Impact of climate change on electricity systems and markets - A review of models and forecasts

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1. Introduction

Climate change has serious implications for the electricity sector, especially for the future of electricity demand and supply. Understanding the climate change phenomenon and its impact on electric power systems is of increasing importance to policy makers across the world. The present increase in global atmospheric carbon dioxide (CO₂) is mainly due to emissions from the combustion of fossil fuels for transportation and electricity generation [1]. In the US, energy-related CO₂ emissions account for more than 80 percent greenhouse gas emissions [2]. In the US alone, generation of electricity accounts for nearly 40 percent of all US carbon dioxide emissions [2]. In addition, the electric power sector is the single largest source of sulfur dioxide (SO₂), oxides of nitrogen (NOx), mercury and other particulate emissions [3]. Even with strong global efforts to mitigate greenhouse gas effects, the effect of climate change are still likely to be pronounced due to historic and extant anthropogenic emissions [1]. Considering the large fraction of emissions associated with electricity generation and use, it is rational to assume that any response to climate change must have a central focus on the electricity sector.

Some of the key environmental effects of climate change are: a rise in global surface temperature, changes to hydrological cycles, rise in mean sea levels and higher incidence of extreme weather events. The disruption to the generation and supply of electricity is likely to be considerable due to these environmental changes. Capital stock in the form of generation, transmission and distribution assets must adapt to meet the challenges of climate change in the future. Unfortunately, the electricity sector

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is burdened with assets that have a long economic life spanning a few decades. To ensure that the electricity sector is best suited to meet the challenges of climate change in the coming decades, there is an imperative need to accurately predict the multi-decadal trends in electricity markets and systems.

As a prelude to the proposed literature review, consider the following two crucial aspects of the problem. First, consider the spatial and temporal scale of the planning problem at hand. A graphical representation of the spatial and temporal scale of planning activities in electricity markets is presented in Figure 1 (adapted from [4]). The X-axis corresponds to increasing geographic/spatial scale while the Y-axis represents the increasing time scale. At the smallest scale of space and time frame, there are the nodal level planning measures such as the hourly Locational Marginal Prices (LMP) and congestion charges determination. At a slightly higher spatial scale i.e. at the level of load zones, there are the issues of load distribution and transmission network constraints. Day-ahead scheduling and load forecasts are carried out at a higher time scale running into a few hours or a day or two. Long-term planning for the electricity sector like Integrated Resource Planning (IRP), regulatory initiatives like Renewable Portfolio Standards (RPS) etc. are carried at a time scale running into a few years and are usually implemented at a state level. Climate change modeling efforts occupies the top-right corner of the graph, with time span extending to a few decades and a spatial scale covering one or more regions or countries. The level of uncertainty increases many folds along the diagonal of the graph. At the bottom-left corner of the graph, planning activities in the form of load or price forecast at a nodal level on an hourly basis have relatively little uncertainty. In contrast, a similar price or load forecast at the scale of climate change modeling faces uncertainties of much greater magnitude.
Figure 1: Temporal and Spatial scale of planning in electricity system (adapted from [4])

Secondly, consider the scope of the problem and its manifestations. Climate change is likely to have significant implications for both the supply- and demand-side components of electricity systems and markets. Some of the predicted implications of climate change on electricity systems and markets are summarized in Table 1 and 3. To get an idea on the vast scope of the problem, consider the implications of a surface temperature increase. In general, higher surface temperatures are expected to increase the demand for cooling, decrease the demand for heating and reduce the efficiency of thermal power generating equipment [5-8]. Research studies have predicted a systematic decline in the efficiency of thermal power generating equipment due to rising cooling water temperatures and accompanying decrease in source-sink temperature differential in a generating unit [9-11]. Although this efficiency loss
is minimal for each of the power plant, its overall impact could be substantial considering the large percentage of electricity generation from thermal power sources. The other concomitant changes associated with climate change are expected to transform the electricity sector by encouraging more non-carbon sources in the generation portfolio (including nuclear) and inducing widespread adaptations to transmission and distribution infrastructure [9, 12]. An economic model to study the climate change effects must at the very least attempt to incorporate these predicted implications.

Although the scale and scope of the problem is vast and uncertain, it is possible to construct a portfolio of limited scenarios and models to make reasonable predictions of the future trends. Complicating the task of building models for the electricity sector are the uncertainties in modeling. In addition to the documented implications, there are structural uncertainties in the form of technological disruptions (say a battery storage technology becomes viable), extreme climate variation (say a 1-in-100 year magnitude storm occurring every 10 years), feedback and interactive effect from mitigating technologies (like energy efficient technology, electric cars etc.), paradigm shift in the market framework (like the emergence of distributed generation in lieu of a central power plant model) etc. Increasingly, countries are restructuring their electricity system from a regime of rate-base monopolies to a restructured system with wholesale and retail competition. This form of policy uncertainty pertaining to the state of electricity market reforms also affects the choice of mitigation and adaptation strategies to long-term climate change effects.

The second major source of uncertainties is the lack of knowledge on important climate change impacts. Although the knowledge frontier has advanced considerably in some aspects of these uncertainties, there exist significant knowledge gaps in understanding the complete effects of climate change on electricity systems. Mideksa and Kallbekken [9] have analyzed the current research literature on this topic and have identified four significant knowledge gaps: regional demand side impacts in Asia, Africa,
Caribbean and Latin America; the effect of extreme weather events on electricity systems; changes to adoption rate of air conditioning; and the sensitivity of thermal power supply to changes in air and water temperature. In case of space heating or cooling, several studies have used regression-based models to predict the future demand for electricity and gas in the event of a temperature rise [5-8, 13, 14]. On the other hand, there is less research on the sensitivity of thermal power supply changes to changes in air and water temperature. Through the efforts of Inter-governmental Panel on Climate Change (IPCC) and others, impact of increased emissions on global climatic parameters and the necessary mitigation targets are documented in great detail. However, a broad based research on impact of climate change on electricity sector has been “surprisingly scant” [9]. Without significant research studies, formulating a policy response to climate change by the electric power industry is a challenging task.

The focus of this paper is limited to a literature review of the impact of climate change on electricity systems and markets. Whereas Mideksa and Kallbekken [9] focused on the results of the energy models that deal with climate change impact on electricity systems, this paper attempts to synthesize and compare the key framework and parameters of the various electricity models themselves. A study of the modeling framework helps in the construction of integrated economic models used in long-term climate change studies. Whereas Ventosa et al. [15] have dealt with the various generation and dispatch models under a competitive market regime; this paper reviews the literature on models that have explicitly incorporated the effects of climate change. Most of the models reviewed in this paper are long-term models spanning a few decades into the future. The list of models covered in this paper is by no means complete. The complexity of models reviewed in this paper varies from straightforward linear
regressions to advanced equilibrium models like NEMS, GCAM\textsuperscript{3} etc. The outcome of this paper could inform the design of future energy-economic models to study the impacts of climate change on electricity markets. The research studies in this topic can be broadly classified into \textit{three} categories: models that focus on demand side effects, on supply side effects, and combined models that deal with both the supply and demand side effects.

2. \textbf{Models focused on demand-side impacts}

Of all the impacts of climate change on electricity markets, the most obvious and studied is the effect of temperature increase on space heating and cooling. Built environments like households and commercial establishments use electricity for comfort heating/cooling, lighting, refrigeration, and operating other equipment. In 2005, households in the US spent nearly $204.5 billion for space conditioning out of which $134.3 billion was spent on electricity alone [16]. Chen and Lie [17] have classified temperature-demand energy models under two broad categories: bottom-up demand models and top-down demand models. Bottom-up models involve actual collection of meteorological, demographic and energy consumption data for each sector to model the temperature-demand relationship. This approach is not popular due to the complexity in gathering such massive data for different sectors of the economy. A top-down demand model employs regression equations to predict the demand from climatic variables like temperature, precipitation etc. In all these regression models, the energy or electricity demand is the dependent variable. Most of the research studies use a linear regression model to study the impact of temperature increase on electricity/gas demands. These models employ the concept of heating and cooling degree days (HDD & CDD) as the key independent variable. HDD or CDD is defined relative to a base temperature - the outside temperature above which a building needs no heating or cooling respectively (base temperature usually ranges from 55°F to 65°F). HDD refers to the negative deviations

\textsuperscript{3} NEMS- National Energy Modeling Systems (US EIA), GCAM- Global Change Assessment Model (PNNL & University of Maryland)
between the average of hourly temperatures and the base temperature in a given day. CDD refers to the positive deviation of the average of hourly temperatures and the base temperature in a given day. For example, on a typical New York City winter day with an average hourly temperature of around 35°F, the HDD can be approximated as \((35 - 55) = 20\). To improve model forecasts, the choice of base temperature should roughly correspond to the daily mean temperature at which the electricity consumption is minimum. Amato et al. [13] have suggested additional factors like built environment characteristics, non-temperature conditions (like humidity, precipitation etc.) and cultural preferences to be taken into account while fixing the base temperature.

Rosenthal and Gruenspecht [8] used the average results from six different climate circulation models to estimate the change in average HDD & CDD values in five distinct climatic zones in the US for a 1°C rise in global temperature by 2010. The change in degree-days is mapped on to the corresponding change in US energy use for space conditioning, taking into account the differences in population and assuming the building stock and the desired baseline temperature to stay the same. Sailor and Munoz [7] computed the sensitivity of electricity and natural gas consumption to climate change at a regional scale. Their approach involved a multiple regression models of historical energy and climate data. The model has been fit with data from eight of the most-energy intensive states in the US. The model employed independent variables that are both primitive such as temperature, relative humidity, wind speed etc. and derived variables like HDD/CDD, enthalpy latent days etc. Statistical results from these model runs suggest that derived variables like HDD/CDD are better suited for electricity modeling and primitive variables like temperature are more suited for natural gas modeling. Considine [18] estimated that on a short-run basis, heating degree-days have a greater impact on energy consumption than cooling degree-days since HDD demand elasticities are larger than CDD demand elasticities. Amato et al. [13] used a similar regression model to determine the temperature dependent demand in the state of
Massachusetts, US. The model calculated historic sensitivity to residential and commercial demand for electricity and heating fuels, using degree-day methodology.

Figure 2 presents the theoretical relationship between temperature and energy use. At balance point temperature, the energy requirement is at a minimum since outside climatic conditions equals the desired indoor temperatures. The underlying assumption in a U-shaped energy demand response functions is that the temperature sensitive demand (TSD) is above the balance point temperature, while the non-temperature sensitive demand (NTSD) is the rectangular area below this point. The U-shaped demand response to temperature is a consequence of the non-linear effect of temperature on demand. To give an example, the effect on electricity consumption is different for a 5°F increase in temperature from 33°F, in comparison to a 5°F increase in temperature from 70°F. NTSD includes energy consumed for lighting, industrial processes, transportation, captive power demands from generating units (like pumped storage) etc. Figure 3 presents the actual temperature and electricity consumption usage for the state of New Jersey in the year 2005. From the graph, the base temperature roughly corresponds to the range of 55-59°F wherein the electricity demand is at a minimum. The peak demand of about 200 GWh constitutes the NTSD for New Jersey. On a peak summer day with a daily mean temperature of 85-90°F the peak demand approaches a high of as much as 300 GWh. The summation of area below the graph gives the annual electricity consumption for the state. The authors are not aware of any significant research studies on the effects of climate change on NTSD. Considine [18] investigated the effect of temperature increase on US energy consumption per unit of industrial production. Industries require energy for operation of machinery, process heating/cooling and to a lesser extent for space conditioning. The study predicts that for a 1°C rise in mean temperature, the net energy demand for the industrial sector in the US would decline by 6.2% due to increase in cooling water temperature.
Some models have studied the impact of climate change on peak demand that indicates the need for additional capacity generation to sustain normal economic growth [14, 19]. Franco and Sanstad [19] have used cubic regression models to explain the relationship between temperature and electricity consumption in California, US. International case studies of climate change impacts have also used multiple linear regression models ([5] on Thailand and [14] on Australia). Chen and Lie [17] have used an
artificial neural network (ANN) approach to forecast electricity demand for New Zealand. There have been studies on the potential impact of increased adoption of air conditioners (AC) on cooling energy demand [8, 20]. Sailor and Pavlova [20] have determined that increased cooling demand in the future is expected to be significant in summer months and will potentially have a considerable impact on capacity reserve margins.

Electricity demand/consumption patterns exhibit wide fluctuations when measured in any order of time scale. Figures 4 and 5 indicate the variation in total electricity demand for the state of New Jersey in one year. The graphs indicate the extent of fluctuation in demand and also the underlying trends and seasonality. An encouraging aspect of forecasting the electricity demand is that the fluctuations can be explained by weather patterns, social habits, conventions and past consumption trends. Hence it is possible to construct quantitative models with high degree of forecast accuracy. Short-term demand drivers like temperature, humidity, day of the week, seasons and holidays can be easily incorporated in a quantitative model. Long-term changes in consumer behavior can also be modeled by incorporating economic forecasts and trend variables in the models. Modelers have employed a range of approaches to predict the electricity demand. These include multiple linear regressions, ARIMA modeling, Vector auto-regressions (VAR), Bayesian VAR, time-varying splines, judgmental forecasts and artificial neural networks (ANNs) [21].
Figure 4: Annual variations in electricity demand for New Jersey (arranged chronologically) [22]

![Figure 4: Annual variations in electricity demand for New Jersey](image)

Figure 5: Annual load duration curve (LDC) for New Jersey [22]

![Figure 5: Annual load duration curve](image)

To get an overall picture of the demand variations, modelers have used the concept of load duration curves (LDCs). An LDC is a curve (see Figure 5) in which the load or the demand data for a given time interval is arranged in a descending order of magnitude, rather than chronologically as shown in Figure 4. The point at which the curve touches the Y-axis indicates the peak demand of the system. The area
under the curves denotes the MWh energy consumption/demand in a given time frame (usually a year as shown in Figure 5). From a theoretical perspective, the effect of climate change is to increase the peak of the LDC. The difference between the peak and the off-peak load is also expected to increase.

The major effects of climate change on LDCs are shown in Figure 6. The increase in peak load demand may have significant implications on the capacity market design and generation expansion planning. Generally, electricity systems are designed to meet the peak load demand. A sharper peaks call for increased capacity installation and availability of peaking units that runs only for a few hours in a year. Market price caps⁴, if any, can also lead to a “missing money” problem if the cap is not set sufficiently high.

![Figure 6: Theoretical effect of climate change on LDCs](image)

Some of the recurring inferences from these models are summarized here. The spatial scale of demand-side modeling usually ranges from a state-level to a region or country-level. HDD/CDD is seen as the best

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⁴ A price cap is a regulatory tool to protect the retail consumers from price spikes. A cap is set on the competitive wholesale prices by the system operator to buffer the consumers from price spikes. A price cap tends to distort market price signals thereby inhibiting adequate capacity investments. This leads to a “missing money” problem for the generators as peak revenues are withheld through a regulatory intervention.
explanatory variable to explain the changes in electricity demand. The choice of baseline/balance temperature to determine the HDD/CDD is best defined on a regional scale. Load duration curves (LDCs) are good modeling tools to study the impact of climate change on electricity system demand. The effect of climate change in transportation sector has no significant direct impact on the electricity sector. Also, the authors are not aware of any significant research studies focusing on the impact of electric cars on overall electricity demand and how it relates to climate change on a national/regional scale. Table 1 lists the documented implications of climate change on demand-side components of the electricity systems. Table 2 compares the different temperature-demand model frameworks, the key parameters the models incorporate and its findings.

### Table 1: Implications of climate change on demand-side components of electricity

<table>
<thead>
<tr>
<th>Demand System Component</th>
<th>Climate Change Effect</th>
<th>Implications</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heating demand</td>
<td>Warmer winters and extended summer/ dry seasons</td>
<td>Decreased electricity usage in winter when compared to the usage in summer</td>
</tr>
<tr>
<td>Cooling demand</td>
<td>Hotter summer seasons</td>
<td>Increased peak demands in summer, increased usage of air conditioners</td>
</tr>
<tr>
<td>Non-temperature sensitive demand (NTSD)</td>
<td>Extended dry seasons and increased cooling water source temperature</td>
<td>Potential generation curtailment and frequent demand response initiations to avoid system blackouts</td>
</tr>
<tr>
<td>Peak demand</td>
<td>Hotter summers, warmer and shorter winters</td>
<td>Annual double peak demand pattern, with high summer peaks and a comparatively lower winter peak</td>
</tr>
<tr>
<td>Load Duration curves (LDCs)</td>
<td>Systematic changes in space-conditioning profile and extreme weather events</td>
<td>Higher curve peaks and greater load variations. Increased chances of breaching the market price cap.</td>
</tr>
</tbody>
</table>
### Table 2: Electricity Market models focused on demand-side impacts

<table>
<thead>
<tr>
<th>Study</th>
<th>Model Type</th>
<th>Key Parameters</th>
<th>Model Framework</th>
<th>Key Findings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rosenthal &amp; Gruenspecht [8]</td>
<td>Non-regression type (temperature rise is assumed)</td>
<td>Dependent Variable (DV): Energy demand</td>
<td>Scope of study: Five typical climate zones in the US.</td>
<td>A global warming of 1°C would reduce projected U.S energy expenditure in 2010 by $5.5 billion (1991 dollars). When increased penetration of air conditioners is taken into account the savings drops to $4 billion.</td>
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<td></td>
<td>Logistic regression to model probability of owning an air conditioner as a function of CDD.</td>
<td>Independent Variable(IV): degree days</td>
<td>Energy demand projection for a 1°C rise in temperature using change in HDD/CDD in five distinct climatic zones.</td>
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<td></td>
<td></td>
<td>Scenarios: baseline and global warming scenario</td>
<td>Corresponding change in degree days is mapped into energy demand for space conditioning.</td>
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<tr>
<td>Sailor and Munoz [7]</td>
<td>Multiple linear regression models</td>
<td>DV: Energy demand</td>
<td>Scope of study: MLR model applied to eight most energy intensive states in the US.</td>
<td>Degree-day approach is best suited for electricity and temperature variable is best suited for natural gas demand models. Constant term in regression equation indicative of NTSD.</td>
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<td>Primitive variables (IV): temperature, relative humidity, wind speed.</td>
<td>logarithmic linear regression was used to avoid heteroscedasticity.</td>
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<td></td>
<td>Derived variables(IV): HDD/CDD, enthalpy latent days (ELD)</td>
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<tr>
<td>Howden and Crimp [14]</td>
<td>Multiple linear regression models</td>
<td>DV: Electricity demand</td>
<td>Scope of study: Four cities in Australia MLR model is used to determine climate sensitivity of electricity demand.</td>
<td>Peak demand was found to be more sensitive to increased temperature. Joint adaptation strategies could reduce the overall peak demand.</td>
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<tr>
<td></td>
<td></td>
<td>IV: HDD/CDD, temperature humidity index (THI), vapor pressure deficit (VPD)</td>
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<tr>
<td>Considine [18]</td>
<td>Linear regression, logit models</td>
<td>DV: total energy demand per day</td>
<td>Scope of Study: US</td>
<td>Warmer climate conditions slightly reduce energy demand and carbon emissions in the US.</td>
</tr>
<tr>
<td></td>
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<td>IV: HDD,CDD, fuel prices, income/output</td>
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<tr>
<td>Sailor and Pavlova [20]</td>
<td>Linear regression models (for demand) Scatter plot based</td>
<td>DV: Electricity consumption per capita, AC saturation(city wise)</td>
<td>Scope of study: Air conditioning (AC) systems saturation data for 39 cities in the US</td>
<td>Strong correlation between AC saturation and CDD.</td>
</tr>
<tr>
<td>Study</td>
<td>Model Type</td>
<td>Key Parameters</td>
<td>Model Framework</td>
<td>Key Findings</td>
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<tr>
<td>curve fitting for AC saturation data</td>
<td>IV: CDD, HDD</td>
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<td>A 20% increase in CDD can increase residential electricity consumption by 1-9% depending on cities. Residential AC consumption alone increases by 20-60%.</td>
</tr>
<tr>
<td>Amato et al. [13]</td>
<td>Multiple linear regression models</td>
<td>Energy demand (per capita per month) (DV) HDD/CDD, annual trend of HDD/CDD, hours of daylight, log electricity price Scenarios: Canadian Climate Centre (CCC) &amp; Hadley Center (HC)</td>
<td>Scope of study: Cities in Massachusetts, US. First step evaluates the historic temperature sensitivity of residential and commercial demand for electricity using degree-days models. Second step, uses the regression equation to predict energy usage under two sets of scenarios.</td>
<td>Potential impacts of climate change are dependent on spatial scale of analysis. Models must also incorporate the intra-annual variation in historic energy demand (using the scale of analysis on a monthly basis preferably). Changes in energy demand to weather patterns differ by energy type (electricity, natural gas) and consumer sectors (residential, commercial), thereby highlighting the need for disaggregation in energy analyses.</td>
</tr>
<tr>
<td>Hadley et al. [6, 43]</td>
<td>Multiple linear regression models</td>
<td>DV: Electricity demand IV: HDD/CDD</td>
<td>Scope of study: US census regions (including Alaska and Pacific) till 2025 Uses EIA’s National Energy Modeling System (NEMS) to predict demand response to temperature increase under</td>
<td>Overall, cooling needs are increased, while heating needs are reduced. In all scenario runs, there was an initial decline in energy expenditure as heating reduction outpaced cooling increase. Eventually, it resulted in an overall</td>
</tr>
<tr>
<td>Study</td>
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<tr>
<td>Franco and Sanstad [19]</td>
<td>Multiple linear regression models</td>
<td>DV: Electricity demand IV: HDD/CDD Scenarios: Hadley &amp; IPCC</td>
<td>Scope of study: Four sites in California, US Uses historic temperature to construct a cubic regression model. The regression estimates are used in Hadley and IPCC scenarios to estimate the impact on electricity consumption and peak demand.</td>
<td>Based on regression equation, the % increase (relative to baseline) in annual electricity consumption and peak demand is estimated under different scenarios.</td>
</tr>
<tr>
<td>Parkpoom et al. [5]</td>
<td>Multiple linear regression models</td>
<td>DV: Electricity demand IV: HDD/CDD, humidity, day &amp; hour of the week</td>
<td>Scope of Study: Thailand (data from a regional electric utility company)</td>
<td>The forecasted demand profile was compared with the actual demand curve for a week in April of 2004. The curve indicates a high degree of correlation between the model forecast and the actual electricity demand data.</td>
</tr>
<tr>
<td>Chen and Lie [17]</td>
<td>Artificial neural networks</td>
<td>Key variables: degree days, diurnal temperature range and holiday loads Nodes: Fifteen supply points in Auckland</td>
<td>Scope of study: New Zealand (for Auckland city) Data: ten years of historic demand data and two years of data for validation.</td>
<td>In New Zealand’s case, global warming of 1°C is likely to reduce electricity demand by about 1.4%.</td>
</tr>
</tbody>
</table>
3. Models focused on supply-side impacts

Apart from research studies that focus on demand side effects, there have been numerous studies that have focused on the supply side effects of climate change. Changes in climate variables like precipitation, mean surface temperature etc. could affect the supply of electricity from both thermal and non-thermal sources. From the reviewed literature, the three most important supply side effects of climate change are decreased thermal efficiency of power units due to increase in air and cooling water temperatures; changes in hydrological cycles and patterns that eventually affect hydropower generation; and extreme weather events and its impact on transmission infrastructure and facility siting decisions [9, 10].

In 2010, nearly 75% of world’s electricity was generated from thermal sources like coal, oil, nuclear, natural gas etc. [9, 23]. As temperature differential between the machine and the environment reduces, the net power generated also reduces. Durmayaz and Sogut [11] investigated the impact of increase in cooling water temperatures on thermal efficiency of nuclear plants. Their findings suggest that a 1°C increase in environmental temperature reduces power output by 0.45% points. Linnerud et al. [24] used country specific data to investigate the impact of thermal efficiency on different types of generation technologies. The study concluded that for a temperature increase of 1°C, nuclear power output reduces by 0.8%, coal and gas power output decreases by 0.6% due to thermal efficiency losses. Ambient air temperature has an immediate effect on gas turbines. Davcock et al. [25] found a 60°F variation in temperature during a day (say in a desert environment) would have a 1-2 percentage points reduction in efficiency and 20-25% reduction in power output. Since they predicted the effect to be linear, a 1°F increase in temperature could result in 0.01-0.03% point reduction in efficiency and a 0.3-0.4% point reduction in power output. Since gas turbines are used as peaking units, such reductions would have a significant impact on actual peak prices of electricity. Also, such reduced plant availability during peak
demand days would have significant implications for the capacity market designs in restructured markets. Although, the drop in efficiency appears negligible at a unit plant level, its cumulative supply-side impact could be very large. For the US, it is estimated that a 1% reduction in efficiency of generators due to increase in ambient temperature would cause a drop in supply by 25 million MWh in a given year [10].

The production of electricity from thermal sources is also linked to the availability of adequate and sustainable water supplies. Freshwater availability is expected to play a crucial role in facility siting decisions in the future. In the US, thermo-electric power generation accounted for nearly 39% of freshwater withdrawals⁵ [26]. On average it is estimated that for every kWh of electricity generated, nearly 25 gallons of cooling water is required (weighted average across all technologies taking into account both consumed and re-circulated water) ([10] p.32). Chandel et al. [27] used a bottom-up approach to forecast the freshwater requirement of thermal power plants. The paper computed the water requirements of individual thermal power plants based on EIA data. In case of missing data, the model imputed the average value of cooling water requirement per MWh, by technology and type of cooling systems. Based on the forecasted demand and generation mix, the model computed the cooling water requirements in the future. Rubbelke and Vogele [28] used the formula for estimating the cooling water demand for power plants to compute the impact of climate change on power generation in Europe. The interaction of ambient and freshwater (stream) water temperatures is also modeled in this study using an empirically derived formula. The study estimated that by 2030 the availability capacity of nuclear and hydro-plants worldwide will reduce by 6 GW and 12 GW respectively due to increase in air and water temperature and decrease in water availability.

⁵ Power plants generally return most of the cooling water used. However, the discharged water is at a higher temperature compared to water drawn at source. Also, a certain portion of cooling water is consumed due to evaporation and diversion for scrubbing (around 3.3% freshwater is consumed for thermo-electric generation in the US in a given year) [26].
The major mechanisms through which climate change can affect hydro-power production are through changes in river flow, increased precipitation/evaporation, melting of freshwater glaciers and capacity of reservoirs. Increased precipitation and river flow indicates a greater potential for hydroelectric generation, provided the flow does not exceed the designed capacity of the reservoir. Erratic river flows and extreme flooding can also affect the safety of dams. Barnett et al. [29] estimated the hydropower production from the Colorado River basin to reduce as much as 40% by the middle of this century. Also, a NWPPC study [30] predicted inter-seasonal variations in hydropower production due to climate change in the Columbia River basin. Winter and spring hydro-production is expected to increase, while summer production is predicted to be considerably lower. Drastic changes to timings of peak flow will also affect flood control schedules. An EPRI [31] study has documented historical cases of generation curtailment due to freshwater scarcity and drought conditions. The climate change effects and its effects on the electricity supply-side components are summarized in Table 3.

**Table 3: Implications of climate change on supply-side components of electricity**

<table>
<thead>
<tr>
<th>Supply System Component</th>
<th>Climate Change Effect</th>
<th>Implications</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hydropower production</td>
<td>Changes in river flow, coastal/inland flooding</td>
<td>Affects plant siting decisions and transmission infrastructure.</td>
</tr>
<tr>
<td></td>
<td>Inter-seasonal variation in river flow</td>
<td>Dam safety, erratic variations in generation of power, increased risk of flooding etc.</td>
</tr>
<tr>
<td>Thermal power generation</td>
<td>Increased ambient air temperature</td>
<td>Decreased efficiencies of power generating units</td>
</tr>
<tr>
<td></td>
<td>Increased cooling water temperature</td>
<td>Decrease in thermal efficiencies of generation units, affects marine life at discharge and sometimes leads to generation curtailment.</td>
</tr>
<tr>
<td></td>
<td>Increased dry spells and reduced water availability</td>
<td>Generation curtailment, expensive adaptation designs etc.</td>
</tr>
<tr>
<td>Transmission Infrastructure</td>
<td>Higher ambient temperature</td>
<td>Reduced equipment lifetime, reduced power carrying capacity (due to thermal limits) and threat of disruption due to power line sagging</td>
</tr>
</tbody>
</table>
Extreme weather events have the potential to cause abrupt and unforeseen disruptions to electricity generation and supply. Like other aspects of supply side effects, there is very little research on this subject [9]. Warmer days in summer are expected to stress the system components (like transmission lines, transformers etc.) due to decreased thermal limits. If generation units are not derated to function within the thermal limit range, chances of equipment failure and system blackout increases. Miller et al. [32] have executed a comprehensive study of the effect of extreme heat days on California’s electricity demand. The study predicts that frequency of extreme hot days (i.e. T90 period- defined as 90% exceedance probability of the warmest historic summer days from 1961-90) is expected to increase by 200% for inland cities and 400% for coastal cities by 2100. When projected extreme heat and electricity demand was mapped onto the current electricity grid, a potential for electricity deficit as high as 17% exists during T90 periods (assuming no demand response/curtailment). US CCSP [10] reports that hurricanes in 2005 alone cost the US energy industry about $15 billion. With climate change, the frequency and the intensity of extreme events may increase in the future. IPCC [1] report has predicted a 66 percent likelihood of stronger hurricane intensity in the next hundred years (also [33]). Such weather events are also expected to affect the delivery of electricity through disruption of transmission infrastructure. Peters et al. [34] assessed the impact of climate change on transmission network. In 2004, the cost of weather-induced transmission outage to utilities in the US amounted to over $2.5 billion. With climate change this cost may increase substantially in the coming years. On an overall regional or macro-economic scale it is necessary to know how a unit degree increase in temperature is expected to affect the frequency of extreme weather events. Cardell et al. [33] valued the total electricity assets in the United States at around $800 billion. Replacing or retrofitting such assets to meet the challenges of extreme weather events may be an unrealistic proposition. Hence adaption strategies are most likely to focus on incremental changes to the electricity supply chain. Cardell et al. [33] have identified key potential research areas in this regard. They include using climate change
predictions to estimate the rate of change of power system design parameters, developing contingency plans to meet extreme events and incorporating extreme weather incidence in blackout risk assessments.

Table 4: Summary of Models focused on supply-side impacts

<table>
<thead>
<tr>
<th>Study</th>
<th>Scale/Scope of analysis</th>
<th>Subject</th>
<th>Key Findings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Durmayaz and Sogut [11]</td>
<td>Nuclear – plant level analysis</td>
<td>Thermal efficiency of nuclear plants</td>
<td>A 1°C rise in cooling water temperature reduces power output by 0.45% points.</td>
</tr>
<tr>
<td>Davcock et al. [25]</td>
<td>Gas turbines-plant level analysis</td>
<td>Thermal efficiency of gas turbines</td>
<td>A 10°F rise in ambient temperature would produce a 0.5% points reduction efficiency and a 3-4% reduction in power output.</td>
</tr>
<tr>
<td>Linnerud et al. [24]</td>
<td>Technology-specific data</td>
<td>Impact of climate change on electricity generation through thermal cooling</td>
<td>For a ambient temperature increase of 1°C, nuclear power output reduces by 0.8%, coal and gas power output decreases by 0.6% due to thermal efficiency losses.</td>
</tr>
<tr>
<td>Rubbelke and Vogeley [28]</td>
<td>Technology-neutral formulations for cooling water requirements for a power plant</td>
<td>Impact of climate change on electricity supply and prices in Europe.</td>
<td>By 2030, nuclear power availability is down by 6GW and hydro-power availability is reduced by 12 GW in Europe. The results confirm the need to supplement autonomous adaptation with planned public adaptation.</td>
</tr>
<tr>
<td>Chandel et al. [27]</td>
<td>United States (regional basis) Scenario-based analysis till 2030 (Low and High Carbon Scenario with/ without CCS)</td>
<td>Freshwater use in thermo-electric generation</td>
<td>Freshwater withdrawal (not consumption) is set to decline by 2-14% relative to BAU (under all scenarios) in 2030. At high carbon prices, retrofitting coal plants for carbon capture (CCS) increases the water use.</td>
</tr>
<tr>
<td>NWPPC [30]</td>
<td>Columbia river basin</td>
<td>Hydropower generation</td>
<td>Inter-seasonal variation in power generation. Changes to timings of peak flows are expected to affect flood control schedules.</td>
</tr>
<tr>
<td>Study</td>
<td>Scale/Scope of analysis</td>
<td>Subject</td>
<td>Key Findings</td>
</tr>
<tr>
<td>------------------------------------------------------</td>
<td>------------------------------------------------</td>
<td>----------------------------------</td>
<td>---------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Barnett et al. [29]</td>
<td>Colarado river basin</td>
<td>Hydropower generation</td>
<td>By 2050, the hydropower production could drop as high as 50% of the current generation due to climate change effects.</td>
</tr>
</tbody>
</table>
| US Climate Change Science Program(CCSP) [10]         | Theoretical analysis of effects under three categories-  
  - On Demand  
  - On Production and distribution  
  - Indirect effects | Impact on energy production and use in the US | On supply side, climate change is expected to decrease the overall efficiency of a thermo-electric generation and decrease the availability of freshwater.  
The indirect effects of climate change could be increased risk to generation utilities, institutional changes to energy supply and increased R&D investments. |
| Miller et al. [32]                                   | California                                      | Impact of extreme heating days on electricity demand | The frequency of extreme heat days (defined as temperatures exceeding the “T90” metric) increases for major cities in CA. On such days electricity deficit for the state can reach as high as 17%. |

4. **Combined models that focus on both demand and supply side impacts:**

Integrated assessment models (IAMs) include models that combine physical and socio-economic aspects of climate change for the purpose of public policy formulation [35, 36]. Under the framework of IAMs, there are the economic models that focus on the effects of climate change on different sectors of the economy. Energy is a key sector for such economic assessment models. A combined model of the electricity sector is one that incorporates both the demand and supply side of the sector within the larger economic modeling framework. Under restructured electricity systems, the electric grid operators and regulators use sophisticated models to forecast load, direct unit commitment and dispatch and ensure reliability (like determining the dispatch schedule, setting operational reserves, computing the locational marginal pricing (LMPs) etc.) (See [15] for an overview of such models). A logical question that
can arise in this context is to whether representations of future climate change can be incorporated in a
unit commitment and dispatch model framework.

Coughlin and Goldman [4] have identified two main challenges to such endeavors. Firstly, most of the
unit commitment/dispatch models function in “an abstract space of loads bubbles and supply nodes
linked by transmission lines” (Ibid.). To incorporate the effects of climate change, these models must be
situated in well-defined geographic space. However, the effect of climate change permeates beyond the
boundaries of a grid network or a country. It is not possible to contain and measure the effects of
climate change in a defined network. Also as the scale and time horizon increases, it becomes
computationally expensive to compute and forecast details at every node in the gird. Secondly, weather
phenomenon exhibits both random and non-random spatial patterns, that are difficult to simulate and
forecasts. The random weather components include extreme weather events like earthquake or
hurricanes etc. that can disrupt the entire electricity supply chain. On the other hand, non-random
patterns like ambient temperature rise etc. can be modeled with reasonable accuracy (on the demand
side at least). The interaction effects can also produce weather patterns that are local in scope and
limited in time, thereby rendering the task of modeling even more complicated.

Climate is an abstract concept which is usually defined as the long-term average behavior of the
weather. Integrated models of climate change impacts usually rely on projections from atmospheric-
ocean general circulation models (AOGCM) output to forecast demand- and supply-side changes.
Climate change studies require information at smaller spatial and time scales than are available from
AOGCMs. This is usually done by a process of downscaling in which AOGCM outputs at larger scales are
used to develop predictions of climate variables at a smaller scale [4]. One approach to downsampling is
the Regional Climate model (RCMs) which fully simulate the climate in a smaller region using data from
AOGCMs to supply climate values at a regional scale. This section covers such models in greater detail.
Since many of the integrated models are in the process of development (at time of the writing), their findings or forecasts are not fully published. Hence, the scope of this section is limited to the overview of the model architecture.

The Global Change Assessment Model (GCAM) is an integrated global energy-economy model. It is disaggregated into 14 geopolitical regions, explicitly connected through international trade in energy commodities, agricultural and forest products, and other goods such as emissions permits [37]. It is a dynamic-recursive market equilibrium model with the energy system playing a key component (Ibid.). The model runs from 2005 to 2300 in a five-year time steps. The key energy output metrics are energy production (including electricity), transformation, end use, and trade. The key climate output variables are GHG concentrations and global mean temperature. The output of GCAM models are not predictive in nature but can be used as a tool for understanding the complexities of interactions of the various systems.

The Integrated Regional Earth System Model (iRSEM) attempts to address regional human-environment system interactions in response to climate change and uncertainties therein. iRSEM framework consists of a suite of integrated models representing regional climate change, regional climate policy and regional economy with specific emphasis on mitigation and adaptation measures [38]. iRSEM is currently being tested in the US Midwest region (ibid.). Some of the key energy interactions that the model attempts to study are: the impact of climate change on energy demand under extreme conditions (like heat waves); location of renewable energy production relative to energy demand centers, and implications for transmission grid (Ibid.).
Golombek et al. [39] have employed a multimarket equilibrium market model called LIBEMOD to study the impact on electricity industry due to climate change. LIBEMOD models three important partial effects: demand for electricity due to changes in temperature; changes in precipitation and temperature on supply of hydro-electric production and efficiency decline of thermo-electric generation technologies due to cooling water temperature increase. LIBEMOD is an economic simulation of the Western European energy industry. The model considers seven types of generating technologies or energy goods markets. LIBEMOD calculates the investment, production, trade and consumption and prices of energy goods in each of those markets. The research concludes that the net effect of the three key partial effects is an increase in average generation cost by 1 percent and a net decrease in electricity production by 4 percent by 2030.

There are four important combined models with exclusive focus on the US energy (including electricity) markets alone. They are EPRI’s PRISM, EIA’s NEMS, EPA’s IPM and NREL’s ReEDS models. The PRISM model is a regional economy-energy model of the US [31]. The model computes parameter estimates for twelve regions in the US. PRISM employs a general equilibrium modeling approach. The National Energy Modeling System (NEMS) is an energy-economy modeling system of U.S. through 2030. NEMS forecasts “the production, imports, conversion, consumption, and prices of energy, subject to assumptions on macroeconomic and financial factors, world energy markets, resource availability and costs, behavioral and technological choice criteria, cost and performance characteristics of energy technologies, and demographics” [40]. Since the price, demand and type of energy resources vary across regions in the US, the various modules of the NEMS forecasts disaggregate data at a regional or sub-regional level. The major modules of NEMS are demand module (for residential, commercial, transportation and industrial), a supply module (for electricity, renewable, oil supply, natural gas, refining and coal supply), an international energy module and a conversion/interaction module. The NEMS integrating module
controls the entire NEMS solution process to determine whether general market equilibrium is feasible across all the NEMS modules (ibid.).

The US Environment Protection Agency (EPA) relies on ICF Consulting Inc.’s Integrated Planning Model (IPM) for modeling the effects of air emissions from the US power sector (for detailed model documentation see [41]). EPA also uses IPM models to predict the power sector response for the various federal proposals on the nationwide GHGs emission reduction proposals. IPM is multi-regional linear programming model that generates optimal decisions subject to specified constraints. Its objective function is the minimization of all the costs incurred by the electricity sector over a given planning horizon. IPM models economic activities in three key components of energy markets – fuel markets, emission markets, and electricity markets (ibid.). IPM models have been used in air regulatory assessment, integrated capacity planning, dispatch modeling and cost estimation.

The National Renewable Energy Laboratory (NREL)’s Regional Energy Deployment System (ReEDS) is a deterministic optimization model of the electricity sector in the US [42]. It models the generation and transmission capacity expansion in the future. Although it is a capacity expansion model, it is designed to analyze critical energy issues like climate change, renewable standards etc (ibid.). The model computes a cost-optimal mix of capital stock to meet the electricity demand of the future. Presently, the model is capable of computing a cost minimization routine for two-year periods from 2006 to 2050. The model factors in constraints in the form load, operating reserve, transmission, resource, emissions and policy stipulations (like RPS).
Table 5: Summary of Combined Models focusing on both demand and supply-side effects

<table>
<thead>
<tr>
<th>Model</th>
<th>Developers</th>
<th>Key Modules</th>
<th>Methodology/Scope</th>
</tr>
</thead>
<tbody>
<tr>
<td>GCAM</td>
<td>Pacific Northwest National Laboratory (PNNL) – University of Maryland</td>
<td>Primary energy, technology, energy demand, energy transformation, agriculture-land use</td>
<td>Global scope. Dynamic-recursive market equilibrium model.</td>
</tr>
<tr>
<td>iRSEM</td>
<td>Pacific Northwest National Laboratory (PNNL)</td>
<td></td>
<td>Regional scope (US Mid-west)</td>
</tr>
<tr>
<td>LIBEMOD</td>
<td>CREE Center- University of Oslo</td>
<td>Seven type of energy goods/markets</td>
<td>Western Europe. General Equilibrium modeling</td>
</tr>
<tr>
<td>PRISM</td>
<td>Electric Power Research Institute (EPRI)</td>
<td>Three policy scenarios: reference case, CCS mandate, Clean energy standard. It also considers two technology cases: limited portfolio &amp; full portfolio.</td>
<td>Entire United States till 2030. Analytical basis is based on LCOE calculations for various technologies.</td>
</tr>
<tr>
<td>NEMS</td>
<td>US Energy Information administration</td>
<td>Demand, supply, international, interaction and integrating modules</td>
<td>Entire United States till 2030. General equilibrium modeling (for overall integrated output) Other optimization techniques for individual modules.</td>
</tr>
<tr>
<td>ReEDS</td>
<td>National Renewable Energy Laboratory (NREL)</td>
<td>Renewables, conventional generators, storage, transmission variables</td>
<td>Contiguous United States till 2050. Deterministic linear programming</td>
</tr>
</tbody>
</table>

5. Conclusions

An extensive literature review on the impact of climate change on the electricity sector is the first step in understanding and building scenario-based or optimization models of electricity markets. This review highlights the research areas where the knowledge frontier has advanced significantly (i.e. on temperature sensitive demand estimation) and areas where it is limited or lacking (e.g. supply side
impacts, modeling extreme events, combined modeling etc.). It is hoped that the outcome of this research review could inform the design of future electricity market/system models.

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