THE INTEGRATION OF SOLAR GENERATION ON A POWER SYSTEM: OPERATIONAL AND ECONOMIC EVALUATION

by

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A Dissertation

Submitted to the Faculty of Purdue University

In Partial Fulfillment of the Requirements for the degree of

Doctor of Philosophy

Department of Agricultural Economics

West Lafayette, Indiana

December 2018

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A dedication to my dad in heaven and family.

ACKNOWLEDGMENTS

I would like to thank my advisor, Dr. Paul Preckel for supporting and guiding me through this research process over the years. His mentorship and constant encouragement made this dissertation possible. I feel so grateful to have had him as my mentor and advisor.

I would like to give a special thanks to the rest of my committee members. Dr. Douglas Gotham for his patience and expert advice; Dr. Andrew Liu and Dr. Otto Doering for their time and feedback that helped to improve my research.

I am also thankful for my colleagues at the State Utility Forecasting Group (SUFG): Dr. David Nderitu, Mr. Timothy Phillips, Dr. Liwei Lu, Mrs. Fang Wu and Mrs. Darla Mize. Thank you all for your understanding and support provided through busy times.

I would also like to thank Dr. Willian Hutzel from Purdue University and Mr. Larry Conrad from the Indianapolis Power & Light Company (IPL) for providing valuable data for this study.

I would like thank my amazing parents and family for their love and always being there for me through the good and bad times.

Finally, this long journey would not have been possible without the help and unconditional support of all my friends, especially Ángel Aguiar and his family, Ricardo Arias and his family, Nathália La Salvia, Regilene Lima, Mario Munive, Rándol Rodríguez, and Ulianova Vidal.

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ABSTRACT

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Institution: Purdue University
Degree Received: December 2018
Title: The Integration of Solar Generation on a Power System: Operational and Economic Evaluation.
Major Professor: Paul V. Preckel

In recent years, the accelerated deployment of renewable electricity generation resources, especially wind and photovoltaic (PV) solar, has added challenges to the operation and planning of the power grid. One of the challenges is that the variability of solar and wind power output may increase the variation of the load that must be followed by dispatchable resources and increase the ramping capacity needs. Moreover, the decision about the configuration of a PV solar generation systems has operational and economic implications because peak solar energy production does not always precisely occur when the wholesale electricity prices of the system are highest. Therefore, as the renewable capacity levels grow, it becomes increasingly important to examine the potential impacts on the system cost and portfolio of conventional generating units to respond to the intermittent nature of some renewable generation technologies. Three related analyses explored in this dissertation address some of the challenges of integrating utility-scale PV solar and wind projects into a power system using a case study for Indiana.

The first analysis identifies the optimal azimuth and tilt angles of solar PV installations that alternatively maximize the annual electricity generation or the economic value of the resource. The economic implications of the configuration of solar PV installations within Indiana are estimated based on wholesale prices of electricity and simulated solar output for different combinations of angles and types of array installations. The results show that solar projects across the state would need to have azimuth angles within the 177 and 182 degrees range to obtain maximum annual energy and 180 to 190.5 degrees to maximize annual value, independently of their array types. Furthermore, southern and northwestern zones showed the highest impacts from using an optimal angle configuration of the solar installations. Nevertheless, on average, the benefits in annual electricity generated or

economic value from their reconfiguration across the state are minor, amounting to less than one percent.

The second analysis explores the effects of additional solar and wind power investments on the 2035 requirements for baseload and peaking generation capacity, the amount of energy supplied by various types of generation technologies and the costs of Indiana's electric supply system. From a capacity planning and unit commitment/dispatch perspective, the results of this analysis indicated that with a portfolio that includes more solar and/or wind power generation, there would be need to add new peaking generation units. However, the total need for additional peaking resources declines as more renewables are added to the generation mix. Because Indiana still heavily relies on coal and other baseload resources to generate electricity, no new baseload capacity is required in the future. Generally, additions of PV solar and wind capacity amplify the variation in load net of renewable generation and create greater needs for ramping services from conventional units. However, results of the analysis show that the existing portfolio of conventional generation resources in Indiana would have sufficient operational flexibility to be able to accommodate ramping requirements even with PV solar and wind capacity penetration levels as high as 30% of total electricity generation. However, at those levels of renewables capacity there are a times during the year when the optimal operational strategy is to curtail solar and wind generation. From a technical perspective, the results indicated that larger thermal generating units are used more for load following and turned on and off (cycled) more frequently with the additional renewables than without them but mainly during days with low levels of demand and high levels of generation from renewable technologies. From the cost perspective, the results of the model support the idea that it would be cheaper in the long-term to invest in a combination of solar and wind generation resources than in solar generation resources alone. Moreover, the reductions in variable costs, driven by the zero variable cost added to the system by the additional solar and wind capacity, were not sufficient to outweigh the increases in capital costs regardless of the levels of capacity additions.

For the third analysis, the proposed capacity expansion model was used to estimate the value of capacity of PV solar and PV solar in combination with wind capacity in terms of baseload/peaking resources from a deterministic system peak load reliability perspective and for various penetration levels of these resources. The capacity values of solar, which refer to the contribution of PV solar plants to reliably meeting the system peak demand, for all the wind capacity levels analyzed, fall as the amount of solar capacity increases. This is because as solar generation increases and closely coincides with the occurrence of the system peak load, there is a shift of the peak load net of renewable generation time to later afternoon hours, when solar installations begin to reduce their production, therefore decreasing their contribution to reliably meeting system peak demand. The calculated solar capacity values are between 2.7% and 67.3% of the corresponding solar nameplate capacity considering all zones and types of PV solar arrays in Indiana, and vary with the level of solar penetration. The range of values obtained are in line with the ones found in other studies using stochastic reliability-based methods.

This dissertation contributes to the literature on the interaction between PV solar with other generation resources and to their economic, operational and policy implications. Furthermore, it provides another decision-making tool from a planning perspective for policymakers, utility companies and project developers.

CHAPTER 1. INTRODUCTION

1.1 Introduction

Renewable energy sources, particularly wind and solar electricity generation, have gained momentum due to their technological progress, reductions in technology costs and the increasing environmental concerns regarding greenhouse gas (GHG) emissions from generation with fossil fuels (i.e. coal, natural gas, and oil). In fact, environmental regulations proposed by the U.S. Environmental Protection Agency (EPA) like the Mercury and Air Toxics Rule (MATS), which went into effect in 2015, are expected to result in increases in electric generating capacity for renewable technologies and accelerated retirements of fossil fuel power plants, especially coal-fired plants (EIA, 2015).

In recent years, solar photovoltaic (PV) generation has grown more rapidly than other renewables in percentage terms, albeit starting from a small base. In the United States, solar photovoltaic energy generating capacity increased about 67% from 2015 to 2016 and projected to have the highest annual growth rate (6.4%) among all the renewable energy sources for the 2016-2040 period. In that sense, wind generating capacity only increased 13% from 2015 to 2016 and was expected to annually grow at slower growth rate than solar (2.6%) for the same forecast period. However, despite the rapid growth of solar PV generation capacity, this resource represented only 4.1% of the total electricity generation from renewables in 2015; meanwhile, wind generation continues to play a leading role, contributing 37% of that total (EIA, 2017).

In Indiana, renewable resources contributed less than 2% of the total energy consumed in the 1990s. However, the recent expansion in ethanol for biofuel and wind for electricity generation increased renewable energy’s share to over 5% for the first time in 2012 and has since continued above that level mainly due to the increase in biofuels consumption. On the other hand, the contribution of renewable energy to Indiana’s annual electricity generation has also shown a significant change in recent years. Starting in 2008, with the arrival of utility-scale wind and solar energy projects, this contribution grew from 0.5% in 2007 to 5.3% in 2015, with wind accounting for about 82% of that increase. Later, solar photovoltaic (PV) electricity generation also showed a significant increase, going from almost none in 2011 to 156 GWh in 2015 which represented about 0.2% of the state's total electricity generation (SUFG, 2017a).

The accelerated deployment of renewable resources especially wind and PV solar power is a result of a combination of factors including government investments, infrastructure development, and federal and state incentives. According to the U.S. Department of Energy (DOE, 2016), decades of investments by federal government and industry have contributed to installation cost reductions of 41% for land based wind and 64% for utility-scale PV systems in the U.S. observed from 2008 to 2015. In addition to declining installation costs, the rapid expansion of these resources was also due to the availability of state and federal financial incentives (e.g. investment tax credits or ITCs), and state renewable portfolio standards (RPS) with specific provisions for wind and solar technologies (SUFG, 2017a; Obi and Bass, 2016).

Based on these factors and the speed of adoption of solar PV generation, electricity generated from this resource may grow more in the future. Therefore, it is becoming increasingly important to understand how the composition of conventional generation capacity changes as the renewable capacity levels grow (Bushnell and Novan, 2018). Consequently, the efforts of this study focus mainly on estimating the system level impacts of incorporating more solar generation, by itself and in combination with wind power, into the electricity supply system.

According to Boroujeni et al. (2012), modern electricity systems are complex, integrated and very large. However, they can be analyzed by focusing on appropriate subsystems or functional areas. These subsystems are generation, transmission and distribution. The function of the generation system is to make sure that the total installed capacity in a system is sufficient and consistent to meet a variable load/demand at any time, at a reasonable cost. Not meeting the demand at every moment would cause huge loss of welfare to society due to load shedding. Meanwhile, transmission and distribution systems need to be reliable in making sure that electricity can be delivered from the generator to the consumers. This dissertation focuses the analysis on the generation subsystem from a resource planning perspective.

Unlike conventional dispatchable generators that can be turned on or off to respond to changes in demand, solar photovoltaic is an intermittent energy resource with electricity generation that depends on the time of day, season and weather patterns (NREL, 2013). In recent years, the higher penetration of intermittent resources has added uncertainty and challenges to the operation and planning of the power grid. Therefore, due to the increase penetration of this resource, power systems are expected to have changes in dynamic and operational characteristics (Eftekharnejad et al., 2013).

Some of the challenges of integrating PV solar power generation into the power grid are to determine the impacts on system cost and the capacity needs for conventional generators to provide the flexibility to compensate for its intermittent nature. The variability of solar power output tends to increase system variation and alter the optimal mix of other generating units. That is, integration of solar power may cause the load that must be followed by the dispatchable generating resources to be more variable and increase the ramping capacity needs.

Another challenge faced by system planners and operators is related to the absence of coincidence between both PV solar and wind generation with the system load. For example, PV solar generation is greatest during the midday hours when demand is generally not at its peak level. Meanwhile, wind generation is even less coincident because its highest generation levels occur during the night or early morning when load usually is at its lowest levels. Moreover, according to Rhodes et al. (2014), optimal placement (azimuth and tilt) of solar PV systems have an impact on their total energy production, peak power production and economic value of that electricity generated. The decision about the orientation and tilt angle for the design of a PV solar generation systems has operational and economic implications because peak solar energy production does not always precisely align with maximum grid load or occur when the wholesale electricity prices of the system are highest.

This dissertation addresses the challenges of integrating renewable resources (PV solar and wind) into a power system in order to meet future energy demand using a case study for Indiana. The first part of this analysis assesses the economic implications of changing the design of PV solar systems. The implications are estimated based on wholesale prices of electricity and the simulated PV solar outputs for different system configurations, as well as on types of array installations that are representative of the predominant technology used by large PV-system owners within Indiana. This estimation accounts for the impact of weather variability by modeling PV solar generation of projects located in different locations across the state. In the end, the results of this section contribute to identifying the appropriate economically optimal system design of solar plants that maximizes the annual economic value of this resource, as opposed to annual electricity generation.

The second part focuses in estimating the capacity and costs impacts of integrating different levels of renewable generation capacity in the need of conventional generating resources in order to meet future load and ramping requirements. Specifically, the objective is to determine the impacts on capacity needs of two types of generic generation resources and to assess system wide impacts for energy and costs for different solar and wind capacity levels. This study uses the framework developed by Davis et al. (2013) that measured the impact of wind generation on the needs for other generation resources and on total system costs in Indiana.

The third part of the analysis focuses on assessing the value of PV solar and PV solar in combination with wind capacity and the impact of integrating these resources on the need for conventional generating technologies from a reliability perspective. That is, since solar generation is a variable source of electricity due to its dependency on sunlight and cannot be controlled like conventional power plants, it is important to determine its capacity contribution to the system as it is compared to a more dependable generating resource. Therefore, the work on the value of capacity is developed in the context of the available portfolio of generation resources and system peak load.

This research contributes to the literature on the interaction between PV solar with other generation resources and to their policy implications. Additionally, this analysis aims to provide insight on how to improve the efficiency and resource planning of the whole system.

This dissertation is organized in five chapters. Chapter two presents a theoretical and technical background of solar PV generation and also a review of literature relevant to this research topic. Chapter three provides detail information about the source of the data and methodology used to achieve the proposed objectives. Chapter four summarizes the findings, compares and contrasts the results of various scenarios. The final chapter discusses the results, provides concluding remarks, limitations of the research and suggestions for future studies.

CHAPTER 2. LITERATURE REVIEW

This chapter presents a review of existing literature regarding PV solar power, system integration of intermittent resources and methodologies previously used to address some of the challenges mentioned in Chapter 1. The first part of the chapter introduces the discussion with definitions, technical explanation and current situation of solar PV power. The second part offers a background of various research approaches that are related to the models proposed in this research. The review of these studies provides a better understanding and support to this work.

2.1 PV Solar power: A general review

The sun is a powerful renewable source of energy that can be used to heat, cool, and light homes and business. There are different solar technologies that convert sunlight to usable energy for buildings, but solar photovoltaics (PV) is the most commonly used technology to generate electricity. PV gets its name from the process of converting light (photons) directly into electricity (voltage) (NREL, 2018a).

A single PV device is known as a cell and an individual cell typically produces about 1 or 2 watts of power. PV cells are connected together in chains forming modules or panels and then several modules can be connected to form arrays. One or more arrays can be connected to the electrical grid as part of a PV system. Aside from modules and arrays, a PV system also includes mounting structures, inverters (convert DC electricity to AC), cabling, and other components (EERE, 2013).

Solar project developers and electric utilities are using solar PV on a massive scale to power cities and towns (NREL, 2018a). According to Solar Energy Industries Association (SEIA, 2015) the robust utility-scale market led Indiana to rank 14th in the nation regarding installed solar capacity in 2014. In that year, the state added more than 50 megawatts (MW) of new installations for the second straight year. These additions were mainly utility-scale installations, but commercial installations increased, too.

In Indiana, favorable incentives that contributed to the rapid deployment of utility-scale PV solar power projects include feed-in tariffs and expansion of the state's net metering rule (SUFG 2017a). However, there are other policy incentives that could also contribute to the expansion of solar in the state. For example, the Solar Energy Industries Association (SEIA, 2017) has identified the following policy priorities that would benefit the solar industry in Indiana: promote distributed generation policies; ensure future access to net metering for solar customers; and work with stakeholders to ensure reasonable and equitable property taxes for PV solar systems.

Proponents of solar PV power argue that standard analyses fail to capture all the intrinsic value of PV power resulting from its temporal (high PV solar generation usually during peak system demand hours) and locational (potential cost savings in transmission and distribution infrastructure for on-site generation) characteristics. Despite these intrinsic advantages, the cost of solar PV power remains many times higher than the market valuation of the power it produces when compared with fossil fuel generation and other renewable technologies (Borenstein, 2008). That comparison, nevertheless, ignores the reduction of the environmental impacts due to the use of this zero emissions technology as an alternative energy source relative to fossil fuel energy plants.

2.2 Integration of Utility-Scale PV Solar Generation on a Power System

This section presents a literature review to support the objective of assessing the impact of adding PV solar capacity on the use of other non-solar generating capacity (i.e. baseload and peaking generation resources) in Indiana's power system. It also includes an overview of existing analyses regarding the operational challenges due to intermittency, non-dispatchability and temporal generation fluctuations of renewable resources. Additionally, it offers a review of previous research about the optimal configurations (e.g. orientation and tilt angle) of PV solar arrays and estimation of the value of solar capacity.

2.2.1 PV Solar Power System Optimal Operational Designs

Solar energy is a free resource that can be utilized in any part of the world by using a photovoltaic (PV) cell. However, the level of solar radiation captured by a solar module depends on the orientation and tilt of the panel. The azimuth refers to the angle of rotation of the solar panel around an axis that is perpendicular to the surface of the earth, where North is designated to be 0˚ and South is 180˚. The tilt refers to the angle relative to the axis that is perpendicular to the earth where an angle of zero is parallel to a tangent to the earth's surface, and 90˚ is perpendicular to the earth's surface. The appropriate choice of these angles is a critical feature that determines the solar panel's efficiency. It has been traditionally accepted that the optimal azimuth angle of solar modules in the northern hemisphere is directly south (180˚ azimuth) with tilt angle equal to the latitude. This takes the perspective that the goal of orienting the panel is to maximize electricity output. However, these parameters may change depending on the relative position of the Earth and the Sun, climate conditions, utilization period of time (seasons of the year) and other factors (Chang, 2009a; Chang, 2009b; Li et al., 2011; Hummon et al., 2013). On the other hand, if the goal is to maximize the economic value of the electricity generated, taking into account the significant variations in the market price of electricity over time, the optimal angles may be different from those that maximize PV solar generation (Haysom et al., 2015; Rowlands et al., 2011; Hummon et al., 2013).

Along those lines, Blumsack et al. (2010) affirms that traditional design criteria orients PV rooftop panels to have a maximum southern exposure with the objective of maximizing peak power production from the installation over a 24-hour period. However, the time of peak electricity generation from PV arrays with southern azimuth does not coincide with peak electricity demand and the peak value of the electricity.

Thus, the optimal values for the azimuth and tilt angles for the design of PV solar generation systems may differ when an economic objective is selected rather than a power output objective. Potential PV solar generation mostly occurs during the midday hours when the demand and wholesale electric prices are not at their peak level. Furthermore, in the summer, average PV solar generation of west-facing plants can be more closely coincident with system demand and electricity prices than south-facing installations (Borestein, 2008). Therefore, due to changes in wholesale prices of electricity that occur at 5-minute intervals throughout the day, it may be better from an economic value perspective that the solar panels are more oriented towards the west to generate electricity during the mid- to late-afternoon when wholesale prices tend to peak during the summer time.

The conventional practice of estimating the optimal orientation and tilt angle has ignored market demand and price considerations. Only a few analyses have optimized azimuth and tilt angles of solar panels with an objective of economic benefit rather than total annual energy yield. Rowlands et al. (2011) determined these optimal angles for a PV panel in two different locations in Canada maximizing revenue using four different pricing regimes (flat rate, time-of-use, spot market and nodal) from 2003 to 2008. For that analysis' purpose, the flat rate regime used fixed electricity rates that are re-adjusted every six months for the summertime and wintertime. Time-of-use refers to an electricity rate that is set for three different periods (on-peak, mid-peak, and off-peak) reflecting historical patterns of demand in the province and two separate seasons. Spot market is the Hourly Ontario Energy Price (HOEP) that has been established by the Independent Electricity System Operator (IESO) in the province price and is paid by wholesale customers. Finally, the nodal price or locational marginal price (LMP) was estimated using the 'shadow price' for the nodes (individual generators) that are tracked by the system operator and were located close to the sites of interest in the province. These pricing regimes have particular temporal and locational characteristics that were later found to increase the value of solar electricity. In that study, the term value refers to the benefit of combining solar electricity information with market data (e.g. solar-PV system owners maximize revenue given the presence of market conditions as reflected by different pricing regimes).

For that analysis, hourly solar generation for 465 different tilt-azimuth combinations were simulated for a single panel and then used to calculate the annual average revenue for each combination, pricing regime and location. The results showed that the desired tilt angle for Ottawa (45˚N latitude) was between 36˚ and 38˚, and for Toronto (44˚N latitude) was between 32˚ and 35˚ depending upon the particular pricing regime. The desired azimuth was found to be close to due south, between 4˚ west of due south and 6˚ east to due south for Ottawa and between 1˚ west of due south and 2˚ east of due south for Toronto depending upon the type of pricing regime. The results also indicate that solar-PV generates more value in pricing regimes that reward time- and location-differentiated electricity generation. That is, some regimes reward not only electricity generated during high demand periods, but also electricity generated in areas with higher congestion on incoming lines.

Hummon et al. (2013) affirmed that developers are unlikely to orient the solar array towards the west because of lost energy production and the potential increased economic benefit has not been sufficiently quantified in previous studies. In that study, they explored the relationship between the patterns of market prices and historical solar irradiance to quantify the benefits of using a variety of orientations for fixed-tilt PV and one-axis tracking arrays on the annual system economic value as opposed to energy production. The System Advisor Model (SAM) was used to simulate the PV solar generation of installations at several locations within various states (e.g. Florida, Texas, California, New York, etc.) in the USA and wholesale price data from different system operators and service territories (e.g. CAISO, NYISO, PJM, etc.) to represent the time-varying cost of electricity. Overall, the results showed that the increase in annual economic value is relatively small when the PV arrays are re-oriented. For example, if PV systems located within the PJM Interconnection service territory were optimally oriented to maximize annual economic solar value (azimuth=189˚± 4˚, tilt=latitude), it would increase the average economic value by only 0.25% (±0.17) compared to the value assessed by a "typical" installation (azimuth =180˚, tilt=latitude). The results show that the azimuth estimated to maximize annual economic value is always oriented more west than the azimuth that maximizes annual generation (e.g. for PJM locations the maximum generation azimuth = 182˚± 3˚ while the maximum economic azimuth = 189˚± 4˚). Finally, the range of the optimal azimuths was from 178˚ to 223˚, but these results are very dependent on the location of the system and market characteristics. Although no specific location in Indiana was considered in that study, part of the state is within the PJM market area. Since the price data for PJM is expected to be roughly representative of the wholesale electricity prices encountered in other parts of Indiana (i.e. within the PJM Regional Transmission Organization footprint), the resulting optimal design obtained in Humon's study may allow for a meaningful comparison with the results from this study.

An analysis conducted by Rhodes et al. (2014) determined the optimal placement (azimuth and tilt) of fixed solar systems that maximize the production (kWh/m^2/year) of AC electricity (after panel, inverter, and other derate losses) and the economic value of electricity generated (\$/m^2/year). That study used available solar insolation data to calculate solar radiation on a given plane, and then along with weather data, a residential system-based solar PV production model was built to estimate the total energy and economic impacts of system placement for Austin, TX. After construction of the models, these impacts were extended to 1,020 locations across the US, among which 11 were in Indiana. The value of solar energy produced was determined using Electric Reliability Council of Texas (ERCOT) wholesale electricity market, or local utility time-of-use rates as a proxy for average local grid conditions. Their work found that the optimal azimuth angle for 10 locations across Indiana fall within the south facing band, with orientations ranging from 170˚ to 190˚ for the maximum energy value, and to slightly west-facing band with azimuth angles between 190˚ and 200˚ for the maximum economic value analysis. Although the rule of thumb is to decide the tilt angle based on the local latitude, the results showed that for most of the locations in the state, the optimal energy tilt is on average about -6˚ to -10˚ lower than Indiana's latitude, which has an average of 39˚. Meanwhile, the average optimal economic value tilt is about -4˚ to -8˚ lower than the state's latitude.

Blumsack et al. (2010) determined the optimal orientation of residential fixed rooftop PV array that maximizes customer revenues from a net-metering perspective, using hourly wholesale electric prices (LMPs) from the PJM Interconnection and power output simulated for different system configurations. This was conducted under the assumption that the system was completely grid-tied, with no storage and the electric energy balance at any given hour determined if the customer-generator sells excess power or must pay for power consumed. The concluding remarks showed that overall East-West panel arrays configuration (array with half of the panels oriented due east and half oriented due west) increases power gains and thus revenues during morning hours relative to a southern orientation (Azimuth = 0° and tilt = 25°). However, in some cases, revenues declined during the afternoon peak. Therefore, considering orienting the panels based on wholesale electric prices may not perfectly correlate with local customer demands on an hour-to-hour basis.

2.2.2 PV Solar Generation and Power Generation System Characteristics

Traditionally, electric power generation has been controlled to balance the time-varying electricity load (Madsen, 2015). That is, generation must match load at each moment in time. In order to meet the demand at any given time, it was common to use primarily traditional non-renewable energy generation resources (e.g. coal-fired plants, natural gas-fired combined cycle plants, etc.) which are characterized as dispatchable. However, renewable energy technologies have different economic and technical characteristics relative to conventional generators.

Halamay et al. (2011), identifies three major technical characteristics that describe most intermittent renewable generating resources (e.g. wind, solar and wave generation): variability, nondispatchability and energy source. These resources are considered variable because the power generation of large-scale solar plants changes over time and may go from low power output to full production or vice versa over relatively short periods of time. The term nondispatchable refers to the limited control that system operators have over the output of large-scale renewable resources. System operators must deal with whatever the output generated from renewable resources is in the same way as dealing with the load. The lack of certainty about the ability to generate from the renewable sources at any given time results in a low “capacity credit”. However, one unit of energy converted by renewable energy sources is equivalent to one unit of energy saved for “traditional” generation. Therefore, these energy sources can make a significant impact on energy requirements of the grid despite their limited contribution towards the power requirements of the grid for planning purposes.

From an economic perspective, Baker et al. (2013) highlights three important features that differentiate solar PV from conventional generators. First, the main and obvious feature is that fuel (sunlight) is free, which consequently makes PV solar’s variable cost close to zero. Second, the increasing solar capacity penetration into the electricity supply system typically displaces fossil fuel generation that reduces operating costs and GHG emissions. Thus, the marginal economic benefit associated with additional solar capacity depends on the operating characteristics of the units displaced in terms of its effect upon operations (operating margin) or capacity additions (build margin). Third, the nondispatchability of solar electricity generation engenders two issues. The time pattern of PV solar power can be advantageous as solar resources are most productive during high-demand hours when the value of energy is greatest. However, the intermittency of this resource can increase system costs due to the additional reserves and backup generation that may be required to maintain system reliability.

The intrinsic characteristics of solar power pose critical challenges for incorporating large-scale PV generation into the electric power system and ultimately may limit its potential contribution to the electricity sector. Since solar cannot be dispatched both up and down as is possible with non-renewable generators it is convenient to net solar generation from load. Then, dispatchable generators can be used to service the load net of solar. While this combines load and renewable output, it treats uncontrolled components of the system together, using the controlled components to follow the uncontrolled net load. The addition of this renewable resource presents the challenge of changing the net of solar load pattern and tends to increase system variation, which is incorporated due to the daily and seasonal fluctuations of solar generation. That is, the additions of solar power to the system may reduce the net demand (normal load minus solar contributions) of electricity during the middle part of the day and move the need for electricity generation coming from other sources to the evening (NREL, 2013). Furthermore, Denholm et al. (2007), affirms that PV solar at low penetration levels is expected to reduce demand during peak periods and to fit well into the demand patterns of summertime because highest demand periods should be correlated with highest PV solar output. However, PV output may be less coincident with demand during other times of the year.

For illustration purposes, Figure 2-1 shows the Indiana seasonal 2015 average hourly load, load net of solar, and a simulated solar output for a hypothetical 5,000 MWac nameplate solar project. The figure exhibits the seasonal variation of solar generation and shows the presence of a strong positive correlation between solar output and Indiana statewide load during the summer (69%) and a weak positive correlation during the winter (30%). As can be seen in Figure 2-1, during the summer season, solar output reduces average hourly peak load and shifts the time of the peak load hour from 4 PM to 8 PM (time equivalent to the peak of the average hourly net of solar load curve). Since Indiana has its annual peak demand during the summer season, the integration of high levels of solar capacity into the system is expected to modify the amount and type of generation resources needed to meet the annual peak load. In winter, spring, and fall, solar generation could have a pronounce dip in the net of solar load because during mid-day hours, between early morning and late evening, load tends to have low levels and solar generation is at its highest. That is, at high PV solar penetration levels, there is the potential to have two peaks in the daily load curves for any of these seasons. According to CAISO (2013), this "duck curve" shape of the net load curve, demonstrates how electric systems are likely to evolve as more renewable power is added to the grid.

According to Vithayasrichareon and MacGill (2015), the energy and capacity value of PV solar can be quite significant when compared to other variable generating technologies because its generation can be reasonably well correlated with daytime peak electricity demand. However, solar generation does not perfectly match the daily variability in the demand profile because of the temporal fluctuations of solar output. In other words, the increase of the system variability due to solar output daily and seasonal swings might result in the need for more flexible generators, in order to satisfy peak load and to meet ramping requirements associated with following the load net of solar generation. In that sense, peaking capacity has more operational flexibility than baseload generation to take care for this increased system variability. This unpredictability of renewable resources (especially wind and solar) means that electric utilities may not be able to properly control and plan for variable electricity demand (Obi and Bass, 2016). Thus, increasing the fraction of intermittent resources within the generation portfolio is one of the challenges that system planners need to address in order to make appropriate decisions regarding the quantity and type of new resource additions.

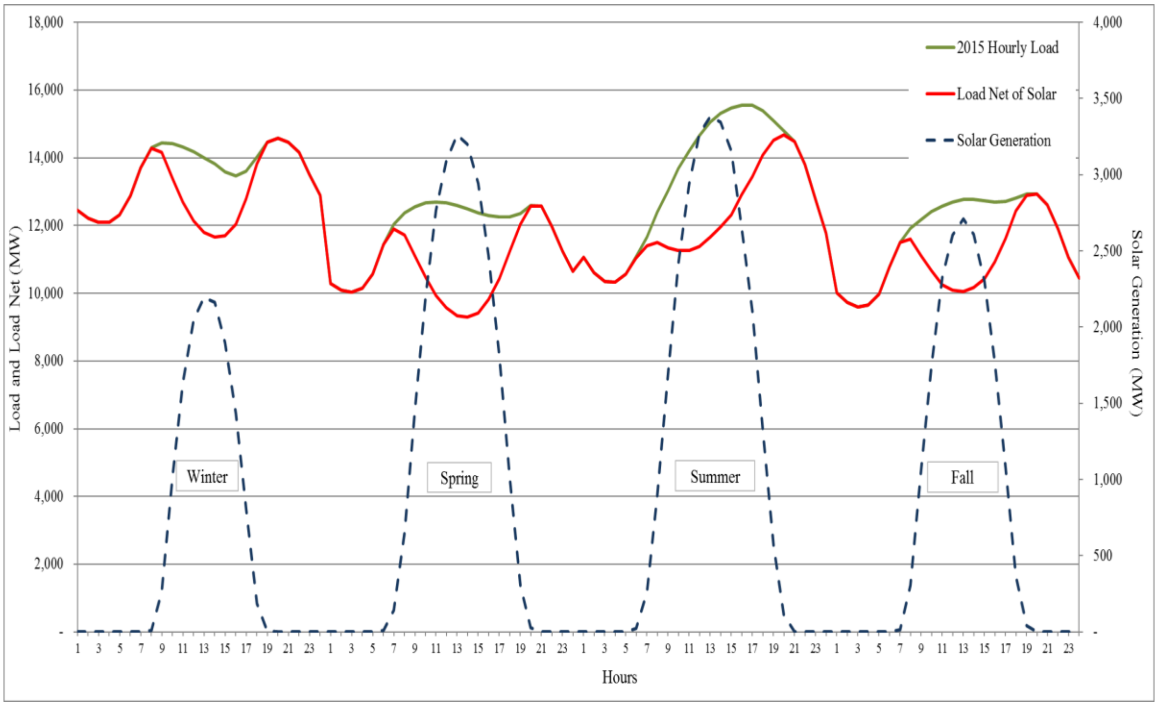

Figure 2-1 Indiana Seasonal 2015 Average Hourly Load, Net Load, and Solar Output (5,000 MWac) Patterns (MW). Source: SUFG and SAM simulated data.

In order to ensure the reliability and efficiency of the system, system planners have been assigned the role of forecasting the demand into the future and planning capacity additions to meet the variable load at a reasonable cost. They also need to provide a level of reliability in case some of the generators are out of commission due to forced or unforced outages (Boroujeni et al. 2012). However, according to Huber et al. (2014), even under perfect forecast circumstances this variability of wind and solar imposes stress in the system operation in two ways: it can cause balancing resources to be cycled more frequently and may create ramp events of extreme duration and steepness.

The level of flexibility to follow load of the power generating system depends largely on the mix of generation technologies. A system dominated by coal or nuclear generators will likely have a lower level of flexibility than a system dominated by gas or hydro units (Denholm et al., 2007). According to Ela et al. (2011), in order to understand the need for flexibility in the generation resources, it is useful to examine the different grid operating timeframes, which are categorized into three different classes: regulation, load following and unit commitment. Regulation typically covers the variability that occurs between subsequent economic dispatches and ranges from several seconds to 5 minutes. Load following typically ranges from 5-15 minutes to a few hours and covers the service provided by generating units that have been previously committed, or can be started quickly, subject to the generator's operating constraints. Unit commitment typically ranges from several hours to several days and involves the starting and synchronizing of thermal power generation needed to meet projected electricity demand. These characteristics are the operational challenges that grid operators need to account for to maintain reliability of the electricity system. Because generation ramping events (both up and down) of solar and wind units can occur rapidly (i.e. over several seconds to minutes), it is considered appropriate to focus the analysis on the regulation and load following services timeframes. In this study, 5-minute load and solar and wind generation data are considered appropriate to use for modeling the economic dispatch of the generation fleet and capture the short-term fluctuations in the load net of solar and wind. Furthermore, this type of data enables evaluation of the magnitude and ramp duration (5-minute periods) of load net of solar and wind generation.

2.2.3 Impacts of PV Solar Integration on a Power System

A number of papers have evaluated the impacts of accommodating PV solar or wind generation in a power system considering the technical and economic limitations using different approaches. For example, Denholm et al. (2007) examined the limitations of a large-scale deployment of PV in a conventional electric power system and its interaction with utility systems considering the flexibility of existing traditional electric generators using hourly data. In that study the authors used a Load Direct Control (LDC) for an electric system in Texas and for planning purposes defined three regions on this curve: base load, intermediate load and peaking. The authors found that due to the mismatch of supply and demand, there is an absolute limit to the economic integration of renewable energy sources. The increase of PV solar generation is limited by the flexibility of conventional power systems, because their lack of ability to reduce output of "must-run" baseload plants. That approach provides some insight into the overall flexibility of systems. However, that study only considers minimum loading constraints, but does not consider ramping rates of the plants or directly address the potential of adding capacity to cover additional ramping requirements.

According to Vithayasrichareon and MacGill (2015), the important role that PV solar might play in the future generation portfolios represents a key policy question in addressing various economic, energy security and environmental challenges. In their study, a Monte Carlo based decision support tool was used to analyze future generation portfolios that include different penetration levels (10-30% of the generation portfolio on an installed generation capacity basis) of large-scale solar PV under uncertainty of future fossil-fuel prices, carbon pricing policy, level of electricity demand and different generation technology capital costs. That study considered an hourly net load duration curve (LDC) after accounting for simulated hourly solar generation in the context of the Australian National Electricity Market (NEM). Their modeling does not consider operating constrains such as ramp rates and minimum operating levels of generating units because it focuses on long-term generation planning and investment. Five generation options were considered in the case study: brown coal (lignite, lower heating value) plant, black coal (Bituminous, higher heating value) plant, combined cycle gas turbine (CCGT), open cycle gas turbine (OCGT) and PV. The System Advisor Model (SAM) was used to simulate hourly solar output in 2010 for 1-MW fixed solar PV plants for specific locations. The results showed, that at moderate carbon prices (\$20/tCO_2), generation portfolio expected costs increase rapidly for portfolios with a majority of coal technologies (>60% of total share) as PV penetration increases. This is because the high proportion of coal technology fixed costs compared with their low variable costs is similar to what PV contributes to the portfolio. Thus, PV is less valuable in that type of portfolio because it offsets a technology with similar low operating and fixed cost generation. In that case, PV solar does not complement coal technologies as well as CCGT and OCGT plants do. While this is the opposite for portfolios with a majority of CCGT and OCGT technologies, where the expected costs decrease or increase very slightly. Therefore, the rate of cost increase depends on the technology mix in the portfolio and highlights the potential of gas-fired and PV generation in complementing each other.

In another study, Huber et al. (2014), focuses on the magnitude and frequency of net load ramps to quantify the future flexibility requirements of a system due to large-scale penetration of both onshore wind and PV solar. That study used a 2011 hourly load profile, and wind and solar output data for each of 27 European countries. Net load ramps were chosen as a measure of the flexibility requirement of power systems since they have to be balanced by flexible resources such as dispatchable power plants. However, according to the authors, many of the conventional power plants considered in the commitment and dispatch process have flexibilities that require a planning period of up to 24 hours. Therefore, it is crucial to plan for ramping capabilities of the power plant fleet in a system over multiple hours when integrating renewable resources into the system. This is because net load ramp requirements over different periods determine the optimal portfolio of conventional power plants. This study does not provide specific estimation of the capacity levels needed to meet future ramping requirements but presents the 1-hour net load ramp rates magnitudes in terms of share of peak load. For example, the results presented for Germany and Ireland for energy penetration of wind and PV represent up to 30% of annual electricity demand (with solar PV accounting for less than 30% of that share) show that conventional plants have to ramp up to less than 25% of peak load in an hour. However, well-interconnected power systems can reduce ramping requirements substantially. The authors concluded that the future flexibility requirements in power systems in Europe depend on the share of variable renewables, their mix and the size of the power system.

The integration of renewable resources can also be analyzed from a commitment and dispatch model perspective. Hetzer et al. (2008) incorporated both wind-powered and conventional generators in an economic dispatch problem. According to the authors, the economic dispatch (ED) problem seeks to find the optimal allocation of electrical power output from different available generators with given constraints. Due to the uncertainty of wind energy available at any time, a random variable with a probability distribution function is incorporated in their model. Furthermore, two penalty terms are included in the cost function to account for the underestimation and overestimation of the availability wind power. The other term in the function accounts for the sum of the costs of conventional generators. The model considered only two conventional generators with a minimum power output of 20% and two wind-powered generators to investigate how variations in the wind power profiles and variations in different cost coefficients will affect the optimum solution of the optimization problem. The results vary depending on the assumed reserve cost coefficient for overestimating the wind energy and the penalty cost coefficient for underestimating it.

Davis et al. (2013) developed a novel optimization methodology for determining the impact of increasing the level of wind capacity in Indiana's generation system. That study used a capacity planning approach and an economic dispatch approach to estimate the impact of wind generation on the needs for other generation resources and total system costs using a load net of wind curve. In the study, 10-minute load and wind output data were used in the capacity planning model for determining the impacts on capacity using capital and variable costs for various generation technology types, but ignoring the potential additional capacity needed to meet ramping events resulting from wind output variability. Conversely, the economic dispatch approach used to estimate the system's energy impacts considered the ramping limits for each type of generation resource as a constraint within the model. The authors showed that increasing wind capacity resulted in a decrease in the total resource needs from non-wind resources. However, the composition of the resource requirements' mix shifted with an increasing need for peaking capacity and decreasing need for baseload and cycling capacity. For this study, an adjusted version of the approach of Davis et al. and several other characteristics of the above-mentioned methods are used as a basis for developing an approach to model the cost of integration of solar generation capacity.

2.2.4 Background: PV Solar Capacity Value Calculation

This section provides definitions of technical terms and explanations of the methodologies used to estimate the capacity contribution to reliability of conventional thermal power generators and renewable resources. The term "contribution to reliability" represents the estimation of the capacity value, which refers to the contribution of a generator or a power plant to reliably meeting the demand. The review of the following research studies helps to lay the foundation for achieving the objective of valuing PV solar capacity and estimating its equivalent value in terms of capacity of baseload and peaking resources within Indiana.

The North American Electric Corporation (NERC) traditional definition of reliability consists of two concepts: adequacy and operating reliability.[1] Adequacy is defined as the ability of the electrical supply system to satisfy the aggregate electric power and energy requirements of the electricity consumers at all times, taking into account planned and reasonably expected unplanned outages of system components. Meanwhile, operating reliability is the ability of the power system to resist sudden faults or disturbances (e.g. electric short circuits or unanticipated loss of system components) (NERC, 2008). According to NERC (2011), variable generation, like wind and solar, contribute towards capacity and energy adequacy. Because most regions are capacity-constrained, that study, similar to this analysis, focuses the discussion on the contributions of the variable generation to capacity adequacy.

Traditionally, system planning considers generation planning and transmission planning. The goal of system planning is to ensure that there are sufficient energy resources and delivery capacity to meet demand requirements in a reliable and economic matter. However, because the transmission system increases the availability of remote generation and changes the diversity of loads that affects the character of the resource mix, transmission ties are disabled in some studies (NERC, 2011). This case study characterizes the Indiana's generation system as if it is an island because the transmission system and imports/exports of electricity are not considered. Furthermore, it is assumed that storage and demand-side resources are unavailable.

In the generation system, the occurrence of generator outages due to mechanical failures, planned maintenance or intermittency of generating resources (such as wind and solar), may leave insufficient capacity to meet the load of a power system. Therefore, estimating the capacity value of a generation facility is crucial for accurate reliability and planning of the system (Madaeni et al., 2012). The capacity value of an electric generation facility is usually assessed with respect to the static conditions of the system (system adequacy) rather than to the ability of the system to react to sudden perturbations (operating reliability)

[1] NERC used the term "security" until September 2001 but it was replaced with the term operating reliability to avoid confusion with homeland protection and critical infrastructure protection.

(Boroujeni et al., 2012; Duignan et al., 2012). The increasing penetration of solar and wind capacity in Indiana is expected to affect the generation system requirements and the reserve margins used for future resource planning. Planning reserve margin[2] is a deterministic measure of the amount of energy generation capacity available to meet expected future peak demand.

There are several methods to calculate capacity value of conventional generators within an electrical supply system, which can be easily adjusted for a renewable resource case. The Effective Load Carrying Capability (ELCC) is one of the most commonly used methods to assess capacity value from a system adequacy point of view (Duigman et al., 2012). The ELCC of a generator is defined as the additional demand which the system may support (when the generator is added to the system) while maintaining the same target reliability level (Duignan, 2012; Madaeni et al., 2012). Loss of load probability (LOLP) and loss of load expectation (LOLE) are evaluation techniques used by the ELCC method to measure system reliability.

Other reliability-based methods used are the Equivalent Conventional Power (ECP) and Equivalent Firm Power (EFP) of a generator. These methods determine the equivalent capacity of a different generating technology that can replace the new generator while keeping the same system reliability level. However, the EFP methodology computes the capacity value using a benchmark plant assumed to be perfectly reliable (e.g. unit has 0% Forced Outage Rate). These methods are attractive in the context of a renewable generator because they allow measuring its capacity value in terms of a conventional generator (Madaeni et al., 2012).

Previous studies have used the ELLC and ECP methods to estimate the capacity value of PV solar power resource. Using a case study of the western U.S., Madaeni et al. (2013) estimated that this resource, on average, has a wide range of capacity values of between 52% and 75% of its AC rated capacity. These estimations vary depending on the

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[2] Reserve margins are meant to ensure that there is sufficient supply available in the system to address reliability challenges such as generation outages or sudden increases in energy demand (Pfeifenberger and Carden, 2013). $\text{Reserve Margin} = \frac{\text{Capacity}-\text{Peak Demand}}{\text{Peak Demand}}$

technology (single- and double-axis sun-tracking systems), location (resource availability) and estimation method used (56% to 75% for the ECP method and 52% to 70% for the ELCC method). In this study, load patterns were fixed at 14 different locations to ascertain the effect of differences in solar availability patterns on the capacity value of PV. Furthermore, the capacity value estimates considered only small plants of 100 MW at each location, thus these estimates do not account for diminishing marginal capacity values due to higher penetrations of PV solar capacity. Additionally, these estimates were computed in isolation and therefore do not account for spatial correlation of solar availability between sites.

In another study conducted by GE Energy (2010) and prepared for the NREL, the capacity values of PV solar and wind generation were calculated using the EFP reliability methodology. The reliability methods historically focus on the peak hour because if a shortage could occur, it would happen at the daily peak load time. However, in their study, in order to capture the potential of having capacity shortages at times other than the peak hour, the proposed model was adjusted to look at all 24 hours in the day. According to the authors, a lower capacity value of intermittent resources compared to traditional thermal units is explained because PV and wind generation tend to occur more during off-peak periods. Some of the results of that study were based on the 2006 load shape for the power system operated by a group of Utilities in Arizona, Colorado, Nevada, New Mexico and Wyoming. For that year and for a 10% wind and 1% solar power levels of penetration from the total of annual electricity sales, the capacity values for wind and PV solar were 12.1% and 33.2%, respectively. For 30% wind and 5% solar penetrations levels, the capacity values were 10.8% and 29.3% for wind and PV solar respectively. It is noteworthy that switching from the EFP method to the ECP or ELCC increases the values by 5% to 10%.

Although, the reliability-based methods are widely accepted and used due to their robustness, their use implies a high level of computational burden and data requirements (i.e. extensive time series data for many years of load and conventional and renewable generation) (Sigrin et al., 2014; Madaeni et al., 2012). In contrast to those methods, there are alternative methodologies and approximation techniques that have been used to specifically quantify the capacity values of solar generation (Perez et al., 2006; Duigman et al., 2012; Madaeni et al., 2013) and some require more modest amounts of system data (Sigrin et al., 2014).

Sigrin et al. (2014) used the Regional Energy Deployment System (ReEDS), which is a generation and transmission capacity-expansion model of the U.S. electricity system, to find the capacity value estimates of solar PV. The ReEDS model employs a measure of a solar generator's ELCC to estimate its contributions to planning reserves in each of 17 periods of a year. That measure is the Z-method, which approximates LOLPs through the distribution of the surplus capacity of the system and supplemented with additional methods that weigh the relative risk of loss of load. That proposed methodology produced capacity values at a fraction of the computational and data requirements of a full reliability-based method because there is no need to conduct an hourly time series analysis. In that study, it is assumed that LOLP is well-correlated with the net system load. That is, the capacity value is well-estimated by a few highest net load hours (reliability-critical hours of the year) due to strong correlation between load and generation. The national solar resource for that study is a representation of 134 areas that allow the model to account for geospatial differences in resource quality and statistical availability during reliability-critical periods. Furthermore, the estimation of solar PV capacity value is also known to be highly sensitive to increasing levels of PV solar capacity because the timing of the reliability-critical hours may shift to later in the day, when solar irradiance is lower, therefore decreasing PV's capacity value. The authors conclude that the capacity values obtained with the ReEDS model compare favorably with the outcomes of a handful of analyses using hourly resolution ELCC-based methods for a range of levels of solar energy penetration.

According to Davis et al. (2013), valuing wind capacity has focused on reliability for serving peak load, but this dimension of the problem does not directly address the impact of investments in wind capacity on system costs. In their study, a capacity expansion model was used to estimate the changes on the total capital costs of Indiana's power system as three different generation resource types were added at various wind capacity penetration levels. However, that methodology also has the potential of being used as an approximation technique to estimate the capacity value of wind in terms of capacity of conventional generation resources while meeting the same peak load level of the system. From their results, it can be inferred that adding 1,000 MW of wind capacity within Indiana’s power system is equivalent to displace from the system about 0 MW of a pulverized coal base load capacity and about 380 MW of a natural gas fired combined cycle capacity. However, this wind addition needs to be complemented with the addition of about 100 MW of a natural gas combustion turbine peaking capacity in order to compensate for the variability of this renewable resource.

For this study, the technique presented by Davis et al. (2013) is considered in order to assess the capacity value of PV solar and PV solar plus wind for the Indiana’s electricity power system. The advantage of that approximation technique is that it provides estimates of the capacity value for renewable resources in terms of specific generation technologies with low computational effort.

CHAPTER 3. METODOLOGY

3.1 Data Collection, Analysis and Simulation

This section provides a description of the data collection and analysis procedures used in this study. It presents an explanation of the sources used to gather Indiana's generation assets, solar generation, wind generation, load and wholesale electricity prices data. Furthermore, this section elaborates on the processes performed to have the load and generation data sets in the same 5-minute time resolution.

3.1.1 Indiana's Conventional Generation Assets Data

Existing generation resources and projected capacity requirements for the Indiana jurisdictional area (e.g. including units in Indiana and other states that generate electricity to meet Indiana's demand only) are collected from the 2015 EIA-860 form, public news reports, independent projects developers and utilities. All the generators or plants dedicated to serve Indiana load are considered as installed generation capacity. The term installed generation capacity includes existing projects, projects under construction and/or already approved by the Indiana Utility Regulatory Commission (IURC). Table 3.6 presents the identified installed generation capacity by technology type.

3.1.2 Simulated PV Solar Generation Data

For this study, the data procedures include the following process steps: calibration of the System Advisor Model (SAM), collection of the locations and technical characteristics of Indiana's solar projects, simulation of hourly solar generation data for those projects, and conversion from hourly to 5-minute solar generation data.

First step is the calibration of the System Advisor Model (SAM), which is a computer tool developed at the National Renewable Energy Laboratory (NREL), Sandia National Laboratories, the University of Wisconsin, and other organizations to model renewable energy projects by simulating power generation of a particular technology on a location specific basis.

After the SAM model calibration process, the next stage is the simulation of hourly solar generation data for all the Indiana's solar assets. In the final step, the hourly data is processed into a 5-minute solar output data. The following sections provide details about all the steps considered to obtain the final solar output data used in this analysis.

3.1.2.1 Calibration of SAM Model

SAM's user program is free to download, and its interface allows one to specify or select default values for many input variables such as the project's location, weather conditions, the type of technology and design of the solar installations, etc. The simulation analysis is based on the installation design parameters and all of the input data entered. Calculations can be made in hour-by-hour or sub-hourly time steps (intervals as short as one minute can be used given weather data with that time resolution), to obtain a chronological series of estimates of the power system generation over a single year using either historical or representative weather conditions.

In order for SAM to simulate hourly generation data comparable to the potential generation of identified installed PV solar capacity generation serving Indiana's ratepayers, the model is first calibrated using actual hourly solar output data provided under a confidentiality agreement by an electric utility (Indianapolis Power & Light (IPL)). The available data is used to calibrate the model and to determine the appropriate values for the input variables.

IPL's hourly generation net of losses data for 2015, and information about the system parameters (e.g. system nameplate capacity, DC to AC conversion ratio,[3] module type such as crystalline silicon or thin film), orientation (e.g. array type, tilt and azimuth degrees), and location are received for different utility-scale PV solar farms or projects. Solar farms are grouped based on three different solar panels array types: horizontal single axis tracking, fixed ground mount, and fixed roof mount.

[3] Represent the ratio at which the inverter convert a DC electrical current into an AC electrical current (type of current used by normal home appliances)

IPL also provides information regarding the ground coverage ratio (GCR). If the project has a one-axis tracking array, SAM allows you to enter a value for this parameter, which is equal to the length of the side of the PV panels in one row divided by the separation distance between rows. This represents the ratio of the area of the PV array to the total ground area, which is used by the model to estimate losses in sunlight capture due to self-shading (Culligan and Botkin, 2007).

The identified array types describe whether the array of the PV panels is fixed or follow the movement of the sun with one axis rotation. Figure 3-1 shows both types of arrays and illustrates the difference between the tilt (angle between the horizontal plane and the solar module) and azimuth (angle measured along the horizon that determines the array's orientation, with zero degrees corresponding to North) angles. Tilt angles of 23 degrees for fixed ground mount arrays, 10 degrees for roof mount projects and 0 degrees (horizontal mount) for axis tracking units are found to be representative of IPL's solar projects. Fixed ground and roof top mounted projects are oriented South and horizontal single axis tracking units have a North to South axis with tracking movement from East to West.

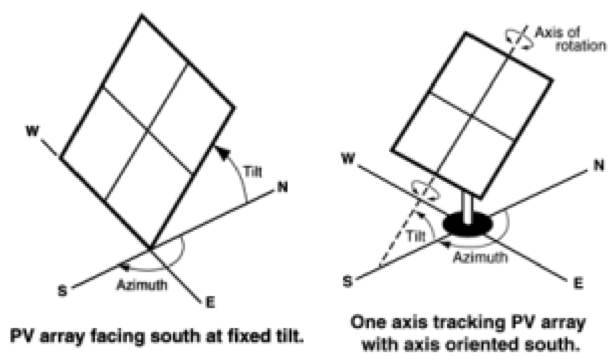

Figure 3-1 Tilt and Azimuth Angles for Fixed and Single-axis Tracking PV Arrays. Source: SAM User's Guide

IPL provides actual hourly generation data for a total of sixteen solar projects located in Marion County. Among these projects, nine of the sites are fixed and ground mounted, two have horizontal single axis tracking arrays, and five are fixed mounted over commercial buildings' roofs. In order to consistently calibrate the SAM model, the solar projects without hourly generation data for a complete year (some sites came on line in the middle of 2015) are removed from the calibration process final sites list. For the remaining projects, days with missing or corrupted observations are also eliminated to obtain the final data set for this process. The data set includes nameplate capacities and DC to AC conversion ratio of the solar sites with complete data. Projects with the same array type are aggregated and averaged, respectively.

For the module type variable, three technology options can be chosen in SAM: standard (glass crystalline silicon), premium (anti-reflective crystalline silicon) and glass thin film. However, all the data provided by IPL correspond to solar projects with only the standard technology. The aggregated and averaged numbers, module type and orientation information, and SAM's weather data file for the specific location (the "USA IN Indianapolis" weather station is used due to its proximity to all IPL's solar projects locations) are selected and entered as input values to later run the model simulations.

After the inclusion of all these values in the model, various combinations of inverter efficiency and loss percentages are also tested as input parameters. Values for inverter efficiency and loss percentages are calibrated to closely match the capacity factor value resulting from the SAM runs and the average capacity factor calculated from the actual data for projects with the same array type (Table 3-1). Note that the loss percentages reflect several types of efficiency losses: soiling, shading, snow, mismatch (e.g. slight differences in performance of individual solar panels in the array), wiring, connections, light-induced degradation, nameplate capacity (accounting for accuracy of manufacturer's nameplate rating), and age. In SAM, losses and inefficiency of the inverter are multiplicative factors, making the amount of these losses proportional to hourly generation.

After obtaining the simulation results, correlations and graphical displays of the observed and modeled solar generation data sets are also created. These analyses provide insight regarding the most appropriate values to be used for the input variables. These analyses also help to identify that differences observed in the results are mainly due to the weather discrepancies affecting the actual observed data year and the representative modeled data. To simulate systems performance, SAM can use a typical year file representing the resource and weather conditions at a specific location. This file is obtained by choosing a data set of twelve months from a multi-year period that best represents average weather conditions over a long time. Since modeled data is estimated using a typical year of climate conditions, these numbers do not reflect the reduction of solar generation that actual data show due to higher than normal rain fall during June and July in 2015. However, the use of typical year weather data is considered acceptable for the purpose of simulating power generation for the total PV solar capacity installed in Indiana. In addition to the numerical analysis, the calibration is considered appropriate because the simulation results tracked the IPL hourly data closely.

The calibration process results in three different sets of parameters corresponding to each array type (ground one-axis tracking, ground fixed, and rooftop fixed). The PV solar installations of the final data set are aggregated by summing their nameplate capacity for each array type. This aggregated capacity and the identified parameters of each set are used to populate the SAM's input parameters section to run the model using the Indianapolis weather station. Table 3-1 shows the three resulting sets of values for each of the array types that were used for obtaining solar generation estimates for this study.

Table 3-1 Input Parameters by Array Type resulting from SAM model calibration*

	Array Type		
Input Variables	Single axis tracking	Fixed ground mount	Fixed roof mount
Module type	Standard	Standard	Standard
DC to AC ratio	1.301	1.284	1.155
Inverter efficiency	96	96	90
Tilt*	0 degrees	23 degrees	10 degrees
Azimuth	180 degrees (South)	180 degrees (South)	180 degrees (South)
Ground coverage ratio (GCR)	0.4	N/A	N/A
Losses	11.22%	15.92%	21.80%
Capacity Factor (SAM Generated = Observed)	17.42%	14.98%	12.30%

*A tilt angle where zero degrees is a horizontal and 90 degrees is a vertical array

3.1.2.2 Indiana's PV Solar Generation Assets

For this analysis, existing and approved utility-scale and medium-scale (>100kWac) PV solar projects dedicated to serve Indiana load are considered as installed solar generation capacity. Detailed information on the solar projects' sizes (kWac), module types (e.g.

standard crystalline silicon and thin film), array type (e.g. single axis tracking, fixed ground, and fixed roof mount), and location (county and state) are gathered from the IURC, utilities and independent developers’ news releases and websites. Most of these solar projects are located within the state of Indiana, with only one project located in the state of Michigan.

Table 3-2 Capacity and Number of Installed PV Generation Solar Projects in Indiana

Counties with PV Solar Projects*	Number of Projects (>100 kWac)	Total PV Solar Capacity by County (kWac)	Share out of total capacity (%)
Bartholomew	1	1,000	0.52
Clark	1	1,000	0.52
Clay	1	5,000	2.60
Daviess	1	4,000	2.08
Dubois	1	2,000	1.04
Elkhart	2	1,002	0.52
Grant	1	2,500	1.30
Greene	1	1,000	0.52
Harrison	1	1,000	0.52
Henry	1	1,000	0.52
Howard	1	7,000	3.63
Jasper	1	1,000	0.52
Johnson	1	1,000	0.52
Lake	2	5,386	2.80
Madison	4	16,200	8.41
Marion	19	92,395	47.98
Marshall	1	700	0.36
Martin	1	17,000	8.83
Miami	1	3,000	1.56
Monroe	1	1,000	0.52
Montgomery	2	3,250	1.69
Newton	1	650	0.34
Perry	1	1,000	0.52
Putman	1	300	0.16
Saint Joseph	2	7,600	3.95
State of Michigan*	1	4,600	2.39
Sullivan	1	5,000	2.60
Vigo	1	5,000	2.60
Wayne	1	1,000	0.52
Total	54	192,583	100

*One PV solar project owned by an Indiana utility is located in the state of Michigan.

Table 3-2 presents the aggregated number and capacity size of PV solar projects organized by county. This table also includes the capacity share of each county out of the total Indiana installed capacity. A total of 54 PV solar projects that add up to about 192.6 MWac are identified, and the majority of projects (48%) are located around the Indianapolis area in Marion County.

Since weather conditions vary from one site to another, weather stations that have preloaded data in the SAM's database are used as reference points to group the identified projects in the state. The projects are grouped into eight different zones based on their proximity to seven different weather stations across Indiana and one located in Illinois. This process is conducted in order to more accurately simulate hourly generation data by capturing the specific regional weather conditions affecting each project. Then, the total PV solar capacity levels (kWac) by county are aggregated for each zone. Table 3-3 presents the specific SAM weather stations, counties or state where projects are located and aggregated capacity generation by zone. Figure 3-2 shows the location of the PV solar projects and the SAM weather stations selected as appropriate for each zone.

Table 3-3 Weather Stations, Counties and Projects Capacity by Zone

Zone	SAM Weather Stations	Counties*						Projects' Combined Capacity (kWac)
1	Chicago Midway Airport	Lake	Newton	Jasper				7,036
2	South Bend	Saint Joseph	Elkhart	Marshall	state of Michigan*			13,902
3	Grissom Air Reserve Base	Miami	Howard	Grant				12,500
4	Lafayette Purdue University Airport	Montgomery						3,250
5	Delaware Co. Airport Johnson Field	Madison	Henry	Wayne				18,200
6	Indianapolis	Bartholomew	Marion	Johnson				94,395
7	Terre Haute Hulman Reg. Airport	Putman	Monroe	Sullivan	Greene	Vigo	Clay	17,300
8	Huntingburg	Dubois	Martin	Harrison	Daviess	Perry	Clark	26,000
	Total							192,583

*The solar project in the state of Michigan is located nearby South Bend weather station

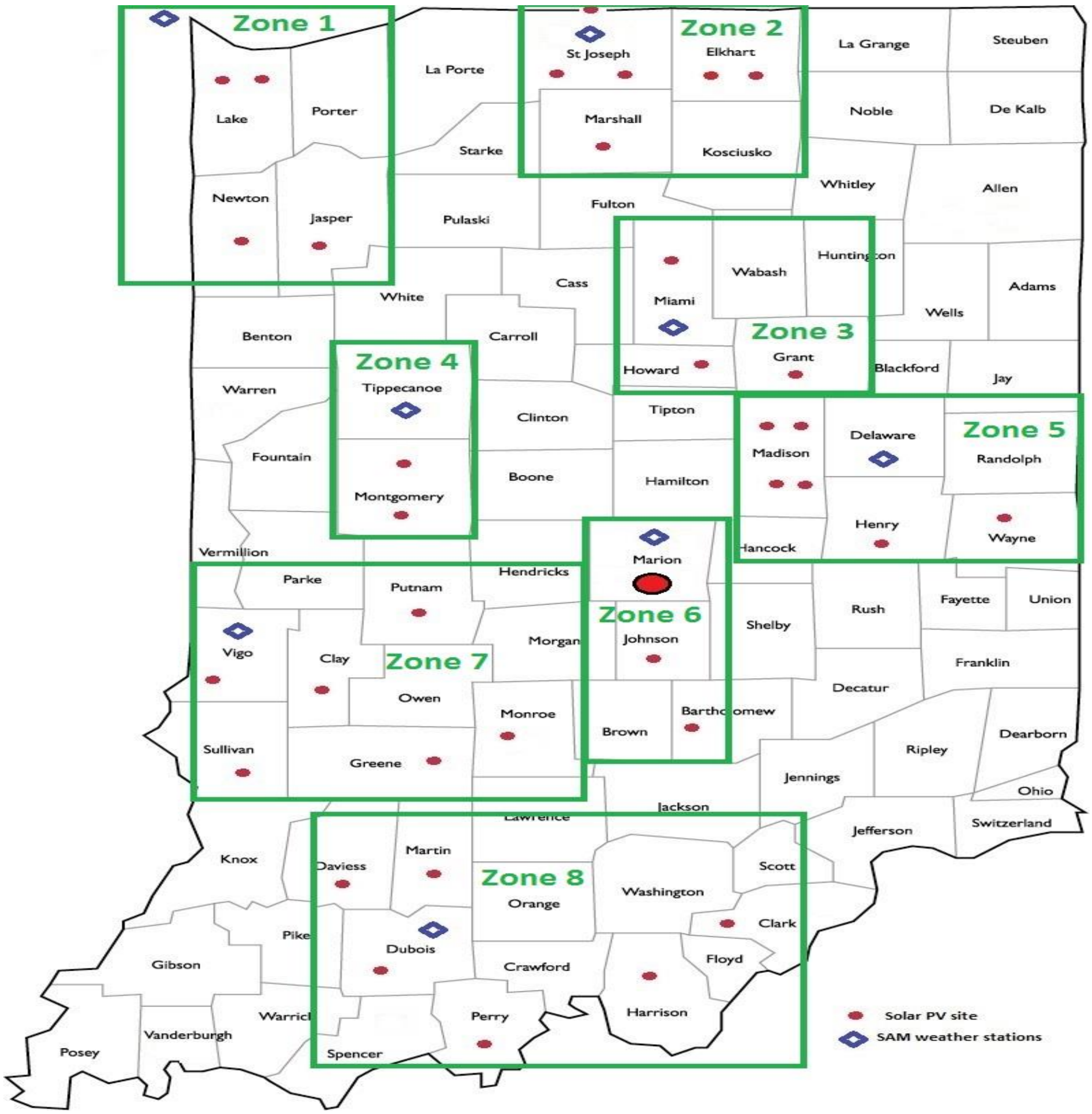

Figure 3-2 PV Solar Projects and SAM Weather Stations. Source: Map outline from www.worldatlas.com

After being organized by zone, the projects are grouped again based on their module type and array type information where only three projects are identified as having a different module technology (thin film in Zone 2) than the other sites. Although, none of the projects used in the calibration process has a thin film module, SAM can reflect the impact of using this or other type of module technologies in the simulation results. Table 3-4 includes the total installed PV solar capacity organized by zone and type of array and module technology.

Table 3-4 Installed PV solar capacity (kWac) by zone, module type and array type

Zone	Single axis tracking	Fixed ground mount		Fixed roof mount	Project Total Capacity
	Standard	Standard	Thin film	Standard	
1	-	7,036	-	-	7,036
2	-	1,075	12,200	627	13,902
3	-	12,500	-	-	12,500
4	-	3,250	-	-	3,250
5	10,200	8,000	-	-	18,200
6	12,000	64,580	-	17,815	94,395
7	2,000	15,300	-	-	17,300
8	2,000	24,000	-	-	26,000
Total	26,200	135,741	12,200	18,442	192,583

The fixed ground mount array with standard technology accounts for about 70% of the total installed solar capacity serving Indiana customers, and the fixed thin film technology is the least used array type, representing only 6% of the overall solar projects total capacity. Both single axis tracking (14 %) and fixed roof mount (10 %) account for about 24% of the total capacity of the projects.

3.1.2.3 Simulation of PV Solar Hourly Generation Data

A total of 15 combinations of zone, module type and arrays type are identified in Indiana. It is noteworthy that the total capacity of each group reported in kWac is converted to kWdc using the DC to AC conversion ratio obtained from the SAM calibration process. This is because the variable parameter interface in SAM only allows a user to enter the system nameplate size values in kWdc.

Due to the removal of some observations with zero values to consistently match the hours of the actual and simulated output at the beginning of the calibration procedure, the estimated operating losses value does not capture the potential curtailment or availability (scheduled and/or unscheduled outages) losses of the PV systems. Therefore, a typical availability derate factor of 2% is added to the loss values estimated at the calibration stage (i.e. the 15.92% losses identified in the calibration process turn into 17.92% in the final run for fixed ground mount array type) (Marion, 2005).

The simulated annual PV solar outputs for each of the 15 combinations of solar projects located in specific zones with different types of technology or design are presented in Table 3-5. The 303,457 MWh represents the simulated total annual energy that may be supplied by the total capacity of the projects (192.6 MWac).

Table 3-5 Simulated Annual System Output (MWh)

Zone	Single axis tracking	Fixed ground mount		Fixed roof mount	Total Energy
	Standard	Standard	Thin film	Standard	by Zone
1		10,847			10,847
2		1,636	18,655	706	20,997
3		18,596			18,596
4		4,616			4,616
5	17,307	11,576			28,883
6	23,305	106,239		21,608	151,152
7	3,296	21,297			24,593
8	3,989	39,784			43,773
Total	47,897	214,591	18,655	22,314	303,457

3.1.2.4 Conversion to 5-minute PV Solar Generation Data

For SAM to simulate solar generation output with a 5-minute time resolution, the input weather data files need to have the same time resolution. However, there is no public weather data available with a level of granularity lower than 30-minute time intervals. One of the alternatives is to purchase 1-minute typical meteorological years (TMY) weather data from Meteonorm, a commercial vendor, and then to process it into 5-minute weather data. However, the solar radiation values in this data set are estimated using the average hourly values of the majority of these weather variables and therefore do not accurately reflect the actual sub-hourly variation in solar radiation.

Therefore, an alternative procedure to generate 5-minute PV solar power output is developed for the Indiana case. The procedure relies on the observed variability of an available 5-minute generation data set that is overlaid on the hourly solar output data simulated with SAM. Figure 3-3 presents the diagram of the steps taken to develop a 5-minute simulated solar output data set for Indiana. The observed 5-minute data set is collected by using solar panels on the roof of the Knoy Building on Purdue University's West Lafayette campus. This is referred to here as the Knoy data. The left-hand side of the diagram explains the processes applied to the Knoy data. The right-hand side of the diagram shows how the hourly SAM data that is simulated and then processed to add in the 5-minute variability that is implied by the Knoy data. The end result is a state-level final 5-minute solar output data set.

The first step of the procedure is to assemble the observed 5-minute generation data set. This data set covers the period from April 2015 through September 2016 and is collected from Knoy's 3-kW PV rooftop solar project. In order to complete a workable data set for a whole year, data from September through December 2015 are combined with data from January through August 2016.

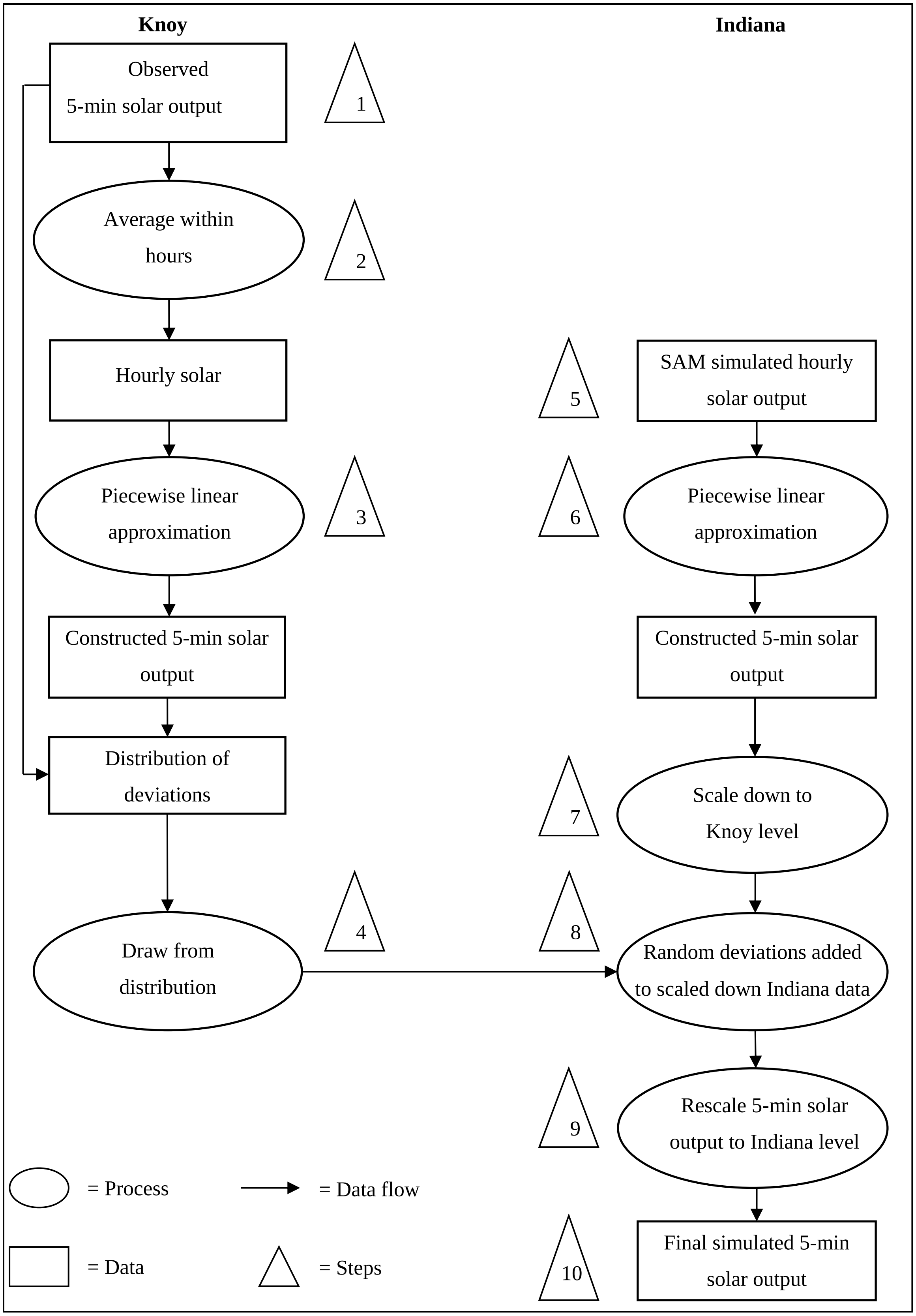

Figure 3-3 Step-by-step 5-minute Solar Data Process Diagram

In the second step of this procedure, the actual 5-minute generation values are averaged for each hour to obtain hourly solar data. This puts this data on the same time granularity as the Indiana-level SAM simulated hourly solar output. In step 3, a continuous, linear piecewise approximation is used to linearly interpolate between the hourly average points as a smoothed approximation to the actual 5-minute PV solar power output. According to Toriello and Vielma (2011), the problem of fitting a function of some prescribed form to a finite set of data points has been studied for hundreds of years, and has applications in various fields. Within the optimization field, fitting problems are modeled as convex norm minimization models. Chua et al. (1977) affirm that the main motivation for the use of a piecewise linear approximation is the possibility for taking advantage of linear techniques of analysis over a region with linear characteristics. Let *z* index the number of minutes, *k* index the number of 5-minute intervals and let *j* index hours. For formulation and calculation reasons *z* and *k* indices start from 0 instead of 1. Each hour contains twelve 5-minute intervals, and the average output for the hour is known and equal to m_j. The objective of the piecewise linear function fitting problem used in this study is to minimize the sum over the year of the squares of the differences between the power output pairs of adjacent 5-minute interval points. This objective function is optimized subject to a set of constraints that require that the approximated average power output for each hour *j* is equal to the actual average power output (m_j) for that hour. The objective and constraints are displayed below:

$$\min \sum_{k}^{K} (-f_{k-1} + f_k)^2 \qquad \forall [k > 1] \qquad (1)$$

$$m_j = \left(\frac{f_{k-12} + 2f_{k-11} + \cdots + 2f_{k-1} + f_k}{24} \right) \qquad \forall j, [k = j \times 12] \qquad (2)$$

where

k = Index for number of 5-minute intervals within a year starting from zero;

K= Total number of 5-minute intervals within a year (105,120);

f_k = The power output at the beginning of each 5-minute interval;

j = Index for hours in a year (8,760); and

m_j = Average power output in hour j.

The average output over each 5-minute interval is then expressed as the average of the power output at the end points as shown below: The values of these parameters represent the constructed 5-minute solar output data set for the Knoy project (see Figure 3-2).

$$p_k = \left(\frac{f_{k-1} + f_k}{2}\right) \qquad (3)$$

where

p_k = Average power output approximation values at each 5-minute interval of the year.

Finally, the equation (4) shows the piecewise linear approximation function (*plin*) indexed to each minute z of the year. This function is defined by the values of the parameters p_k and is linear between the points of each of the 5-minute intervals.

$$plin_z = \left[\frac{5 \times (k+1) - z}{5}\right] \times p_k + \left[\frac{z - 5 \times (k)}{5}\right] \times p_{k+1} \quad \forall k, [5(k) \leq z < 5(k+1)] \qquad (4)$$

where

z = Index for number of minutes within a year [0, 525,600]; and

$plin_z$ = Piecewise linear approximation value for each 1-minute interval of the year.

Figure 3-4 illustrates the 5-minute actual Knoy solar power output data for three hours randomly selected in a year with the first hour showing the output values from the different pieces used to define the piecewise linear approximation function $plin_z$. All the f_k values obtained from the optimization process form a step function for the whole year. The total area below this function must equal the sum over the year of the areas under the hourly average *ml* output level.

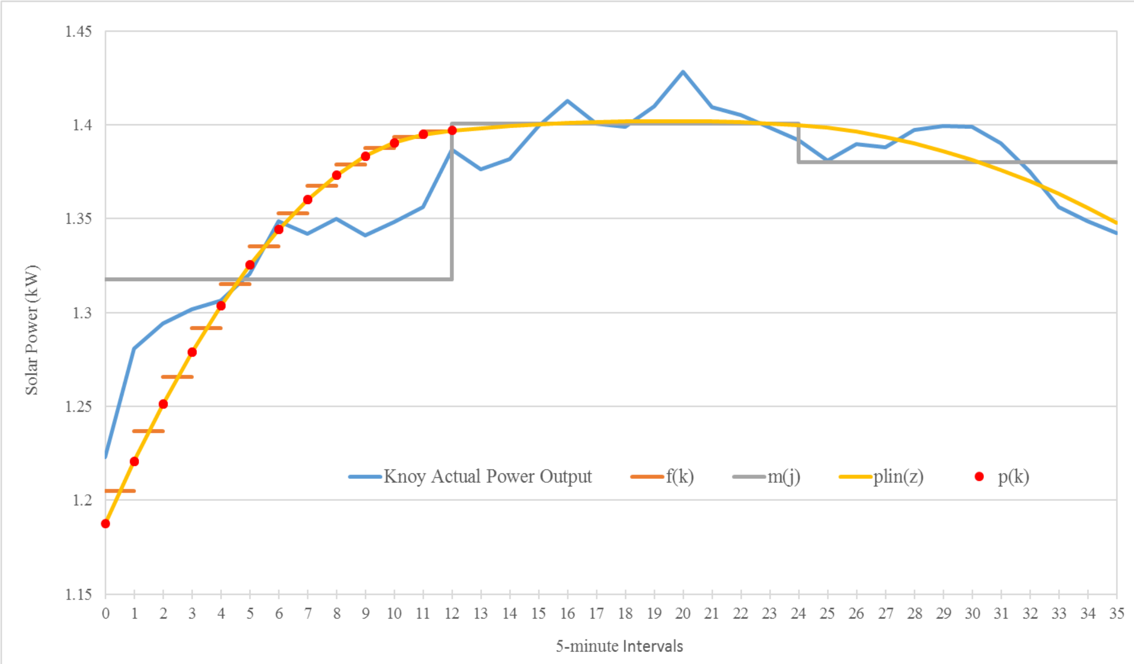

Figure 3-4 5-minute Actual Data and Piecewise Linear Approximations for Three Random Hours

The differences between the constructed 5-minute approximation and the 5-minute actual data represent the positive and negative deviations from the piecewise linear approximation for each of the 5-minute intervals. At this point, all the observations with zero values (collected between 11 PM and 6 AM) in the piecewise linear data series are temporarily removed from the data set before continuing with the rest of the simulation procedure. In the end, after a satisfactory 5-minute solar output simulated data set is obtained for the morning and afternoon hours, the observations with zero values are added back with zero values to get the complete final data set.

The next steps provide details of a procedure to obtain simulated 5-minute data with statistical characteristics similar to the actual 5-minute solar data. The main idea of this procedure is to sample the distribution of random deviations by month of the Knoy observed data from the piecewise linear approximation to generate deviations from a piecewise linear approximation for Indiana to obtain a 5-minute simulated solar generation data set. The calculations for each month are scaled down to the level of the Knoy data by multiplying it by the ratio of the maximum solar output of the month of the Knoy project divided by the maximum output value for the same month. Then, random deviations are sampled as is explained below, and added to the piecewise linear approximation. The data sets for all the months are sorted into chronological order to arrive at an annual data set for the state. This process is performed independently eight times for the eight Indiana solar zones. Each of the eight data sets are then scaled by the nameplate capacity identified in each zone and aggregated to the Indiana level to obtain a 5-minute simulated solar output pattern for the state.

An important aspect of step 4 in Figure 3-3 is that the deviations of the observed Knoy power output data from the piecewise linear approximation are heteroscedastic. That is, the magnitudes of the deviations vary with the magnitudes of the power output. In order to capture this heteroscedasticity, the observed deviations are grouped in a couple of ways. First, the values are separated by month. Then, within each month, the paired observations of piecewise linear values and deviations are sorted into ascending order of the piecewise linear values. This sorted data set for each month is partitioned into consecutive bins of 40 observations each, and then a series of deviation values are randomly drawn from each bin. Meanwhile, the solar hourly output simulated in SAM for the three array types (ground one axis tracking, ground fixed, and rooftop fixed) for each of the eight different locations across Indiana are aggregated to a statewide level as part of step 5 of this procedure. Then, in step 6, Indiana's simulated hourly solar output data series is also approximated with a piecewise linear function, using procedures parallel to step 3 to construct a 5-minute data series. This constructed 5-minute solar output for the state is grouped by month, and then the values are also sorted into ascending order within each month.

The next step (7) of this procedure scales down the state piecewise linear approximation of each month by a multiplicative factor, so that the maximum generation value of the piecewise linear data series is equal to the maximum value of the piecewise linear series for the Knoy installation. Then, the scaled constructed data set for the state is grouped into bins according to the lower and upper cutoff values of the 40 bins by month used to partition the piecewise linear data for Knoy.

In step 8, for each month, a random draw from the stratified distributions of deviations (obtained in step 4) from each of the original bins is added to the corresponding created bins (created in step 7) with the Indiana's piecewise linear generation values. Then, as part of step 9, the data with the added deviations from all the 40 bins are merged together resulting in one data series for each month. This data series is resorted into chronological order, and using the same multiplicative factor determined in step 7, the chronological dataset is scaled back up to the original capacity levels for the state. For the last part of this process, the zero values temporarily removed before step 4 are added back. This process is repeated independently eight times for the eight different zones. Then, each of the eight state's 5-minute solar output data sets is scaled by the nameplate capacity of each zone to obtain eight regional data sets.

Despite the fact that this procedure is based on the distribution of the observed deviations, there are a few cases in the final data set with negative solar generation values. These negative values are replaced with zeros. Also, there are a few observations with values greater than the maximum possible generation that can be achieved with the capacity installed of each zone. In these cases, the observations' values are clipped at the maximum output level that could be generated with the solar capacity of each zone. Finally, for the 10th and last step of this procedure, the eight regional data sets are aggregated, in order to get a final 5-minute solar generation output data set for Indiana that is used in the capacity planning and cost measurements models.

3.1.3 Indiana's Wind Assets and Generation Data

Annual simulated 5-minute wind turbine power data for the 2010-2012 period are collected using the Wind Integration National Dataset (WIND) Toolkit. This is an updated and expanded project of the Eastern and Western Wind Datasets, which was designed by NREL to provide estimated power production from hypothetical wind farms for 2004, 2005 and 2006. The WIND Toolkit contains meteorological conditions and turbine power for more than 126,000 sites in the United States. In that project, the data set of the power produced at each of the turbine locations was created considering the wind resource data at 100-meter hub height and site-appropriate turbine power curves. The WIND toolkit allows a user to download the wind power data for a specific point using GPS coordinates or by selecting pre-identified wind farm sites. For this analysis, the specific points or wind farms are selected based on their close proximity to the sites of the 2017 wind power purchase agreements (PPA) contracted to Indiana utilities (SUFG, 2017a). Figure-3.5 shows the spatial distribution of the wind farms selling electricity to the state.

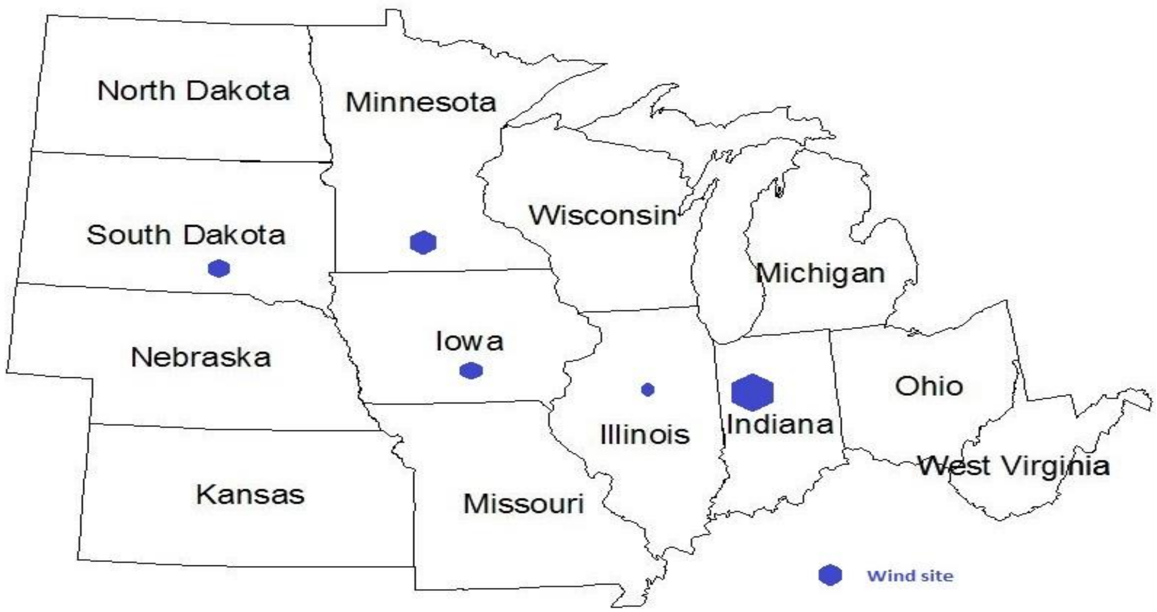

Figure 3-5 Locations of Wind Farms with PPA contracted with Indiana Utilities.[4] Source: Map outline by angga (www.selventhiran.com)

The capacity of PPAs for various wind farms located in Indiana represents about 68% (866 MW) of the total PPA capacity (1,282 MW). The capacity of the wind PPAs located in Minnesota is 201 MW, in Iowa is 146 MW, in South Dakota is 50 MW and in Illinois is 18 MW, accounting for 32% (416 MW) of the total.

The wind power data corresponding to the selected wind farms' capacities are scaled using the PPAs' capacities, totaling about 1,282 MW. Three scaled 5-minute wind power data sets are obtained - one for each year in the 2010-2012 period.

[4] Note: The size of the hexagon is proportional to the PPA capacity contracted with wind farms of in every state. The capacity of wind PPAs are 866 MW in Indiana, 201 MW in Minnesota, 146 MW in Iowa, 50 MW in South Dakota, and 18 MW in Illinois.

3.1.4 Indiana's Load Data

In order to develop the case study for Indiana, the analysis is performed using actual hourly load data for 2010, 2011 and 2012, which are collected from the individual utilities and summed to obtain a state-wide load (SUFG, 2017b). Three distinct projected annual load profiles for 2035 are developed by scaling the load data for each of the three years (2010-2012) to have the equivalent projected annual energy consumption (131,105 GWh) in 2035 (SUFG, 2017b). Because 2012 was a leap year, data from that additional day is removed from the final data set.

Each of the three hourly load profiles scaled to the equivalent load in 2035 are converted from hourly to 5-minute data using a piecewise linear approach identical to the one previously described in the solar simulation data section. This procedure is considered sufficient because aggregate load is expected to have relatively low variation within each hour due to its slow response to temperatures and weather changes. This is confirmed by calculating the coefficient of variation (CV) of the actual MISO 5-minute load data for several months. These CVs are roughly a factor of fifteen times lower than the CV calculated for the observed Knoy 5-minute solar generation data.

3.1.5 Wholesale Electricity Price Data

One of the goals of this study is to estimate the PV solar installation design that maximized the annual economic value of solar generation. This estimation uses the SAM simulated hourly PV solar output from various combinations of tilt and azimuth angles and the electricity prices from the wholesale electricity market operated by PJM. Hourly price market data from the WEST INT PJM trading hub is collected directly from PJM's website. The system marginal cost that is represented by the locational marginal price (LMP) is used to estimate the change in value of the different angle combinations. The LMP reflects the patterns of load, characteristics of generating facilities, and physical limits of the transmission system at different locations (ISO New England, 2016). Actual 2010-2012 hourly real-time LMPs are collected, resulting in three years-worth of hourly data, which together with the hourly solar generation data set were used to estimate the optimal azimuth and tilt angles of stationary and single axis tracking solar panels that maximizes the total economic value over the three years of the study. Because in reality these angles are not adjusted at the field from year to year, the aggregated 3-year economic value approach provides an estimate of the average payoff to a given combination of angles. The 3-year economic value is obtained by first converting from nominal to real dollars (2016$) each of the three years revenue values and then aggregating them. Furthermore, due to known installation technical limitations on field for setting a configuration with higher tilt angles, only the tilt angle of the fixed ground mount array type is allowed to vary relative to the angles identified in the typical set up. For this array, the maximum tilt angle allowed is 25 degrees.

3.2 PV Solar Capacity within a Power System

3.2.1 Load Net of Renewables

The simulated 5-minute load minus the combination of simulated 5-minute solar and wind power output enables construction of a 5-minute time resolution load net of renewables dataset. Halamay et al. (2011) affirms that it is common to analyze the impact of a renewable resource within a system by subtracting its generation contribution from the load. For this study, three load net of solar plus wind series are constructed using Indiana's annual load profiles and simulated data for various levels of solar and wind generation capacity and/or PV solar configurations. The three years of load data are used to capture the load variation across years and model the impacts of solar photovoltaic (PV) and wind generating capacity additions as if they are installed by 2035. These impacts are estimated for each of the three annual load profiles and then averaged.

Since electric utilities cannot inventory electricity, they must generate power on demand. The load duration curve represents this phenomenon (Murphy et al., 1988). For this study three load duration curves (LDC) net of renewable generation are built by sorting the 5-minute load net of renewable generation curves into descending order. This procedure is repeated for each of the three years of load profiles and for each of the scenarios presented in the next section. These LDCs are used for calculating the capacity level of two conventional generating technologies needed to meet the electricity demanded within a determined number of 5-minuite periods. The chronological load net of renewable generation is also used for estimating the increase in system operation cost due to renewable generation.

3.2.2 Scenarios Considered

A base case and three alternative scenarios are designed to assess the implications of alternative levels of renewable capacity on the effective system generation capacity, energy generated by technology, and costs. The results of these four scenarios provide perspective on the impacts of integrating these resources at various penetration levels and/or with different PV solar system configurations (panel orientation and tilt, tracking technology, etc.).

The base case incorporates the simulated 5-minute wind generation data scaled to the capacity level (1,281.5 MW) of all the existing PPAs. This scenario also includes simulated 5-minute solar generation data scaled to the capacity level of the existing PV solar projects (192.6 MW) located within the identified eight zones in Indiana. This solar generation dataset is created using what is assumed to be the typical type of technology (e.g. array and module) and design for three different system configurations (e.g. fixed ground, single-axis tracking, and commercial fixed rooftop) currently in place in different solar installations across the state.

As an alternative, Scenario 1 examines the future impact of adding more wind and solar generation capacity. Scenario 1 uses the same typical setup and angles as the base case, but adds about 3,125 MW of wind and 2,146 MW of solar capacity, which are the long-term estimates presented by Indiana utilities in their latest Integrated Resource Plan (IRP) as their preferred resource expansion. Thus, for this scenario the capacities were scaled to a total of 4,407 MW for wind and 2,339 MW for solar.

Scenario 2 is designed to identify the impact of only expanding PV solar capacity without any additions of wind generation power. For this scenario, the results are based on similar assumptions and angles as the ones used in Scenario 1, but assuming that utilities would have solar generation as their only renewable resource option. Therefore, instead of adding 3,125 MW of new wind capacity to the analysis, that number is added to the existing and new solar capacity identified in the IRPs. Thus, this scenario uses 5,464 MW of total solar generation capacity and only the existing wind capacity of 1,281.5 MW.

The final scenario (3) considers the same 5-minute solar generation data set used in the Base Case Scenario but explores the impact of integrating up to 30% renewables electricity generation levels of all the projected Indiana annual electricity generation in 2035. This scenario emulates one of the targets considered by NREL in a scenario-based study (Bloom et al., 2016). For this scenario, solar and wind resources are assumed each to provide proportionally about 15% of the future total annual electricity of the state. These percentages in energy terms correspond to have additional 12,375 MW of solar capacity and 3,845 MW of wind capacity by 2035. Therefore, the total future installed capacity levels for solar and wind for this scenario equal 12,567 MW and 5,126 MW, respectively.

3.2.3 Impacts of Integrating PV Solar on Other Generation Resources

For this study, the approach of Davis et al. (2013) is adapted to develop a new method to estimate the costs of integrating solar and wind generation capacity into the power grid. Davis et al. calculated the impacts of incorporating only one intermittent generation resource (wind) on four specific aspects of the system. They were the effects in capacity requirements for peaking, cycling and baseload, the change of the energy (MWh) generated by each of these three type of resources, changes in capital cost because of the changes in the capacity needs of the generation portfolio mix, and the impacts in variable costs due to changes in fuel mix for the dispatched generators. In this study, the approach is modified to determine the impacts of adding only PV solar capacity and also adding solar capacity in combination with wind capacity into the Indiana's power system, and optimize the utilization of conventional generation resources. The impacts of additional renewable generation capacity are calculated for capacity, energy, ramping costs due to additional ramping needs, capital costs, and variable costs. Unlike Davis et al. (2013), the present study models the commitment process as well as the dispatch process. The commitment/dispatch model takes into account minimum and maximum generation, minimum up or minimum down time and ramping limits for all units.

3.2.3.1 Impacts on Capacity

This analysis finds the level of additional future capacity requirements by generation resource class needed by 2035 as renewable generation capacity is added to the power system. Indiana's 2015 existing capacity levels plus planned capacity changes (approved planned generation additions and retirements) represent the starting point to project the resource types of current and future additions that will be in place by 2035.

In order to determine what additional capacity level by technology will be needed in the future, the installed capacity is first organized by grouping all the generators based on the size and the type of fuel use or particular technology. The following are the representative generators technologies by specific groups: Coal (Conventional Steam Coal), IGCC (Edwardsport Coal Integrated Gasification Combined Cycle plant), Oil (Petroleum Liquids and Coke), NGST (Natural Gas Steam Turbine), NGCC (Natural Gas Combined Cycle), NGCT (Natural Gas Combustion Turbine), Hydro (Conventional Hydroelectric), Landfill (Landfill and other gases) and Nuclear (Donald C. Cook nuclear plant). The aggregated capacities of each of these groups are adjusted to reflect Indiana's electric utilities' ownership and jurisdictional shares of some generating plants. Since these shares are confidential, the adjustment is performed using the following approximations to the actual rates: 84% for Coal, Landfill and Nuclear, 100% for IGCC and NGST, 85% for Oil, and 97% for NGCC, NGCT and Hydro. Finally, Coal, NGCC and NGCT units are then subdivided by unit size to approximate the commitment decisions on a unit-by-unit basis. Then, in order to account for forced outages (equipment unavailability due to unanticipated breakdown), the installed nameplate and summer capacity are derated using a Forced Outage Rate (FOR). Table 3-6 presents the resulting installed derated nameplate and derated summer generation capacity for Indiana by technology and generic generation types. FOR estimates presented in Table 3-7 are collected for each unit type from the SUFG and the 2016 Generating Unit Statistical Brochure, which is part of the Generating Availability Data System (GADS) program (NERC, 2016).

Table 3-6 Indiana Installed Derated Capacity by Generation Type

Technology	Generation Type	Derated Nameplate Capacity (MW)	Derated Summer Capacity (MW)	Number of Units	Average Unit Size (MW)
Coal	Baseload	14,667	13,181	43	341
Small (1-199 MW)		1,735	1,560	17	102
Medium (200-599 MW)		6,809	6,119	17	401
Large (600-999 MW)		6,123	5,502	9	680
IGCC	Baseload	775	573	3	258
Oil	Peaking	430	392	23	19
NGST	Baseload	564	534	3	188
NGCC	Baseload	2,104	1,956	14	150
Small (1-179 MW)		529	492	7	76
Large (180-400 MW)		1,575	1,465	7	225
NGCT	Peaking	3,619	2,914	55	66
Small (1-59 MW)		863	695	21	41
Medium (60-89 MW)		1,887	1,519	26	73
Large (90-150 MW)		870	700	8	109
Hydro	Baseload	95	60	51	2
Landfill	Baseload	84	78	74	1
Nuclear	Baseload	1,896	1,717	2	948
Total		24,233	21,405	268	

The installed conventional technologies are classified into two types of generic generation resources, which are used for resource requirements planning purposes: baseload and peaking. Cycling (also known as intermediate) resources are excluded from consideration because they are becoming more difficult to differentiate from the other two resources as a result of their projected similarities in future operation and costs characteristics (SUFG 2017b). Baseload plants are characterized by having low variable cost, high capital cost and limited ability to vary output in a short time. Because of these characteristics, this type of resource is utilized for continuous operation during most of the hours of the year. Peaking plants are characterized by having low capital cost, high variable cost and the highest level of flexibility to vary output that make them the appropriate resources for generating electricity during few hours of the year. It is hypothesized that additions of solar capacity will increase the need for both of these types of resources but mainly for peaking capacity.

Based on the characteristics that represent the generic generation resources, the Coal conventional technology group is classified as baseload capacity. The same classification is given to all the other conventional technologies except for NGCT and Oil plants, which are classified as peaking generating units. In order to model future resource additions, baseload resources are expected to be advanced natural gas-fired combined cycle (ANGCC) plants with a fixed nameplate capacity of 429 MW, and peaking units are expected to be advanced natural gas-fired combustion turbines (ANGCT) with a fixed capacity size of 237 MW (EIA, 2016). The capacity levels of the identified resource additions are specified to be individual plants so that there is a better approximation to the unit-by-unit commitment problem. In this study, natural gas-fired combined cycle units are used instead of pulverized coal plants as the appropriate technology to represent baseload generation assets. This modification is considered appropriate because NGCC units are expected to be a lower cost option than Conventional Steam Coal technology in the future based on fuel price predictions and capital costs estimates reported by the Energy Information Agency (EIA). Furthermore, this determination was made by the SUFG (2017b) based on parameters such as capacity factor, projections of future fuel and equipment costs.

Capacity additions of these two types of generation resources are determined for the various scenarios using the identified installed summer capacity (for planning purposes the installed capacity must meet Indiana's peak demand which happens during the summer) and with different levels of PV solar and wind generation capacity. This study assumes no technological changes over time for any of the generation resources considered in the analysis.

Capacity impacts are obtained for each of the three annual net of renewables load duration curves and then averaged for each scenario. At this stage it is assumed that this curve accurately represents a typical demand net of renewables, and that all of the solar and wind output is going to be used by the utilities for the resource capacity planning process. This is because utilities sign long-term contracts with solar project developers (this is similar to the wind power purchase agreement contracts signed by utilities) that force them to pay a preferential price for solar generation whether the power is needed or not. Since the variable cost for solar and wind is almost zero, it makes sense to use all the solar and wind generation to build the net of renewables load duration curves. This ignores the inherent characteristics of "must-run" baseload generators due to their limited ability to reduce output. Furthermore, it is possible that in conventional power systems, at high penetration levels, solar PV output may reduce the load net of solar generation to the point that it could surpass the minimum level of generation coming from must-run generators. However, since solar PV represents only a small share from the total installed capacity in Indiana even with an aggressive capacity expansion plan, forcing curtailment due to excess PV solar generation is assumed not to occur in the analysis based on the capacity expansion model. Contrarily, this assumption is relaxed to allow curtailment of solar and wind resources in the commitment/dispatch analysis.

The calculation of the overall capacity impacts considers two parts. The first part calculates the required capacity expansion levels to meet the expected demand in 2035 for the two resource technologies using a planning model originally proposed by Murphy et al. (1988). The second part includes a calculation of the potential additional capacity needed to cover the ramping capacity change.

The model developed by Murphy et al. (1988) includes a deterministic mathematical program that uses a break-even total cost (fixed plus variable) analysis for three plant types in combination with a load duration curve to determine the least cost mix of capacity resources dispatched to meet power demand for every hour in a year. A modified version of this approach proposed by Davis et al. (2013) considered capacity running to meet a load net of wind curve, but not considering the ramping capacity needs calculation that is included in the second part of this section.

Unlike the three generic generation types and the hourly LDC originally used in Murphy's capacity expansion planning model, this approach uses two generic resources and a 5-minute net of solar and wind LDC that is shown in the lower diagram of Figure 3-6. The horizontal axes of Figure 3-6 range from 0 to 105,120 and represents the total number of 5-minute intervals in a year (8,760 hours per year times twelve 5-minute intervals per hour). The upper diagram of this figure shows the break-even cost curve with one break-even point corresponding to different levels of cumulative 5-minute intervals of operation during the year of the two conventional generic generation technologies. The slope of each of these lines represents the variable cost ($/MWh) of each technology. Meanwhile, the intersection point of those lines with the vertical axis represents the annualized per unit capital cost ($/MW/Yr) for each of the two generation resources.

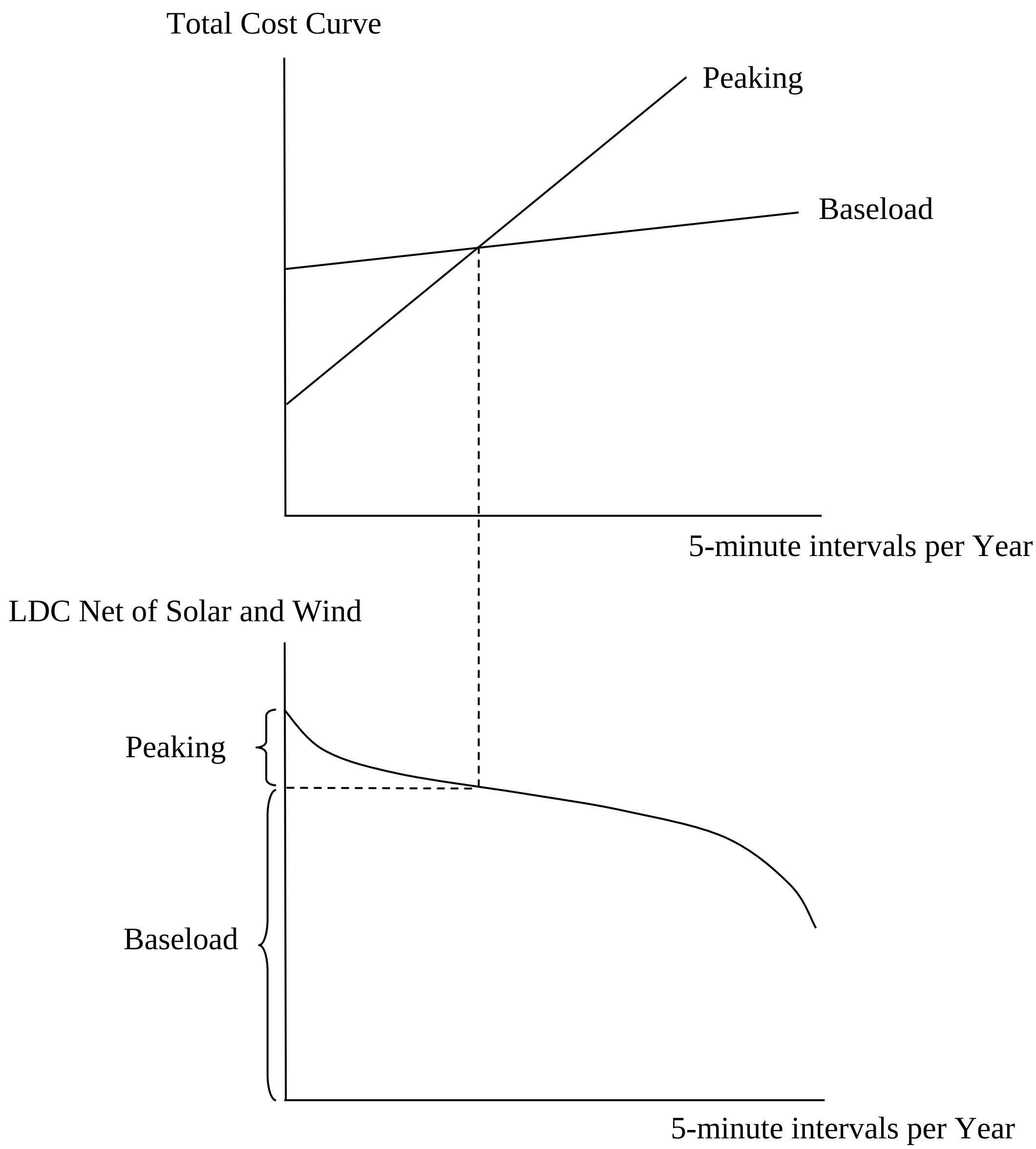

Figure 3-6 Break-even Cost and Net of Solar Load Duration Curve

The new capacity requirements needed to meet the 2035 load net of solar and wind curve are estimated by finding the difference between the new capacity levels for the two generation resources resulting from the modified Murphy capacity expansion planning model and the installed (existing and planned) capacity levels. If the new baseload capacity requirements are less than the installed baseload capacity levels, then there is no need for additional baseload capacity and the excess is recategorized as peaking capacity. When new baseload or peaking capacity is needed, the identified level of capacity is rounded up to the fixed nominal size capacity of the appropriate new plant.

The identified capacity additions consider a percent reserve margin equal to the corresponding FOR estimates of each technology type. Previously, Davis et al. (2013) used a similar approach, but he applied a ten percent reserve margin for all the unit types as a method to limit the loss of load probability.[5]

After determining the capacity expansion requirements needed to meet projected demand, an additional calculation is used to ensure that enough ramping capacity is available. That is, at this stage, the identified capacity requirements ignore the ramping down and ramping up capacity limits of the non-solar and non-wind generation technologies and the potential need for additional conventional capacity to respond to sudden short-term variations in the load net of solar and wind curve. Therefore, the technical limitations (e.g. minimum and maximum load and ramping limits) of the power plants are considered to determine the range of capacity levels of each of the generation resources available to serve the ramping capacity changes of the load net of wind and solar. Table 3-7 shows the technical minimum load and ramping rates by technology applied to the identified resources of the system. For this calculation, the maximum ramping up and down capabilities are assumed to be the same and were calculated by multiplying the ramp rates in percentage terms times the nameplate capacity (differently than in the first part where the summer capacity is used to focus the analysis in the annual peak which usually happens during the summer time in Indiana). The generators' maximum load capacity is assumed to equal the nameplate capacity. The minimum load is calculated using the nameplate capacity and the minimum load rates presented in Table 3-7. Then, the load capacity levels for each generation resource technology is determined by finding the difference between the maximum and minimum generation limits and then comparing them to the calculated typical generator 5-minute ramping capability levels. The lesser of the load and ramping capability of each technology is selected as the final generation capacity available to respond to ramping

[5] Madaeni et al. (2012) defined the probability of a loss of load as the likelihood of an event where the load of the system is greater than the available generating capacity over a given time period.

variations. These capacity levels are aggregated to represent the maximum ramping capacity level available in the system.

Table 3-7 Indiana Installed Capacity and Technical Parameters by Generation Type

Units Vintage	Technology	Forced Outage Rate (% of nameplate capacity)*	Minimum Load (% of derated nameplate capacity)**	Ramping Rates (% of derated nameplate capacity /5-min)***	Minimum uptime (Hours)	Minimum downtime (Hours)
New Units						
	Baseload	3.7	40	29	4	2
	Peaking	14.9	43	68	2	2
	Wind		0	100	0	0
	Solar		0	100	0	0
Installed Units						
	Coal	6.6	37	19	6	4
	IGCC	3.7	60	29	4	2
	Oil	8.4	33	67	4	3
	NGST	14.9	40	33	5	3
	NGCC	3.7	40	29	4	2
	NGCT	14.9	43	68	2	2
	Hydro	8.6	0	100	0	0
	Landfill	5.0	0	100	0	0
	Nuclear	2.4	34	26	59	21

* FOR estimates are collected from NERC for all the generating unit types except Landfill gas units (NERC, 2016). FOR estimates for Landfill gas units were provided by the SUFG using an average estimate of those units across Indiana. ** Maximum load assumed to be equal to the nameplate capacity therefore 100%. Minimum load values and minimum up- and downtimes are equal to the average of acceptable values in Table 27 (Schröder et al., 2013). *** Ramping rates are the average of acceptable values of rates in Table 26 (Schröder et al., 2013). Hydro, landfill, solar and wind technologies assumed to have zero minimum load rates. Also, due to their fast response ability for ramping from zero to the level of generation available, 100% ramp rates are assumed. For solar and wind the levels of generation depend respectively on the availability of sunlight and wind resources at a given period.

Since the one concern is the magnitude of the ramping levels, the ramping capacity level available is compared to the greatest drop and increase events (e.g. steepest ramping down or up event) of every 5-minute interval of the net of solar and wind load curve. This comparison determines whether supplementary capacity is required to satisfy ramping needs or not, and how much of this capacity is needed. Based on the characteristics of Indiana's generation fleet and this simple back-of-the-envelope calculation of ramping capacity, even with significant solar and wind capacity additions, supplementary capacity due to ramping events is not expected to be needed in the state. In the case that supplementary ramping capacity is needed, further technical and cost analysis of the type of generators to be installed (e.g. peaking, baseload, etc.) would be required. Finally, the identified new capacity plus potential ramping capacity levels for each generation resource technology is used to calculate the impact on energy in the next section.

3.2.3.2 Impacts on Capital Costs

Plant costs used in this analysis are on an annualized basis in 2016 real dollars. The costs associated with new units are shown in Table 3-8 organized by generation type. Capital cost includes annualized overnight capital cost and fixed operating and maintenance (O&M) costs per year. Capital costs for installed units are sunk costs and not considered in this analysis. For new units, overnight capital and fixed O&M costs of advanced natural gas combined cycle (ANGCC) generators are assigned to baseload units and costs of advanced natural gas-fired combustion turbines (ACT) are assigned to peaking capacity. Costs collected for Onshore Wind and PV solar with fixed panels are respectively assigned to new wind and solar units. The conversion of the present overnight capital cost to a series of uniform annual future payments involves the use of the capital recovery factor.[6] Overnight capital costs are annualized using a plant lifetime of 30 years for baseload and peaking (DOE, 2013), 24 year for wind, and 30 years for solar (NREL, 2016). A discount rate (interest rate) of 4.5% is considered for the capital recovery factor calculation as a financial investment assumption from a society perspective. In a previous analysis, a discounted cash flow model used this same interest rate as financial parameter (DOE, 2013).

[6] The capital recovery factor formula is: $A = P\left[\frac{i(1+i)^N}{(1+i)^N-1}\right]$, where A = Annuity , P = Present payment, N = Number of years, i = Interest rate (Steiner,1996)

Table 3-8 Annualized Capital, Variable, and Start-up Costs for Units by Generation Type*

Units Vintage	Generation Type	Annualized Capital Cost (2016 $/MW/Yr)	Variable Cost (2016 $/MWh)	Start-up Cost (2016 $/MW)
New Units				
	Baseload	77,531	28.93	43.79
	Peaking	48,976	52.60	55.32
	Solar	179,826	0	0
	Wind	168,430	0	0
Installed Units				
	Small Coal	N/A	Confidential	107.08
	Medium Coal	N/A	Confidential	82.53
	Large Coal	N/A	Confidential	57.97
	IGCC	N/A	Confidential	43.79
	NGST	N/A	Confidential	44.15
	NGCC	N/A	Confidential	43.79
	NGCT	N/A	Confidential	55.32

* Indiana specific overnight capital costs for new baseload, peaking, wind and solar units are obtained from Table 8-2, Table 10-2, Table 14-2, and Table 15-4. Capital cost for existing units are sunk costs and irrelevant for this analysis. Fixed and variable O&M for new units were collected from Table 1 (EIA, 2016). Variable O&M costs for existing units come from a confidential technical assessment guide (EPRI, 1989) and from reports of the State Utility Forecasting Group (SUFG (2017a). Because variable costs for existing units are equal to the sum of confidential variable O&M costs and publicly available fuel prices, this table does not present these costs numbers. Fuel prices are 2035 projections for the East North Central Region (EIA, 2018). Variable costs for solar and wind were considered as zero. Start-up costs are equal to the average of acceptable start-up costs of hot and warm start values from Table 25 (Schröder, 2013).

The total capital cost for each of the scenarios is estimated using the resulting new capacity requirements obtained from the two-step (capacity expansion planning and back-of-the-envelope ramping needs) model. The specific additions for each generation resource type together with their specific capital costs provide estimates of the total system capacity cost for the base case which are then compared to the estimated total costs of the alternative scenarios.

In order to account for the potential future capital cost reductions of solar and wind technologies, two additional cost projections for each of these resources are included in this analysis. Specifically, 2035 overnight and fixed O&M costs projections for median (median of literature projections of future costs) and low (low bound of literature projections of future costs) technology performance scenarios are collected from NREL 2018 Annual Technology Baseline (NREL, 2018b). Capital costs values for utility PV solar technologies in Chicago and land-based wind technologies within the TRG4 resource group are used to reflect the variation in solar resource and wind speed ranges in Indiana. The rate of change between the 2035 capital costs of NREL's "constant" or base case scenario and alternative scenarios would provide an approximate measure of future technology cost reductions. Assuming that the capital costs for solar and wind presented in Table 3.8 correspond to the capital costs of NREL's "constant" scenario, the annualized capital cost for solar would decrease by approximately 33% (to $120,867/MW/Yr) in the median scenario and 53% (to $85,334/MW/Yr) in the low scenario. On the other hand, the annualized capital cost for wind would decrease by 17% (to $140,164/MW/Yr) in the median scenario and 49% (to $86,058/MW/Yr) in the low scenario. These reductions in solar and wind technology costs reflect different levels of adoption of innovations but they still cannot make these resources cheaper than conventional generation.

3.2.3.3 Impacts on Energy

In general, for power system operations purposes, the energy impacts are estimated using the generation capacity of each technology or resources type available in the system. For this analysis, the energy impacts of incorporating solar and wind generation in the Indiana's power system are estimated using a minimum cost economic commitment/dispatch model. This model is used to minimize the variable and start-up costs of meeting load and to find the optimal mix units by technology that are committed and dispatched in every day of the year.

Table 3-8 presents the variable costs for new units and the start-up cost parameters for installed and new units used in this optimization model. Variable costs, that include fuel prices and variable O&M costs, are associated with each generation resource technology based on generators' representative characteristics (e.g. age, technical specifications). Fuel costs are collected from the 2018 EIA Annual Energy Outlook which presents the projections of fuel prices for East North Central region in the U.S. Variable O&M costs are obtained from EIA, the confidential Technical Assessment Guide (EPRI, 1989), 2017 Renewables Report (SUFG 2017a) and utilities' IRPs. These costs are separately defined for installed and new units because newer technologies are expected to be more efficient due to lower heat rates and thus to have lower variable costs (Davis et al., 2013).

Furthermore, a variable O&M cost distinction for installed coal units is considered to better represent the difference in heat rate characteristics between large and medium/small units. Similarly to the distinction made for fixed O&M costs, variable costs of advanced natural gas combined cycle (ANGCC) and advanced combustion turbine (ACT) generators are chosen to represent respectively the costs for new baseload and peaking resources. Variable costs for solar and wind installations are assumed to be zero.

Power plant cycling or start-up costs capture the O&M cost increase in response to the cycling of a unit. According to Kumar et al. (2012) cycling refers to the operation of electric generating plants at varying load levels, including load following, on/off status, and minimum load operation, due to changes in system load requirements. There are three types of start-up costs corresponding to each of the cold, warm and hot start-up times of conventional energy generation facilities. A cold start considers a power plant that has been shut down for more than 50 hours. A warm start is for a plant that has been turned off for more than 8 hours and less than 50 hours. Hot starts are for a power plant that has been switched off within 8 hours of the next start-up (Schröder, 2013). Cost of start-up fuels and depreciation of components (greatly observable in a cold start) are among the factors that contribute to the total start-up costs. Since the focus of the cost minimization process is on determining the units scheduled to operate during each day of the year, it is assumed that the units would only have either a warm or a hot start in those 24 hours. Therefore, the start-up cost estimates used in this analysis are equal to the average of the warm and hot start-up costs of each unit type. Thus, these estimates only capture the start-up fuel cost component of the total start-up costs.

According to Schröder (2013), the minimum up- and downtimes (or online/offline times) are helpful in modeling the power plant unit commitment and dispatch problem. These times are used to indicate the limitations on flexibility of thermal units but, in principle, they can be considered as economic limits rather than 'hard' physical limits. That is, the interest of operators is to keep a low number of start-ups and shut-downs in order to avoid excessive thermal stress on power plant equipment. Table 3-7 show the minimum up- and downtime parameters by technology type used in the model.

The approach developed in this analysis is partially similar to the method used by Davis et al. (2013). He used a minimum cost dispatch model to determine the impact of wind generation additions allowing wind curtailment and incorporating operating ramping limit constraints but not minimum generation limits for the non-wind generation technologies. The main distinction is that this analysis determines what conventional generation units are committed to run by paying attention to their minimum generation constraints. Furthermore, in this study there are differences in the time intervals of the data (10-minute vs 5-minute periods) and the types of ramping limits considered in the model. The approach used in this analysis dispatches to a load net of solar and wind, and considered other technical and cost features (e.g. minimum output levels, minimum uptime and downtime, and start-up costs) affecting the economic generation dispatch problem. However, some aspects such as start-up and shut-down ramp constraints, specific start-up times, operating ramping costs and the cost of the transmission and distribution systems are not modeled here.

A mixed-integer linear programming method is applied to minimize the cost of generating electricity to meet the future demand for each 5-minute period chronologically ordered and the possibility of wind and solar curtailment is allowed. This proposed combined unit commitment and dispatch formulation minimizes the operational cost considering the specific technical and economical limits on the committed generating units. Unit commitment (UC) is a mathematical optimization problem used in the electrical power production system to determine the optimum operation schedule of generating units to satisfy a varying demand for electricity at least possible operating cost over a given period of time (Bhardwaj et al., 2012). According to Morales et al. (2013) the mixed-integer linear programing (MILP) (some decision variables are not restricted to be integers) has become a popular approach for solving this type of problem due to the improvement in MILP solvers based on the branch-and-cut algorithms. For this study, the proposed MILP model formulation is solved using CPLEX under GAMS with 1.0% relative optimality tolerance. This means that the branch-and-cut algorithm terminates when the difference between the objective values for the best possible solution and the best integer feasible solution is reduced to one percent.

The original MILP formulation is intended to solve a daily cost minimization problem so it would determine the units committed and dispatched from hour 1 to hour 24 of each day of the year. However, from an annual perspective, this would not consider the potential discontinuity between the units that are online/offline at the end of a day and beginning of the next day. The possibility of having inconsistencies with the units running or not from one day to the next would have an impact in the estimation of the total annual costs and fail to enforce the minimum up/downtime constraint assumptions. In order to overcome this issue, the power system operation cost is minimized for each period of three consecutive days that roll across the year recording the results of the middle day. The only exceptions are for the first and last periods of the year where the results for day 1 and 2 and results for day 2 and 3 are used respectively for those specific periods. In this rolling three-day window methodology, the units that resulted to be committed/dispatched in the last hour of the first day of one period are fixed to be online in the first hour of the first day of the next three-day period to reduce the discontinuity problem.

The objective function for each of the three-day windows of a year is shown in equation (5). This equation is defined as the sum of the variable cost and start-up cost components. For the first component, the variable cost is expressed as a linear function of the power output. The second component includes a start-up variable that multiplies the start-up cost, which is also a function of the nameplate capacity of a specific unit.

$$\min \sum_{t}^{T} \sum_{i}^{I} VC_i G_{i,t} + \sum_{h}^{H} \sum_{i}^{I} \sum_{u}^{U} O_{u,i,h} N_i SC_i \tag{5}$$

where

i = Index for a non-solar and non-wind generator technology types;

I = All non-solar and non-wind types of generator technologies;

u = Index for generating unit number within each of the non-solar and non-wind technology types;

U = Maximum number of generating units among all the non-solar and non-wind technology types (74 units);

T = Total 5-minute intervals in a 3-day period (equal to 864 intervals);

t = Index of 5-minute interval;

$G_{i,t}$ = Generation level of technology type i in period t;

VC_i = Variable cost of generating technology type i;

h = Index of hour;

H = Total number of hours in a 3-day window (equal to 72 hours);

$O_{u,i,h}$ = Start-up of unit number u of technology type i in hour h. Equal to 1 if the unit starts up and has been previously offline;

N_i = Nameplate capacity of technology type i; and

SC_i = Start-up cost of technology type i.

This objective function is optimized subject to a set of constraints that capture the operational limitations and characteristics of the power system. Since demand is given, a constraint (6) is imposed to require the total conventional generation of electricity to equal the 2035 load net of wind and solar at each 5-minute interval. Furthermore, solar and wind generation may be dispatched respectively up to the simulated solar and wind generation level or totally curtailed at each time interval via constraint (7) and (8). The dispatch of the non-solar and non-wind generating resources may be between the maximum (equal to nameplate capacity) and minimum generation limits of the capacity levels determined in the capacity calculation section for each generation resource with an "online" status (9). Note that while $O_{u,i,h}$ is not restricted to be binary, optimal values of all of these variables will always be either 0 or 1 due to model structure. The typical minimum generation limits presented in Table 3-7, expressed in percentages of total installed and new derated nameplate capacity, are used for each of the generation resource types. The following constraint (10) reflects the restrictions of generating units with an "online" status to increase or decrease power output. Typical 5-minute ramping limits are set as a percentage of the derated nameplate capacity for each of the generation technologies (see Table 3-7, above). Another constraint (11) guarantees consistency between the integer start-up variables and the binary status variable so the variables take the appropriate values when the units are online or offline. The status variable $X_{u,i,h}$ is a binary variable that takes a value of 1 when the unit generates power and zero otherwise. This variable is also used to map and tie the online units from hour 24 of the first day of a previous 3-day window to hour 1 of the first day of the next window (12). Finally, the following equations (13) and (14) ensure that the unit operates within the minimum up- and downtimes limits. These constraints guarantee the minimum number of hours that the unit has to be online and offline according to the parameters presented in Table 3-7.

$$\sum_{i}^{I} G_{i,t} + S_t + W_t = L_t \tag{6}$$

$$0 \le S_t \le S_t^{max} \tag{7}$$

$$0 \le W_t \le W_t^{max} \tag{8}$$

$$G_{u,i}^{min} \sum_{u}^{U} X_{u,i,h} \le G_{i,t} \le G_{u,i}^{max} \sum_{u}^{U} X_{u,i,h} \quad \forall h, t \in [((h-1) \times 12) + h, h \times 12] \tag{9}$$

$$-R_{u,i} \sum_{u}^{U} X_{u,i,h} \le G_{i,t} - G_{i,t-1} \le R_{u,i} \sum_{u}^{U} X_{u,i,h} \quad \forall h, t \in [((h-1) \times 12) + h, h \times 12] \tag{10}$$

$$O_{u,i,h} - F_{u,i,h} = -X_{u,i,h-1} + X_{u,i,h} \tag{11}$$

$$X_{u,i,h} = \bar{X}_{u,i,h-1} \qquad \forall h \in [1] \tag{12}$$

$$X_{u,i,h} \ge \sum_{h}^{H} O_{u,i,h} \qquad \forall u, i, h \in [h - \ MU_i, h] \tag{13}$$

$$1 - X_{u,i,h} \ge \sum_{h}^{H} F_{u,i,h} \qquad \forall u, i, h \in [h - MD_i \ , h] \tag{14}$$

where

St = Solar generation in period t;

S_t^{max} = Maximum solar generation in period t;

Wt = Wind generation in period t;

W_t^{max} = Maximum wind generation in period t;

Lt = Load in period t;

$G_{u,i}^{min}$ = minimum generation level of unit number u of technology type i;

$G_{u,i}^{max}$ = maximum generation level of unit number u of technology type i;

Xu,i,h = Commitment status of unit number u of technology type i in hour h. Equal to 1 if the unit is online and 0 otherwise;

$\bar{X}$u,i,h-1 = Fixed commitment status of unit number u of technology type i in hour 24 of first day of previous 3-day window. Equal to 1 if the unit is online and 0 otherwise;

$R_{u,i}$ = ramping level of unit number u of technology type i;

Fu,i,h = Shut down of unit number u of technology type i in hour h. Equal to 1 if the unit shuts down and has been previously online;

MUi = Minimum up time parameter of unit i; and

MDi = Minimum down time parameter of unit i.

Energy impacts are determined by finding the difference between the energy generated by each technology type to meet the load for the base and for the alternative cases. This difference provides the impact of adding solar and wind generation on the optimal amount of energy supplied by each technology and for different cases.

3.2.3.4 Impacts on System Operations Costs

Since the model minimizes the operational cost for each 3-day window during the year, the daily variable and start-up costs are estimated using only the operational results corresponding to the middle day (except for the first and last window of the year where the first two days and last two days were used respectively) of each 3-day window. That is, the daily variable cost is calculated considering the cost values reported in Table 3-8 and the energy generated by each generation resource type in each middle day of every 3-day window of each year. On the other hand, the daily start-up cost for each technology type is estimated accounting for the start-up cost values (See Table 3-8) and the number of units turned on (variable $O_{i,h}$ = 1) within the 24 hours of that middle day of that generation resource. Then, all of the 365 daily variable and start-up costs are summed across days and technology type to find the total annual values for both cost categories. These calculations are done for the three annual load profiles and the results are averaged for each scenario.

The difference between the averaged variable and start-up costs of the base scenario and other scenarios represents the impact on the system costs due to changes in operations as the result of additions of wind and solar capacity expansions.

3.2.3.5 Estimation of PV Solar and PV Solar plus Wind Capacity Value

The estimation of the capacity value of PV solar and wind resources uses the same capacity expansion model explained previously for measuring the impact of PV solar generation on the capacity needs for other generation resources. This methodology is used as an approximation technique to estimate the capacity value of a solar generator or power plant with and without wind in Indiana from a generator reliability perspective. The capacity expansion model provides the capacity levels of baseload and peaking resources needed in the system in order to accommodate various combinations of solar and wind capacities while meeting the same annual system peak load. For this analysis, the model is applied to each of the three 5-minute net of renewables LDCs profiles built for each year of the 2010-2012 period. These LDCs considered the Indiana aggregated 5-minute simulated solar generation data set created using the typical design configuration for the state. They also account for the 5-minute simulated wind generation data set for the state.

In order to account for diminishing marginal solar PV capacity values and their sensitivity to increasing levels of PV solar penetration, a handful of scenarios for each of the LDCs profiles are considered to obtain a set of several baseload and peaking capacity levels, as different levels of renewable generation capacity are added to the generation mix. Four scenarios are selected for this analysis to determine the capacity value differences between having 0 MW (no wind), 500 MW, 1,000 MW, and 2,000 MW of wind capacity. All of these four scenarios include various solar capacity levels, which are obtained by scaling from the installed solar capacity of 193 MW to a total of 4,000 MW in steps of 200 MW (e.g. 193 MW, 200 MW, 400 MW,…, 3,800 MW, 4,000 MW). The same levels of scaled capacities are used in each scenario and for each LDC profile to make the results of the scenarios comparable.

The resulting capacity requirement levels for each type of resource at every solar capacity step are averaged across years within each scenario (e.g. PV solar, PV solar + 500 MW of

Wind, etc.). Then, the capacity value in terms of baseload/peaking resources at each specific solar capacity step is estimated by subtracting the averaged capacity level of that step from the capacity level of the previous step and dividing by 200 MW to get a capacity value per MWac of solar capacity. Finally, a complete series of capacity values in terms of baseload and peaking resources is calculated for each of the solar capacity levels and four alternative wind capacity levels scenarios.

CHAPTER 4. RESULTS

This chapter presents the results obtained to accomplish the different objectives of this research. The first section includes the optimization of tilt and azimuth angles with alternative objectives maximizing annual energy or economic revenue for the three system configurations described in Chapter 3. The second section presents the capacity, energy and cost impacts of incorporating solar and wind capacities in each of the four proposed scenarios, plus a comparison of these impacts across them. The last section of this chapter shows the results obtained from increasingly scaling up the solar and wind plus solar capacity levels and their corresponding capacity values.

4.1 Comparison of Results for Three System Configurations

4.1.1 Tilt and Azimuth Optimal Configuration Results

Table 4-1 displays the tilt and azimuth angles for three different system configurations organized by zone, array and module type. This table presents a comparison of the identified typical tilt and azimuth angles used in solar generation projects across Indiana, and the optimized angles for each of the configurations that either generates the maximum annual electricity output or the maximum 3-year (2010-2012) aggregated revenue. Typically, the tilt angles observed in the solar projects across all the zones in the state have respectively an average of 23 (range from 20 to 25 degrees), 10 and 0 degrees for the fixed open rack, fixed roof mount, and single axis arrays. Independently of the zone or the module type of the solar project, the results show that the tilt angles that maximize solar generation output and revenue are 25, 10 and 0 degrees for fixed open rack, fixed roof mount, and single axis arrays, respectively. These angles represent the upper bounds in the optimization process, that reflect the technical infeasibility of using greater tilt angles in the field. Therefore, relaxation of those tilt angles constraints would result in higher annual generation and revenue.

No constraints were imposed in the optimization for determining the optimal azimuth angles. The typical orientation of the solar panels in Indiana is directly toward the south (180°) but the azimuth angles that would produce the highest electricity generation range from 177 to 182 degrees across zones, array and module types. However, across these parameters, the azimuth angles that would maximize the 3-year economic value range from 180 to 190.5 degrees. Therefore, in Indiana, the system configuration that maximizes the annual generation output would have solar panels practically oriented straight south similar to the state's typical configuration, but more oriented to the east compared to the maximum revenue configuration. Considering the results, across zones and technology types, the azimuth angles of the configuration that maximizes output are about 1 degree and 5 degrees lower than the angles respectively in the typical configuration and in the optimal economic value configuration. In general, the latter configuration has panels oriented more toward the west, with an average azimuth angle of about 4 degrees higher than the state's typical system configuration.

The results also show that there is no significant difference between the configurations of projects located in the northern, middle and southern regions within the state. However, a few regions with specific array types show some differences from the rest. Regions 1 and 8 with fixed open rack, and region 6 with single axis array types, consistently have solar panels facing more toward the west for both the maximum output and revenue configurations, relative to the typical configuration case. For the rest of the regions and array types, except for single axis tracking array type in region 7, the configuration that maximizes output and economic values shows contrasting results with opposite orientations of panels, facing respectively more toward the east and west compared to azimuth angles of the typical configuration.

Table 4-1 Typical and Optimal Angles for Three System Configurations by Zone

Zone	Array Type	Module Type	Tilt Angles (Degrees)			Azimuth Angles (Degrees)		
			Typical	Max. Output	Max. Econ.	Typical	Max. Output	Max. Econ.
1	Fixed open rack	Standard	23	25	25	180	181.0	190.5
2	Fixed open rack	Standard	23	25	25	180	177.0	184.0
	Fixed open rack	Thin film	23	25	25	180	177.5	184.5
	Fixed roof mount	Standard	10	10	10	180	177.5	184.0
3	Fixed open rack	Standard	23	25	25	180	178.5	185.5
4	Fixed open rack	Standard	23	25	25	180	179.5	186.5
5	Fixed open rack	Standard	23	25	25	180	178.5	183.5
	Single axis	Standard	0	0	0	180	179.0	181.5
6	Fixed open rack	Standard	23	25	25	180	178.5	184.5
	Single axis	Standard	0	0	0	180	181.5	182.0
	Fixed roof mount	Standard	10	10	10	180	178.5	184.0
7	Fixed open rack	Standard	23	25	25	180	179.0	185.0
	Single axis	Standard	0	0	0	180	179.0	180.0
8	Fixed open rack	Standard	23	25	25	180	182.0	186.5
	Single axis	Standard	0	0	0	180	179.0	181.0
			Average (Degrees)					
	Fixed open rack		23	25	25	180	179.1	185.6
	Fixed roof mount		10	10	10	180	178.0	184.0
	Single axis		0	0	0	180	179.6	181.1

Across all the zones, the results indicate that the azimuth angles for single axis arrays would require a small adjustment of only about ±1 degree from the typical azimuth angle (180˚), whether the objective is to maximize generation output (-0.4˚) or economic value (+1.1˚). In order to achieve the maximum economic value, on average, solar projects with fixed open rack and roof mount arrays would respectively require azimuth angles to be about 5.6 degrees and 4.0 degrees higher than the angles in a typical configuration. The deviations from the typical azimuth angles for those arrays are lower if the objective is to maximize annual electricity generation (-2˚ for fixed roof mount and -0.9˚ for fixed open rack).

Therefore, the fixed open rack and roof mount arrays due to their lack of sun tracking ability would need a greater azimuth angle adjustment from the typical configurations, compared to the projects with single axis arrays, for obtaining the maximum revenue from the electricity generated. That is, due to the pivoting mechanism of the single axis array, the solar panels of this array would need small orientation adjustments independently of their location in Indiana.

4.1.2 Optimal Electricity Generation and Revenue Results

This section presents the annual electricity and 3-year average economic values in 2016 dollars obtained for the three optimal system configurations. These values and the percent changes for the referred optimal system configurations are displayed in Table 4-2, organized by zone, array and module type identified in Indiana. According to these results, if all the solar projects in the state had an optimal configuration with the objective of maximizing annual energy (revenue), they together would produce on average about 0.30% (0.23%) more electricity compared with projects using the typical system configuration. On the other hand, these same projects with maximum output and revenue system configurations would respectively generate on average 0.18% and 0.25% more annual 3-year average revenue compared to the revenue obtained by a project with the typical configuration.

Table 4-2 Annual Energy and Revenue for Three System Configurations by Zone*

Zone	Array Type	Module Type	Annual Energy (GWh) From 192.6 MW Solar Capacity			Annual Revenue (million $)		
			Typical	Max. Output	Max. Econ.	Typical	Max. Output	Max. Econ.
1	Fixed open rack	Standard	10.847	10.909	10.886	0.517	0.520	0.521
				(0.57)	(0.35)		(0.48)	(0.70)
2	Fixed open rack	Standard	1.636	1.642	1.640	0.079	0.079	0.080
				(0.36)	(0.26)		(0.18)	(0.29)
	Fixed open rack	Thin film	18.655	18.722	18.702	0.910	0.912	0.913
				(0.36)	(0.25)		(0.18)	(0.30)
	Fixed roof mount	Standard	0.706	0.706	0.706	0.034	0.034	0.034
				(0.01)	(-0.04)		(-0.03)	(0.02)
3	Fixed open rack	Standard	18.596	18.657	18.637	0.895	0.897	0.897
				(0.33)	(0.22)		(0.17)	(0.27)
4	Fixed open rack	Standard	4.616	4.633	4.628	0.223	0.223	0.224
				(0.36)	(0.25)		(0.21)	(0.30)
5	Fixed open rack	Standard	11.576	11.624	11.617	0.552	0.553	0.554
				(0.41)	(0.35)		(0.25)	(0.30)
	Single axis tracking	Standard	17.307	17.307	17.306	0.826	0.826	0.826
				(0.00)	(-0.01)		(-0.01)	(0.00)
6	Fixed open rack	Standard	106.239	106.636	106.55	5.120	5.131	5.134
				(0.37)	(0.29)		(0.21)	(0.29)
	Single axis tracking	Standard	23.305	23.305	23.305	1.126	1.126	1.126
				(0.00)	(0.00)		(0.01)	(0.01)
	Fixed roof mount	Standard	21.608	21.609	21.601	1.050	1.049	1.050
				(0.00)	(-0.03)		(-0.01)	(0.02)
7	Fixed open rack	Standard	21.297	21.370	21.354	1.022	1.024	1.025
				(0.34)	(0.26)		(0.19)	(0.27)
	Single axis tracking	Standard	3.296	3.296	3.296	0.158	0.158	0.158
				(0.00)	(0.00)		(0.00)	(0.00)
8	Fixed open rack	Standard	39.784	39.949	39.930	1.894	1.900	1.901
				(0.42)	(0.37)		(0.33)	(0.38)
	Single axis tracking	Standard	3.989	3.989	3.988	0.190	0.190	0.190
				(0.00)	(0.00)		(-0.01)	(0.00)
		Total:	303.458	304.354	304.14	14.597	14.624	14.633
	Difference of totals from typical:			0.896	0.689		0.027	0.036
	Percent change of totals from typical:			(0.30)	(0.23)		(0.18)	(0.25)
			Average Percent Change (%)					
	Fixed open rack			(0.39)	(0.29)		(0.25)	(0.34)
	Fixed roof mount			(0.00)	(-0.03)		(-0.02)	(0.02)
	Single axis tracking			(0.00)	(0.00)		(0.00)	(0.00)

* Numbers in parenthesis are the percent change of the values relative to the typical configuration.

If all the solar projects (192.6 MW) in Indiana move away from the typical system configuration to either of the two optimal configurations, the annual average increase in revenues would be about $26,718 for the annual maximum output configuration, and $36,240 for maximum the 3-year revenue configuration. Meanwhile, if all these solar projects across the state were adjusted from a typical system configuration to a configuration that maximizes annual output and economic value, the annual electricity generation would increase by 896.2 MWh and 689.4 MWh, respectively. In perspective, these increases in annual electricity generation would be sufficient to provide electricity for approximately 77 and 59 additional residential homes[7] in the state.

In percentage terms, the greatest revenue benefits of readjusting the azimuth and tilt angles occurs in Zone 1, followed distantly by Zone 8. In Zone 1, the revenues would increase around 0.48% and 0.70% due the switching from a typical configuration to a configuration that maximizes annual power output and economic value, respectively. Meanwhile, the greatest percentage in annual energy changes, within the maximum output configuration, occurs in Zone 1 with an average of 0.57% increase when the tilt angles are adjusted from 23 to 25 degrees and azimuth ones from 180 to 181 degrees. However, within the optimal economic value configuration, Zone 8 shows the greatest average increase (0.37%) in annual energy when compared with the energy generated with a typical configuration in the same zone.

The type of array used by the solar projects in Indiana, independently of their location, has a direct impact on annual energy rate of change of the two optimal system configurations. In that sense, a modification of the system configuration, from typical to maximum output and revenue configurations, considerably affects the electricity generated by solar projects, with fixed open racks arrays showing respectively an average percent increase of 0.39% and 0.29%. However, the impact on annual energy due to variations of the system configurations is almost unnoticeable in solar projects with fixed roof mount (range from -0.03% to 0%) and single axis arrays (0%).

[7] In 2016, according to EIA, the average annual electricity consumption for an Indiana residential customer was 11,705 kWh. https://www.eia.gov/electricity/sales_revenue_price/

Finally, the results also show that on average the fixed open rack array has also a bigger impact on the annual revenue change than the other two arrays. Solar power plants with fixed open rack arrays would increase the annual revenue by 0.25% and 0.34% if a typical setup were adjusted to maximize annual electricity generation and revenue, respectively. Changes of the azimuth and tilt angles in a fixed roof mount and single axis arrays would respectively have a slightly (±0.02%) to none impact on the annual revenue for solar projects switching from a typical system configuration to an optimal energy production or economic value configuration.

4.2 Results for Solar and Wind Additions Scenarios

The following section presents the projected impacts on capacity, energy and costs resulted from scaling solar and wind capacities in proportion to their installed capacity levels. The focus of this section is to compare the impacts across the three alternative scenarios with the findings of the Base Case Scenario.

For all the scenarios considered in this analysis, the results are organized and presented by representative technology or fuel type (e.g. one category named Natural Gas Baseload includes the values from NGST and NGCC technologies).

It is important to highlight that the relative optimality tolerance used to solve the commitment/dispatch model for one year of the Base Case Scenario was relaxed to 2% due to extremely long solving time. This change is considered to have no significant impact in the final average value across years for that scenario and for the comparison analysis between scenarios.

4.2.1 Capacity Impacts Results

Table 4-3 summarizes the total installed capacity requirements and the total energy that must be produced by each resource type in 2035. At the current solar and wind capacity levels, the capacity planning results indicate a need for 2,291 MW of new resources by 2035. All of these identified capacity additions are made up of only new peaking resources, because no added baseload capacity is required in the future for the base case or any other scenario. The peaking capacity requirements for all scenarios are lower relative to the base case. Furthermore, the future capacity addition of 5,271 MW of renewable resources would increase the solar and wind combined contribution to the state's total energy generating capacity from about 5% in the Base Case Scenario to 20% in Scenarios 1 and 2. This would reduce the contribution of new peaking resources to Indiana's 2035 total capacity by more than half, going from about 8% in the base case to only 3% in both scenarios. Although this contribution, in percentage terms, is the same in both scenarios, the requirements of new peaking capacity differ. When only PV solar generation capacity is added into the system (Scenario 2), the peaking capacity required is higher (1,106 MW) than the one needed (869 MW) when the same level of renewable capacity is added with a mix of solar and wind power (Scenario 1).

Table 4-3 Annual Capacity and Energy for Alternative Solar and Wind Capacity Levels

	Installed Capacity in 2035 (MW)*				Energy Generated in 2035 (GWh)			
	Base Scenario	Scenario 1	Scenario 2	Scenario 3	Base Scenario	Scenario 1	Scenario 2	Scenario 3
Coal	15,700	15,700	15,700	15,700	98,928	85,575	92,074	70,786
IGCC	805	805	805	805	6,578	5,896	6,354	3,783
Oil	469	469	469	469	1	1	1	0
NG Baseload	3,063	3,063	3,063	3,063	1,668	921	944	376
NGCT	4,253	4,253	4,253	4,253	88	46	49	17
Hydro	103	103	103	103	827	827	827	784
Landfill	88	88	88	88	690	581	657	403
Nuclear	1,943	1,943	1,943	1,943	16,610	16,610	16,610	15,978
New Baseload	0	0	0	0	0	0	0	0
New Peaking	2,291	869	1,106	395	501	76	79	9
Solar PV	193	2,339	5,464	12,567	303	3,681	8,600	19,449
Wind	1,282	4,407	1,282	5,126	4,912	16,891	4,912	19,519
Total	30,189	34,039	34,275	44,512	131,105	131,105	131,105	131,105

Energy Curtailment in 2035 (GWh)				
Solar PV	0	0	0	335
Wind	0	0	0	126
Total	0	0	0	461

* These numbers are installed nameplate capacity before derating. Therefore, they are different than the derated numbers presented in Table 3-6.

This result is explained by the higher amount of electricity per year that could be generated by one unit of wind power (e.g. due to the availability of the energy source, wind power could generate electricity 24 hours a day) relative to electricity generated per unit of PV solar power. Therefore, solar and wind annual generation combined causes the load net of renewable duration curve for most hours, including the peak hour, to be located below the curve created considering the annual electricity generated only by solar capacity. Scaling solar and wind capacity from the existing 1,474 MW (Base Case Scenario) to 17,693 MW (Scenario 3), increases the share of renewable generation capacity from 5% to 40% of the state's total installed capacity in 2035. This expansion of renewable resources results in a significant increase of total capacity, but a comparatively small reduction of new peaking capacity requirements. That is, this net addition of 16,219 MW of solar and wind capacity offsets only 1,896 MW of peaking capacity, but Indiana's power system continues to require additional conventional resources to be built.

Table 4-4 shows the potential 5-minute ramping capability of Indiana's non-solar and non-wind installed generation capacity and the system's maximum ramping up and down capacity levels required to be met in each scenario. Additionally, this table shows the annual average of the absolute 5-minute ramping capacity levels for all the scenarios. The identified 5-minute ramping capability focuses in baseload and peaking resources and does not consider the potential contribution of solar and wind generation units to ramping down capacity when they are running and have their energy curtailed. By 2035, if all the non-solar and non-wind units identified in the base resource case were operational, turned on and not at maximum capacity, the maximum level of ramping service available would be 8,387 MW per 5-minute interval. Under the base scenario, the system would use only a maximum of 282 MW and 435 MW of that ramping capacity to satisfy 5-minute ramping up and ramping down requirements, respectively. Increasing levels of solar and wind capacity cause the magnitude in megawatts of the greatest ramping events to grow, resulting in increasing pressure on the system's ramping capability. Based on the results of the Scenario 3, Indiana's power system would have enough 5-minute ramping capability (7,098 MW) to support the largest ramping up (4,989 MW) and down (5,642 MW) fluctuations resulting from a substantial expansion of renewable resources. Since the maximum ramping down event of Scenario 3 already represents close to 80% of the ramping capacity available in the system, greater penetration levels of PV solar and/or wind power might impose a need for more dispatchable and more flexible generating units to have sufficient system flexibility in the future.

The results of Table 4-4 also indicate that the average magnitude of every absolute 5-minute ramping event in a year increases, as solar and wind capacity levels increase. However, this average is about 57 MW lower in the scenario with a combination of solar and wind generation capacity (Scenario 1) than in the scenario with solar generation capacity alone (Scenario 2). Therefore, on average, solar power has more 5-minute ramping capacity needs than wind does.

Table 4-4 System 5-minute Maximum Ramping Capacity Availability and Requirements

	Base Scenario	Scenario 1	Scenario 2	Scenario 3
Ramping Capability in 2035 (MW)	8,387	7,420	7,582	7,098
Greatest Ramping-up Need in 2035 (MW)	282	1,054	2,184	4,989
Greatest Ramping-down Need in 2035 (MW)	-435	-1,342	-2,458	-5,642
Absolute Average Ramping in 2035 (MW)	38	87	144	310

From the unit commitment/dispatch perspective, Table 4-5 shows the sum of the number of times every baseload and peaking generating unit is turned on, or committed, in a year. Furthermore, the table presents the sum of the cumulative 5-minute ramping capacity committed for each technology type unit over the year in each scenario. Cumulative ramping capacity for one unit is equivalent to the total number of times that units from a specific technology are committed in a year times the 5-minute ramping capacity of that type of unit. This cumulative ramping capacity could represent either ramping up or down capacity because the ramping up and down rates of this study are assumed to be the same for each technology. In the Base Case Scenario, the sum of the number of times baseload and peaking units are turned on represent about 87% and 13%, respectively, of the 2,055 number of times that units would be committed and dispatched in 2035. In aggregate terms, on average, fewer numbers of units are turned on in the alternative scenarios than in the base case. However, in percentage terms, the contribution of the total number of times baseload (peaking) units are committed from the total number in a year increases (decreases) as renewable resources capacity increases. This contribution of baseload generating units goes from 87% in the base case to about 91% in Scenarios 1 and 2 and to 96% in Scenario 3. This is because, in Scenario 3 some large baseload units are used more for load following and turned on and off (cycled) more frequently than peaking units mainly during some days with low levels of demand and high levels of renewables generation.

Although the sum of the number of times units are committed decreases in all the scenarios compared with the base case, the sum of cumulative ramping capacity committed in a year varies depending on the type of units that are turned on in each scenario. For example, the results show that even with a lower total number of units committed in Scenario 3, the 5-minute cumulative ramping capacity contributed by those units in a year is approximately 6% higher than in the Base Case Scenario. Additionally, the cumulative ramping capacity of the baseload and peaking units committed in a year in this scenario, are respectively 20% higher and 70% lower than the cumulative ramping capacity scheduled to operate in the base case. This is because larger capacity and cheaper to operate baseload power plants such as large coal or IGCC units are turned on and off more frequently over the year in the Scenario 3 than in the Base Case Scenario (See Figure 5-1 and Table 5-1 for an example).

Table 4-5 Annual Number Times of Units and Ramping Capacity Committed in 2035

	Sum of the Number of Times Units are Turned on in a Year				Sum of Cumulative 5-minute Ramping Capacity of Units Turned on in a Year (MW)			
	Base Scenario	Scenario 1	Scenario 2	Scenario 3	Base Scenario	Scenario 1	Scenario 2	Scenario 3
Baseload	1,791	1,647	1,561	1,750	75,577	75,443	65,079	90,661
Peaking	264	159	168	79	14,024	8,628	9,467	4,244
Total	2,055	1,805	1,729	1,829	89,601	84,071	74,546	94,905

Furthermore, the start-up costs assigned to the baseload units do not account for the potential additional depreciation (e.g. shortened lifespans of the equipment) and O&M cost due to higher ramping variation and power plant cycling when following the load. In the base scenario, smaller size and more expensive to operate baseload and peaking units like NGCCs and NGCTs are turned on more times but providing smaller incremental levels of 5-minute ramping capacity to the total sum of cumulative capacity committed in a year. Therefore, the addition of significant capacity levels of renewable resources (Scenario 3), on average, increases the number of times that larger coal and natural gas baseload units are committed and operates them more like a load-following units. That is, a high level of solar and wind generation greatly offsets the number of times peaking units are turned on and off which consequently leaves the larger baseload unit with the necessity of meeting the ramping capacity requirements of the load net of renewables. Additionally, the results indicate that adding solar generation by itself (Scenario 2), would increase the cumulative ramping capacity committed in a year from peaking resources by 10% compared to the levels observed in the solar and wind generation case (Scenario 1). In Scenario 1, wind complements solar generation and contributes to the displacement of the number of times peaking generation units are tuned on mainly between the late afternoon to the early morning hours, when peaking units in the no new wind capacity case (Scenario 2) would otherwise be committed/dispatched.

4.2.2 Energy Impacts Results

For the Base Case Scenario, the results projects that the coal fleet would generate 75.5% of the total annual energy supplied to meet the 2035 Indiana's system load (See Table 4-3 and Figure 4-1). This resource is followed by nuclear (12.7%), IGCC (5%) and wind (3.7%) as the next most important contributors of the total power produced in the state. For this case, baseload, peaking and renewable resources would generate respectively 95.7%, 0.4% and 3.9% of the total annual electricity generation. Despite the dominant contribution of coal resources to the state's total energy, these resources are not expected to be fully utilized in 2035. According to the results, the average capacity factor[8] of all the installed coal power units is 72%, where larger percentage values represent more electricity generation per unit capacity. Meanwhile, for this Base Case Scenario, IGCC, hydro, landfill, and nuclear generation units have average capacity factor of 90% or greater. The capacity factors of solar and wind power installations are respectively 18% and 44%, which reflects the intermittent availability of these resources to generate electricity at their full capacity continuously over the year.

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[8] Capacity factor is the ratio of the average energy generated over a given period of time divided by the energy that could have been produced if the unit ran at 100% rated nameplate capacity continuously during the same period. An example for all the coal units is: $\frac{98{,}928\ GWh}{\left(8760\,\frac{hours}{year}\right)\times(15{,}700\ GW)} = 72\%$

The amount of energy produced by conventional power generating units is lower in Scenarios 1-3. This happens because the economic benefit of generating the greatest possible amount of energy from resources with zero “fuel” cost. Relative to the Base Case Scenario, as penetration of renewable resources increases, the contribution of the energy supplied by baseload capacity decreases in Scenarios 1-3. This contribution goes from 96% in the base case to 84% in Scenario 1, 90% in Scenario 2 and 70% in Scenario 3. Meanwhile, the energy contribution of peaking resources barely changes across scenarios at less than 1% of total generation.

Because electricity generation from solar and wind resources depends on the intermittent availability of sunlight and wind, their capacity factors are lower than the capacity factor of the dispatchable resources. Furthermore, since additions of renewable capacity resources cannot equally offset the needs of conventional resources, the overall system average capacity factor drops from 47% in the Base Case to 43% in Scenario 1, 45% in Scenario 2 and 36% in Scenario 3. In Scenario 1, among all the power generators, coal, IGCC and landfill units show the greatest capacity factor reductions with values declining more than 9 percentage points for each technology, relative to the Base Case Scenario. In Scenario 2, the average reduction of the capacity factors of each of these power generating units is only about 5 percentage points. In this case, these generators, with low variable cost, are utilized more to compensate for lower generation per unit of renewables obtained for expanding only solar capacity rather than solar and wind capacity together. Since nuclear and hydro generators are the cheapest option to generate electricity within the system, these resources have respectively a 98% and 91% capacity factors and are fully utilized[9] in all scenarios except Scenario 3.

In Scenario 3, each of these resources not only shows a lower capacity factor, but also occasional energy generation curtailment, which was not observed in any of the other scenarios (See Table 4-3). However, the amount of solar and wind energy curtailed per year only represents 1.7% (335 GWh) and 0.6% (126 GWh) of their total potential annual output. Additionally, in order to accommodate all the electricity generated by solar and

[9] The capacity factor for both of these units is 100% if forced outages are not considered.

wind projects, nuclear and hydro are less utilized and show slight reductions of their capacity factors. Landfill and IGCC resources have the greatest reduction in capacity factors with an average of 38 percentage points lower than the capacity factors in the base case, followed by reductions of 20 percentage points for coal units.

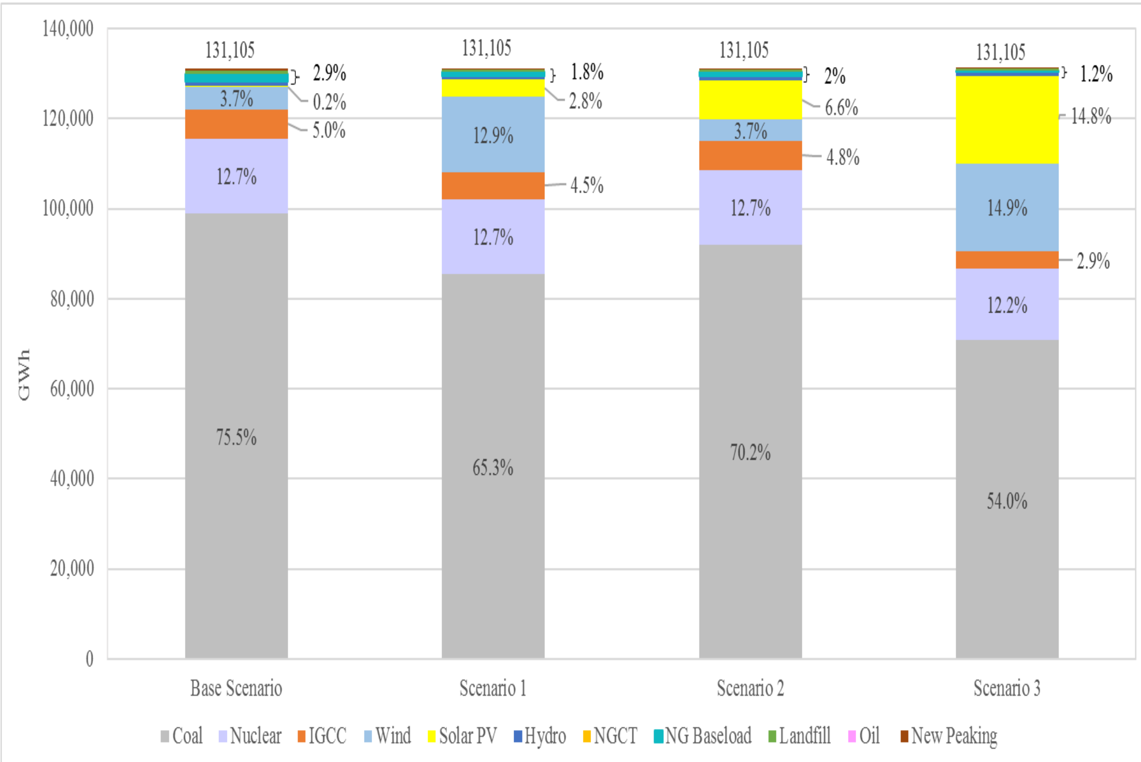

Figure 4-1 Indiana’s Annual Electricity Generation Mix in 2035

The principle impact of increasing renewable capacity levels is a reduction in the electricity generation coming from coal, as illustrated in Figure 4-1. As solar and wind capacities considerably increase their contribution to the system’s annual electricity generation, energy generated from coal falls from 75.5% in the Base Case to 65.3% in Scenario 1, 70.2% in Scenario 2 and 54% in Scenario 3. The energy contribution of the other non-solar and non-wind resources slightly declines across scenarios, but these reductions are not greater than approximately 2 percentage points relative to the base case.

4.2.3 Cost and Wholesale Electricity Rate Impact Results

Annualized capital, variable, start-up and system total costs by technology generation type are detailed in Table 4-6 and Table 4-7. Since no additional baseload capacity is needed, there are no capital costs associated with this resource type. Relative to the Base Case Scenario, total annualized capital cost increases when more intermittent renewable energy sources are added to the system.

Table 4-6 Annualized Capital and Variable Costs by Resource Type for Alternative Scenarios

	Capital Costs (million 2016$)				Variable Costs (million 2016$)			
	Base Scenario	Scenario 1	Scenario 2	Scenario 3	Base Scenario	Scenario 1	Scenario 2	Scenario 3
Coal	-	-	-	-	2,568.96	2,209.33	2,383.11	1,821.02
IGCC	-	-	-	-	177.01	158.67	170.99	101.81
Oil	-	-	-	-	0.30	0.23	0.15	0.07
NG Baseload	-	-	-	-	70.03	38.66	39.62	15.71
NGCT	-	-	-	-	6.36	3.33	3.54	1.22
Hydro	-	-	-	-	2.20	2.20	2.20	2.08
Landfill	-	-	-	-	17.56	14.77	16.72	10.26
Nuclear	-	-	-	-	133.71	133.71	133.71	128.62
New Baseload	0	0	0	0	0	0	0	0
New Peaking	112.20	42.56	54.17	19.35	26.33	4.00	4.13	0.49
Solar PV	0	385.98	947.94	2,225.24	0	0	0	0
Wind	0	526.43	0.00	647.53	0	0	0	0
Total	112.20	954.97	1,002.11	2,892.12	3,002.46	2,564.90	2,754.17	2,081.29

The annualized capital costs associated with new peaking resources in all the scenarios are lower relative to the Base Case Scenario. However, the capital cost for these resources is lower when solar capacity is added in combination with wind capacity (Scenario 1) rather than when solar capacity is added without additional wind (Scenario 2).

A comparison between the total capacity cost of the no new solar capacity case and the cost of the case with only solar capacity additions (Scenario 2) would determine what the optimal annualized capital cost per MW of solar capacity should be. Dividing the difference between both costs by the level of solar capacity additions, results in an annualized capital cost of $168,830 per MW in 2016 dollars. This cost is 6.1% lower than the estimated capital cost used in the analysis and represents the optimal average investment cost of adding one MW of solar capacity in Indiana's electric power system.

All the alternative scenarios have a total annualized capital cost substantially higher than the base case, because the capital costs of solar and wind technologies are still much higher than the costs of conventional generation resources. The higher capital costs of these renewable technologies are compensated by the zero variable cost incurred to operate them. Therefore, across scenarios, increasing solar and wind capacity results in reductions in aggregate variable cost when compared with the Base Case Scenario.

Table 4-7 Annualized Start-up and System Total Costs by Resource Type for All the Scenarios

	Start-up Costs (million 2016$)				Total Costs (million 2016$)			
	Base Scenario	Scenario 1	Scenario 2	Scenario 3	Base Scenario	Scenario 1	Scenario 2	Scenario 3
Coal	14.36	19.50	14.57	23.74	2,583.32	2,228.83	2,397.68	1,844.76
IGCC	0.034	0.471	0.166	2.755	177.05	159.14	171.16	104.57
Oil	0	0	0	0	0.30	0.23	0.15	0.07
NG Baseload	6.52	4.29	4.77	2.61	76.55	42.95	44.39	18.32
NGCT	0.922	0.557	0.633	0.274	7.28	3.88	4.17	1.49
Hydro	0	0	0	0	2.20	2.20	2.20	2.08
Landfill	0	0	0	0	17.56	14.77	16.72	10.26
Nuclear	0	0	0	0	133.71	133.71	133.71	128.62
New Baseload	0	0	0	0	0	0	0	0
New Peaking	0.201	0.131	0.127	0.066	138.74	46.70	58.43	19.91
Solar PV	0	0	0	0	0	385.98	947.94	2,225.24
Wind	0	0	0	0	0	526.43	0.00	647.53
Total	22.038	24.946	20.269	29.441	3,136.70	3,544.82	3,776.55	5,002.85

Relative to the base case, total variable cost is respectively 15% and 8% lower for Scenario 1 and Scenario 2. This difference is mainly due to the greater contribution of coal, IGCC and landfill units to the total variable cost in the Scenario 2. These dispatchable units are utilized more to compensate for the generation losses resulting from not having new wind capacity expansion as part of the renewables portfolio mix.

On the other hand, aggregated variable cost in Scenario 3 is 31% lower than the base case (see Table 4-6). This is due to the significant additions of capacity with “zero” variable cost, which reduce the electricity generated from conventional units and therefore, their contribution to the total variable costs. In every scenario, the variable cost associated with coal generation resources contributes an average of 86% to the system total variable cost. The next big contributors to the system total variable cost are IGCC units, contributing an average of 6%, nuclear with 5% and natural gas baseload units with 2%.

The total number of times that units are committed per year by generation type is used to estimate the annual start-up costs for each scenario (See Table 4-7). Since the start-up cost of oil, nuclear, hydro and landfill generation resources are treated as zero in this analysis, there is no total start-up costs reported in Table 4.7 for these units. The results show that due to the solar and wind capacity additions, the future annual start-up costs associated with baseload units would increase 16% in Scenario 1 and 39% in Scenario 3 and decrease about 7% in Scenario 2 relative to the base case scenario. Furthermore, the projected annual start-up costs resulting from the commitment of peaking units decreases by 39% in Scenario 1, 32% in Scenario 2 and 70% in Scenario 3 when compared with the same cost in the Base Case Scenario.

Adding only new solar capacity generation (Scenario 2) in the system causes the annual aggregate start-up cost to drop about 8% relative to the cost in the base case. Conversely, the impact of adding new solar and wind capacity increases the aggregate start-up cost by 13%. The main reason for this difference is that a higher number of medium and large coal and IGCC units are committed annually in Scenario 1 than in Scenario 2. For Scenario 3, the aggregate annual start-up cost is 34% higher than in the base case. This increase is mainly due to the significant number of times large coal and IGCC units that are committed and therefore dispatched in a year at these additional levels of solar and wind capacity. These types of baseload units, that are normally running or maintained in stand-by mode for most of the year, are utilized more like cycling units and are turned on and off relatively frequently.

The contributions of each cost category to the projected total annual cost for every scenario are shown in Figure 4-2. As shown in this figure, the reductions in total variable cost and changes in the start-up costs at any level of new renewable resources are not enough to offset the increases in capital cost. This makes the total system costs in all the alternative scenarios higher than in the base case. Consequently, under the scope of this study, the base case with no new solar or wind capacity would be optimal in terms of total future costs. However, adding solar and/or wind capacity may be more cost effective if other externalities like carbon costs and production incentives are considered in the analysis.

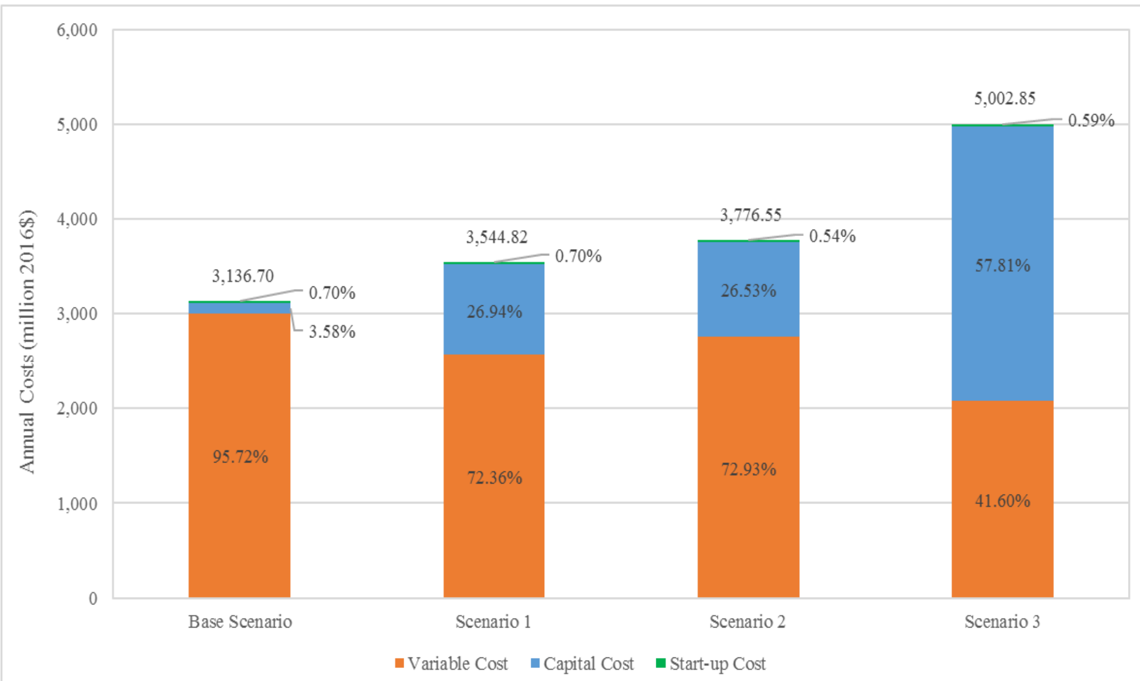

Figure 4-2 Indiana Annualized Costs Mix across Alternative Scenarios in 2035[10]

At the current installed solar and wind capacity levels, variable costs would represent 95.7% of the total cost of meeting the capacity and energy requirements in 2035 (See Figure 4-2). In this case, the investment in new peaking capacity represents only 3.6% of the total system cost because this type of resources has lower capital cost than solar and wind

[10] Note: Annualized capital costs for existing generators are sunk costs and not included in this analysis.

resources. The start-up cost in the Base Case Scenario contributes only 0.7% of the total cost, but represents the highest contribution of this type of costs across scenarios.

The addition of 5,271 MW of renewable resources capacity, having solar capacity combined with wind capacity or individually, practically does not change, in percentage terms, the contribution of variable and capital costs to the total system cost identified in Scenarios 1 and 2. The capital, variable, and start-up costs represent respectively about 72%, 27% and less than 1% of the total cost. Therefore, as the penetration of renewable resources increases, the share of variable cost in the total decreases. At substantial capacity levels of renewable resources (Scenario 3), the contribution of capital cost (58%) offsets the share of variable costs (42%) which are significantly reduced when compared with the base case and the other alternative scenarios.

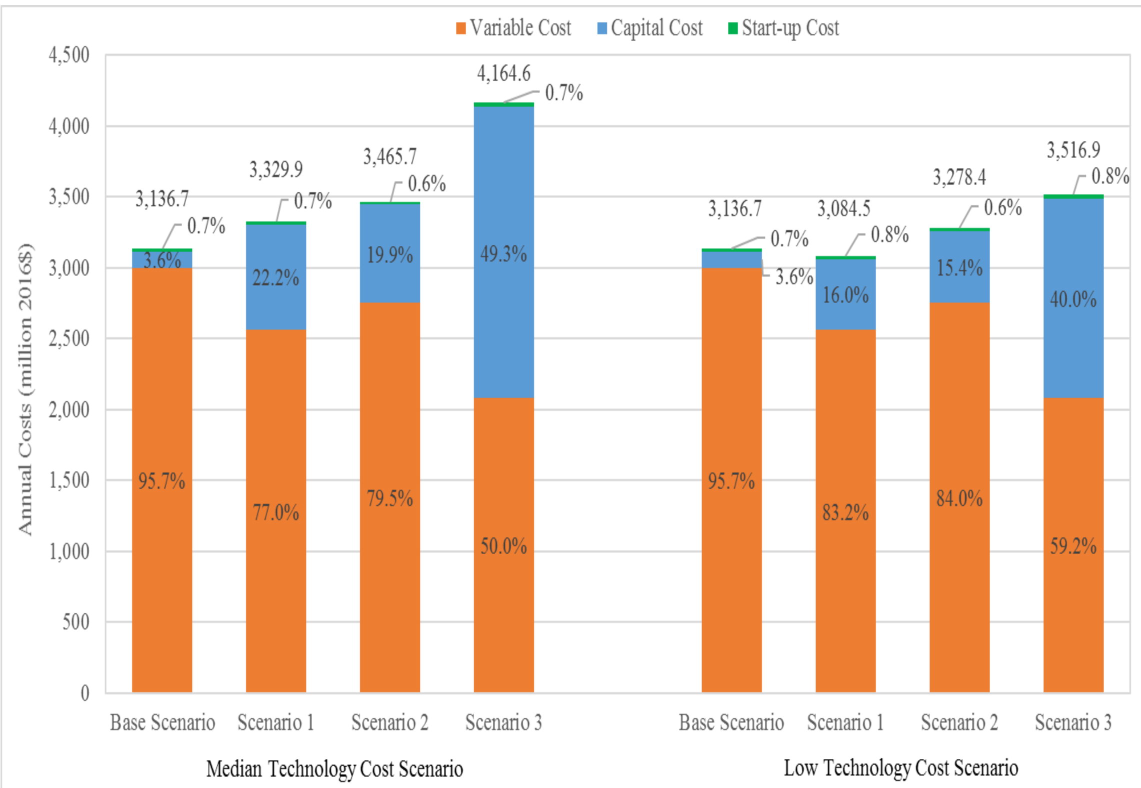

Figure 4-3 Indiana Annualized Costs Mix across Alternative Scenarios for Different Renewable Technology Capital Costs in 2035[11]

[11] Note: Annualized capital costs for existing generators are sunk costs and not included in this analysis.

Figure 4-3 shows the changes in total system costs across scenarios due to assumed future capital cost reductions of solar and wind technologies. Projected lower capital costs of these resources would considerably reduce the total system costs of the median and low technology cost scenarios relative to the current capital cost scenario. Across technology cost scenarios, as the penetration of renewable resources increases and capital cost of solar and wind decreases, the share of variable costs in the total increases. However, in the median technology cost scenario, the increase of this share of variable cost is still not sufficient to outweigh the increase in capital cost and therefore reduce the total system costs at any capacity levels of solar and wind resources. On the other hand, if solar and wind technologies reach even lower capital costs in the future (low technology cost scenario), the total system cost of Scenario 1 would decrease by 1.7% relative to the Base Case Scenario. This cost of Scenario 1, in the low technology cost scenario, is about 13% lower than the total cost of the same scenario in the current technology cost case. However, even considerably lower capital costs of solar and wind technologies would not reduce the total system costs for Scenario 2 and Scenario 3 relative to the Base Case Scenario.

The numbers available in this study allow for the estimation of an electricity rate, that approximates the wholesale rate, by dividing the total system cost values (Table 4-7) by the projected 2035 energy consumption (131,105 GWh). The various solar and wind capacity additions would increase future wholesale rates by approximately 13% in Scenario 1, 20% in Scenario 2 and 60% in Scenario 3 (See Table 4-8).

Table 4-8 Impacts of Alternative Renewables Capacity Additions on 2035 Wholesale Rates

	Base Scenario	Scenario 1	Scenario 2	Scenario 3
Wholesale Electricity Rate (2016 cents/kWh)	2.39	2.70	2.88	3.82
% Rate Change from Base Case	-	13.0%	20.4%	59.5%

4.3 Capacity Value of Solar

This section presents the additional resource needs identified by scaling solar and wind capacities and the resulting value of solar capacity in terms of peaking resources. Table 4.9 details the future peaking resource requirements identified by running the capacity additions model and the value of solar capacity calculated for the different solar and wind capacities cases. The planning results show that, relative to 2015 installed generation capacity levels, no new baseload capacity needs to be built. The need for new peaking resources also decreases as solar and wind capacities increase. Since the model identified no new additions of baseload resources for all these cases, the zero values for this technology are not displayed in Table 4-9 or Figure 4-4.

The identified new peaking capacity requirements in 2035 fall as the amount of solar capacity increases in the system. On average, if 2,000 MW of installed wind capacity is complemented with 1,000 MW of solar capacity, the requirements of new peaking capacity in the state's power system would fall by about 718 MW relative to the case with 4,000 MW of solar (See Table 4.9). At the 3,000 MW of renewables capacity level (2,000 MW of wind and 1,000 MW of solar), for each proportionally mixed 1 MW of renewables added to the system, the system requirements for peaking capacity are 473 kW. Differently, if 4,000 MW of solar capacity is added to the system accompanied with the same 2,000 MW of wind capacity, this would reduce the total peaking resources requirements to 117 kW for each 1 MW of renewables added to the system.

Figure 4-4 illustrates the decreasing variation in the levels of peaking capacity as additional solar and wind generation is added to Indiana's power system. As displayed in the figure, the peaking capacity requirements for all the wind capacity cases show a downward trajectory with steeper rate of change between 200 MW and 2,800 MW than the rate of change observed between the 3,000 MW and 4,000 MW of installed solar capacity. For this first section of the trajectory of the case with 0 MW of wind capacity, every increase of 200 MW levels of solar generation causes an average reduction of 52 MW from the identified total peaking resource requirements.

For the same 0 MW wind case, beyond 3,000 MW of installed solar capacity, this average reduction (19 MW) from total new peaking resource requirements, starts to slow down (i.e. the slope is flatter) as solar generation increases. For the 3,000-4,000 MW range of installed solar capacity, solar capacity additions to the system highly reduce the load net of solar in the middle part of the day and shifts the time of greatest electricity need to even later evening hours. That is, the need for conventional resources increases. Therefore, the displacement rate of new peaking resource requirements is lower relative to the observed rate between the 200 MW to 2,800 MW range of installed solar.

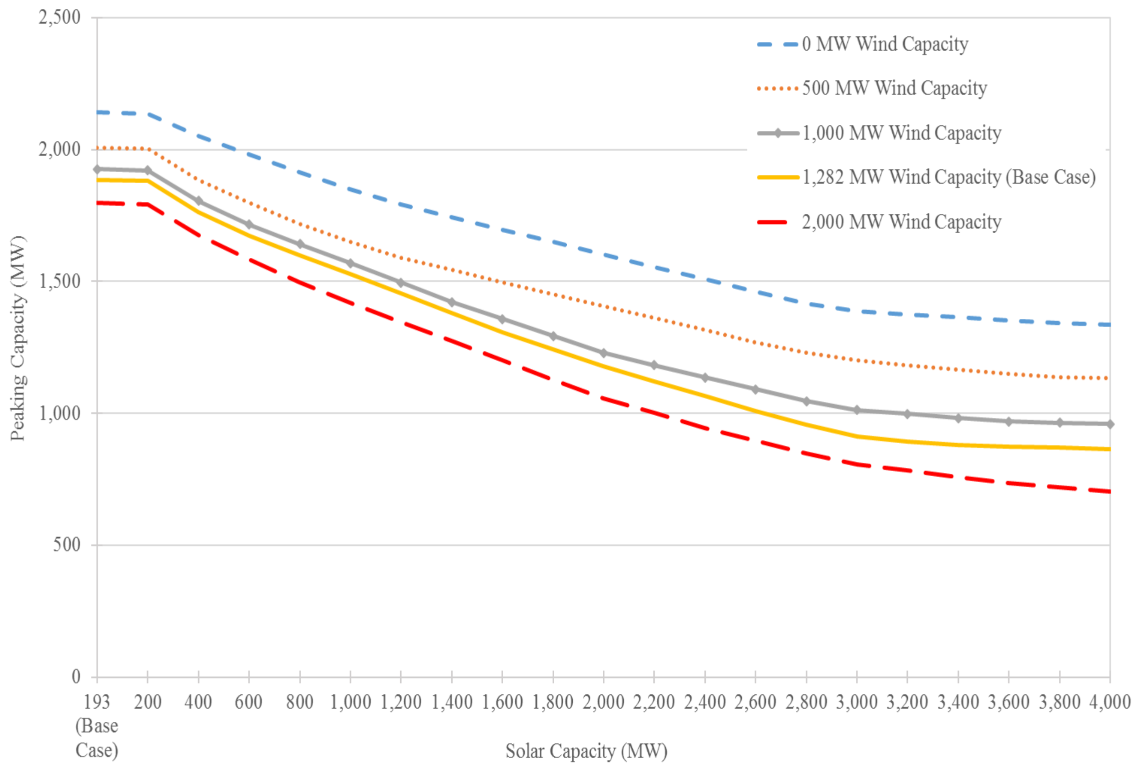

Figure 4-4 Change in Peaking Capacity Requirements Due to Solar and Wind Additions

Table 4-9 also shows the values of solar capacity in percentage terms for various wind and solar capacity levels considered for this section of the study. These percent values for each of the wind capacity cases, represent the absolute incremental change of peaking resources requirements divided by the incremental addition from the giving level of solar capacity to 200 more megawatts. Because the load pattern changes with every addition of wind generation capacity, the identified solar capacity values correspond, specifically, to each of the wind capacity cases and cannot be compared across cases. Increasing levels of solar generation in the power system of the state reduces the capacity value of this resource. These values are confirmed to be highly sensitive to increasing levels of solar capacity. As solar capacity is added to the system, the timing of the peak load hour begins to shift to a later time in the day when solar generation begins to significantly drop, therefore decreasing its contribution to reliably meeting the peak demand.

In Indiana's power system, the addition of 1,000 MW to 2,000 MW of wind capacity in combination with up to 3,400 MW of installed solar capacity levels, in most cases, increases the average value of solar capacity in comparison with the values resulting of only adding solar capacity with no wind.

Table 4-9 Peaking Capacity Requirements and Solar Capacity Values for Alternative Solar and Wind Capacity Levels

Solar Capacity in 2035	Peaking Resources (MW)* Wind Capacity in 2035					Solar Capacity Value (%)** Wind Capacity in 2035				
	0 MW	500 MW	1,000 MW	1,282 MW (Base Case)	2,000 MW	0 MW	500 MW	1,000 MW	1,282 MW (Base Case)	2,000 MW
193 MW (Base Case)	2,140	2,006	1,925	1,885	1,796	-	-	-	-	-
200	2,136	2,002	1,920	1,880	1,791	58.3	60.6	65.7	65.7	67.3
400	2,051	1,885	1,804	1,763	1,675	42.1	58.3	58.0	58.6	58.3
600	1,982	1,796	1,715	1,673	1,583	34.7	44.5	44.6	44.9	46.0
800	1,915	1,719	1,642	1,600	1,495	33.6	38.6	36.7	36.7	44.0
1,000	1,851	1,651	1,569	1,527	1,420	32.1	34.2	36.7	36.7	37.4
1,200	1,790	1,591	1,495	1,453	1,347	30.1	30.1	36.7	36.7	36.7
1,400	1,743	1,543	1,422	1,380	1,273	23.9	23.9	36.7	36.7	36.7
1,600	1,696	1,497	1,358	1,308	1,200	23.4	22.7	32.2	36.1	36.7
1,800	1,649	1,452	1,294	1,244	1,127	23.4	22.7	32.0	32.0	36.7
2,000	1,602	1,406	1,229	1,180	1,057	23.4	22.7	32.0	32.0	34.6
2,200	1,555	1,361	1,182	1,121	1,001	23.4	22.7	23.8	29.2	28.2
2,400	1,509	1,315	1,136	1,065	945	23.4	22.7	22.7	28.0	28.0
2,600	1,462	1,270	1,091	1,009	895	23.4	22.7	22.7	28.0	25.3
2,800	1,416	1,228	1,045	957	847	23.1	20.8	22.7	26.1	23.6
3,000	1,387	1,200	1,013	913	807	14.2	14.2	16.1	22.1	20.1
3,200	1,376	1,182	997	893	783	5.8	9.0	7.9	9.9	12.1
3,400	1,364	1,166	981	879	759	5.7	7.9	7.9	6.9	12.1
3,600	1,353	1,150	970	874	734	5.7	7.9	5.9	2.7	12.1
3,800	1,343	1,137	964	869	718	4.9	6.5	2.7	2.7	8.2
4,000	1,337	1,132	959	863	702	3.1	2.7	2.7	2.7	7.9
Average of Total:						22.9	24.8	27.3	28.7	30.6
Average 200 MW - 2,800 MW:						29.9	32.0	35.9	37.7	38.5
Average 3,000 MW - 4,000 MW:						6.6	8.0	7.2	7.8	12.1

* Peaking resources come from the capacity expansion model
** Solar capacity value represents the capacity contribution of solar power to meeting system peak demand in percentage terms of capacity of peaking resources. For example, the percentage value at the 1,000 MW solar capacity step and 2,000 MW of wind capacity level is calculated as follows: $\left(\frac{1{,}495\ MW - 1{,}420\ MW}{200\ MW\ of\ Solar}\right) \times 100 = 37.4\%$.

Across all the renewables capacity levels studied in this section, the 2,000 MW of wind and 200 MW of solar capacities case has the highest average capacity value of solar with 67.3% of the solar AC rated capacity. Therefore, a 67.3% capacity value means that for every 1 MWac of additional solar capacity installed at this renewables capacity level, there is a 0.67 MW reduction in the levels of peaking capacity additions. For the 2,000 MW of wind capacity level, the average capacity value of solar is about 30.6% of the AC rated capacity for the solar capacity steps, ranging from 200 MW to 4,000 MW. However, at higher ranges of solar capacity levels, the average capacity values drop going from about 38.5% to 12.1% when comparing the values of the 200 – 2,800 MW and the 3,000 – 4,000 MW ranges, respectively. A similar pattern is observed in all the other wind capacity cases, where the average capacity value of solar generally falls as installed capacity of this resource increases. However, there are particular cases where the percentage values stay the same as the solar capacity additions increase by 200 MW. This is because, for these cases, each of the consecutive incremental levels of solar generation contributes by the same magnitude to the creation of each of the new peaks of the load net of solar curve. Since each of these new peaks are contrasted with the same system peak load, then the levels of additional peaking resources decrease by the same proportion than the solar generation incremental levels.

CHAPTER 5. DISCUSSION AND CONCLUSIONS

This chapter is composed by four sections and aims to summarize the questions posed throughout this investigation. While the first section covers the discussion of the results, the second one presents the conclusions of the different analyses developed in this research study. The third and fourth sections present respectively the caveats identified in the proposed methodology and the potential future work to improve or complement the present findings.

5.1 Discussion

5.1.1 Discussion of Optimal PV Solar System Configuration Results

The results of the optimization of PV solar configuration provide the optimal combination of azimuth and tilt angles that maximizes in turn the annual energy generation and the economic value of that energy generated by various PV solar panel arrays in eight zones across Indiana. These results confirm that the solar radiation captured to generate electricity varies depending on the orientation and tilt angles of the panels. Therefore, the differences between the angles identified in the optimal cases and the ones in the Indiana's typical system configuration are small but noticeable especially in some geographical zones.

Earlier studies applied a rule-of-thumb approach of deciding an optimal tilt angle based on the local latitude of the analyzed solar projects. However, in this study, the identified optimal tilt angles are lower than the local latitude of every solar project in all the regions. Since Indiana is located within a latitude range of about 37.9˚ and 41.7˚, at these potential tilt angles, there would be an increase in materials and labor costs for installing taller poles or racks mounts and drilling holes deep enough for them. Furthermore, another factor considered by PV solar designers is that PV panels with those potential tilt angles would need to withstand enormous stress from heavier wind loads. For that reason, the upper bounds imposed in this study reflect these limitations, and are equal to the resulting optimal tilt angles of 0˚, 10˚ and 25˚ for single axis tracking, fixed roof top mount and fixed open rack arrays, respectively. This means that the tilt angle for fixed open rack arrays is on average 14˚ lower than the state's latitude, and consequently, is significantly lower than the optimal tilt angles estimated in other studies (Blumsack et al., 2010; Rhodes et al., 2014).

The results show that all the locations and array types in Indiana would have optimal azimuth angles within the 177˚ and 190.5˚ range. This indicates that the traditional design criteria of orienting the solar module directly south (180˚ azimuth) might be an acceptable approximation to obtain annual energy and revenue values close to the amounts obtained in an optimal setup, independently of the location and array type of the solar project. This band of optimal azimuth angles is consistent with the one estimated by Rhodes et al. (2014) for maximizing energy value. However, the results suggest that the best practice might be to orient the panels in some specific zones of the state, especially Zone 2, slightly more towards the east if the objective is to maximize annual generation. This result might indicate that the annual average degree of cloudiness in those regions is slightly higher in the late afternoon than in the morning hours.

Furthermore, the findings of this analysis show that there might be a small advantage to use different azimuth angles depending on the type of array installed. On average, the annual energy generation could somewhat increase if solar project developers configure the installation of fixed open rack, fixed roof mount, and single axis tracking arrays using an azimuth angle of 179.1˚, 178˚ and 179.6˚, respectively.

On the other hand, if the objective is to maximize the economic value of the energy generated per year, the panels must be configured slightly more towards the west. From this economic perspective, if wholesale electricity prices maintain the same hourly pattern in the long term, electric utilities could benefit from having PV solar installations with an average azimuth angle of 185.6˚for fixed open rack, 184˚ for fixed roof mount and 181.1˚ for single axis tracking arrays. These angles are somewhat lower than the optimal azimuth angle range (185˚- 200˚) found by Hummon et al. (2013) and Rhodes et al. (2014), but their optimal angles were determined in combination with tilt angles higher than 25˚. Nevertheless, the identified average gain of 0.25% in revenues resulting from shifting the typical configuration of the solar panels to a maximum economic value setup is similar to the results obtained by Hummon et al. (2013).

These findings confirm that the increases in annual electricity generated or revenue are minor compared to the typical configuration in Indiana. However, the results show that in certain zones of the state, orienting the panels more towards the west, based on the wholesale electricity prices, slightly increases the revenues due to the higher observed prices during the afternoon hours.

It is noteworthy that, since the optimal placement of the solar panels and their corresponding energy and revenues numbers were estimated using a combination of azimuth and constrained tilt angles, the use of higher tilt angles could change the current results. However, the restrictions that limit the use of higher tilt angle provide a closer representation of reality by reflecting a design that considers and balances among other things the number of panels per area, wind loading on solar panels, and installation costs of utility-scale solar PV projects.

5.1.2 Discussion of the Base Case and Alternative Scenarios Results

The findings of the capacity expansion model show that in a cleaner portfolio of power generation, consisting of higher levels of solar and wind capacity resources, there would still be need of adding traditional forms of generation like peaking generation units. However, the total need for additional conventional resources declines as more renewables are added to the generation mix, which is consistent with the results obtained in a previous analysis for Indiana (Davis et al., 2013).

Meanwhile, the results from the back-of-the-envelope procedure identify that in all the installed dispatchable generators are sufficient to meet even significant 5-minute ramping events that are on average amplified by new solar and wind capacity into the electric system. Furthermore, the results from the commitment model do not show evidence that the number of power units committed in the alternative scenarios would be higher than the Base Case Scenario, due to the new ramping conditions. Therefore, the additional requirements of non-solar and non-wind resources are added mainly to complement solar or wind resources at times, when their generation is not at full capacity, and to ensure that the summer peak load is met.

In this study, the commitment and dispatch model allows us to identify the optimal annual electricity composition of power output produced from different generators and how it shifts across scenarios to meet the same 2035 annual load. From the minimum cost dispatch perspective, at high levels of solar and wind resource capacity, renewable generation mainly substitutes the power output supplied by baseload generation resources only after the generation coming from peaking resources have already been displaced. From the commitment perspective, the results show consistency in providing higher annual capacity factors for groups of larger thermal generating units (e.g. coal and IGCC units) given the cheaper operating costs that motivate the use of these units for the primary purpose of meeting baseload demand.[12]

The calculated capacity factor values provide a clearer picture of how the groups of generators are utilized in a year and how the generation needs from available resources change at different solar and wind capacity levels. As originally expected, the results confirm that the generators that supply electricity at lower variable cost are the ones with the highest capacity factors and utilization levels in a year. For example, hydro and nuclear generators have respectively 91% and 98% capacity factors in all the scenarios except for Scenario 3, where their generation slightly declines in favor of a cheaper electricity generated by the abundant solar and wind capacities. Furthermore, in Scenario 3, there are cases where the energy requirements in the load net of renewables is so low that it falls below the sum of nuclear and hydro capacity explaining the reduction in energy needs and annual variable costs from these resources.

However, higher annual capacity factors do not necessarily mean that the units are continuously generating electricity day after day without being turned off or utilized less during the year. For example, there are days when low levels of electricity demand coincide with high levels of power generation from renewables (Scenario 3), especially solar

[12] Baseload demand is the minimum level of electricity demand required over a period of time, for example 24 hours.

generation during the middle part of the day, which significantly reduce the minimum daily load net of renewables that is required to be met by dispatchable resources. One of these days is Day 105, or April 15, from the 2011 load profile of Scenario 3, which has the highest amount of solar energy curtailment and relatively low levels of load compared with other days of that year. For illustration purposes, Figure 5-1 shows the 2035 load, load net of renewables, and the identified generation mix from various types of generation technologies for Day 105 and for two different scenarios. The top and bottom parts of the figure illustrate the results for the Base Case Scenario and Scenario 3, respectively.

During the midday hours, Figure 5-1 and the results of the model show that it is more cost-effective in Scenario 3 to reduce generation from large thermal units or even turn them off (despite their high minimum up/down times and substantial start-up costs) to give way to the “free” generation from solar and wind resources. Table 5-1 lists the number of times generating units of various types of technology are turned on and off on Day 105 in the Base Case Scenario and Scenario 3. For Scenario 3, the table indicates that large coal and IGCC units, which are cheaper to dispatch than other generation resources, would be frequently turned off and on respectively during the morning and afternoon hours, even though they have higher start-up costs. This explains why the total start-up cost in Scenario 3 is higher than the Base Case Scenario, even though the identified total number of units turned on annually (see Table 4-5) is lower than in the case without new solar and wind generation. However, in aggregate, this type of cost makes a very small contribution to the total cost of the system.

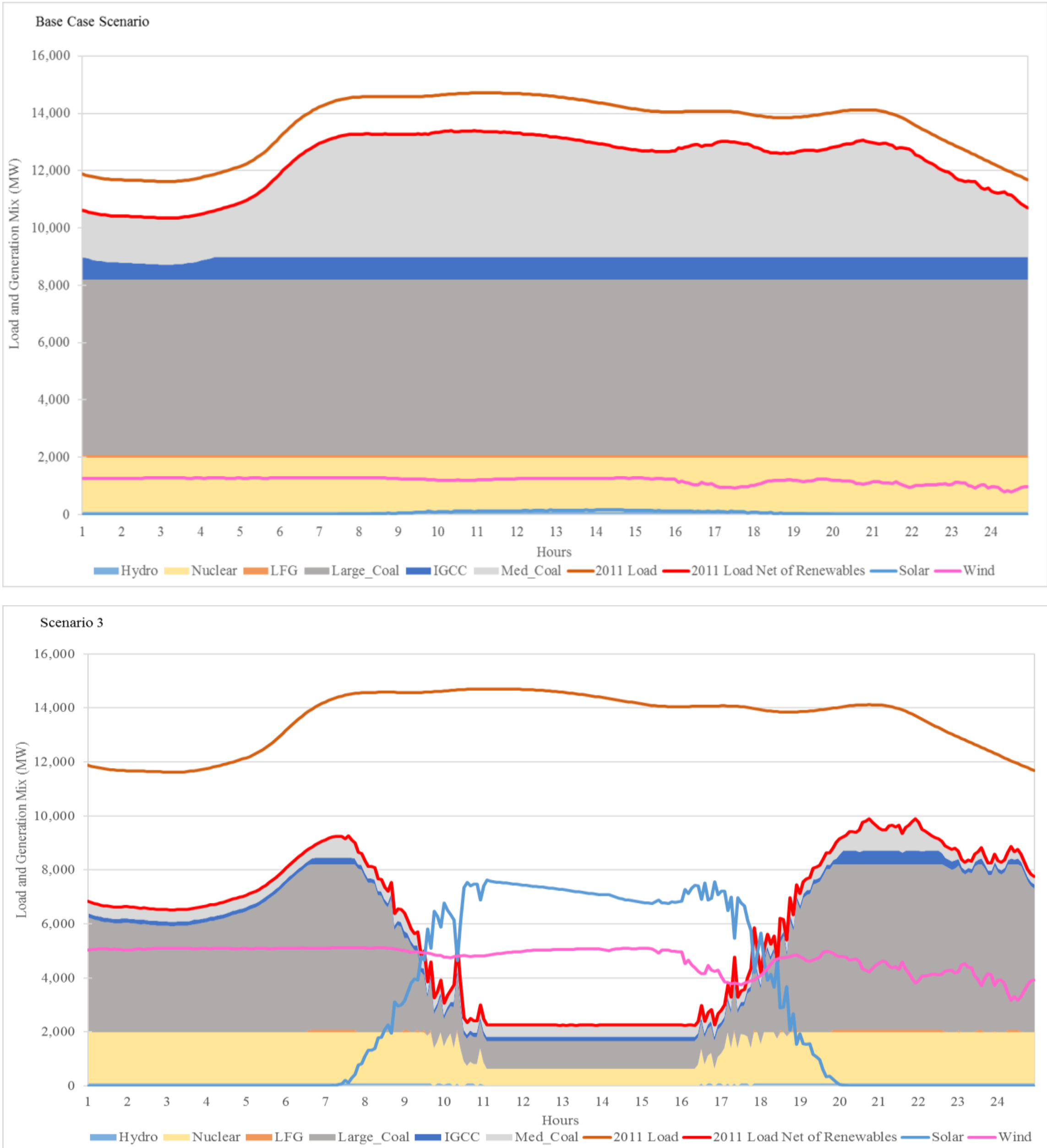

Figure 5-1 2035 Load and Generation Mix (MW) for Day 105 and Two Scenarios.

The results of the models show that the total variable operational cost of the system across scenarios substantially declines, driven by the zero variable cost added to the system by the additional solar and wind capacity. On the other hand, the decline in the incremental capital cost for installing less new peaking capacity resources does not offset the increase in the total capital costs for investing in renewable generation capacity as cleaner but more expensive forms of generation.

Table 5-1 Number of Times Generating Units are Turned On and Off on Day 105 in the Base Case Scenario and Scenario 3.

Scenario	Technology	Number of Additional Units Turned On	Number of Units Turned Off
Base Case			
	Medium coal	2	2
Scenario 3			
	Medium coal	0	1
	Large coal	5	5
	IGCC	1	1

Except for the Scenario 1 in the low technology cost scenario, the decline in total variable cost across scenarios is not sufficient to offset the increase in capital costs and therefore total system costs. These findings indicate that in most of the scenarios these increments in total cost would directly translate into higher wholesale and retail electricity rates in Indiana. However, an approximately 50% reduction in each of the technology costs of solar and wind resources (from current to low technology cost scenarios) would allow incorporation of expanded renewable generation resources, at the capacity levels of Scenario 1, without increasing the total system costs or electricity prices in the state.

5.1.3 Discussion of the Solar Capacity Value Results

The results of this analysis confirm that only new peaking capacity would be required in Indiana’s electric system to complement the additions of renewable generation capacity. The amount of new peaking capacity required decreases as solar and wind capacity levels increase. This is because generation by either wind or solar, while not perfectly correlated with Indiana load nor available at the same time at full capacity during the annual peak demand, still offsets some of the peaking requirements. Furthermore, findings of this analysis indicate that, for all the wind installed capacity levels analyzed, additions of solar power capacity in most of the cases reduce the capacity value of this resource in Indiana.

The results show a range of PV capacity values that vary widely depending on the combination of solar and wind capacity levels. These calculated capacity values are between 2.7% and 67.3% of the corresponding solar nameplate capacity, and represent the average capacity values of solar power in Indiana considering all types of PV solar arrays. Recall that, for the 200 MW solar and 2,000 MW wind capacity levels, a 67.3% capacity value means that 1 MWac of solar capacity can provide an equivalent level of reliability as a 0.67 MW advanced natural gas-fired combustion turbine. This range of values for solar capacity is somewhat similar to the range found by Duignan et al. (2012) in their review of several solar capacity studies. However, it would be difficult to compare and find consistency with the findings presented in that or other previous studies (Madaeni et al., 2013; GE Energy, 2010) because estimated capacity values for solar vary a lot depending on the methodology and the key assumptions considered. For example, the evaluation technique, the coincidence of solar generation with the specific system peak demand and daily load patterns, and other intrinsic characteristics of the solar plants such as size, location, configuration, array type, etc., directly affect the capacity value results.

Additionally, the calculated aggregated solar capacity values differ based on the solar penetration levels. For the 2,400 MW of solar and 1,282 MW of wind aggregated capacity levels, the average solar capacity value is about 28%. These solar and wind capacity levels would respectively represent penetration levels of 2.9% and 3.7% of the 2035 electricity generation for the state. However, if the penetration level of solar power increases to 4.8% of the electricity generation in Indiana (4,000 MW total solar nameplate capacity), the average solar capacity value for the state falls considerably to 2.7%.

5.2 Conclusions

The increasing importance of solar power as one of the preferred choices among renewable resources motivates the need to identify the benefits and challenges of integrating this intermittent form of generation into the Indiana's power supply system. The intermittent and unpredictable aspects of this resource pose operational and economic challenges that need to be understood for improving the electric resource planning process and utilization of renewable energy. The different analyses included in this study represent another relevant piece of information that contributes to a better understanding of the impacts and potential implications of integrating solar and wind power in an electricity supply system.

5.2.1 Conclusions of Using Various PV Solar System Configurations in Indiana

This part of the analysis determines the optimal combination of azimuth and tilt angles that maximizes the annual energy generation and the economic value of that energy generated by various PV solar panel arrays in eight zones across Indiana. The resulting optimal orientation angles presented in this research are consistent with the findings of other studies regarding the range of azimuth angles that maximizes annual energy, although they are somewhat lower than the range of angles that maximize annual revenue. However, the magnitudes of the impacts on revenues from using a maximum economic value configuration instead of a typical configuration is similar to the impact found in previous studies. Nevertheless, the results of this study demonstrate that there are only minor economic and energy generation benefits from the reconfiguration of solar PV installations across the state.

Having optimal azimuth angles slightly oriented more towards the west than the typical configuration to maximize the annual revenue, results because the timing of solar generation in Indiana exhibits a positive correlation with wholesale electricity prices. However, at the current installed solar capacity levels, the maximum additional revenue per year that could be obtained by aligning the solar energy production of all solar projects of the state with the wholesale market electricity prices is only about $36,240. This represents about 0.25% of the total economic value of the energy generated from solar power projects across Indiana. Meanwhile, the maximum additional annual electricity (896 MWh) resulting from a hypothetical reconfiguration of all of the state's solar installations represents only 0.30% of the solar output generated from the same existing installations with typical configurations. This additional annual electricity generated from solar is observed to occur more during the morning and midday hours, and therefore make only a minor contribution on average to reducing any afternoon daily peak load in the year.

Different from other studies, this analysis contributes to the literature by considering three specific array types and various locations using Indiana as a case study. In that sense, fixed open rack installations have the potential to return higher annual energy and revenue than either fixed rooftop and single axis tracking arrays. Also, although in all the zones of the state the optimal placement of the solar installations increases the energy and revenue generated in a year, the southern and northwestern zones of the state show the highest impacts from that reconfiguration.

Therefore, in some zones across the state, solar project developers would be motivated to use one optimal configuration over the other depending on the system tariff agreed with the utilities under a power purchase agreement. If this agreement considers a tariff per kilowatt-hour produced that varies accordingly with the hourly wholesale electricity market prices, then developers would definitely prefer a slightly west-facing configuration strategy that more closely aligns higher solar generation levels with higher electricity prices. On the other hand, an annual fixed tariff would incentivize the developer to install solar panels facing slightly more towards the east to produce the maximum amount of electricity annually, which also translates into maximum annual revenue.

However, in a regulated market environment like Indiana, the electric utilities that act as system planners and operators, reach an agreement with the state's regulatory commission to receive a fixed levelized rate per kilowatt-hour that guarantees they can recover operational expenses and a rate of return on equity. In this scenario, the utilities might prioritize a solar installation placement that maximizes annual electricity over annual revenue because of the potential planning advantages and operational flexibility that the excess energy generated would give to the overall system. For example, from the system planning perspective, if an annual maximum energy configuration of solar installations is accompanied with energy storage technologies, this potential additional annual energy available can be stored during off-peak hours (lower demand) and used during on-peak hours (higher demand). The success of that strategy would depend on the efficiency of storage and the differences in energy value across time within the day. These complementary measures can have a greater impact in reducing the annual system peak load and therefore the need for additional resource capacity. Then, the application of measures as the use of a competitive electricity market price in combination with west-facing solar installations or the use of east-facing solar panels for exploiting operational and planning advantages, might bring reductions to the costs and final electricity rates paid by Indiana customers.

These results show that electric utilities and project developers could benefit in energy or economic terms from an optimal placement of solar installations, which is viable particularly for fixed open racks, without incurring significant additional costs. Furthermore, incentives could be provided to encourage the use of optimal configurations in future solar project investments and prioritize the installation of utility-scale fixed open racks at specific locations across the state. While the northwestern (Zone 1) and southern (Zone 8) regions of Indiana might be better locations to maximize the impact of applying an optimal configuration, other factors must be considered, such as the distance from the electricity demand centers and the need for additional investments in electric transmission infrastructure. Furthermore, the agglomeration of solar installations in only one specific zone would reduce their geographic diversity and increase the magnitude of the intermittent changes in the aggregated solar power generation.

5.2.2 Conclusions Regarding the Impacts of Integrating PV Solar into a Power System in Indiana

This proposed analysis explores the effects of additional solar and wind power investments on the future requirements for conventional generation capacity, the amount of energy supplied by various types of generation technologies and the costs of Indiana's electric supply system. From this study perspective and holding everything else constant, the results of this analysis indicate that the existing capacity generating fleet of the state in combination with only few additional megawatts of new conventional peaking resources is sufficient to support substantial additions of utility-scale PV solar and wind generation capacity resources in the system.

The comparison of the results among scenarios sheds some light on the possible economic, technical, and policy implications of expanding the share of renewables within the generation portfolio of the state. For example, the fact that there is solar and wind generation curtailment and a reduction in generation of the cheapest dispatched generating resources – nuclear and hydro – in Scenario 3 relative to the other scenarios, implies that utilities and ultimately consumers would be paying an additional hidden cost for dumping unused electricity or having units operating inefficiently within the system.

The comparison of the total costs of Scenario 1 and Scenario 2 provides support to the idea that it would be cheaper in the long-term to invest in a combination of solar and wind generation resources than in solar generation resources alone. Therefore, policy makers could promote tax incentives or pricing mechanisms (e.g. feed-in tariff rates) for prioritizing a more balanced investment making sure the portfolio of renewable energy technologies include solar and wind resources in complementary proportions. Furthermore, if there is a substantial decline in the technology costs of solar and wind resources, it would be cheaper in the future to invest in renewables resources up to the capacity additions levels of Scenario 1 than only in peaking generation resources.

Results show that in all the scenarios except for Scenario 1 in the low technology cost case, the reductions in variable costs are not sufficient to outweigh the increases in capital costs regardless of the levels of solar and wind capacity additions. Therefore, in those scenarios, any level of additional capacity from those resources will contribute to an increase in wholesale rates. However, the cost-effectiveness of solar and wind power investments should consider, among other things, the benefits related to a less polluted environment, a risk reduction from having a more diversified generation portfolio, or better human health from having low-emission forms of generation within the power supply system. All these benefits may be taken into account by policy makers to determine if it would be acceptable to pay these additional costs in order to promote solar and wind power development.

From a technical perspective, the results indicate that the existing blend of conventional generation resources in Indiana would have sufficient operational flexibility to meet any new 5-minute ramping events from the integration of solar and wind capacity penetration levels of up to 30% of total electricity generation. However, additional capacity of flexible generation resources or energy storage technologies may be required to address system operational challenges such as deviations from nominal frequency or power and voltage fluctuations that could occur as a consequence of substantial integration of renewable generation resources.

Since Indiana still heavily relies on coal to generate electricity, the state might face the retirement or the need to convert some of the coal generating units to natural gas in order to comply with potential future environmental regulations that seek the reduction of greenhouse gas (GHG) emissions. Therefore, this study contributes to a better understanding of the implications of solar and wind power within the state's power supply system and provides another decision-making tool from a planning perspective for policymakers, utility companies and project developers.

5.2.3 Conclusions of the Solar Capacity Value Calculation Methodology

This analysis focuses on determining the capacity contributions of PV solar power and in alternative combinations with wind power to Indiana's electricity supply system at various penetration levels of these resources. The proposed capacity expansion model is used to estimate the equivalent amount of 1 MW of solar power in terms of the capacity of a conventional plant from a deterministic system peak load reliability perspective. Although most of the traditional metrics use a full adequacy reliability-based approach to assess renewables capacity values, the range of values obtained with this simplified method are in line with the ones found in other studies.

The results for this section show that no new baseload resource capacity is necessary even at substantial solar and wind capacity levels. This is because Indiana's installed generating fleet predominately consists of baseload generation resources (89%), and the new renewable resources of the system have a greater impact on reducing the minimum load that is usually supplied by baseload units than by peaking units. This is because, like baseload units, renewable resources have low variable operating costs. Therefore, renewable resources are closer substitutes to baseload than peaking generating resources.

The model also indicates that the need for additional peaking resources falls as the additions of new solar and wind capacity levels increase. However, the impacts of reducing the requirement of additional peaking capacity in Indiana's electricity supply system are higher at lower levels of renewable capacity additions. Therefore, the initial benefits of higher PV solar capacity values decline as more solar installations are built in the state; this reduction in capacity value is particularly evident at solar capacity levels higher than 3,000 MW. This reduction of the capacity value of solar is due to the lower contribution that each additional unit of solar capacity has in reducing the system peak demand. As solar generation increases and closely coincides with the occurrence of the system peak load, there is a shift of the peak load net of renewable generation time to later afternoon hours, when solar installations begin to reduce their production.

These findings could create incentives for implementing demand side management programs or build storage facilities to modify the daily load pattern and peak time starting at specific solar capacity levels, in order to maintain or increase the capacity credit of these resources. Furthermore, a feed-in tariff project (policy that requires electric utilities to pay solar projects developers a price high enough to generate a reasonable return on their initial investment) could be arranged to incorporate up to a given number of megawatts of solar capacity into the generation portfolio that would bring a desired contribution level of solar power to the peak load. System planners would identify the appropriate contribution level that allows them to have a more diversified portfolio and maintain system reliability at affordable electricity rates for customers.

Despite diminishing marginal solar capacity values, a large amount of solar and wind capacity can be accommodated in the power supply system while still continuing to reduce the level of additional peaking capacity requirements and therefore the system's carbon footprint. The results presented also improve our understanding of the potential capacity tradeoff between peaking, solar and wind resources at different future levels of solar and wind capacity. These results provide a guide on how to use low-emissions generation resources and plan for reaching a long-term equilibrium of the system's capacity mix. Furthermore, the results contribute to our understanding of the magnitude of the responsiveness of Indiana's electric power system to different sizes of solar and wind capacity levels, and the potential to complement renewable generation capacity with alternative supply and demand resources.

5.3 Caveats

The following section discusses some of the factors that are not considered in the present study and may affect the current results. This discussion also reviews some of the limitations encountered during the research process that could be further analyzed or improved in future studies.

5.3.1 Factors Affecting the LDC, Capacity Additions and Costs

The time horizon assumed in this study implies that the current technology of solar and wind resources and their capital costs would be unchanged for many years. However, more efficient and cheaper solar panels and wind turbines are highly likely to be available in the short- and medium-term due to the rapid pace of innovation and development of new technologies. These changes in technology may significantly increase the solar and wind generation produced per unit of land with potential lower installation and capital costs per watt. The lowering of capital cost could make solar and wind more cost-effective and economically attractive compared to conventional generation resources. Ultimately, higher additions of new solar and wind capacity would affect the current generation resource mix and the total capital cost of the system. Additionally, the potential future retirement of coal generation units in the state due to age or to comply with environmental regulations could reduce the installed baseload capacity levels and improve the value of the contribution of solar and wind to the generation portfolio. On the other hand, a substantial retirement of baseload units would modify the level of new baseload and peaking resources requirements identified by running the capacity planning model and therefore impact the resulting capital and variable costs of the system. Moreover, the integration of renewable resources in the system has the potential to simultaneously provide some types of ancillary services to the grid and would require other types of services from the grid. This study ignores the respectively impact of solar and wind generation resources on the ancillary services markets. The consideration of these services could cause a shift in the optimal utilization of the conventional generating units needed to provide ancillary services and directly affect the identified system variable costs. In addition, it can be expected that using baseload generating units to follow load may decrease their efficiency, raise their variable maintenance costs and shorten their economic lives. These costs are not accounted for here; and hence the total system costs for the scenarios with expanded renewable generating capacity may be understated.

5.3.2 Weather, Load and Solar Patterns

As the solar generation data is simulated using typical weather conditions, but the three load profiles are associated to three different weather patterns, there is a partial disconnect in the relationship between the solar generation and load data series. The use of similar weather conditions for creating a solar output profile might have changed the correlation between solar generation and demand for electricity in each year. For example, during the summer time, days with higher temperatures accompanied by less cloudy skies could increase the demand of electricity for air conditioning and the sunlight captured by solar panels to produced energy at the same time. In that case, solar power would have a greater impact on reducing the need for generation from non-solar resources to meet the load net of solar. Furthermore, a closer coincidence in daily patterns of solar generation and load might contribute to a reduction of the system peak load and the need for conventional resources. However, if the typical weather conditions had lower (higher) annual temperatures or solar irradiation levels compared to the weather conditions of each of the individual three years, the results might show a reduction (improvement) in the overall impacts of solar power in the system.

5.3.3 Factors Affecting Capacity Value Calculation

The method proposed to calculate the capacity value of solar power in the state does not capture the randomness of sudden disturbances of the electrical supply system. The capacity values estimated using this simplified approach without considering risk or adequacy calculations need to be carefully compared and validated against values calculated specifically for Indiana with a traditional system adequacy methodology. Moreover, the capacity values vary depending on the spatial distribution and dispersion of the solar resource with respect to the load it serves and the solar technologies. The consideration of these factors would refine the results reported in this analysis which only represent an approximated average values across zones and array types.

5.3.4 Transmission Line Constraints

Additional investments in transmission infrastructure may be required to accommodate the integration of new solar and wind capacity, and these investments are not considered in this study. However, as more solar and wind power is added into electricity supply system, determining their potential impact on transmission costs and operational challenges becomes more relevant. For example, significant transmission investment costs and/or congestions could occur depending on the distance between solar plant sites' locations and the loads they serve. The identification of these transmission impacts might also affect the choice of the most appropriate zone in the state and size for a new PV solar installation.

5.3.5 Potential Environmental Impacts

The use of solar and wind energy sources is expected to reduce the levels of natural gas and coal that are burned for generating electricity and the carbon dioxide (CO_2) and other greenhouse gases (GHG) emission levels in the atmosphere. The levels of emissions from coal- and natural gas-burning power plants would also change due to the potential loss of operating efficiency of these units when following the load net of renewables. Because this study only considers a constant heat rate (a measure of the efficiency of a generator) for each technology type across scenarios, the results do not reflect or capture the impact of having reductions of efficiency in those power plants. Therefore, this study ignores the potential economic impacts of changes in the heat rates or the environmental implications of increasing the supply of renewable electricity generation from solar and wind in the Indiana's electric power system. This means that the reduction in GHG emissions may not be as large as they would be if electricity from renewables replaced thermal electricity generation on a kWh per kWh basis.

5.3.6 Geographic Diversity and Non-Interconnected Generation System

The scope of this study is limited to Indiana and therefore treats its power system as being isolated from the rest of the regional power grid. However, an interconnected grid could have planning and operating benefits due to the potential access to additional power supply resources located in geographically diverse regions. Accounting for solar and wind output generated outside the state could contribute to reducing the magnitude of the ramping events and the cost of managing the variability added by these resources to the load. Furthermore, due to the solar and wind power resource availability and time zone differences between states (e.g. Indiana and Illinois), the peak generation from solar and wind installations in each of these states would occur at different times. For example, there would be times when solar generation begins to drop in one state but peaks in another state, which would modify the magnitude and timing of their greatest contribution to reduce Indiana's daily system peak load. Thus, considering solar and wind generation from other sites would change the levels of future capacity requirements and system costs identified in this study.

5.4 Future Work

This section suggests other possibilities, besides the ones covered in the caveats section, for future research work that could complement or improve the analysis of the impacts of integrating solar power into an electric supply system.

Considering energy storage technologies or demand response (DR) programs in combination with solar power could improve the relative solar capacity value in Indiana. For example, the use of Direct Load Control (DLC) programs, that reduce customers' electricity consumption during peak hours, could help to shift the time of the new system peak load to coincide with the solar generation peak time. This combination would increase the capacity credit of solar to meet the system peak load. Furthermore, the identified energy curtailment that occurs in our analysis at higher levels of solar and wind capacity would obviously create a potential opportunity for energy storage as a resource option within the system. A type of battery could store the energy generated from solar during the morning hours that usually are off-peak periods and make it available during on-peak hours when solar generation begins to decline which would improve the relative economics of solar capacity in the system.

Future analysis could also incorporate different levels of uncertainty and risk for load demand and fuel costs. These model inputs could be affected by potential changes in the weather, wholesale fuel markets and technology conditions, which will ultimately affect the levels of the capacity, generation and cost impacts in all the scenarios. For example, changes in weather conditions will not only affect the amount of electricity demanded in the future, but may also change the shape of the hourly load net of renewable generation profile. While changes in coal and natural gas prices due to competition and availability of more efficient and effective ways to extract these fossil fuels will directly modify the results of the unit dispatch process and therefore the variable costs of the system. Then, the cost effectiveness of solar generation would depend on the magnitude and direction of the changes observed on these inputs.

Compliance with increasingly tighter environmental regulations makes it indispensable to quantify the environmental and economic impact of integrating solar and wind resources within the generation portfolio. Increasing capacity levels of renewable resources reduce the fossil fuel power plants generation needs and consequently the level of emissions of toxic emissions in the environment (e.g. carbon dioxide (CO_2), nitrogen oxides (NOx), sulfur dioxide (SO_2), Mercury (HG), etc.). A future study could determine the potential economic benefits of incurring investment costs from installing additional cleaner electricity generation resources such as wind and solar generation instead of costly environmental control equipment in existing thermal power plants. In general, stricter emission regulations and potentially higher cost of traded emission allowances would make solar and wind energy more economically attractive.

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APPENDIX A. GAMS CODE FOR INDIANA PIECEWISE LINEAR APROXIMATION

```
$onUNDF
* Create a .gdx file from the Indiana.xlsx file
$CALL GDXXRW U:\Indiana.xlsx par=p rng=A1:b8761 rdim=1 cdim=1 set=l rng=b1:b1
cdim=1
$GDXIN Indiana.gdx

Set i number of knots per season (every 5 minutes) / 0*105120 /,
    j number of hours per season /1*8760/,
    u number of 5-minute periods per season / 1*105120 /,
    l(*) SAM projects ;
$LOAD  l

*Import hourly data from Excel to GAMS
parameter
 p(j,*)  hourly SAM power output over interval u ;
$LOAD p
$GDXIN
option limrow=0,limcol=0;
p(j,l)=p(j,l)/1000000;
option p:7;
display p;

*Allocate appropiate hourly data in each 5-minute period of each hour.
parameter power5(u,l) Organized hourly Avg. of actual power output interval u;
power5(u,l)= sum(j$(trunc((ord(u)-1)/12)+1 eq ord(j)),p(j,l)) ;
option power5:5;
power5(u,l)$(Not power5(u,l)) = EPS;
display power5;

parameter pl(j),
          fl(i,l);
*Linear 5-minute approximation model
Variables
 f(i)  Height at lattice point i
 z     Derivative minimizing objective ;

Equations
 obj   Phony objective definition
 ap(j) Average power on interval i is right ;
*Objetive Function
obj .. z =e= sum(i$(ord(i) gt 1),
             sqr(-f(i-1)+f(i))) ;
```

```
*Constraint
ap(j) .. sum(i$((ord(i)-1)/12 eq ord(j)),
 f(i-12)+2*f(i-11)+2*f(i-10)+2*f(i-9)+2*f(i-8)+2*f(i-7)+2*f(i-6)
+ 2*f(i-5)+2*f(i-4)+2*f(i-3)+2*f(i-2)+2*f(i-1)+f(i))/24
 =e= pl(j) ;

Model plm / obj,ap / ;
Loop(l,
     pl(j)=p(j,l);
f.lo(i) = 0 ;
f.up(i) = 2*smax(j,pl(j)) ;
Solve plm using nlp minimizing z ;
fl(i,l)=f.l(i);
) ;
display fl;

*plin approximation
parameter plin(u,l) Piecewise linear five-minute approximation ;
plin(u,l) = sum(i$(trunc((ord(u)-1)/1)+1 eq ord(i)),
  fl(i,l)*(1-(ord(u)-(ord(i)-1)*1)+.5)/1
 + fl(i+1,l)*(ord(u)-(ord(i)-1)*1-.5)/1) ;
option f:5:0:1;
option plin:7:1:1;
plin(u,l)$(Not plin(u,l)) = EPS;
display plin ;

*Create and display output table
parameter smry(l,u,*) ;
smry(l,u, 'j hour') = trunc((ord(u)+11)/12);
smry(l,u,'5 min') = 1/24 + (ord(u) -1)/12 ;
smry(l,u,'plin')  = plin(u,l) ;
smry(l,u,'actual')= power5(u,l) ;
smry(l,u,'diff')  = power5(u,l) - plin(u,l) ;
option smry:7:1:1;
display smry ;

parameter plinwozeros(l,u,*);
plinwozeros(l,u,'5 min')=smry(l,u,'5 min')$(smry(l,u, 'plin') ne 0);
plinwozeros(l,u,'plin')=1000000*smry(l,u,'plin')$(smry(l,u, 'plin') ne 0);
plinwozeros(l,u,'actual')=1000000*smry(l,u,'actual')$(smry(l,u, 'plin') ne 0);
plinwozeros(l,u,'diff')=1000000*smry(l,u,'diff')$(smry(l,u, 'plin') ne 0);
display plinwozeros;

*Group data by month
parameter jan(l,u,*);
```

```
jan(l,u,'plin')$(ord(u) le 8928)=plinwozeros(l,u,'plin')$(plinwozeros(l,u,'5 min') ge 0 and plinwozeros(l,u,'5 min') le 744) ;
jan(l,u,'diff')$(ord(u) le 8928)=plinwozeros(l,u,'diff')$(plinwozeros(l,u,'5 min') ge 0 and plinwozeros(l,u,'5 min') le 744);
option jan:7:1:1;
display jan;
execute_unload "U:\January\janxls.gdx";
execute'gdxxrw.exe U:\January\janxls.gdx o=U:\January\Jan.xlsx par=jan';
```

APPENDIX B. GAMS CODE FOR INDIANA 5-MINUTE DATA SIMULATION

```
$call gdxxrw U:\January\knoyjanplin.xlsx set=s rng=a2:a3472 rdim=1 set=i rng=b1:c1
cdim=1 par=data rng=A1:C3472 rdim=1 cdim=1
$gdxin knoyjanplin.gdx

Sets     t     Total 5_minutes observations in SAM projects data for this month before
removing zeros /1*8928/
         s(*)  Indexed Knoy 5-minute data with no zeros in plin
         i(*)  Labels of the two input columns 'plin' and 'diff'
         copy / reg1*reg8 / ;
$load s i

parameter data(s,*) Includes input Knoy data with no zeros for the month;
$load data
option data:7;
display data;
*Execute_load 'data', fin=data;
parameter fin(s,*) Rename 'data' parameter to 'fin' with only plin data;
fin(s,'plin') = data(s,'plin') ;
option fin:7;
display fin;
*Create parameter plin1 with plin values to create the bins
parameter plin1(s);
plin1(s)=fin(s,'plin');
option plin1:7;
display plin1;
*Create specific # of bins with specific range
alias (s,ss,sss) ;
sets bin(s)
    map(s,ss) Observation s is in bin ss ;
scalar
    noinbin Number of obs in each bin /40/
    bigbin  Last bin is bigger to include more obs than 40
    nobins  Number of bins;
nobins = trunc(card(s)/noinbin) ;
bigbin = card(s) - noinbin*(nobins - 1) ;
bin(s)$(ord(s) le nobins) = yes ;
display noinbin,bigbin,nobins ;

*Allocate data in plin1 to each bin
execute_unload "rank_in.gdx", plin1 ;
execute 'gdxrank rank_in.gdx rank_out.gdx' ;
```

```
parameter plinindex(s) ;
execute_load "rank_out.gdx",plinindex=plin1 ;
option plinindex:2:0:1;
plinindex(s)$(Not plinindex(s)) = EPS;
plin1(s)$(Not plin1(s)) = EPS;
display plinindex ;
parameter result(s,*) ;
result(s,'plin1') = plin1(s) ;
result(s,'position') = plinindex(s) ;

*Indentify the bin location of each obs.
map(s,ss)$(bin(ss) and ord(ss) lt card(bin)) =
  yes$(plinindex(s) gt 40*(ord(ss)-1) and plinindex(s) le 40*ord(ss));
map(s,ss)$(bin(ss) and ord(ss) eq card(bin)) =
  yes$(plinindex(s) gt 40*(ord(ss)-1));
display result,map;
*Put Knoy "diff" values in corresponding bin
fin(s,'diff') = sum(ss,ord(ss)$map(s,ss)) ;
fin(s,'diff') = data(s,'diff') ;
display fin ;
parameter
 diffs(s,ss) Difference s between plin and observed in bin ss
 bpoint      Bin position pointer;
loop(ss,
 bpoint = 1 ;
 loop(sss,
  if (map(sss,ss),
   diffs(s,ss)$(ord(s) eq bpoint) = fin(sss,'diff') ;
   bpoint = bpoint+1 ;
  ) ;
 ) ;
) ;
option diffs:7;
display diffs ;

* Load 5-minute "plin" and "diff" SAM project's data with no zeros in plin for each month
$call gdxxrw U:\January\Jan.xlsx set=m rng=b2:b3760 rdim=1 set=n rng=c1:d1 cdim=1
par=data1 rng=B1:D3760 rdim=1 cdim=1
$gdxin Jan.gdx

Sets     m(*)  Indexed data with no zeros in plin
         n(*)  Labels of the two input columns 'plin' and 'diff';
$load m n

parameter data1(m,*) Includes input data for the month;
$load data1
```

```
option data1:7;
display data1;
parameter hourly(m,*) SAM project plin data ;
hourly(m,'plin') = data1(m,'plin');
*Found the upper bounds of bins determined using plin Knoy data
parameter
cuts(ss) Upper cutoff for plin for bin ss ;
cuts(ss)$(ord(ss) le nobins) = smax(s$map(s,ss),fin(s,'plin')) ;
cuts(ss)$(ord(ss) eq nobins) = inf;
display cuts ;

scalar
   Knoyw    Max Knoy plin value for each month
   Projectw Max Indiana plin value for each month
   KPratio  Ratio to scale down Indiana data to Knoy;
Knoyw = smax(s,fin(s,'plin'));
Projectw=smax(m,hourly(m,'plin'));
KPratio = Projectw/Knoyw;
display Knoyw, Projectw, KPratio;

*Scale down the original plin SAM projects data to be about the same scale than Knoy plin
parameter hourlyscal(m,*) SAM project plin data ;
hourlyscal(m,'plin')=hourly(m,'plin')/KPratio;
display fin, hourlyscal;

parameter hourlyfin(copy,m,*) Data set with new diff and rescaled up SAM project data ;

*Identify bins, draw from distribution out of identified bin and
*then add random deviations to Indiana data

scalar random Random number for drawing from the distribution of diffs ;
parameter finaldata(copy,t,i);
loop(copy,
loop(m,
 loop(ss$bin(ss),
  if (hourlyscal(m,'plin') le cuts(ss) and hourlyscal(m,'plin') gt cuts(ss-1),
   if (ord(ss) lt card(bin),
    random = uniform(0,noinbin) ;
    hourlyfin(copy,m,'sim') = hourlyscal(m,'plin')
     + sum(sss$(ord(sss) le noinbin and
      random le ord(sss)+1 and random gt ord(sss)),diffs(sss,ss)) ;
    hourlyfin(copy,m,'rand') = random ;
    hourlyfin(copy,m,'diff') = sum(sss$(ord(sss) le noinbin and
      random le ord(sss)+1 and random gt ord(sss)),diffs(sss,ss)) ;
   else
    random = uniform(0,bigbin) ;
```

```
    hourlyfin(copy,m,'sim') = hourlyscal(m,'plin')
     + sum(sss$(ord(sss) le bigbin and
      random le ord(sss)+1 and random gt ord(sss)),diffs(sss,ss)) ;
    hourlyfin(copy,m,'rand') = random ;
    hourlyfin(copy,m,'diff') = sum(sss$(ord(sss) le bigbin and
      random le ord(sss)+1 and random gt ord(sss)),diffs(sss,ss)) ;
   ) ;
  ) ;
 ) ;
) ;

*Rescale data to Indiana level
hourlyfin(copy,m,'sim')$(hourlyfin(copy,m,'sim') lt 0) = 0 ;
hourlyfin(copy,m,'plin')=hourlyscal(m,'plin')*KPratio;
hourlyfin(copy,m,'diff')=hourlyfin(copy,m,'diff')*KPratio;
hourlyfin(copy,m,'sim')=hourlyfin(copy,m,'sim')*KPratio;
option hourlyfin:8 ;
hourlyfin(copy,m,'plin')$(Not hourlyfin(copy,m,'plin')) = EPS;
hourlyfin(copy,m,'diff')$(Not hourlyfin(copy,m,'diff')) = EPS;
hourlyfin(copy,m,'sim')$(Not hourlyfin(copy,m,'sim')) = EPS;
hourlyfin(copy,m,'rand')$(Not hourlyfin(copy,m,'rand')) = EPS;
option hourlyfin:7;
display hourlyfin ;

*Merge non-zero plin data with zeros
finaldata(copy,t,i)=0;
loop(t,
    loop(i,
         loop(m,
         finaldata(copy,t,i)$(t.val EQ m.val)=hourlyfin(copy,m,i)
         );
       );
     );

finaldata(copy,t,i)$(NOT finaldata(copy,t,i))=EPS;
);
option finaldata:7;
display finaldata;
```

APPENDIX C. GAMS CODE FOR BASE CASE CAPACITY EXPASION AND COMMITMENT/DISPACTH MODEL

```
*2011 5-minute load scaled to 2035, solar and generation data
option limrow=0 ;
option limcol=0 ;
option optcr=0.01, optca=10 ;
option iterlim=1000000,reslim=1000000 ;
option solprint=off ;
$onsymlist
$call gdxxrw U:\InputData2011.xlsx set=t rng=a2:a105121 rdim=1 set=s rng=b1:d1
cdim=1 par=data10 rng=A1:D105121 rdim=1 cdim=1
$gdxin InputData2011.gdx

Sets      t(*)  Total 5_minutes observations in a year
          s(*)  Labels of the input columns 'load1x' 'solar' and 'wind1x'
          h     Hour index -- allow for leap year / 1*8784 /;
Alias (t,tt),(h,hh);
$load t s
parameter data11(t,*) Data input parameter. Units (MW);
$load data11
option data11:7;
Alias (t,tt) ;

*Create parameters for load, solar and wind all in MW
Set      k/yr11/;
parameter load(t,k)
          load11(t)
          solar(t)
          wind(t,k)
          wind11(t);
load(t,'yr11') = data11(t,'load11');
solar(t)= data11(t,'solar');
wind(t,'yr11') = data11(t,'wind11');
option load:7;

Set       i   Types of generation /Small_Coal
Med_Coal, Large_Coal, IGCC, Oil, NGST, Small_NGCC
Large_NGCC, Small_NGCT, Med_NGCT, Large_NGCT,
Hydro, LFG, Nuclear, Solar, Wind, base, peak, newWind, newSolar/
          ii(i) Generation technologies / Small_Coal
Med_Coal, Large_Coal, IGCC, Oil, NGST, Small_NGCC
Large_NGCC, Small_NGCT, Med_NGCT, Large_NGCT,
Hydro, LFG, Nuclear, base, peak/
          r   Indiana existing generation technologies /Small_Coal
```

```
Med_Coal, Large_Coal, IGCC, Oil, NGST, Small_NGCC
Large_NGCC, Small_NGCT, Med_NGCT, Large_NGCT,
Hydro, LFG, Nuclear, Solar, Wind, extbase, extpeak/
        day          Loop the 365 days of the year /1*365/
        window(t)    All t's of each 3-day period
        hwindow(h)   All h's of each 3-day period
        subwindow(t)  t's in the middle day of the 3-day period
        hsubwindow(h) h's in the middle day of the 3-day period ;
Table units(*,*)
             Number    Capacity    Total_Capacity   Summer_Adjust
Small_Coal     17       102.08       1735.35       0.90
Med_Coal       17       400.52       6808.83       0.90
Large_Coal     9        680.29       6122.62       0.90
IGCC           3        258.19       774.57        0.74
Oil            23       18.68        429.73        0.91
NGST           3        188.07       564.21        0.95
Small_NGCC     7        75.54        528.77        0.93
Large_NGCC     7        224.99       1574.92       0.93
Small_NGCT     21       41.09        862.86        0.81
Med_NGCT       26       72.57        1886.85       0.81
Large_NGCT     8        108.72       869.78        0.81
Hydro          51       1.85         94.58         0.64
LFG            74       1.13         83.62         0.93
Nuclear        2        948.04       1896.08       0.91
Base
Peak ;
Set
 uno      Unit number / 1*74 /
 u(ii,uno) Mapping of unit numbers to types ;
u(ii,uno) = yes$(ord(uno) le units(ii,'Number')) ;
display u ;
parameter capcost(ii)    Annualized capital cost by generation technology (2016 $ per
MW per Yr)
        varcost(ii)    Variable cost by type of generation (2016 $ per MWh)
        sumrcap(r)     Installed summer capacity levels by type of generation technology
        ttlsumcap      Total installed summer capacity
        extsumcap(r)   Total installed summer capacity levels by baseload and peaking
generation
        braik          braikeven hour at baseload-peaking capacity limit
        capbraik       Capacity corresponding to braikeven hour baseload-peaking
        loadnsw(t)     5-min load net of 5-min solar and wind generation
        loadnsw2(t)    Copy of loadns to be modified
        ldcnsw(t)      Load net of solar and wind duration curve
        capldcnsw(ii)  Capacity needed by generation type to meet load net of solar and
wind
        unewcap(ii)    Aprox of number of new units needed by type
```

newcap(ii) Lumped new capacity needed by generation type to meet load net of solar and wind
ttlcaptype(ii) Capacity by type of generation: Installed plus new capacity available to meet load net of solar and wind
totalcap Total capacity includes new and existing
namecap(ii) Installed Nameplate capacity levels by type of generation technology
minload(ii) Min load rates(% of full load)
midlcap(ii) Capacity between Max load (Nameplate) capacity and Min load capacity
ramprate(ii) Ramp rates (fraction of nameplate capacity per 5-min) by generation type for existing capacity
rmpavlexity(ii) Ramping capacity available from nameplate capacity per 5-min by generation type
finexramp(ii) Ramping capacity available per 5-min by generation type (lowest value between midlcap and rmpavlexity)
rampavlexi Total ramping capacity available per 5-min (lowest value between midlcap and rmpavlexity)
rampavladd(ii) Additional capacity available for ramping per 5-min
ttlrampavai Total capacity available for ramping per 5-min
difflnsw(t) Used to find 5-min difference series or 5-minute drop or increase in the Load net of solar and wind
rampupreq Ramping UP requirements per 5-min (greatest positive diff period-to-period Load net of solar and wind)
rampdwnreq Ramping DOWN requirements per 5-min (greatest negative diff period-to-period Load net of solar and wind)
addrampup Additional ramping UP capacity needed
addrampdwn Additional ramping DOWN capacity needed
ramplim(ii) Exisiting plus New Units ramping limits for period t
upprlim t upper limit of day d
lwrlim t lower limit of day d
windcrtlmnt(t,k) Level of wind cutailment
solcrtlmnt(t,k) Level of solar curtailment
hourly_startcost(h,ii) Results hourly start-up costs by i
total_startcost(ii) Results total start-up costs per year by i
total_gentype(*,k) Results total generation per year by i
total_varcost(ii,k) Results total variable cost per year by i
total_capcost(ii,k) Results total capita cost per year by i
total_genwind Results total wind generation per year
total_gensolar Results total solar generation per year
total_capacity(ii,k) Results total capacity per year by i
maxgentype(*,k) Resukts max generation by i
objvalue(*) Objective function value
bestsol(*) Estimate of the best possible solution for a mixed-integer model
gap(*) Annual calculation gap
exetime(day) Elapsed time it took to execute a solve statement in total

```
          solvtime(day)  Elapsed time taken by the solver only
          exealgo(day)   Elapsed time it took to execute the solve algorithm;
Scalar    gapyear;
Table minupdown(ii,*)    Minimum up and down time by unit class in hours
                MinUp    MinDown
Small_Coal       6       4
Med_Coal         6       4
Large_Coal       6       4
IGCC             4       2
Oil              4       3
NGST             5       3
Small_NGCC       4       2
Large_NGCC       4       2
Small_NGCT       2       2
Med_NGCT         2       2
Large_NGCT       2       2
Hydro            0       0
LFG              0       0
Nuclear          59      21
Base             4       2
Peak             2       2 ;
*Capital cost (2016$/MW/yr) only for new units because this cost is assumed to be sunk
for existing
capcost("base") = 77531 ;
capcost("peak") = 48976;
*For example: Generic Variable cost (ful + O&M) by type of generation (2016 $ per
MWh) for installed and new units
varcost("base") = 28.93;
varcost("peak") = 52.60;
varcost("Small_Coal") = 27;
varcost("Med_Coal") = 27;
varcost("Large_Coal") = 27;
varcost("IGCC") = 27;
varcost("Oil") = 290;
varcost("NGST") = 40;
varcost("Small_NGCC") = 40;
varcost("Large_NGCC") = 40;
varcost("Small_NGCT") = 73;
varcost("Med_NGCT") = 73;
varcost("Large_NGCT") = 73;
varcost("Hydro") = 3;
varcost("LFG") = 25;
varcost("Nuclear") = 8;
*Existing Summer capacity by generation type derated using FOR estimates
sumrcap(r) = units(r,'Total_Capacity')*units(r,'summer_adjust') ;
ttlsumcap = sum(r,sumrcap(r));
```

```
extsumcap("extpeak") = sumrcap("Oil") + sumrcap("Small_NGCT")
 + sumrcap("Med_NGCT") + sumrcap("Large_NGCT");
extsumcap("extbase") = ttlsumcap - extsumcap("extpeak");
display ttlsumcap, extsumcap;
*     Ramping resources
*Exisiting Nameplate capacity by generation type already derated using FOR estimates
namecap(ii) = units(ii,'capacity') ;
minload("Small_Coal") = 0.37;
minload("Med_Coal") = 0.37;
minload("Large_Coal") = 0.37;
minload("IGCC") = 0.60;
minload("Oil") = 0.33;
minload("NGST") = 0.40;
minload("Small_NGCC") = 0.40;
minload("Large_NGCC") = 0.40;
minload("Small_NGCT") = 0.43;
minload("Med_NGCT") = 0.43;
minload("Large_NGCT") = 0.43;
minload("Hydro") = 0;
minload("LFG") = 0;
minload("Nuclear") = 0.34;
minload("base") = 0.40;
minload("peak") = 0.43;
*Ramp rates for exisitng technologies
ramprate("Small_Coal") = 0.19;
ramprate("Med_Coal") = 0.19;
ramprate("Large_Coal") = 0.19;
*IGCC ramping rate same as NGCC rate
ramprate("IGCC") = 0.29;
ramprate("Oil") = 0.67;
ramprate("NGST") = 0.33;
ramprate("Small_NGCC") = 0.29;
ramprate("Large_NGCC") = 0.29;
ramprate("Small_NGCT") = 0.68;
ramprate("Med_NGCT") = 0.68;
ramprate("Large_NGCT") = 0.68;
ramprate("Hydro") = 1;
ramprate("LFG") = 1;
ramprate("Nuclear") = 0.26;
*NGCC ramp rate used for baseload capacity additions
ramprate("base") = ramprate("Large_NGCC");
*NGCT ramp rate used for peaking capacity additions
ramprate("peak") = ramprate("Med_NGCT");

**+    Economic Commitment/Dispatch      **+
Equations cost            Objective function min total cost
```

```
        engry(t)        Aggregated energy allowed to be produced in each period t
        genmax(ii,t)    Maximum generation alowed by i in period t
        genmin(ii,t)    Minimum generation alowed by i in period t
        rampup(ii,t)    Constraint ramping up limit for type of technology in period t
        rampdwn(ii,t)   Constraint ramping down limit for type of technology in period t
        upmin(ii,uno,h) Constraint minimum up time of unit i
        dwnmin(ii,uno,h)Constraint minimum down time of unit i
        onoffdef(ii,uno,h)Contraint to guaratee consistency with bstatus and switch
variables;
Variables totalcost       Aggregated cost of meeting projected annual load ;
Positive Variables
        gen(ii,t)       Generation produced by unit ii in period t
        sgen(t)         Solar generation in period t
        wgen(t)         Wind generation in period t
        switchon(ii,uno,h)  Start-up equals 1 when i is switched on
        switchoff(ii,uno,h) Start-up equals 1 when i is switched off;
switchon.up(ii,uno,h)  = 1 ;
switchoff.up(ii,uno,h) = 1 ;
Binary Variable   bstatus(ii,uno,h) Commitment status of unit uno in hour h;
bstatus.up(ii,uno,h) = 1 ;
parameter cstartup(ii) Startup costs in 2016 dollars per MW capacity
/Small_Coal  107.08, Med_Coal 82.53, Large_Coal 57.97, IGCC 43.79,
Oil 0, NGST 44.15, Small_NGCC 43.79, Large_NGCC 43.79, Small_NGCT 55.32,
Med_NGCT  55.32, Large_NGCT   55.32, Hydro 0, LFG 0, Nuclear 0,
base 43.79, peak 55.32 /   ;

cost..      totalcost =e=
 sum(t$window(t),
 sum(ii,(varcost(ii)/12)*gen(ii,t)))
* Startup costs
 + sum(h$(hwindow(h)),
   sum((ii,uno)$u(ii,uno),
   switchon(ii,uno,h)*units(ii,'Capacity')*cstartup(ii)));
engry(t)$window(t)..
          sum(ii,gen(ii,t)) + sgen(t) + wgen(t) =e= load(t,"yr11");

set hmap(t,h) Mapping from five minute intervals to hours ;
hmap(t,h) = yes$(ord(t) ge (ord(h)-1)*12 + 1 and ord(t) le ord(h)*12) ;

genmax(ii,t)$window(t)..
gen(ii,t)=l=(namecap(ii)+newcap(ii))*sum(uno$u(ii,uno),
 sum(h$hmap(t,h),bstatus(ii,uno,h)));
genmin(ii,t)$window(t)..
gen(ii,t)=g=
 ((namecap(ii)+newcap(ii))*minload(ii))*sum(uno$u(ii,uno),
 sum(h$hmap(t,h),bstatus(ii,uno,h)));
```

```
rampup(ii,t)$(window(t) and window(t-1))..
gen(ii,t)-gen(ii,t-1) =l=
 ramprate(ii)*(namecap(ii)+newcap(ii))*sum(uno$u(ii,uno),
 sum(h$hmap(t,h),bstatus(ii,uno,h)));
rampdwn(ii,t)$(window(t) and window(t-1))..
gen(ii,t)-gen(ii,t-1) =g=
 -ramprate(ii)*(namecap(ii)+newcap(ii))*sum(uno$u(ii,uno),
 sum(h$hmap(t,h),bstatus(ii,uno,h)));
onoffdef(ii,uno,h)$(hwindow(h) and u(ii,uno)
 and minupdown(ii,'minup') gt 0 and minupdown(ii,'mindown') gt 0)..
switchon(ii,uno,h) - switchoff(ii,uno,h) =e= -bstatus(ii,uno,h-1) +
 bstatus(ii,uno,h) ;
upmin(ii,uno,h)$(hwindow(h) and u(ii,uno)) ..
 bstatus(ii,uno,h) =g=
 sum(hh$(ord(hh) ge ord(h) - minupdown(ii,'minup') and
  ord(hh) le ord(h)),
 switchon(ii,uno,hh)) ;
dwnmin(ii,uno,h)$(hwindow(h) and u(ii,uno)) ..
 1 - bstatus(ii,uno,h) =g=
 sum(hh$(ord(hh) ge ord(h) - minupdown(ii,'mindown') and
  ord(hh) le ord(h)),
 switchoff(ii,uno,hh)) ;

model meritmod /cost
                engry
                genmax
                genmin
                rampup
                rampdwn
                onoffdef
                upmin,dwnmin/ ;
meritmod.solvelink=0 ;

**  Capacity Expansion Planning   **+
*Calculation of braikeven hour period where technologies total generation costs functions
intersects
braik = round((capcost("peak")- capcost("base"))/( varcost("base")- varcost("peak")));
*Construct load and load net of solar and wind duration curves
parameter loadnsw_index(t);
parameter loadnsw_index2(t);
parameter ldcnsw(t);
parameter switchlog(*,*,*),switchlog2(*,*,*,*);
parameter gentab(t,*) ; option gentab:0 ;
* Create load net of solar and wind
loop(k,
loadnsw(t) = load(t,k) - solar(t) - wind(t,k);
```

```
loadnsw2(t)= loadnsw(t);
execute_unload "rank_in.gdx", loadnsw;
execute 'gdxrank rank_in.gdx rank_out.gdx';
execute_load "rank_out.gdx", loadnsw_index=loadnsw;
loadnsw_index2(t) = card(t) - loadnsw_index(t) +1;
* Create load net of solar and wind duration curve
ldcnsw(t + (loadnsw_index2(t)- ord(t))) = loadnsw(t);
* Determine optimal capacity levels
loop(t ,
capbraik $(ord(t) eq 12*braik) = ldcnsw(t);
);
* Total capacity requirements for load and load net of solar and wind curves
capldcnsw("peak") = max(0,ldcnsw("1") - capbraik);
capldcnsw("base") = max(0,capbraik);
* New capacity requirements aproximated to new plants' capacity
unewcap("base") = ((max(0, capldcnsw("base") - extsumcap("extbase")))*1.0372)/429;
unewcap("peak") = ((max(0, capldcnsw("peak") - extsumcap("extpeak") - max(0,
extsumcap("extbase") - capldcnsw("base"))))*1.149)/237;
newcap("base") = (round(unewcap("base")+0.499))*429;
newcap("peak") = (round(unewcap("peak")+0.499))*237;
units('base','number')   = round(unewcap("base")+0.499) ;
units('peak','number')   = round(unewcap("peak")+0.499) ;
units('base','capacity') = 429 ;
units('peak','capacity') = 237 ;
u('base',uno) = yes$(units('base','number') ge ord(uno)) ;
u('peak',uno) = yes$(units('peak','number') ge ord(uno)) ;
* Total capacity by generation type for economic dispatch
ttlcaptype("peak") = extsumcap("extpeak") + newcap("peak");
ttlcaptype("base") = extsumcap("extbase") + newcap("base");
totalcap = ttlcaptype("base") + ttlcaptype("peak");
display capbraik,capldcnsw,unewcap,newcap,ttlcaptype,totalcap,units;

**+**+*     Ramping resources  **+**+
*Load available of capacity (=Nameplate-Min load) by generation type
loop(ii,
midlcap(ii) = (namecap(ii) - (namecap(ii)*minload(ii)))*units(ii,'number');
);
* Available ramping capacity from nameplate
loop(ii,
rmpavlexity(ii) = (namecap(ii)*units(ii,'number'))*ramprate(ii);
);
*Ramping resources availability per 5-minute period
loop(ii,
finexramp(ii) = min(rmpavlexity(ii),midlcap(ii));
);
rampavlexi = sum(ii,min(rmpavlexity(ii),midlcap(ii)));
```

```
*Additional units
rampavladd("peak") = ramprate("peak")*newcap("peak");
rampavladd("base") = ramprate("base")*newcap("base");
ttlrampavai = rampavladd("base") + rampavladd("peak") + rampavlexi;
*Ramping requirements
difflnsw(t)$(ord(t) le 105119) = loadnsw(t+1)-loadnsw(t);
*Find max ramp up and down values
rampupreq = smax(t,difflnsw(t));
rampdwnreq = smin(t,difflnsw(t));
*Additional ramping resources
addrampup = rampupreq - ttlrampavai;
addrampdwn = - rampdwnreq - ttlrampavai;
ramplim(ii) = rmpavlexity(ii) + rampavladd (ii);
gen.lo(ii,t) = 0;
gen.up(ii,t) = (namecap(ii) + newcap(ii))*units(ii,'number') ;
sgen.lo(t) = 0;
sgen.up(t) = solar(t);
wgen.lo(t) = 0;
wgen.up(t) = wind(t,"yr11");
display difflnsw, midlcap, rmpavlexity, rampavlexi, finexramp, rampavladd, ttlrampavai,
rampupreq, rampdwnreq, addrampup, addrampdwn;

**+  Run Economic Dispatch Model   **+
loop(day$(ord(day) le 364),
*option solprint=on ;
lwrlim = (ord(day)-1)*288 + 1;
upprlim = lwrlim + 288*3 - 1 ;
window(t) = yes$(ord(t) ge lwrlim and ord(t) le upprlim) ;
hwindow(h) = yes$(12*(ord(h) - 1) + 1 ge lwrlim and 12*(ord(h) - 1) + 1 le upprlim) ;
subwindow(t) = yes$(ord(t) ge lwrlim + 288$(lwrlim ne 1)
  and ord(t) le upprlim - 288$(upprlim ne 288*365)) ;
hsubwindow(h) = yes$(lwrlim/12 + 24$(lwrlim ne 1) le ord(h)
  and upprlim/12 - 24$(upprlim lt 288*365) ge ord(h)) ;
display lwrlim,upprlim,window,hwindow,subwindow,hsubwindow ;
option mip=cplex ;
if (ord(day) ge 364, option solprint=on);
solve meritmod using mip minimizing totalcost;
windcrtlmnt(t,k)$window(t) = wind(t,"yr11")- wgen.l(t);
solcrtlmnt(t,k)$window(t) =  solar(t)- sgen.l(t);
maxgentype(ii,k) = smax(t,gen.l(ii,t));
display lwrlim,upprlim, hsubwindow ;
objvalue(day)=meritmod.objVal;
bestsol(day)=meritmod.objEst;
gap(day)=objvalue(day)-bestsol(day);
exetime(day)=meritmod.etSolve;
solvtime(day)=meritmod.etSolver;
```

```
exealgo(day)=meritmod.etAlg;
loop(h$hsubwindow(h),
  switchlog(h,"status",ii)=sum(uno,bstatus.l(ii,uno,h));
  switchlog2(h,ii,uno,"switchon")=switchon.l(ii,uno,h);
  switchlog2(h,ii,uno,"switchoff")=switchoff.l(ii,uno,h);
) ;
loop(tt$((ord(day) eq 1 and ord(tt) le 288) or subwindow(tt)
        or (ord(day) eq 365 and ord(tt) ge 364*288)),
  gentab(tt,ii) = gen.l(ii,tt) ;
  gentab(tt,'wind') = wgen.l(tt) ;
  gentab(tt,'solar') = sgen.l(tt) ;
  gentab(tt,'load') = load(tt,"yr11") ;
) ;
* Now fix the bstatus for days prior to the current window.
bstatus.fx(ii,uno,h)$(ord(h) le (lwrlim-1)/12 + 24)  = bstatus.l(ii,uno,h) ;
);
) ;
switchlog(h,"status",ii)$((ord(h) le 8760) and (Not switchlog(h,"status",ii))) = EPS;
display switchlog,switchlog2 ;
gentab(tt,ii)$((ord(tt) le 105120) and (Not gentab(tt,ii))) = EPS;
gentab(tt,'wind')$((ord(tt) le 105120) and (Not gentab(tt,'wind'))) = EPS;
gentab(tt,'solar')$((ord(tt) le 105120) and (Not gentab(tt,'solar'))) = EPS;
gentab(tt,'load')$((ord(tt) le 105120) and (Not gentab(tt,'load'))) = EPS;
display gentab ;

**+  Display Results  +**
parameter switchlog2F(h,ii);
switchlog2F(h,ii)=(sum(uno,switchlog2(h,ii,uno,"switchon")));
hourly_startcost(h,ii) = (switchlog2F(h,ii)*cstartup(ii));
total_startcost(ii) =  (sum(h,switchlog2F(h,ii)*cstartup(ii)));
*Total Generation by technology type in (MW/h)
total_gentype(ii,k) =  sum(tt,gentab(tt,ii)/12);
total_gentype('wind',k) =  sum(tt,gentab(tt,'wind')/12);
total_gentype('solar',k) =  sum(tt,gentab(tt,'solar')/12);
*Total Load in (MW)
total_gentype('load',k) =  sum(tt,gentab(tt,'load')/12);
*Total Variable cost by technology type in (2016$)
total_varcost(ii,k) = sum(tt,gentab(tt,ii)*(varcost(ii)/12));
*Total Capacity in the system
total_capacity(ii,k) = (namecap(ii) + newcap(ii))*units(ii,'number');
*Maximum generation by technology type
maxgentype(ii,k) = smax(tt,gentab(tt,ii));
maxgentype('wind',k) = smax(tt,gentab(tt,'wind'));
maxgentype('solar',k) = smax(tt,gentab(tt,'solar'));
*Total annual gap
gapyear = sum(day,gap(day));
```

```
option total_startcost:3:0:1;
display windcrtlmnt,solcrtlmnt,hourly_startcost,total_startcost,total_gentype,
total_varcost, total_capacity,maxgentype;
display objvalue,bestsol,gap,gapyear,exealgo,exetime,solvtime;
```

VITA

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Education

Master of Science in Agricultural Economics, Louisiana State University, (2008).

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