacity is what happened in 1970 in the United States. Since

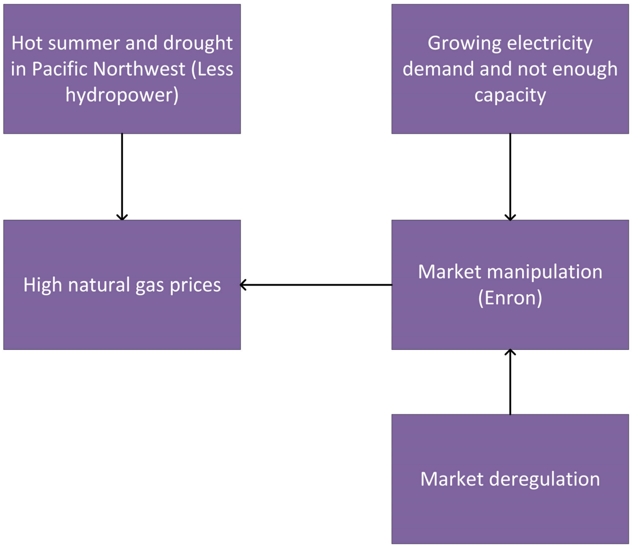

FIGURE 32. **Impact of the critical shortage challenges in the case of the Pacific Northwest of the United States.**

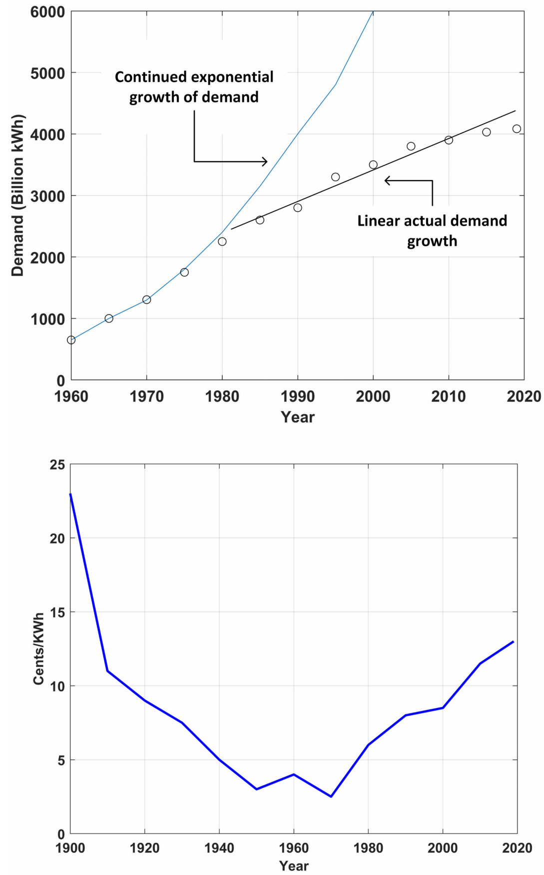

FIGURE 33. **Impact of overestimating electricity demand resulted in a higher price.**

the end of the World War-II till 1970, there observed an unprecedented industrial growth, and hence an exponential increase in electricity demand. This phenomenon inspired the utilities overbuilt the nuclear power capacity to meet the exponentially growing demand. After 1970, a change was observed in the pattern of demand growth; it started showing an almost linear behavior in contrast to the previous exponential behavior. When demand started increasing in a considerably slower fashion, the annualized capital costs associated with these plants had to be spread over fewer individual units of electricity, and eventually, retail prices increased. Figure 33 is the illustration of the impact of overestimating electricity demand resulted in a higher price. This overinvestment-underinvestment dilemma posits that If it is an overinvest, then it just sets to have higher electricity prices, if it is an underinvest, it sets up for the actual physical failure of the grid [125].

Apart from the demand, there is another source of uncertainty in analyzing capacity expansion: Market, or in particular, fuel prices. Fluctuations in fuel prices can have a tremendous impact on which technologies are more preferable. Sometimes, the change in fuel prices may experience a behavior which is not predictable, or even statistically not well-characterized, before making decisions regarding capacity expansion. The other considerable sources of uncertainties are technologies, regulations, construction time, and retirement. The technological and industrial innovations are correlated to the price projections about future capacity costs. In particular, renewable energy technologies can be a crucial driver in predicting future capacity cost; and its predictability in generation mix over decades can change the capacity cost dynamics dramatically. After that, the uncertainties come with regulations are beyond the scope of describing it in a statistical manner. For instance, it is near to impossible describing the likelihood of the United States enacting a carbon tax or some other legislation that eventually makes the fossil fuel power plants more expensive. Construction time is also a crucial factor since the decision regarding plant construction needs to be made many years before they are actually built. Retirement, though studied as a factor of uncertainties, can– more or less– be planned. These retirements of existing capacity ultimately add to the need for new capacity. Besides, in the case of capacity expansion, it is incumbent to consider the scenarios, such as if the growth in electricity demand is considerably lower than expected, if the future electricity demand is related to the cost of solar and batteries, if the technological innovation happens faster than that was expected, and most importantly, if the US transportation is shifted to be electrified [126]–[128]. Addressing these all sorts of possibilities is a pressing concern of infrastructural planning for the power industry, and with the time being, the electric power industry is continually being linked to irreducible and unquantifiable uncertainty. Ensemble prediction [128], [129] followed by the decision analysis is the most frequently used academic approach to address these challenges [129], [130]. Decision Analysis is a formal structure for decision making under uncertainty that includes numerous methods for adequately identifying, clearly representing, and precisely assessing the essential aspects of a decision, and for suggesting a course of action by applying the maximum expected value axiom [130], [131]. A decision tree is a commonly used tool in the decision analysis that involves decision nodes, chance nodes, and end nodes to interpret the flow of time, decisions, uncertainty, and consequences to come up with the evaluation measures realizing how well the objectives are achieved in the final outcome [131].

VI. INTERNET-OF-ENERGY

In the last section, we intend to capture the most crucial areas centered around the concept of Internet-of-Energy. In a nutshell, we discuss the Grid Overview of the United States; Weather and Climate and its impact on the entire energy generation and consumption dynamics; Peak Load Forecasting and its techniques and burgeoning challenges; Variable Renewable Energy, its reliability challenges and how we can take advantage of this variability; Commodity Prices and its criticality; Energy Disaggregation and its impact on consumption awareness; and Generation Expansion and Decision Analysis and trade-offs.

Internet-of-Energy, as well as IoT, preserves the essence of sustainability– coordinated development of life and its habitat, society, culture, work, and material production environment, well-reflected by the social-economic-natural complex ecosystem theory. Though the conceptualization of the Internet of Energy is centered around the motivation of assuring electric mobility and full deployment of the must-take-resources, such as renewable sources, Internet of Energy can answer numerous energy and reliability challenges, and provide solutions and theoretical underpinnings leveraging the recent advancements in microsystems, nanoelectronics, embedded systems, control, communications, algorithms and analytics, software, and the internet technology. In the Internet-of-Energy, the area for IoT realization can be manifold. From the aspect of energy delivery and peak demand, IoT realization is incumbent for online generation monitoring, smart meter reading, and advanced control system for transmission and distribution. From commercial, industrial, and residential point-of-view, demand response modeling, electric vehicle charging, and home energy management are crucial for IoT effectuation. Besides that, utilities or consumers are one of the key sectors to be realized using IoT. Microgeneration and asset management are crucial in this regard. Figure 34 captures the essential layers of IoT deployment with the smart grid in the realization of the internet-of-energy. There may have multiple avenues in IoT deployment yet to be explored to enact smooth and effective communication between the smart meters attached at the consumers' place and the sensors [37], [48], [132], [133].

There are four key functionalities of IoE: Motivating consumers, self-healing, improve power quality and resist attack. IoE offers interactive options in transferring consumption and reliability information between the user and utility, and thereby, motivates users to plan their cost and select suitable tariff, creates awareness regarding demand response features and their impact on reliability and cost, and eventually, lets the consumers control their power usage more effectually. With the capacity to analyze on the fly, IoE can identify and react to the major faults swiftly and in a more intelligent way. In particular, smart metering approaches with wireless connectivity facilitate identifying black-outs immediately and in a nonintrusive manner. Next, IoE promotes improving power quality. The major consumer demands in all the commercial, industrial, and residential sectors are of constant voltage, and abrupt fluctuations in the voltage may be detrimental to electric appliances. IoE has tremendous potential to maintain constant voltage, thereby reducing commercial productivity loss. Apart from that, IoE adopted numerous privacy preservation methods for smart grids to protect itself from cyber and physical attacks [47], [134], [135].

The technology synthesis allows perceptive technology, advanced analytics and machine learning, advanced network technology, artificial intelligence and automatics to be employed together into machine-to-machine and human-to-machine interactive systems to realize the functional interconnection of humans and objects. It motivates the internet-of-energy to leverage the elements and functionalities of IoT, such as flexible structure, autonomous process, multi-role participants, scalability, event sharing, interconnectivity, and semantic sharing. Besides that, third parties are welcome to develop complex and compound applications with the provision of APIs. Figure 35 illustrates the concepts of the internet-of-energy integration– a framework realized by the approach of IoT paradigm with the smartgrid [47], [133], [136].

A. IoE ARCHITECTURE AND IoT INTEGRATION

Internet-of-Energy architecture is dynamic and progressive, as such with respect to time factor, the system elements can be reconfigured. However, the myriad number of devices, functionalities, and technologies in IoT, and consequently, in the internet-of-energy, makes interoperability a crucial issue. Thereby, data deluge (by smart metering), extensibility, and scalability should be taken into consideration, resulting in enormous computational tasks. Parallel computing may obtain a significant speedup and get the analyses and results faster. However, extrapolating the performance from the small size of the problem on small systems to the larger size of the problem on larger configurations is a primary concern. For a given problem size, computational overhead increases with the increase of the number of processing elements. Hence, the overall efficiency of the parallel program goes down in a meaningful manner. Besides that, according to Amdahl's law, speedup tends to saturate with the increase in the number of processing elements. On the other hand, since the total overhead function is necessarily a function of both of the number of processing elements and the size of the problem, in many cases, we observe the overhead grows sublinearly with the increase of the problem size. If we keep the number of processing elements constant for such cases, the efficiency will increase with the increase of the problem size. Leveraging this insight, we can simultaneously

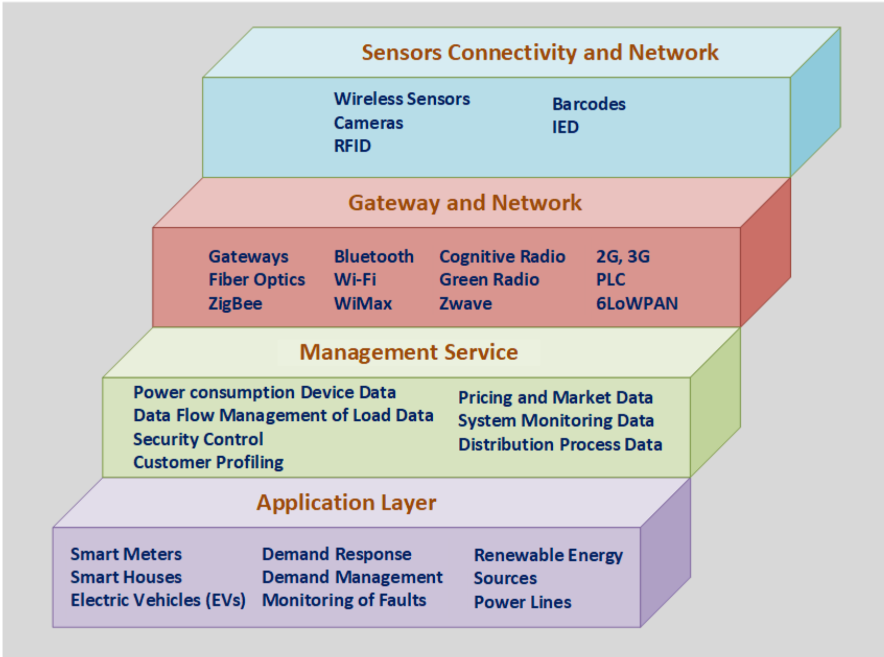

FIGURE 34. Essential layers of IoT deployment with the smart grid in the realization of the internet-of-energy.

increase the number of processing elements and the problem size at a particular rate to keep the efficiency of the system constant. Such a system is called the scalable parallel system, and assuring scalability of a system is a critical challenge in large scale IoE deployment. Another major concern, which may lead to severe repercussions, in this technology is privacy and security. The security and privacy threats are even more serious in the case of smart meters in residential buildings. The privacy concern with residential users are easily susceptible to the hackers, and sometimes, to other consumers intending their per day energy consumption reduction. These challenges and concerns come up with future research opportunities regarding suitable remedial measures, such as encryption methods, authentication schemes, public key infrastructure, and standardized application program interfaces [47], [132], [137].

The principal features of internet-of-energy is aquainted as follows in the lens of advantages and disadvantages. To begin with, automation realizes the control of numerous smart devices, leading to the uniformity of tasks. This secures a transparent process over the entire machine to machine communication. Then, the efficiency of the system can be perceived in two aspects: the ratio of useful output energy and total input energy, and the opportunities it creates to retarget human efforts in other fields. The internet-of-energy facilitates more machine to machine interaction; the more the interactions between machines, the more the opportunities are created to target on other jobs that require human efforts. Besides, advanced analytics help optimizing the efficiency (the first aspect) of the energy production and management ecosystem. It also brings cost-effectiveness as another advantageous aspect of IoE. Again, communication is crucial to improve the quality and time factor; internet-of-energy facilitates a platform for daily basis communication with the devices. Implementation of IoE may facilitate instant data access (with proper authentication and user verification), which further helps the research community to conduct exploratory research in this domain and delivers useful data-driven insights. Figure 36 depicts the benefits of the internet-of-energy from the functional aspect [47], [137]–[139].

One of the major disadvantages of internet-of-energy deployment is paramount privacy and security concerns. The more the appliances and services are dynamically connected, the more the information stored are readily available, the more the risks of the data-security breach as the information may get susceptible to hackers and unauthorized concerns. It brings a surge in multidisciplinary research opportunities regarding more robust data authentication tools, privacy policies and standards, and firmware standards. Again, due to the lack of sufficient international compatibility standards available for internet-of-energy, it is tricky and confusing both for the manufactures and stakeholders to interact with the services; thereby, compatibility is a significant concern in the massive deployment. In this regard, new standards with common protocols are being developed for residential, commercial, and industrial sectors. Next, as far as the complexity is concerned, an extremely large network is connected across in the IoE; a small failure in the software and hardware components may lead to a damage in the entire system. On the flip side, the immediate failures at the junction

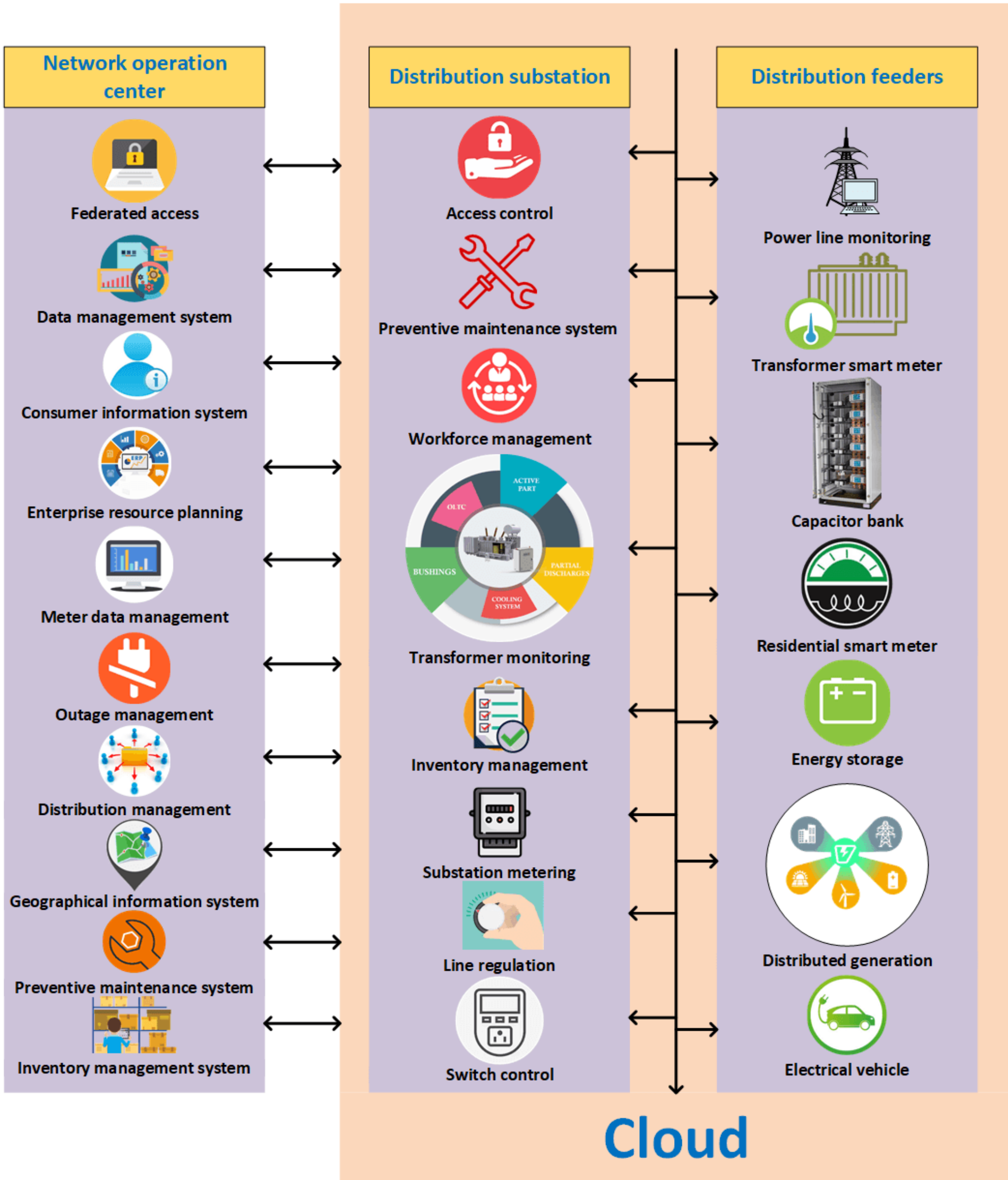

FIGURE 35. Internet-of-Energy integration.

of nodes can be addressed through a common control center; remedial action is next to instant [47], [140], [141].

B. BROADER IMPACT

Adopting the internet-of-energy comes up with a tremendous social impact as it steps forward into the future energy ecosystem with smart technologies and new regulatory structures and services. First, it changes the classical perception regarding generation, transmission, and consumption to both the consumers and utilities. From the consumers' aspect, this contemporary avenue is critical for ecological awareness and convoluted for energy management, underscoring their daily comfort behaviors as a dynamic factor in the complex system. Furthermore, the intricacy involved in adopting and controlling different smart devices with numerous distinct sensors governed by different operating systems leads to interoperability concerns for the consumers, in particular, the senior citizens and the people from a non-technical background. As technology progresses, the internet-of-energy– to enhance the acceptability of these new technologies– requires training as well as mentoring opportunities for a diverse group of consumers and operators. This new technology opens up scopes for researchers around the world to study and understand the concept properly. The results and insights generated on

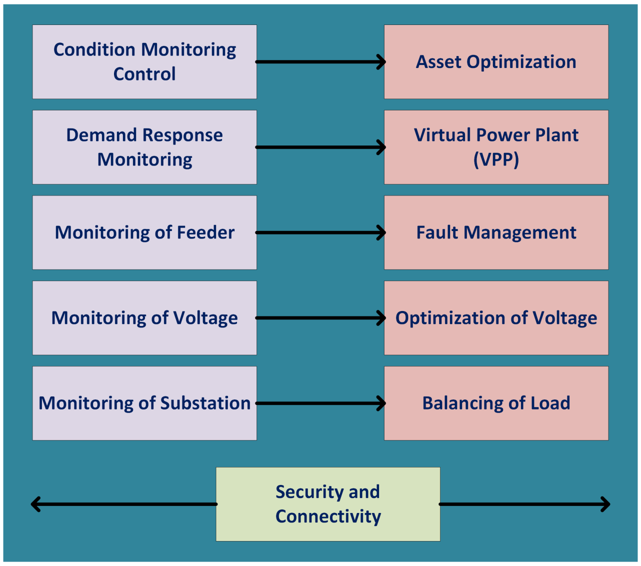

FIGURE 36. benefits of adopting internet-of-energy from the functional aspect.

this new technology need to be widely disseminated through publications, professional presentations, and online access to raise awareness and motivate advancement. These collective efforts will– soon– change the understanding of consumer devices, from a black box to a source of multivariate information based on the pricing scheme [47], [142], [143].

On the bright side, the recent technology transformation makes the world propelling at a rapid and exponential change, creating a tremendous impetus, as well as brunt, at different avenues and courses of action, such as professional and personal aspects. Again, embodying the consumer in the intersection of multiple domains centered around embarking fourth industrial revolution, technology innovations, and social impact, the internet-of-energy has the potential to make the user more empathetic about consumption, and hence reduce the wastage. The interactive energy system– enabled by internet-of-energy leveraging new intelligence in information technology infrastructures– makes the user not only aware of the consumption but also active in controlling. The advent and evolution of the internet-of-energy have an impact in other sectors of the economy, in particular, the development of many fast-growing smart cities. predicts a full-fledged IoT eon by 2030 [144], [145].

C. CHALLENGES AND FUTURE RESEARCH OPPORTUNITIES

Before moving on to the full capability of IoE, it is incumbent to have a proper understanding of the challenges that the combination of IoT in the smart grid may bring into the dynamics. The most cardinal challenge is the possible data leakage; consumers' sensitive information can be revealed from the data obtained from the appliances scheduling. For example, heater usage data in the wintertime or air-conditioner usage data in the summertime implies the availability (or absence) of the residents. This data, if leaked, can lead to burglary or undesirable events and practices. Again, as all the consumers' information are readily available in the central server of the utility provider, consumers' privacy in the network can be compromised by cyberattacks. Cyberattack is another major concern. Cyberattackers can– by rifting the IoT-enabled-smart-grid-infrastructure– manipulate the data transferred between users and utilities and present incorrect decisions to the sensors connected to all the smart meters. Subsequently, the appliances operate in an incorrect way and get damaged, thereby causing a serious financial meltdown. Especially, these challenges involved in commercial and industrial sectors can lead to an economic catastrophe around the world. For instance, any industrial enterprise integrated with the internet-of-energy, if subjected to cyberattacks, may need to compromise their functioning, and it can discredit the entire production. Unreliable or unpredictable internet connectivity is another concern followed by swifter connectivity requirements for on-the-fly energy management analysis [47], [146], [147].

The future directions and research opportunities regarding the IoT enabled smartgrid are multifacted. In the physical layer of the internet-of-energy, energy acquisition and considering IoT based devices for different conditions, situations, and environment opens up research opportunities for scholars and new entrants in the future. In the network layer, more research is required in data fusion technologies, deployment techniques for new power supply products, and communication technologies. As the number of data sources grows with the deployment of IoE, a single source may not be effectual in providing useful insights and information. On the flip side, it is cumbersome and expensive – from the data collection and management point of view– to store data from all the available sources. Advance data fusion techniques can help integrating multiple data sources and deliver more accurate, consistent, and useful insights. In the transport layer of this new technology, data transfer at data centers avoiding network congestion and data traffic can be the future research challenge and directions. Network congestion is the reduced quality of service in a network due to carrying more data in its link or node than that it can typically handle, affecting queueing delay, blocking of new connections, and packet loss. In the application layer of the internet-of-energy, research challenges centered around the integration of IoT enabled devices, edge servers, and data handling issues are required to address more efficiently and consistently in the future. The integration of IoT enabled devices requires logical connectors, commonly known as APIs, allowing applications to communicate with other IoT devices. They expose data that enables devices to transmit data to applications, functioning as a data interface. The other avenues of the internet-of-energy that may draw the attention of the research community in the future for further research and development are standardization, authorization and privacy with authentication, and avoiding cyberattacks with robust security management [148].

TABLE 7. Transferable Computational Techniques and Their Prospective Applications in IoE Conceptualization.

Computational Techniques	Prospective Applications in IoE Conceptualization
Mathematical Modeling	✓Physical System Modeling ✓IoE Characterization ✓Interpreting System Dynamics
Statistical Modeling	✓Energy Predictive Modeling ✓Inventory Management ✓Market Segmentation
Neural Networks	✓Generation and Demand Variability Forecasting ✓Machine Translation for Energy Systems ✓Classification, Categorization, and Clusterization of Energy Prosumers and Consumers
Reinforcement Learning	✓Understanding Consequences of Different Strategies ✓Resources Management in Energy Systems
Linear and Nonlinear Algebra	✓Matrix Representation of Physical System for Convenience of Analysis ✓Identifying Eigen Value of a System ✓Determining Overdetermined and Underdetermined System of Energy Dynamics ✓Dimensionality Reduction to Analyze Higher Dimensional Matrix
Machine Learning Regression, Classification, and Clustering Techniques	✓Prediction/Forecasting ✓Machine Translation for Energy Systems ✓Classification, Categorization, and Clusterization of Energy Prosumers and Consumers ✓Generating Prosumers' and Consumers' Insights towards Efficient Energy Management
Computer Vision	✓Identifying Critical Objects for Solar and Wind Energy Producers ✓Automatically Detecting Need for Network Maintenance Using Regular Drone Images ✓Automatic Search and Information Gathering From Policies and Billings
Data Mining and Visualization	✓Data Management System ✓Decision Analysis ✓Generation Expansion ✓Generation and Demand Variability Forecasting ✓Energy Storage and Analytics
Bayesian Modeling and Causal Inference	✓Tariff Designing ✓Causal Discovery ✓Preventive Maintenance
Stochastic Optimization	✓Energy Management ✓Generation Planning ✓Advanced Controlling
Generative Modeling	✓Photo/Video Prediction for Fault Detection ✓Generate Examples for Datasets for Different Generation, Demand, and Maintenance Contexts ✓Aging Determination of Energy-related Instruments
Time Series Analysis	✓Seasonality and Trend Analysis for Decision-makers ✓Generation and Demand Variability Forecasting ✓Visual Analytic Interpretation of Physical Events
Game Theoretical Modeling	✓Understanding Complex Energy Market ✓Developing Multiplayer Oligopoly Games to Promote Renewable Resources
Artificial Intelligence	✓Energy Democratization ✓Algorithmic Trading ✓Smart Home/Smart City ✓Coordination of Decentralized Plants ✓Coordination of IoE Maintenance
Deep Learning	✓Predicting Cataclysmic Events ✓Energy Market Price Forecasting ✓Energy Storage and Analytics ✓Fault Maintenance
Unsupervised Learning	✓Renewable Energies Intermittent Data Processing ✓Cluster Computing of Distributed Energy to Find ✓Hidden Patterns or Grouping in Data ✓Anomaly Detection for Preventive Maintenance
Natural Language Processing	✓Summarize Policy Contents for Users ✓Sentiment (Satisfaction) Analysis of Consumers ✓Scam Detection ✓Encryption/Decryption/Deidentification
Parallel and Distributive Systems	✓Analyzing Big Data and Controlling Many Generation ✓Units at Different Time Scales ✓Faster Decision Making ✓Bringing Concurrency in Energy Analytics
Change Point Detection and Identifying Regime Switch	✓Identifying Failures and Problems in Energy Networks and Fixing Them Virtually ✓Addressing Cyber Security Concerns ✓Addressing Outlier and Anomalous Data Problems in IoE

D. IoE AND COMPUTATIONAL SUSTAINABILITY

The overarching goal of the computational sustainability network (CompSustNet) is to promote a platform that unites and helps more and more scholars, across the domain, use data mining techniques to solve the most complex and pressing problems of this time. The most compelling aspect of this virtual network– besides making a platform for computational science researchers to put their muscle towards making the world a more sustainable and livable place– is that a new method or solution created to solve one particular problem can be repurposed for another distinct problem. Table 7 presents the broader computational techniques addressed in the CompSustNet publications from 2016 to date and their prospective application in the IoE conceptualizations [149]. We followed a multi-blind Delphi method to extract the broader (mother) computational techniques from more than 175 papers indexed in the CompSustNet publication section. Besides, this study relied on the comments and suggestions by the domain experts at Oregon Renewable Energy Center (OREC) at Oregon, United States, to summarize the prospective application in the IoE conceptualizations.

VII. TAKEAWAYS

The theoretical underpinnings covered in this paper are discussed as follows.

- It summarizes the evolution of the energy grid, grid distributions and it is affected by the availability of the resource.
- It outlines the United States grid from the administrative point of view.
- It highlights the impact of weather, climate, and extreme events from both demand and generation aspect, discussing challenges and possible solutions regarding this.
- It contextualizes the load forecasting and its necessity in the energy workflow, classifies the time horizons of forecasting, and clusters and discusses the existing forecasting techniques from the computational aspect.
- It infers the burgeoning computational complexity and the trade-off between (almost) exponential technology trend and weather impact in developing forecasting models and algorithms.
- It delineates the variability and unpredictability of renewables (particularly, solar and wind) and how it poses challenges on multiple time scales, affecting planning and operations in power systems.
- It infers growing multi-aspect reliability challenges that come with growing renewable-penetration.
- It discusses how commodity prices end in impacting electricity prices in the case of both conventional and renewable energy.
- It highlights CMI, their objectives, and categorizations of materials based on criticality for short-term and medium-term clean energy.
- It contextualizes the energy disaggregation and advocates how it can bring positive impact in energy consumption dynamics in US residences.
- It discusses different state-of-the-art nonintrusive load disaggregation techniques recently surged in the literature.
- It discusses capacity expansion, its different avenues, such as the impact of critical shortage challenges, and impact of overestimating electricity demand.
- It delineates the IoE architecture, broader impact, challenges, computational sustainability and IoE, future works, and opportunities.
- It summarizes frequently used computational techniques that can be used across the domain and help to gather valuable insights for large scale IoE deployment and analysis, joining into the movement for computational sustainability.

VIII. CONCLUSION

This qualitative study has encompassed the elements of the energy and power management ecosystem and internet-of-energy in the United States. This study has addressed the sustainability issues in the lens of Grid Overview of the United States; Weather and Climate and its impact on the entire energy generation and consumption dynamics; Peak Load Forecasting and its techniques and burgeoning challenges; Variable Renewable Energy, its reliability challenges and how we can take advantage of this variability; Commodity Prices and its criticality; Energy Disaggregation and its impact on consumption-awareness; and Generation Expansion and Decision Analysis and unpacked useful insights on these domains. After that, it has focused on IoE integration, associated trade-offs, challenges, research opportunities, and transferrable computational techniques that can be repurposed for problems across the domain. Proper schematics and quantitative analysis have been presented to support this study.

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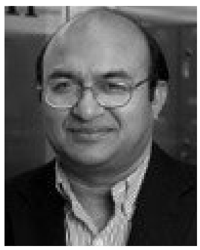

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