Economic and technical impacts of wind variability and intermittency on long-term generation expansion planning in the U.S

by

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ABSTRACT

Electricity power systems are a major source of carbon dioxide emissions and are thus required to change dramatically under climate policy. Large-scale deployment of wind power has emerged as one key driver of the shift from conventional fossil-fuels to renewable sources. However, technical and economic concerns are arising about the integration of variable and intermittent electricity generation technologies into the power grid. Designing optimal future power systems requires assessing real wind power capacity value as well as back-up costs.

This thesis develops a static cost-minimizing generation capacity expansion model and applies it to a simplified representation of the U.S. I aggregate an hourly dataset of load and wind resource in eleven regions in order to capture the geographical diversity of the U.S. Sensitivity of the optimal generation mix over a long-term horizon with respect to different cost assumptions and policy scenarios is examined.

I find that load and wind resource are negatively correlated in most U.S. regions. Under current fuel costs (average U.S. costs for year 2002 to year 2006) regional penetration of wind ranged from 0% (in the South East, Texas and South Central regions) to 22% (in the Pacific region). Under higher fuel costs as projected by the Energy Information Administration (average for the period of 2015 to 2035) penetration ranged from 0.3% (in the South East region) to 59.7% (in the North Central region). Addition of a CO_2 tax leads to an increase of optimal wind power penetration. Natural gas-fired units are operating with an actual capacity factor of 17% under current fuel costs and serve as back-up units to cope with load and wind resource variability. The back-up required to deal specifically with wind resource variations ranges from 0.25 to 0.51 MW of natural gas-fired installed per MW of wind power installed and represents a cost of $4/MWh on average in the U.S., under current fuel costs.

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1 INTRODUCTION

Power systems are on the edge of a revolution worldwide. Like other human activities, the generation of electricity requires producing more with a smaller environmental impact in order to follow a sustainable path. Electricity is a key factor of economic development. Therefore, a rapidly increasing global population and the economic growth of developing countries are expected to lead to a dramatic increase in electricity demand. Moreover, major changes in the electricity industry are necessary to face the challenge of climate change. Indeed, the electricity sector currently generates about 40% of U.S. Greenhouse gases (GHG) emissions (EPA 2011). Conventional electricity generation units are using limited fossil fuel resources. These technologies are also associated with environmental externalities. All these characteristics constitute strong motivations to support the development of renewable energy sources, such as wind power. But the increasing penetration of these renewable energy technologies in existing power systems is a complex issue. Indeed, wind and solar power technologies have unique features because they rely on variable and unpredictable natural resources. Therefore, legitimate concerns about the preservation of the system reliability arise and the assessment of the capacity of renewables is gaining an increasing focus. The objective of this thesis is to identify critical shortcomings in traditional tools for capacity expansion planning that have to be overcome in order to address the evolution of power systems. A better understanding of the economic and technical impacts of the large-scale integration of renewables in the energy mix is needed to design appropriate energy policy and regulatory support. In this following chapter, I describe the motivation for the thesis and I provide context by presenting a brief overview of the electricity sector. I then discuss the unique aspects of electricity as a commodity and I also present the major factors of change in the electricity sector. I then present my research questions and my methodological approach to answering those questions.

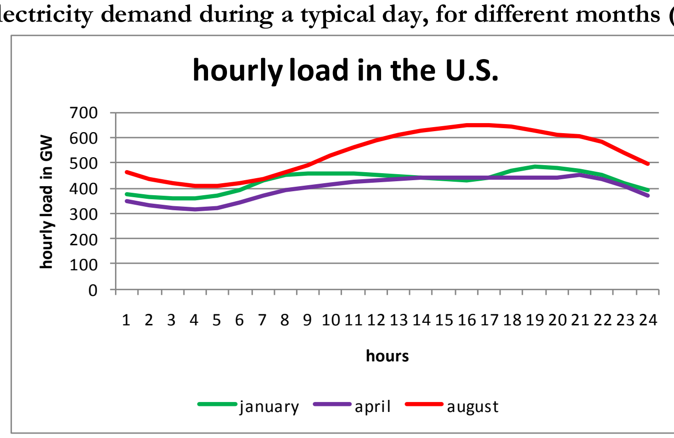
1.1 Motivation and context

1.1.1 Electricity, a commodity with unique features

Electricity is an essential commodity with very specific characteristics. In particular, electricity cannot be economically stored at large scale. The direct implication of this limitation is that electricity supply has to match electricity demand at any given time. The nature of electricity also determines the conditions of its transportation from the generator to the user. Indeed, Kirchhoff's law determines electric transmission over the grid and the path cannot be chosen at will. Moreover, any disturbance causes a reconfiguration of power flows. Electric power systems are thus one of the most complex engineering systems designed and operated.

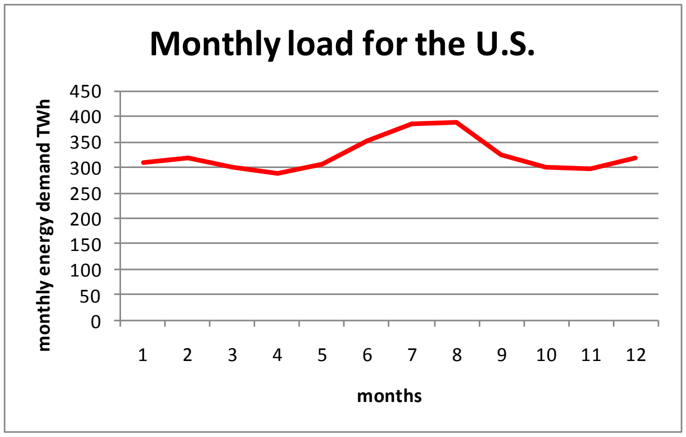
Since electricity is only marginally stored, electric generation plants are planned to withstand maximum power load. For this reason, determining the chronological demand profile is critical to adequately supply electricity in a system. For the same total energy consumed over a given period, different load profiles are met at different costs. A relatively flat load curve is generally less expensive to supply than a spiked one because ramping units are expensive to operate. Demand varies over timescales ranging from seconds to years. Over a day, the load follows the pattern of a workday. Demand is typically higher during the workday, from 8am until 7pm. The Figure 1 represents the hourly electricity demand for the U.S. during an average day in January, April and June.

Figure 1. Electricity demand during a typical day, for different months (NREL 2006)



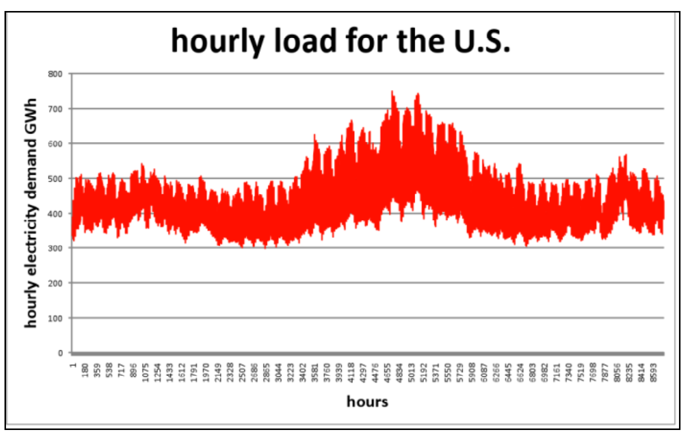
Over a week, the electricity demand follows the pattern of workdays and weekends. And finally over a year, the demand has a seasonal pattern due to climate variations. Electricity demand is typically higher during winter, due to high heating consumption, and during summer due to extensive air conditioning usage. The Figure 2 represents the monthly electricity demand for the U.S. during a year.

Figure 2. Monthly electricity demand in the U.S. (NREL 2006)



The load also varies around the average profile described above. Thus, uncertainty on the actual load compared to the forecasted load is another challenge for system operators balancing electricity demand and supply. Therefore, developing sophisticated demand forecasting tools is essential to reduce this uncertainty. Forecasts are generally based on historical data, adjusted with information about temperature or special events. The Figure 3 represents the actual hourly electricity demand for the U.S.

Figure 3. Hourly electricity demand in the U.S. (NREL 2006)



Electricity generation units have variable availability over time. Conventional units incur planned outages for maintenance, essentially when demand is low because plant owners have an economic incentive to produce when the demand is high. Renewable energy units such as wind power units have variable power output due to the variation of the wind. The wind varies at different timescales: seconds, days, months, and seasons. It also varies geographically, due to latitude, temperature, large-scale topography, small-scale site-specific topography or built environment.

Moreover, there are different sources of uncertainty on the electricity supply-side. Conventional units suffer unplanned forced outages, often due to mechanical problems. But the main source of uncertainty in the electricity supply is the generation from renewable units. Indeed, the actual output from a wind plant varies widely around the average wind profile. The uncertainty of the natural resource is not of a different nature than the uncertainty of the forced outages for conventional units. However the frequency of non-availability events is much larger for a wind power plant than for a conventional unit. Therefore, this uncertainty is often considered as a key factor reducing the value of wind as a generation capacity, as I will discuss in the present thesis.

1.1.2 Major factors of change in the electricity sector

Global population is expected to increase to nine billion in 2050, according to the 2008 World Population Prospects of the United Nations (UN 2008). Developing countries with a large population such as China, India or Brazil are rapidly increasing their electricity consumption per capita. Thus, electricity demand is expected to boom. Moreover, the conventional fossil fuel technologies use limited natural resources and fuel prices are likely to increase, as less accessible resources are extracted. Finally, a carbon policy may contribute to rising fossil fuel prices.

The electricity sector represents 40% of the total GHG emissions in the U.S. (EPA 2011) and is consequently required to change dramatically in the next decade. Among the different activities in the electricity sector, the generation process emits the greatest amount of GHGs. Carbon dioxide (CO_2) is the major cause of climate change and is a byproduct of coal, oil and gas combustion in steam plants. Coal plants are also emitting Nitrous Oxide (NOx) and Sulphur Dioxide (SO_2), both having a large environmental impact. NOx and SO_2 are causing acid rains and NOx is also a major component in the formation of tropospheric ozone. Conventional steam power plants are also responsible for heavy metals and particle emissions. While the emissions caused by the nuclear energy are mainly due to the mining of the fossil fuels and the construction period, the nuclear technology has also an uncertain but potentially large environmental impact. Indeed, the production of nuclear waste from nuclear power plants is an unsolved issue and the risk of contamination by nuclear particles is existing, though difficult to quantify. Technologies using renewable energy sources have a lower carbon footprint than fossil-fuel technologies and are generally more environmentally friendly. However, the environmental impact of renewables technologies is not zero. Hydroelectric power plants in particular may greatly disturb the environment. All generation technologies have also a land and visual impact. Methodologies such as Life Cycle Analysis are used to assess the environmental impact of one product from its conception to its end of life (EPA 2006).

Sudden changes in power generated are difficult to absorb in current power systems due to the mechanical inertia of conventional generators. By managing up and down reserves, system operators can match fluctuating and uncertain demand. The minimum amount of reserves in a system depends on the generation mix, the local weather pattern and the system interconnections. Indeed, a relatively isolated system requires higher level of reserve than a much interconnected one. A significant increase in renewable energy technologies is likely to increase the necessary reserves.

Demand-side management and efficiency in the electricity sector constitute other key factors of change. The expression "demand-side management" designates all techniques designed to rationalize consumption of electric power. It is also associated with the notion of "Smart grid", which has gained an increasing focus in the last few years. It refers to a system where distributed generators are directly connected to distribution networks and where digital technologies optimize the overall system operation. A rapid growth of distributed generators is due to a favorable economic and regulatory context as well as a rationale for isolated location. All these elements above add more complexity in the electric sector. Finally, the energy independence is another factor to justify a diversification in the energy supply.

Due to the characteristics described above, the electricity supply has long been considered to be a public service. In some cases, vertically integrated utilities were required to meet minimum quality standards and their costs were covered by regulated prices, with reasonable rate of return. In other cases, such as in many European countries until the nineties, electricity generation was nationalized. There have been changes toward liberalization in many countries. The de-regulation that has changed many sectors of the economy (telecommunications, aeronautics, etc.) has also impacted the electricity sector, leading to an increasing competition between firms. Competition between generators became possible after the interconnection of grids. Different areas of the electricity sector require various levels of centralized regulation. Indeed, the transmission impacts generators competitiveness and has also been modified following the deregulation of the electricity generation sector. However distribution has not been subjected to large changes. The competition in electricity generation brought new challenges in the electricity sectors. Regulatory authorities need to design market rules ensuring that profit maximization behaviors lead to the minimization of the system costs. Utilities plan and operate to maximize their profit but are not responsible for the system security. In a decentralized context, electricity firms are thus more exposed to risk, in theory, than in a regulated market. Therefore the challenging issue of the wind power integration concerns all stakeholders in power systems, including utilities.

1.2 Thesis Research Questions

These goals lead to the following more specific questions:

- What is the optimal electricity generation mix with large-scale integration of onshore wind power in the long term?
- What are the economic impacts of the variability and the intermittency of the renewable energy sources on power systems?
- What are the key features of a power system determining the cost of integrating renewables?

1.3 Methodology

To answer the research questions I have identified, I developed a cost minimizing static linear programming model, CAPacity Expansion model with Wind variability (CAPEW), in the present thesis. It optimizes the generation mix to supply variable demand during a year with conventional as well as wind power technologies. I focus on the long term planning of the electricity generation capacity expansion in the U.S. to illustrate the impact of the geographical diversity of U.S. regions. The CAPEW does not include the existing installed units in order to find the optimal generation mix in a long-term time horizon without the constraints of peculiar existing power systems. I focus on the integration of onshore wind power technology but future explorations can include offshore wind power, solar power or other renewable sources.

1.4 Structure of the thesis

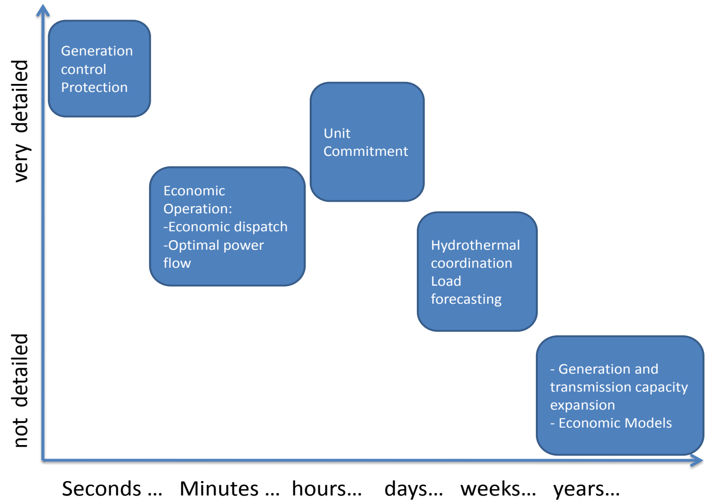
The chapters are organized as follows. Chapter one introduces my motivations and looks at the fundamental features of electricity and reviews the major factors of change in the electricity sector. In this part, I also present the methodology developed and I summarize the results of my analysis. In chapter two, I describe the different modeling approaches at various timescales and I explore the methodologies used to integrate wind power in traditional power system representations. I particularly focus on reliability measures and capacity credit assessment. In chapter three, I present the static CAPacity Expansion model with Wind variability (CAPEW) I developed for the purpose of the present analysis. Chapter four reviews the results of the study. Finally in chapter five, I offer some conclusions and future possible extensions and I present the implications of the result for the regulatory and policy design to support efficient wind power technology. .

2 INTEGRATING WIND IN THE REPRESENTATION OF POWER SYSTEMS

2.1 Different timescales require different models

Utilities face both planning and operating decisions. For their part, regulators and investors need long-term projections to support their decision process. At any decision level, sophisticated models provide forecasts and assessments to help decisions-makers to optimize planning and operation activities. Different types of models have been developed to help different stakeholders (utilities, system operators, regulators, policy makers, etc.). In the long term, utilities design capacity expansion plans and secure fuel contracts. In the medium term, they schedule facility maintenance and hydroelectric plant management. Finally, in the short term, they operate capacity in reserve and connect generation units during the generation unit dispatch. For long-term considerations, generation and transmission capacity expansion models have been developed. Economic models with a broader scope are also particularly useful to capture interactions between sectors decades ahead. Unit Commitment models are tools used for planning operation in the medium term, from hours to a day ahead. This type of model integrates detailed technical aspects but does not include investment considerations because of its limited time scope. Load forecasting and hydrothermal scheduling is done for a day or a week. For the short term, minutes to hour ahead, economic dispatch and optimal power flow models are used. In general, generating units are called to operate, or dispatched, in order of their increasing operating costs, until demand is met, with some units kept in reserve. Optimal power flow models have the advantage to account for transmission constraints. Finally operators use generation control and protection models to ensure the stability of the system at very short term. In the Figure 4, different type of models are represented as function of timescales and details level.

Figure 4. Different models at varying time scales



Long-term models are useful tools to provide insights into relative trends, as well as implications of various policy measures. However the quantification from exploratory models does not take into account numerous uncertainties. Thus these models, such as the capacity expansion model developed in this thesis, should only be considered as imperfect tools helping discussion and illustrating key trade-offs.

2.2 Expansion planning

Generation expansion planning models optimize the capacity installed and the power generated in order to meet demand at the lowest cost. Several parameters are considered to plan a generation capacity expansion in a power system. The ratio of capital costs to operating costs is a key characteristic to determine the role of a technology. To meet base load demand, capital-intensive plants with low operating costs are used. On the contrary, peak demand is better served by "peakers"; plants, which are cheap to build but have high operating costs. To build new generation units represents a large investment and requires long-term projections on the performance of the plants over their lifetime. In a centralized system, the system operator uses expansion planning models to design optimal future power systems. Expansion models are also tools used by regulators to assess the economic and technical impacts of new regulations of power system. Finally, in a liberalized market context, firms benefit from expansion planning models to maximize their profit. For long-term decisions, technical details can be roughly approximated because of the high level of uncertainty. Different approaches of generation planning are used, depending on the level of details needed: screening curve methodology or detailed reliability analysis optimization.

2.2.1 Screening curve and the representation of wind power

The basic approach for expansion modeling is referred to as "screening curves". It is a standard methodology used to determine the optimal installed capacity to meet demand (Shaalan 2003; Kelly and Weinberg 1993). A screening curve is a basic way to find the optimal generation mix of baseload, intermediate and peaking capacities. It offers a sufficient representation when the time profile of load does not matter in first approximation, as it is the case for dispatchable generations (Knight 1972; Stoft 2002). In this approach, load is represented by a cumulative probability distribution during a year, referred to as a "load duration curve". Electricity demand is traditionally divided in three load periods from the longest to the shortest: base load, shoulder and peak demand. The monotonic load curve represents the length of time that demand exceeds a threshold. In the Figure 5 is represented the load duration curve from U.S. electricity demand in 2006. The peak demand is found to be close to 650 GW and the total annual energy demand around 3 890 TWh.

Figure 5. Load duration curve for the U.S. (from NREL 2006)

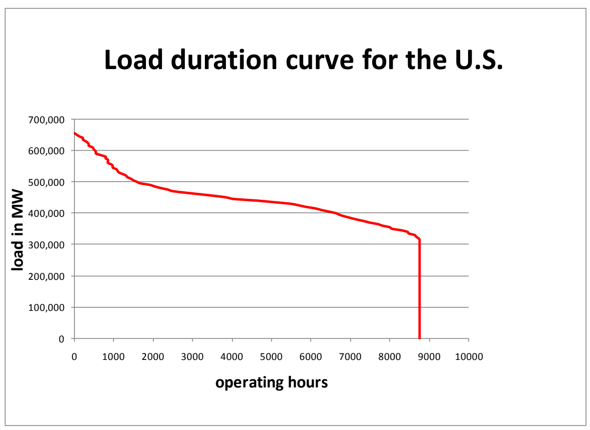
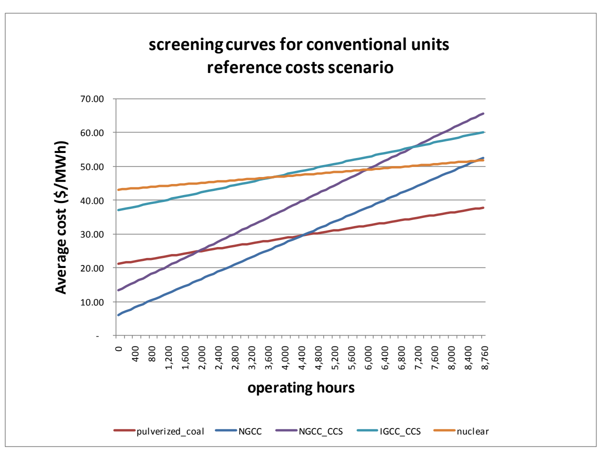


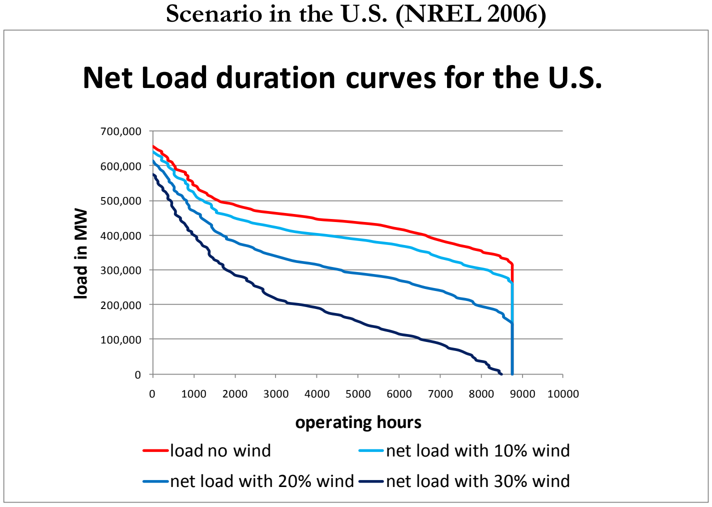
Figure 6. Screening curves (from EIA 2010 data)



A common modeling approach to integrate renewables with the screening curve methodology is to use the "net load duration curve". This curve results from subtracting hourly wind power output from hourly load. Wind is thus modeled as a deterministic load-modifier or negative load. Using this approach implies a prior assumption on the capacity of installed wind power units. Three load duration curves of the net demand are shown in the Figure 7 for different penetration levels of wind power in the U.S. from 10% to 30 % of peak demand.

The difference between the reference load curve and one of the net load curves represents the wind power available. At the right hand side, a more pronounced downward tail for any of the net load duration curves than for the reference load duration curve can be explained by a high availability of wind during periods of low demand. On the contrary, a similar upward tail between net load curves and reference load curve at the left hand side is due to a low availability of wind power during periods of high demand. In conclusion, the negative-load representation of wind power in the traditional screening curve approach enables us to illustrate some key aspects of wind integration in power systems. Wind power is more likely to displace base-load units because it is in general not available during peak demand. The CAPEW model gives similar results. However, the optimization model offers more flexibility and can be used to illustrate different impacts of large-scale deployment of wind in the U.S.

Figure 7. Net load duration curve for different wind penetration Scenario in the U.S. (NREL 2006)



This thesis argues that the characteristics of wind power violate assumptions of the traditional screening curve tool. Indeed, wind resource profile is considered as deterministic and intermittency is not captured in the screening curve approach. Moreover, this approach presents some limits, as it requires forcing the installed capacity of wind. Another approach for expansion planning is to use an optimization model.

Wind power is classically also represented as a negative load in most optimization capacity expansion models. In CAPEW, I consider wind power technology as any other technology except that wind availability is limited by the hourly wind resource profile. Regional supply limitations of the wind resource are also added as a constraint for each region and wind power class. This approach offers flexibility to incorporate uncertainty and regional resource limitations. It also has the advantage to avoid forcing the installation of wind power capacity.

2.2.2 Optimization of generation capacity expansion planning

Inputs in the capacity expansion model include variable costs (variable operation and maintenance or O&M, heat rate, fuel prices), fixed costs (fixed O&M, capital costs), plant lifetime, carbon emissions and average capacity factors. Technologies have different variable and fixed costs. To optimize the production of a certain amount of electricity with different available technologies, the first criterion is to minimize the total cost to meet a given demand. Decisions for generation and transmission expansion are based on forecasts of future demand, fuel prices, technological evolution and regulation. Long term models are however usually based on average constraints and do not generally include details necessary to capture the wind power intermittency and variability. In short-term and real-time planning models the goal is to minimize actual generation cost while maintaining the overall system reliability. Therefore, more details are taken into account. For example, generation costs in Unit Commitment models include start-up and shut-down costs. Palmintier and Webster offer an approach to combine the objective of long-term and real time-planning (Palmintier 2011).

There are multiple sources of uncertainty in an expansion-planning problem relating to:

- Macroeconomic data (economic growth, electricity demand, fuel prices, etc.),
- Technological innovations (costs reduction, efficiency, storage capacity, etc.),
- Financial parameters (inflation, discount rate),
- Climate evolution (temperature, solar irradiation, wind resource, hydrological reserves),
- Technical characteristics of units (retirement assumptions of generators, building period, reliability),
- Regulatory changes,
- Public opposition or support for a technology, ect.

Many models do not represent these uncertainties and rely on long-term projections for relevant model inputs.

2.2.3 The representation of wind power in capacity expansion optimization models

A standard indicator of the economic performance of electricity generation technologies is the Levelized Cost of Electricity (LCOE). It measures the annualized total cost of a new generator over its lifetime in $/MWh and is calculated by the ratio of the Net Present Value (NPV) of all costs divided by the amount of electricity produced. The critical assumptions in a LCOE calculation are the investment cost (referred to as the "overnight" cost), discount rates, financing options and capacity factor. In the LCOE, all costs are equally allocated across all generated units. [1]The LCOE appears to be inappropriate for renewables (Marcantonini and Parsons, 2010). A key point to understand the debate over the value of electricity produced by renewable technologies is that electricity is not a homogeneous good. Indeed some technologies produce base-load power and are not flexible (such as nuclear plants), while others have the capacity to ramp quickly and provide intermittent power (such as renewables).

A common approach to assess the economic value of the electricity produced by renewables is to associate a back-up generating unit to a wind or solar power unit in order to get a more comparable dispatchable resource (Morris, 2010). In this case, costs of renewable energy technologies are assessed in a worst-case scenario. Indeed, this representation suggests that renewables need 100% back-up. But it has been demonstrated that interconnection between wind turbines significantly reduces the no-wind case probability. It is then reasonable to assume that a relevant back-up amount should be less than 100%. However, determining a back-up quantity still lies upon the hypothesis than renewable compete on the base-load power generation.

[1] Therefore this approach implicitly implies that the evaluated generation technology produces base-load power and can be dispatched. Indeed, the amount of energy produced in the LCOE is calculated as the product of the installed capacity and the average capacity factor. This annual average capacity factor depends on the natural resource and thus on the location of the plant.

2.2.4 ReEDS model

The National Renewable Energy Laboratory (NREL) has developed a model called ReEDS (Regional Energy Deployment System), in order to study the expansion of generation and transmission capacity in the U.S. electricity sector. ReEDS (Short 2003; Short et. al. 2009) is a recursive-dynamic capacity expansion and dispatch linear programming model.

In addition to the standard technical constraints taken into account to minimize total system cost (meeting demand, reserve requirements, regional resource supply limitations and transmission constraints), ReEDS includes state and federal policy requirements and national renewable requirements (e.g. a national 80% RE-by-2050 target). The optimization and dispatch occurs every two years from the start period to 2050. Every period is divided in 17 time slices to represent the seasonal and diurnal variation in demand and resource profile (morning, afternoon and night for every season and a "peak" slice in the summer). The planning and operating reserve requirements are then satisfied in all time slices.

Among capacity expansion models, ReEDS differentiates by its high regional discretized structure and statistical treatment of the impact of variability. This methodology is intended to capture location-dependent quality of natural resources. Moreover, the detailed regional and temporal representation enables ReEDS to consider the cost of transmission expansion. Using hourly data, standard deviations of power output are calculated during each time slices for each wind power class and region. This calculation relies on the geographically aggregated variability in each reserve-sharing region. Correlation statistics are also included in standard deviations to reflect the smoothing of variability from geographically dispersed wind turbines. It is assumed that the degree of positive correlation between turbines is higher for turbines located in the same area, which increases the standard deviation. One key assumption is also than the profiles of load and wind resource are uncorrelated. CAPEW does not include transmission constraints and statistical treatment of the variability of the natural resources. However, its structure also captures the location-dependent quality of the wind resource and the correlation between temporal variation of the load and the wind resource.

2.2.5 Power system reliability measures

Conventional units such as coal-fired and gas-fired turbines are dispatchable, meaning that they can be turned on or off upon demand. For this reason, conventional units can count their full capacity, minus an average forced outage rate, toward the planning of reserve requirement. On the contrary, renewable energy technologies are not dispatchable and cannot count their full capacity, minus an average "no-resource" rate toward the planning of reserve requirement because their availability is variable. The capacity value can be defined as the fraction of the total capacity, which can reliably count toward the long term planning of reserve requirement. This capacity value is commonly estimated with the effective load carrying capacity (ELCC).

Different operating reserve requirements are commonly distinguished by their timescales. The timescale necessary for a generator to change its output defines its flexibility. Generators constitute spinning reserves if they are not producing at full capacity but can "ramp-up" quickly (e.g. in less than 10 minutes) on a given capacity amount. "Quick start" reserves are provided by technologies able to start up in less than minutes, such as natural gas combustion turbines. Interruptible load can also be considered as a demand-side reserve requirement option. Contingency reserve requirement ensures that the system will adapt to an unforeseen change in generation or transmission, typically due to outages at a 10-minutes timescale. Both spinning and interruptible load are considered as contingency reserves. The frequency regulation reserve requirement deals with sub-minute deviation between electricity demand and supply. There is no standard approach to determine required level of operating reserves. In some NERC areas (North American Electric Reliability Corporation), the operating reserve is at least as large as the largest single system. In others, the operating reserve is typically around 7% if the peak demand and lower if hydro is serving a large share of the demand (NERC). This level of detail in operating reserves described above is not included in the CAPEW model but a reserve margin of 10% is modeled.

Stochastic reliability assessment methodologies using probabilities to represent uncertainty are briefly described below. The LOLP is a measure of the probability of inadequacy of the electricity generation to serve the load. It is calculated from the hourly load levels, the generation capacity and the forced outage rates. This reliability measure can also be expressed through the Loss Of Load Expectation (LOLE). It represents the number of hours per day, days per years or days during ten years, during which the load might not be served. A standard target LOLP level is one day in ten years. In reliability models, forced outages rates reflect equipment malfunctions or other unplanned events for conventional units. Similarly, the availability of a wind plant can be captured in a forced outage rate taking into account the intermittency of the wind. This rate will derive from the probability distribution of the wind speed.

The statistical Effective Load Carrying Capability (ELCC) is generally calculated in order to evaluate the capacity value of a technology. It represents the amount of electricity demand that may be added in each time slice for an incremental increase of the capacity in a given technology, without any increase in the LLOP, as defined below. In other words, the ELCC represents the share of available capacity for one incremental unit of installed capacity at a constant reliability level of the system. In order to capture the magnitude of the energy not served, the Expected Energy Not Served (EENS) is also calculated. It represents the amount of energy that has to be curtailed. (Chowdhury 2003)

2.2.6 Average capacity versus Firm Capacity

The debate about the cost of integrating renewables is embedded in the question of the power system reliability and the plant's capacity value of renewable technologies. Determining the capacity credit of wind is important from an operational perspective. But it also matters from an economic standpoint because it changes the economic value of wind from the utility's point of view. Therefore, a clear definition of the term "capacity" is essential. The **average availability** is defined as the average power production that can be sustained permanently over a period of a year. For conventional technologies, this average availability depends essentially on the technical availability of generators. However, for the wind power technology, the average availability also largely depends on the wind resource. This average availability is commonly called annual **capacity factor**. It is calculated by the ratio of the expected power output divided by the annual rated output. Average capacity factors are useful in terms of planning to estimate production on the long-term. But this number alone does not capture the value of wind in a system. For example if the wind resource profile is negatively correlated with the system load profile, the wind capacity factor during peak will be lower than the annual capacity factor. And on the contrary, if the wind resource profile is positively correlated with the load profile, the wind capacity factor during the peak demand period will be higher than the annual average capacity factor.

In term of operations, the priority is to avoid a loss of load. Therefore the focus is on the peak hours when most generation units installed are operating. The **firm capacity**, also called **capacity credit** or **load carrying capability**, is the readiness to operate during high demand or emergencies. Firm capacity is expressed as a fraction of the total installed capacity. For renewables, the term 'capacity credit' is generally used to refer to the magnitude of the conventional units capacity that can be displaced by a unit of capacity from these renewables. The firm capacity is generally higher than the average availability for conventional technologies because of economic incentives for plant owners to operate during peak times. On the contrary, the firm capacity is generally lower than the average availability for wind power plants because wind power technology is not dispatchable and plant owners cannot choose to produce during peak hours if the wind is not blowing.

To conclude, the average capacity factor, or availability, of a wind plant depends on the wind quantity while the firm capacity, or capacity credit, depends on the adequacy of the wind resource, given a load profile (i.e. the wind plant production during peak demand). Some studies argue that arrays of wind farm produce some firm capacity because of the diversity of wind at geographical dispersed sites. (Chowdhury 1991).

3 CAPEW, A CAPACITY EXPANSION MODEL WITH WIND VARIABILITY

3.1 Objectives of the model

The integration of the renewables[1] is a chicken-and-egg problem in the sense that the initial design of power systems with conventional technologies makes the increase of the share of renewables costly, but this increase is also likely to modify the structure of the power systems and lower integration costs in the future. The objective of the CAPEW model is to tackle this issue and to offer an answer to the question of the optimal generation mix, given the available technologies and the variability and intermittency of wind power.

3.2 Hypothesis

CAPEW is a linear program minimizing the power system total cost subject to basic constraints: meeting demand, reserve requirements and regional resource supply limitations. CAPEW is a static electricity generation capacity expansion model developed in a centralized planning context. Indeed the cost minimization formulation is coherent in a context of cost of service remuneration[2]. Different cost minimizing optimization models represent wind variability by modeling wind as a negative demand (De Jongue et al. 2010). This approach necessitates a prior assumption on the installed capacity of wind and does not enable to differentiate between power class resources. It also lacks the chronological description of wind and load profile by using load duration curves, and thus does not allow capturing the correlation effect between load and wind resource profiles. In order to illustrate the impact of the variety of the regional wind resource in term of quantity and adequacy, a different and innovative approach is taken in the CAPEW model. More specifically, wind power is modeled as any other technology but its non-dispatchable characteristic is represented by a variable cap on the generated electricity profile as a percentage of the installed wind capacity.

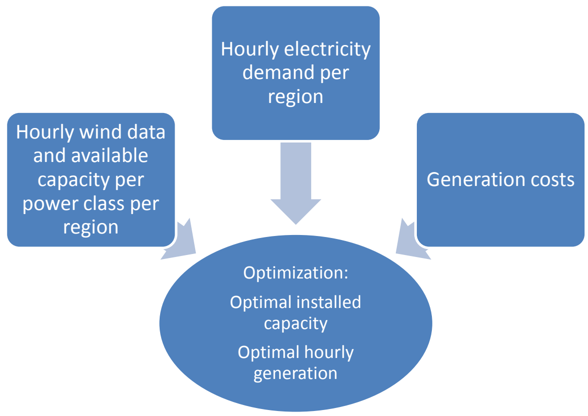
For the sake of simplicity, I also assume that all the revenues come from the sale of electricity, neglecting ancillary services or remuneration for providing capacity. Some operational aspects, as start-up costs,

[1] The focus of the model is on wind, but future extension include the integration of other renewable source technologies

[2] To consider a decentralized approach, the objective function of the model has to be the maximization of firms' profit.

minimum operating level, minimum up and down times introduce binary variables. It requires using a mixed integer linear programming (MILP) formulation. Solving a MILP problem poses some computational difficulties for a one-year dataset. For these reasons, these operational constraints are not considered in CAPEW. Transmission constraints are also not considered and no storage capacity is included in the system. Figure 8 represents the different inputs in the CAPEW model.

Figure 8. Model inputs



The types of conventional generators that can be built in the model are based on the DOE Energy Information Administration (EIA 2009) and the costs hypotheses are presented below. I focus on the onshore wind power technology but future extensions could include the integration of offshore wind power or solar power. The reserve margin is fixed at 10% for every region. In the reference scenario, the fuel cost of coal is $1.4/MMBtu and the fuel cost of gas is $6.08/MMBtu. These hypotheses are inputs from EIA 2009 Energy Outlook data and result from an average of prices during 5 years, from 2002 to 2006, chosen to be consistent with the 2006 reference year of the load data. Planned and forced outages rates are neglected. Detailed calculations of generation costs are presented in Appendix.

Table 1. Generation costs S1 current fuel costs, wind

	Units	Pulverized Coal	NGCC	NGCC with CCS	IGCC with CCS	Advanced Nuclear	Wind	Biomass
"Overnight" Capital Cost	$/kW	3167	978	2060	5348	5335	2438	3860
Total Capital Requirement	$/kW	3674	1056	2307	6418	7469	2633	4478
Fixed O&M	$/kW	36.0	14.4	30.3	69.3	88.8	28.1	100.5
Variable O&M	$/kWh	0.0043	0.0034	0.0065	0.0080	0.0020	0.0000	0.0050
Project Life	years	20	20	20	20	20	20	20
Capacity Factor	**%**	**85%**	**85%**	**80%**	**80%**	**85%**	**32-46%**	**80%**
Operating Hours	hours	7446	7446	7008	7008	7446	3066	7008
Heat Rate	BTU/kWh	8800	7050	7525	10700	10488	0	13500
Fuel Cost	$/MMBTU	1.40	6.08	6.08	1.40	0.63	0.00	1.03
Fuel Cost per kWh	$/kWh	0.0123	0.0429	0.0458	0.0150	0.0066	0.0000	0.0140
total annualized fixed costs	$/MW-yr	**185,485**	**53,532**	**116,873**	**324,345**	**377,888**	**133,056**	**228,905**
total variable costs	$/MWh	**17**	**46**	**52**	**23**	**9**	**0**	**19**

3.3 Model Structure

3.3.1 Objective Function

The model optimizes the total cost of expansion and operation of the power system. Total system cost is defined as the sum of total variable cost and total fixed cost.

$$\mathbf{TC = TCvar + TCfix}$$

- TC is the total system cost ($)
- TCvar is the total variable cost ($)
- TCfix is the total fixed costs ($).

3.3.2 Equations

The total fixed cost is the sum of all the installed capacity multiplied by their annualized fixed cost.

$$\mathbf{TCfix = \sum_{G,r} c\_fix(G) * InsCap(G,r)}$$

- c_fix (G) is the annualized fixed cost for the technology G ($/MW-year)
- InsCap (G,r) is the total installed capacity of units of the technology G, in the region r (MW)
- TCfix is the total fixed costs ($).

The variable cost is the sum of the energy generated multiplied by the variable generation cost. The hourly energy generation is equivalent to the instantaneous power, averaged over a time step of one hour.

$$\mathbf{TCvar = \sum_{G,r,h} c\_var(G) * PwrOut(h,G,r)}$$

- c_var (G) is the variable generation cost ($/MWh)
- PwrOut (h,G,r) is the power available during an hour, for the technology G in the region r (MW) and is equivalent to the hourly energy generated during an hour.
- TCvar is the total variable cost ($).

3.3.3 Constraints

Supply has to meet demand

The power generated during an hour in the region r has to be equal to the sum of the demand and an operating reserve margin1.

$\forall \boldsymbol{h}, \boldsymbol{r}$

$$\sum_{G} \textbf{PwrOut (h,G,r) = load (h,r) * (1+r)}$$

- r is the reserve margin %
- load (h,r) is the electricity demand during the hour h in the region r (MWh)
- PwrOut (h,G,r) is the power produced during the hour h, by technology G in the region r (MW)

Electricity generated by conventional units

The power generated by each type of conventional technology G* is limited by the available capacity defined as the product of the installed capacity and the annual average capacity factor.

$\forall \boldsymbol{h}, \boldsymbol{r}$

$$\textbf{PwrOut (h,G*,r)} \leq \textbf{InsCap(G*,r)*CF(G*)}$$

- PwrOut (h,G*,r) is the power produced during the hour h, by the conventional technology G* in the region r (MW)
- InsCap (G*,r) is the total installed capacity of units of the conventional technology G*, in the region r (MW)
- CF (G*) is the annual average capacity factor of the conventional technology G*

Electricity generated by wind power units:

The power generated by wind plants is limited by the available capacity, defined as the product of the installed capacity, the capacity factor and the variable wind resource profile. The wind power technology is represented by five distinct technologies in the model, from class 3 to class 7, indexed by "wind i", I = 3, …, 7.

[1] The planning reserve margin r required by system planners represents generally 12-20% of the peak load margin of extra capacity (Holttinen 2008), the value chosen in CAPEW is 10%

$\forall h, r$

$$\mathbf{PwrOut\ (h,wind\ i,r) \leq\ InsCap(\ wind\ i,\ r)*CF\ (wind\ i)*wind\_profile(h,r)}$$

- PwrOut (h,wind i,r) is the power produced during the hour h, by wind power of class i in the region r (MW)
- InsCap (wind i,r) is the total installed capacity of units of the wind of class i, in the region r (MW)
- CF (wind i) is the capacity factor of the wind of class power i
- Wind_profile (h, r) is the wind profile by hour and region (%).

Installed wind capacity:

The installed capacity of wind power units for each wind power class is limited by the available capacity by region derived from land requirements.

$\forall r$

$$\mathbf{InsCap\ (wind\ i,r) \leq MaxWind(wind\ i,r)}$$

- InsCap (wind i,r) is the total installed capacity of units for the wind power class i, in the region r (MW)
- MaxWind (wind i, r) is the maximum available capacity by region and wind power class derived from the regional resource supply function.

The nuclear plants are operating at full capacity

The power produced by the nuclear plants is considered to be equal to the installed capacity times the capacity factor to represent the absence of flexibility in the operation of nuclear plants.

$\forall r$

$$\mathbf{PwrOut(h,nuclear,r) \geq InsCap(nuclear,\ r)*CF(nuclear)}$$

- InsCap (nuclear,r) is the total installed capacity of nuclear, in the region r (MW)
- CF (nuclear) is the capacity factor of nuclear plants
- PwrOut (h,nuclear,r) is the power produced during the hour h, by nuclear power plants in the region r (MW).

3.4 Data

The U.S. include a wide variety of climate types, due to latitudes, solar irradiation, local topography, etc. Consequently load and wind resource are both strongly dependent on the location. CAPEW distinguishes 11 regions which are aggregations of U.S. states as defined in Table 2 and visualized in Figure 9 (from the USREP model, Rausch 2010).

Figure 9. Regional aggregation in the CAPEW model, from the USREP model (Rausch 2010)

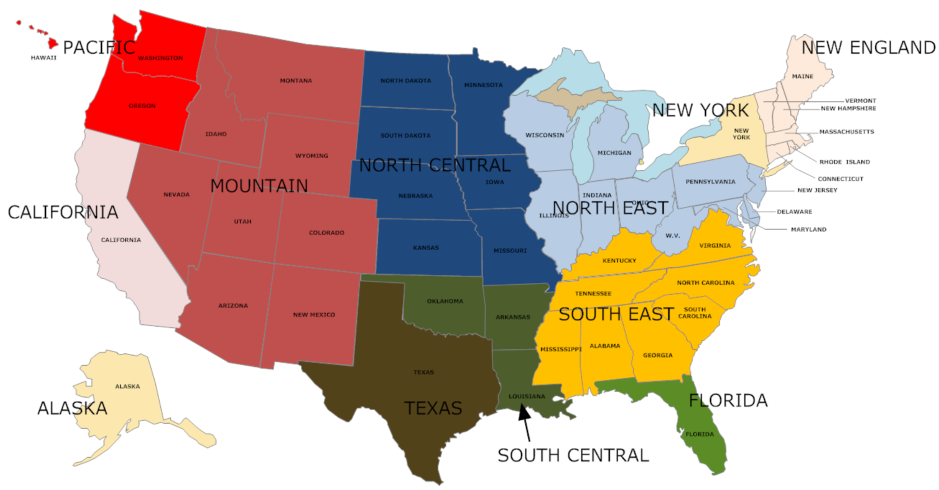


Table 2. Regional Aggregation in the CAPEW model, from USREP model (Rausch 2010)

Regions in CAPEW	**CA**	**FL**	**NY**	**NENGL**	**SEAST**	**NEAST**	**SCENT**	**NCENT**	**TX**	**MOUNT**	**PACIF**
States	CA	FL	NY	ME	VA	WV	OK	MO	TX	MT	WA
				NH	KY	DE	LA	ND		ID	OR
				VT	NC	MD	AR	SD		WY	
				MA	TN	MI		NE		NV	
				RI	SC	IL		KS		UT	
				CT	GA	IN		MN		CO	
					AL	OH		IA		AZ	
					MS	PA				NM	
						NJ					
						WI					
						DC					

Hourly load and hourly wind resource in CAPEW are aggregated over 720 time slices within each year: twelve months, each with twenty-four hours to illustrate a typical day. The optimization is done with a constraint of meeting the load during each of the 720 periods and in each of the 11 regions. These time slices allow CAPEW to capture the intricacies of meeting peak demand for electricity generators.

3.4.1 Load data

The database used in CAPEW consists of hourly electricity demand for the year 2006 in the 356 U.S. regions defined in the ReEDS model. The high geographic and temporal resolution enables the model to capture seasonal and daily variability of the load. The optimization in CAPEW is done for each time slice and each region as defined above in order to capture temporal and geographical patterns. By representing the yearly pattern of the electricity demand, differences between the eleven regions of CAPEW appear. In particular, the "PACIF" region, including the states of Oregon and Washington, has a very distinct yearly load profile from the other states. Indeed, the load demand is quite flat and does not include a peak in summer.

3.4.2 Wind resource profile

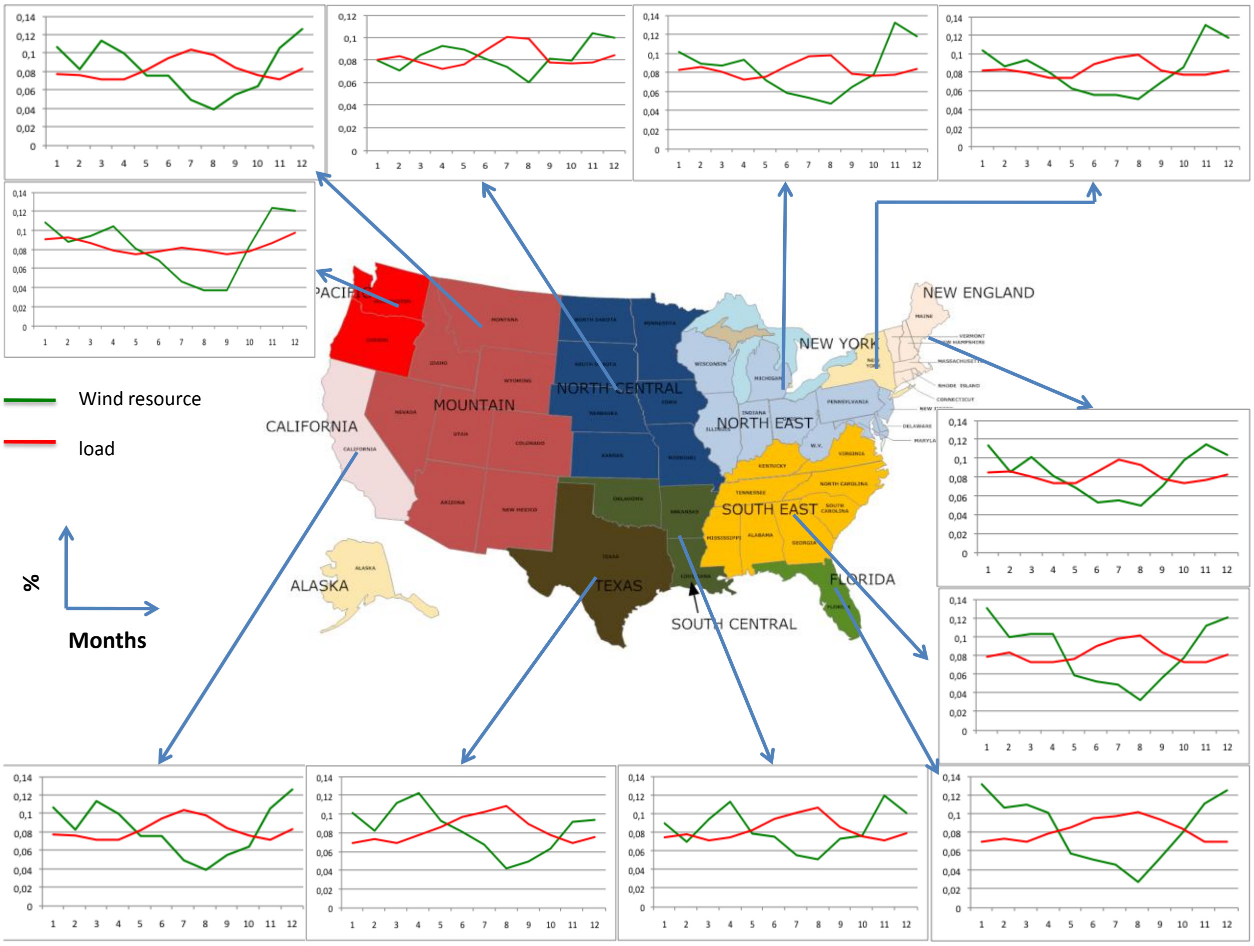
The United States possesses abundant wind resources. I consider five wind power classes based on wind speed at 50 meters above ground and wind power density, ranging from Class 3 to Class 7, as defined in the Table 3. Wind power classesTable 3.

Table 3. Wind power classes

wind power class	wind power density (W/m^2)	speed (m/s)
3	300-400	6.4-7.0
4	400-500	7.0-7.5
5	500-600	7.5-8.0
6	600-800	8.0-8.8
7	>800	>8.8

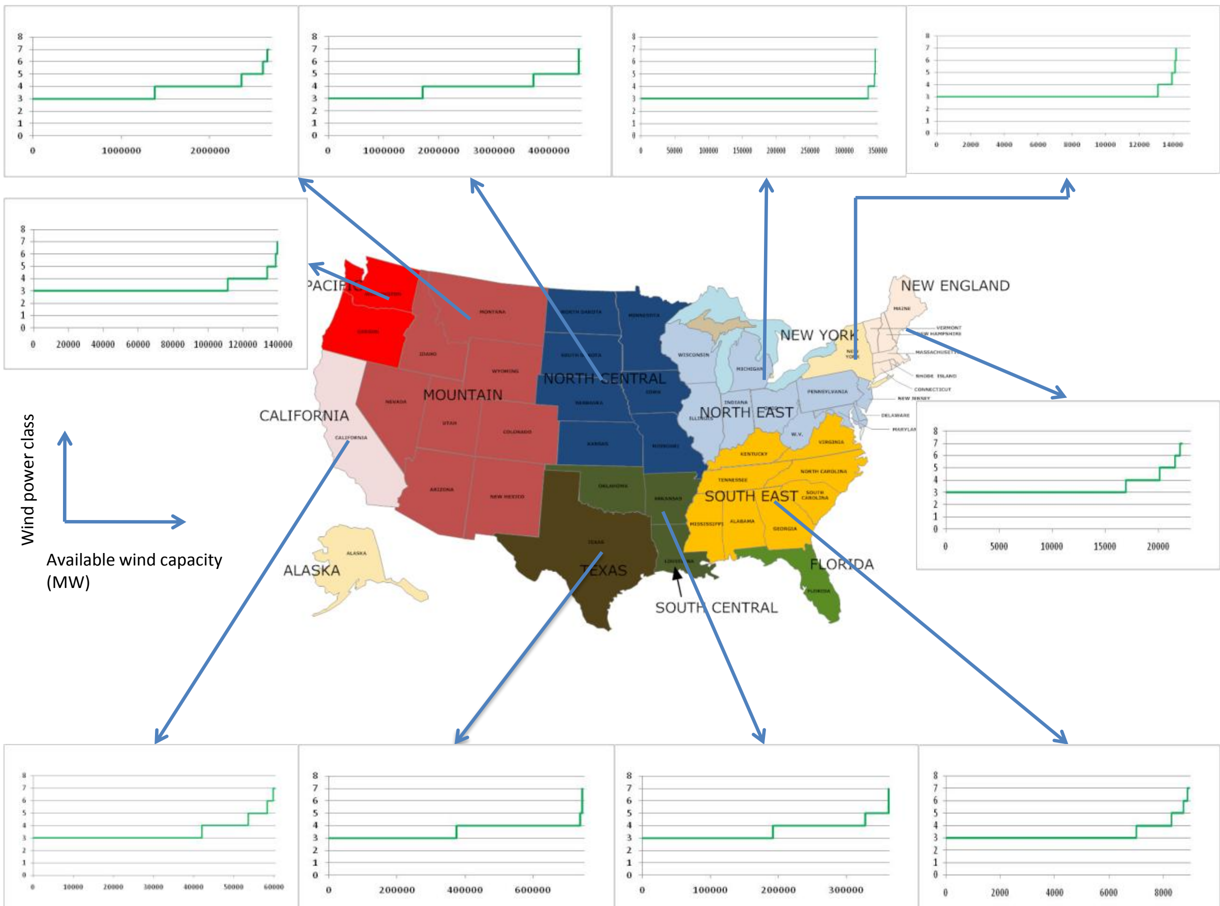
Below in the Figure 10 are represented the wind resource profile and load profile during the year in each CAPEW region. The negative correlation coefficient calculated above is illustrated in the profiles. Indeed, one can observe that there is a drop of wind during July and August (months 7 and 8), while the demand is peaking.

Figure 10. Yearly load and wind profile by region



The available land area per wind class has been derived from wind resource maps, after the exclusion of used land and protected area in the NREL dataset. A constant multiplier of 5MW/km2 has then been applied to convert available land into available wind capacity. The available wind capacity by region and wind power class is plotted in regional wind supply curves in the Figure 11.

Figure 11. Wind available per power class



3.4.3 The adequacy of the wind resource

From hourly wind resource profile and hourly load profile, I calculate a 'correlation coefficient'. Correlation is a measure of the strength and direction of a linear relationship between two datasets, here the wind resource (w) and the load (l). Pearson's product moment correlation coefficient (Moore 1995) r is given by:

$$\boxed{r(w,l) = \frac{\sum_i (w_i - \bar{w})(l_i - \bar{l})}{\sqrt{\sum_i (w_i - \bar{w})^2 \sum_i (l_i - \bar{l})^2}}}$$

Where $\bar{l}$ and $\overline{w}$ are the sample means of l and w.

All the regional load profiles, except for the region "PACIF" are negatively correlated with the wind resource profiles. This result can be related to the shape of the net load duration curves described above. Indeed, these negative coefficients of correlation are an illustration of the fact that there is generally less wind when the demand is higher. Below, the regional coefficients of correlation are calculated between hourly load profile and hourly wind profile, and listed for each region defined in CAPEW.

Figure 12. Coefficient of correlation between the load and the wind profiles

region	correlation coefficient betwen load and wind profiles
CA	-0.573
FL	-0.745
NY	-0.500
NENGL	-0.567
SEAST	-0.609
NEAST	-0.555
SCENT	-0.756
NCENT	-0.679
TX	-0.706
MOUNT	-0.617
PACIF	0.259
US	-0.722

3.5 Scenarios

The results are compared between different scenarios to reflect uncertainties on future costs and energy policy. The first scenario, S1 "under current fuel costs with wind", results from averaged fuel costs from 2002 to 2006 for coal and natural gas. A scenario S2 "under current fuel costs without wind" is run to assess the back-up costs. In the scenario S3 "under projected fuel costs", coal and gas fuel costs are average projected fuel costs from 2015 to 2035 (EIA 2011) Projected fuel costs assumptions in the scenarios S2 consider higher coal fuel cost ($2.36/MMBtu) and higher gas fuel cost ($6.45/MMBtu). Both scenarios S4 "under current fuel costs with CO_2 tax" and S5 "under projected fuel costs with CO_2 tax" result from the addition of a CO_2 tax ($15/ton of CO_2). The Table 4 summarizes the different cases.

Table 4. Scenarios summary

SCENARIOS	fuel costs	wind technology available	CO2 tax $15/ton CO2	fuel costs coal $/MMBtu	fuel costs NG $/MMBtu
S1 under current fuel costs with wind	average 2002-2006	yes	no	1.4	6.08
S2 under current fuel costs without wind	average 2002-2006	no	no	1.4	6.08
S3 under projected fuel costs	average projection 2015-2035	yes	no	2.36	6.45
S4 under current fuel costs with CO2 tax	average 2002-2006	yes	yes	1.4	6.08
S5 under projected fuel costs with CO2 tax	average projection 2015-2035	yes	yes	2.36	6.45

The CO_2 tax is set at $15/ton of CO_2 and represents and additional variable cost of up to $12/MWh (for coal) depending on the carbon intensity of each technology. The total emissions generated are then calculated in the model as illustrated in the Figure 13.

Figure 13. Costs of a CO_2 tax

CO2 tax $15/ ton CO2	Units	Pulverized Coal	NGCC	NGCC with CCS	IGCC with CCS	Advanced Nuclear	Wind	Biomass
emissions	g/kWh	800	300	200	700	60	0	60
tax	$/MWh	12	4.5	3	10.5	0.9	0	0.9

4 RESULTS

4.1 S1 "under current fuel costs with wind power"

In the S1 scenario "under current fuel costs with wind power", wind technology is available. The fuel costs are 1.4$/MMBtu for coal and 6.08$/MMBtu for natural gas. These hypotheses are inputs from EIA 2009 Energy Outlook data and result from an average of prices during 5 years, from 2002 to 2006, chosen to be consistent with the 2006 reference year of the load data (EIA 2009).

It is found that the coal-fired units represent 52% of the installed capacity on average in the U.S. The remaining of the generation mix is composed of wind power units and natural gas-fire units. Nuclear technology is not included in the generation mix. One explanation for this is that the operating constraint formulated in the model for nuclear plants allows no flexibility in the operation of the plant. Consequently, it increases the costs of nuclear technology compared to other technologies. In order to identify the role of the wind power technology in the simulated power system, I compare the S1 scenario "under current fuel costs with wind power" and the S2 scenarios "under current fuel costs without wind power", where wind power technology is not available. As illustrated in the Figure 14 and Figure 14, wind power displaces coal technology. Indeed, coal-fired units represent only 52% of the installed capacity on average in the U.S. when wind power is introduced. But they represent almost 58% of the installed capacity if wind power technology is not available.

Figure 14. Installed capacity (%) S1 "under current fuel costs with wind power"

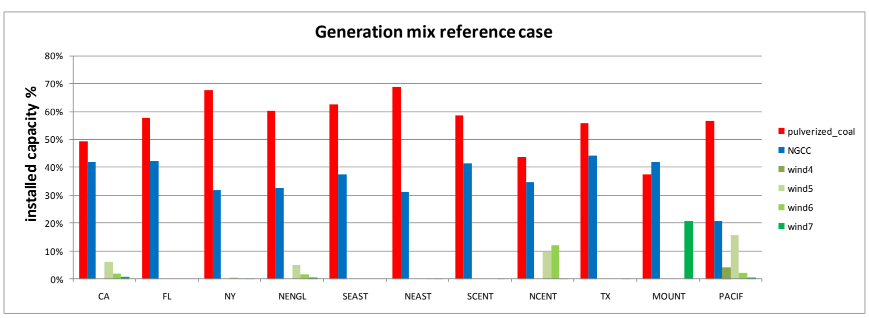
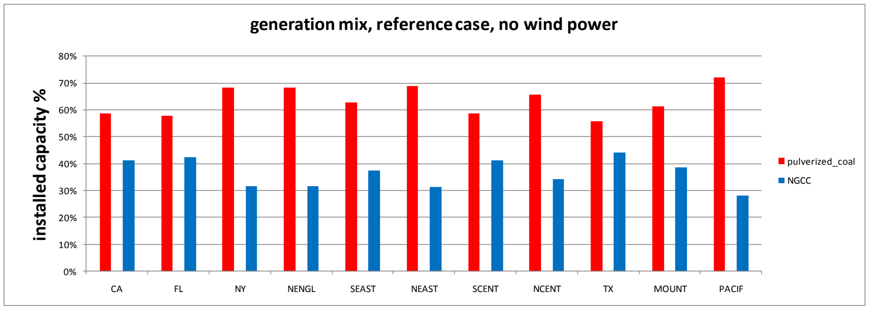
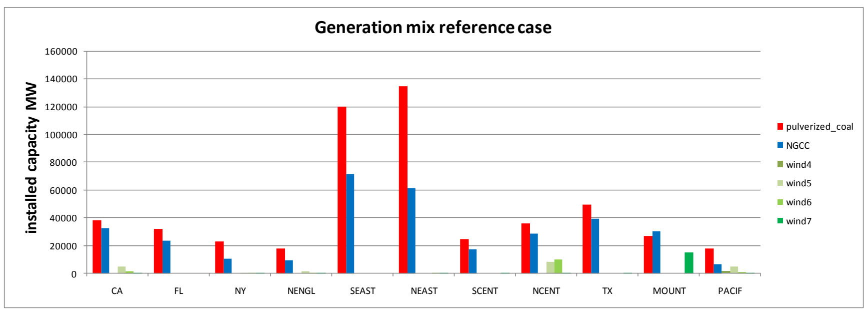


Figure 15. Installed capacity (%) S2 "under current fuel costs without wind power"



I also represent in the figure below the installed capacity for each region to illustrate the various sizes of the power systems considered.

Figure 16. Installed capacity (MW) S1 "under current fuel costs with wind power"



Natural gas-fired units serve as reserves units in the system to handle both load and wind resource variability. I calculate the actual capacity factor of the installed gas-fired plants as a ratio of the actual energy generated to the installed capacity. This indicator ranges from 15 to 20% in the different regions. The gas-fired plants are used with an average capacity factor of 17% in the U.S. due to the high variable cost.

Table 5. Operation of gas-fired units with and without wind

scenarios	S1 "under current fuel costs with wind power"	S2 "under current fuel costs without wind power"
Regions	Average actual capacity factor of the installed gas-fired units	Average actual capacity factor of the installed gas-fired units
CA	15%	28%
NY	18%	36%
NENGL	19%	38%
SEAST	16%	27%
NEAST	15%	27%
SCENT	17%	26%
NCENT	18%	30%
TX	18%	27%
MOUNT	18%	29%
PACIF	23%	38%
average US	17%	31%

Wind power integration varies widely across regions (from 0 to 22%). The total wind power installed capacity is 49GW[1], representing 5% of the total installed capacity in the U.S.

Figure 17. Integration of wind per region, S1 "under current fuel costs with wind power"

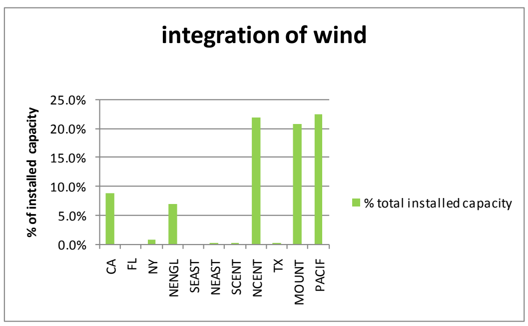


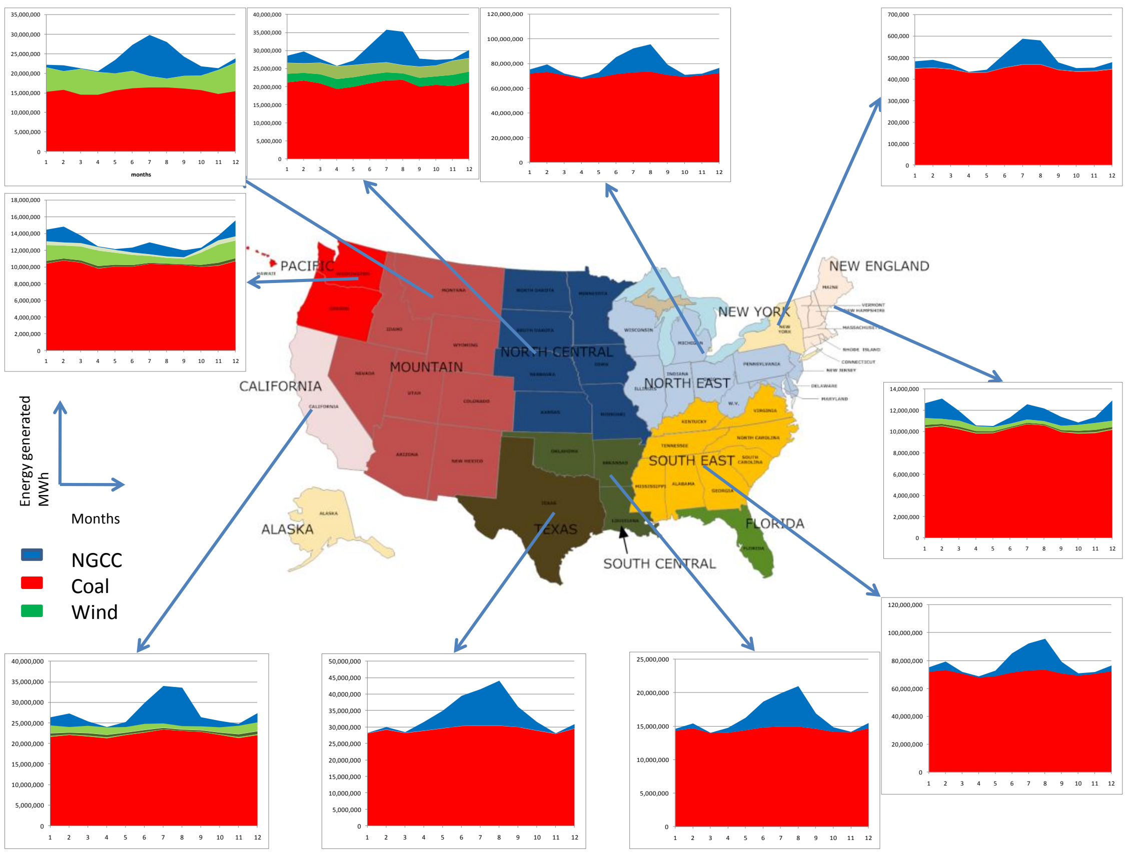
Table 6. Integration of wind per region, S1 "under current fuel costs with wind power"

integration of wind power	CA	FL	NY	NENGL	SEAST	NEAST	SCENT	NCENT	TX	MOUNT	PACIF	US
% total installed capacity	8.73%	0.00%	0.72%	7.01%	0.00%	0.13%	0.00%	21.87%	0.02%	20.76%	22.55%	5.5%

[1] The current wind power installed capacity in the U.S. is around 40GW.

In order to illustrate the seasonality of the generation profile, I represent in the Figure 18 the energy generated by different technologies during the year. Gas-fired units are required to ramp up and down because of load and wind variability. The amplitude of this generation variation is different in each region.

Figure 18. Generation by technology, region and month S1 "under current fuel costs with wind power"



The actual capacity factor of the installed gas-fired plants varies from 14.7 to 21.5%. Indeed, gas units plants serve as reserve units in the system to handle both the load and the wind resource variability. In order to quantify the back-up role of gas-fired units due to wind power, I compare the optimized generation mix in two cases, the "dispatchable case" and the "variable case". In the "dispatchable case", the wind technology is represented as any other conventional dispatchable technology. In this approach, the availability of a wind plant is considered as constant over the year and results of the product of the installed capacity and the average capacity factor. In the "variable case", the available capacity of a given wind plant varies during the year. This approach takes into account the non-dispatchable nature of the wind power technology. The installed capacity of wind in the "dispatchable case" is fixed to be the same as the installed capacity of wind in the "variable case" in order to have comparable generation mixes. Indeed, if the installed capacity of wind power is not a constraint in the "dispatchable case", the CAPEW model produces an optimal generation mix with a larger amount of wind power installed. The optimized solutions obtained by running CAPEW in the two cases are different. It appears that wind power displaces coal in both cases, but it can be noted that the installed capacity of gas is different in the two cases. The increase of peak suppliers in the "variable case" can be interpreted as a back-up capacity, due to the wind variability. Below are calculated the extra-capacity of gas installed in each region and the ratio of this extra-capacity to the wind power capacity installed. This ratio represents the back-up capacity and ranges from 0.25 to 0.51 MW of gas-fired units per MW of wind power installed.

Table 7. Operation of gas-fired units with flat and variable in S1 "under current fuel costs with wind power"

installed capacity (MW)		CA	FL	NY	NENGL	SEAST	NEAST	SCENT	NCENT	TX	MOUNT	PACIF
flat wind	NGCC	29,790	23,360	10,756	8,817	71,589	61,065	17,242	23,978	39,453	22,924	8,238
	wind	6,775	-	246	2,074	-	245	0	18,010	22	14,895	7,124
	total	75,515	55,247	34,053	28,898	191,764	195,725	41,669	78,843	89,183	66,153	33,077
variable wind	NGCC	32,590	23,360	10,811	9,693	71,589	61,147	17,242	28,515	39,464	30,011	6,573
	wind	6,775	-	246	2,074	-	245	0	18,010	22	14,895	7,124
	total	77,608	55,247	34,121	29,611	191,764	195,807	41,670	82,366	89,192	71,748	31,597
extra NGCC capacity (MW)		2,799	-	55	876	-	82	0	4,538	11	7,087	(1,665)
NGCC back-up capacity (MW per MW of wind installed)		**0.41**		**0.22**	**0.42**		**0.33**	**0.36**	**0.25**	**0.51**	**0.48**	**-0.23**

Back-up cost

I calculate the back-up cost for wind using two different methodologies. The first is an estimation of the extra capacity of gas-fired plants built by the system to cope with the wind variability. The second is an estimation of the saving from using wind unit instead of coal units in the case of perfect substitutability minus the actual saving from the total system (in Appendix 3).

In order to estimate the back-up cost, I compare the optimized generation mix in two cases, the "dispatchable case" and the "variable case", as described above. In the "dispatchable case", the energy generated depends on the location of the plant, which determines the wind quality, or wind power class, but not on the wind profile. In the "variable case", the energy generated still depends on the location of the plant through the wind power class. But in addition, the available capacity of a given wind plant varies during the year. This availability follows the seasonal wind pattern and determines the maximum power generated. The installed capacity of wind in the "dispatchable case" is fixed to be the same as the installed capacity of wind in the "variable case", as mentioned above. The optimized solutions obtained by running CAPEW in the two cases are different. It appears that wind power displaces coal in both cases, but it can be noted that the installed capacity of gas-fired is different in the two cases. The increase of peak suppliers in the "variable case" can be interpreted as a back-up capacity, due to the wind variability.

Table 8. Difference of costs in the "variable" wind resource and "flat" wind resource cases

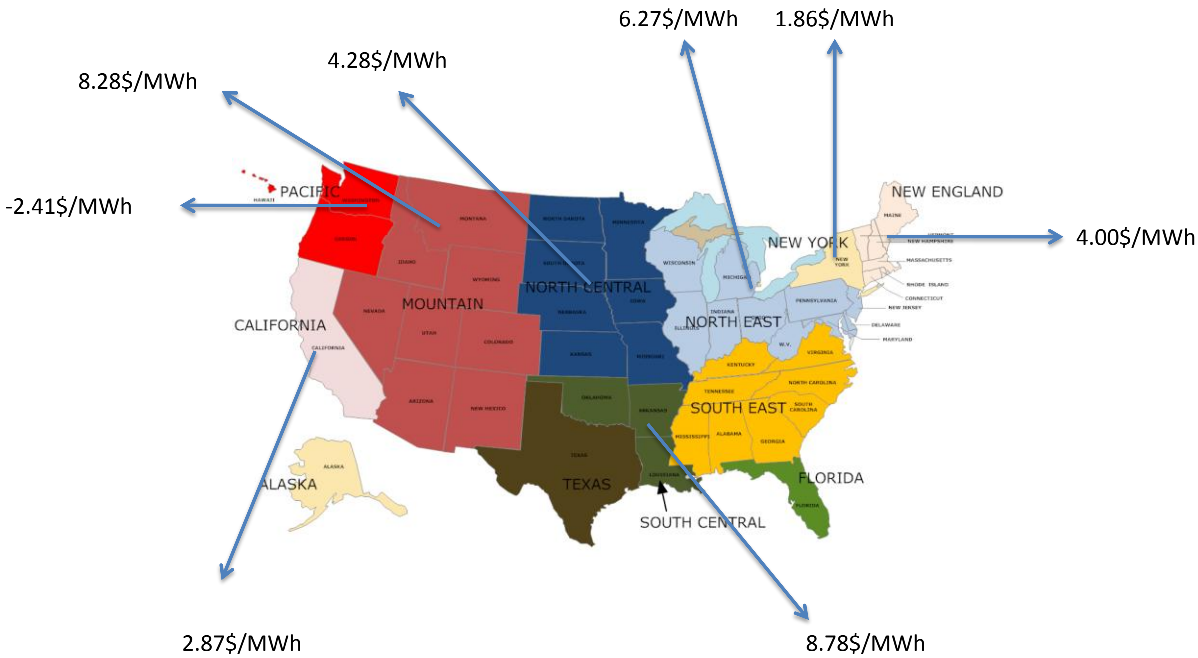
total system cost with variable wind resource	$M	202,853
total system cost with "flat" wind resource	$M	202,019
extra back-up cost	$M	834
energy generated from wind	MWh	182,429,163
average back-up cost in the U.S.	$/MWh	**4.57**

On the map below I represent the back-up costs calculated with this approach, by region. A wide variety of back-up cost between different regions can be observed. A negative cost in the region PACIF can be interpreted by looking at the positive correlation coefficient between load and wind resource. In this particular case the scenario with a variable wind resource is less expensive than the scenario with a flat wind resource leading to a "negative back-up cost". The back-up cost is not calculated in the regions of Florida and South East because the integration of wind is zero in the optimal mix. The highest back-up cost can be found in the region South Central region at $8.78/MWh. The average cost of wind power in CAPEW[1] are

[1] It is assumed that there variable costs for wind are zero and that fixed costs are $133 056/MW-year installed.

ranging from $33/MWh (for wind power of class 7) to $47.5/MWh (for wind power of class 3). Consequently, the back-up cost estimated here is up to 27% of the installed cost of wind.

Figure 19 Wind back-up cost by region



A key element to interpret this number is the absence of uncertainty in the wind resource data used as input in CAPEW. Modeling the intermittency of the wind resource may increase dramatically the back-up cost assessed above.

4.2 S3 "under projected fuel costs"

In the S3 scenario, "under projected fuel costs", the fuel costs are \$2.36/MMBtu for coal and \$6.45/MMBtu for gas. There is no carbon tax in this scenario S3. The penetration of wind power in the generation mix is larger than in S1 "under current fuel costs" because other technologies (coal-fired plants, IGCC with CCS, NGCC and NGCC with CCS) have higher variable costs due to higher fuel costs. Wind power integration varies widely across regions (from 0 to 55.6%). The total wind power installed capacity is 229GW[1], representing 22% of the total installed capacity in the U.S.

Figure 20. Installed capacity, S3 "under projected fuel costs"

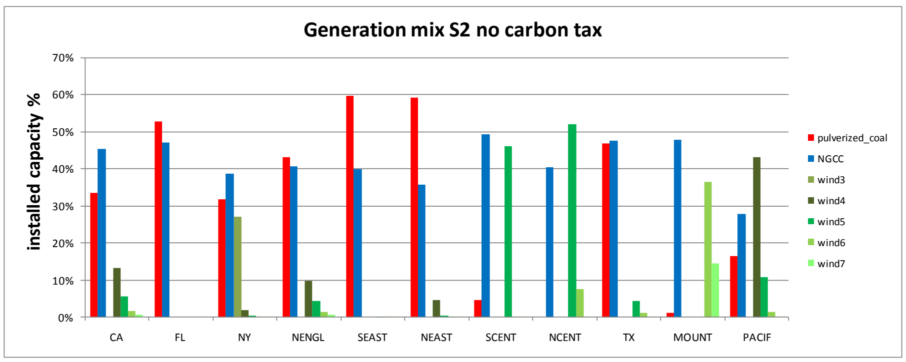


Figure 21. Integration of wind per region S3 "under projected fuel costs"

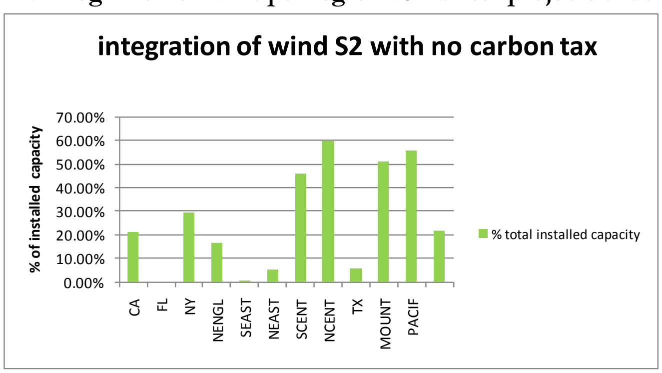


Table 9. Integration of wind per region, S2, no carbon tax

integration of wind power	CA	FL	NY	NENGL	SEAST	NEAST	SCENT	NCENT	TX	MOUNT	PACIF	US
% total installed capacity	20.96%	0.00%	29.42%	16.31%	0.33%	5.15%	46.14%	59.69%	5.60%	50.93%	55.63%	21.85%

[1] The current wind power installed capacity in the U.S. is around 40GW.

4.3 S4 “under current fuel costs with CO2 tax”

In the S4 “under current fuel costs with CO2 tax”, the fuel costs are \$1.4/MMBtu for coal and \$6.08/MMBtu for coal. I add a carbon tax of \$15/ton of CO_2. The coal technology is not cost competitive anymore. This result is also illustrated in the screening curves (Appendix 2). Biomass units are supplying base load demand. This result does not incorporate supply limitation of biomass resource and should not be interpreted as more than an illustration of the impact of a carbon tax on conventional technology cost structure.

Figure 22. Installed capacity, S4 “under current fuel costs with CO2 tax”

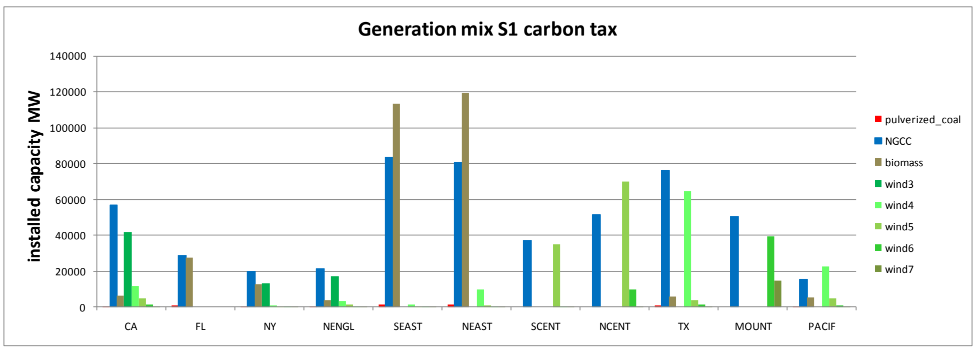


Figure 23. Integration of wind per region, S4 “under current fuel costs with CO2 tax”

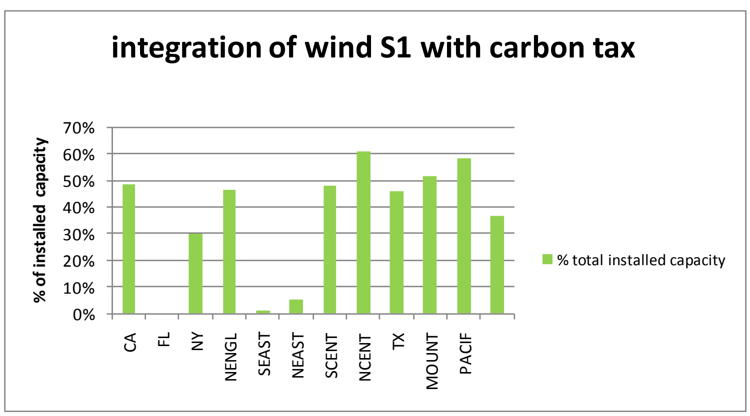


Table 10. Integration of wind per region, S4 “under current fuel costs with CO2 tax”

integration of wind power	CA	FL	NY	NENGL	SEAST	NEAST	SCENT	NCENT	TX	MOUNT	PACIF	US
% total installed capacity	48.79%	0.00%	30.17%	46.42%	0.96%	4.98%	48.24%	60.75%	45.81%	51.83%	58.24%	36.65%

4.4 S5 "under projected fuel costs with CO2 tax"

In the S5 "under projected fuel costs with CO2 tax", the fuel costs are \$2.36/MMBtu for coal and \$6.45/MMBtu for gas. I add a carbon tax of \$15/ ton of CO_2 . The coal technology is not competitive. This result is also illustrated in the screening curves (Appendix 2). Biomass units are supplying base load demand. This result does not incorporate supply limitation of biomass resource and should not be interpreted as more than an illustration of the impact of a carbon tax on conventional technology cost structure.

Figure 24. Installed capacity, S5 "under projected fuel costs with CO2 tax"

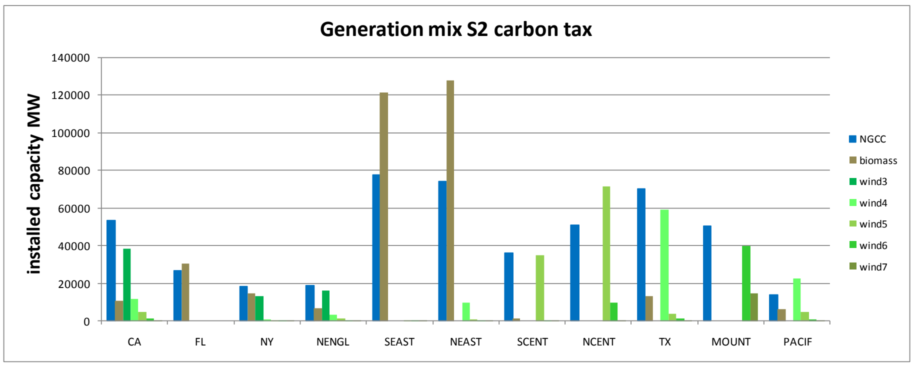


Figure 25. Integration of wind per region, S5 "under projected fuel costs with CO2 tax"

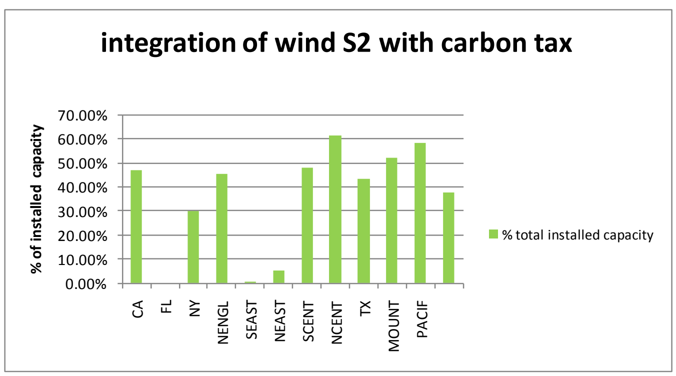


Table 11. Integration of wind per region, S5 "under projected fuel costs with CO2 tax"

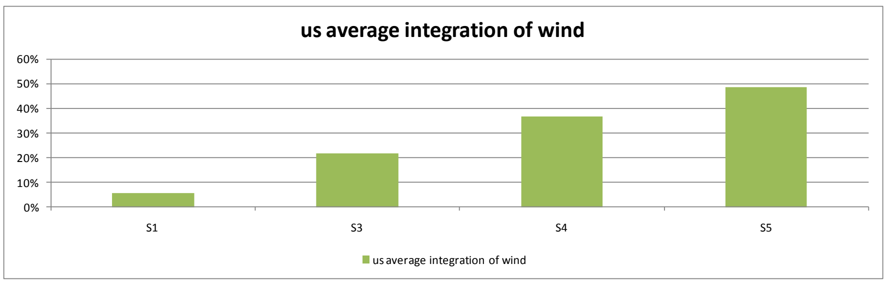
integration of wind power	CA	FL	NY	NENGL	SEAST	NEAST	SCENT	NCENT	TX	MOUNT	PACIF	US
% total installed capacity	22.69%	35.97%	26.28%	23.94%	38.99%	41.69%	49.93%	61.38%	50.56%	52.07%	64.56%	48.46%

The conclusion from the scenario with a carbon tax is that a carbon tax mainly penalizes coal technology.

1. Cost and CO_2 emissions

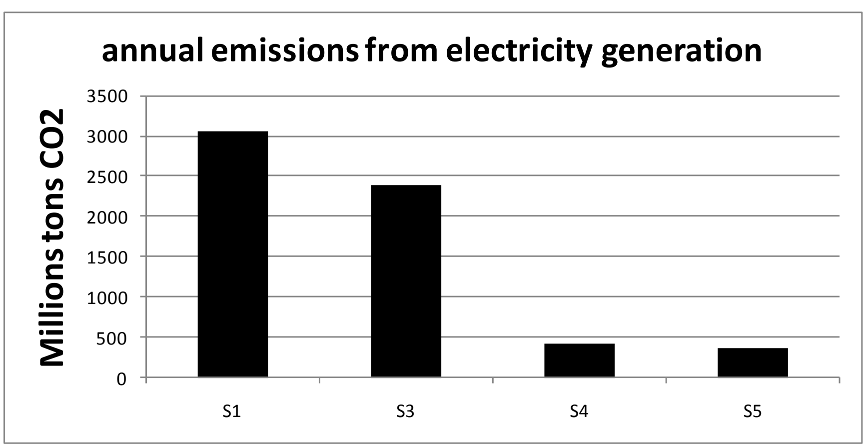
In order to summarize the effect of the different scenarios on the optimal integration of wind in the system, I represent the average integration of wind for the U.S. for the four scenarios. The introduction of CO2 tax increases the optimal penetration rate of wind from 5% to 37% between scenario S1 "under current fuel costs with wind power" and S4 "under current fuel costs with CO2 tax". An increase in coal fuel costs increases the optimal penetration rate of wind from 5% to 22% between scenario S1 "under current fuel costs with wind power" and S3 "under projected fuel costs".

Figure 26. Average share of wind in the installed capacity for different scenarios



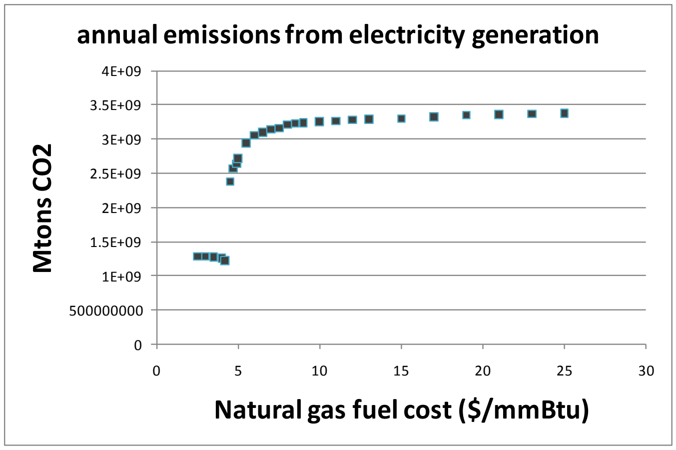
Carbon Dioxide emissions from electricity generation are calculated and compared in different scenarios. Introducing the carbon tax divides the total emissions by seven. An increase in fuel costs in scenario S3 reduces the emissions by 22% compared to S1 (because coal fuel prices increase relatively more than natural gas prices).

Figure 27. Emissions of CO_2



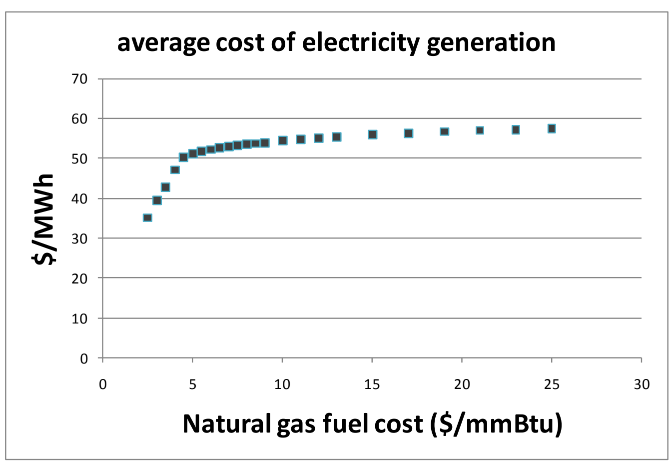
Carbon emissions are very sensitive to gas fuel cost assumptions. Indeed, gas-fired technology is much less carbon intensive than coal-fired technology. If gas prices are very low and NGCC units have a lower average price than coal units, total carbon emission from electricity generation decreases dramatically. For the costs hypothesis of the CAPEW model, NGCC units are displacing coal for a gas fuel cost inferior to $4.3/mmBtu.

Figure 28. Emissions of CO2 for different natural gas fuel cost



Finally, we can represent the average cost of electricity generation from the total cost of the system and the total energy generated, in different fuel cost scenarios. I run CAPEW for natural gas fuel cost ranging from 2.5 to 25$/mmBtu, without carbon tax. As expected, the cost increases when gas fuel costs increases. At very low gas fuel cost, gas-fired are more competitive than coal units as base load suppliers and the average cost is very low. When gas-fired average cost become higher than coal average cost, the curve below stabilizes.

Figure 29. Total system cost



5 CONCLUSION

There is an increasing interest in the technical and economic impacts of large-scale deployment of wind power. This thesis develops a model in order to illustrate key factors determining wind power costs and assess those costs in the U.S. power system. Major findings are summarized below.

5.1 Summary of the results

5.1.1 Wind power units as base-load units with back-up

Onshore wind power tends to displace conventional base load capacity due to their similar cost structures, low variable costs and high fixed costs. The variability of the wind power output over time leads to an increase of the peak suppliers installed. Those gas-fired units serve as back-up for the wind units. The back-up capacity ranges from 0.25 to 0.51 MW of NGCC per MW of wind power installed.

5.1.2 Optimal wind penetration rate

Wind integration in the optimal power system ranges from 0 to 22.5% of the installed capacity in the different states. The average optimal penetration rate in the U.S. is 5.5%[1] with the current technology available and no carbon tax.

5.1.3 Reserve units

Peakers are operating as reserve units to cope with load and wind resource variability over time. It is found that gas-fired units operate with an actual average capacity factor of 17% in a power system with wind and 31% without wind.

5.1.4 Back-up cost

The back-up cost associated with wind is estimated at $4/MWh on average in the U.S. but vary widely between regions. It represents up to 27% of the wind installation cost in some regions.

5.1.5 The adequacy of the wind resource

The correlation between wind and load profiles is negative in all of the eleven U.S. regions studied in the model, with the exception of the Pacific region. Its average value in the U.S. is - 0.72.

[1] It represents an installed capacity of 49GW. The installed capacity of wind in 2010 is estimated at 40GW.

5.1.6 Introduction of a CO_2 tax

Introducing a carbon tax of $15/ton of CO_2 increases the optimal penetration rate of wind from 5% to 37%. It also divides the total annual CO_2 emissions from electricity generation by 7 (from 3050 to 429 Mtons CO_2/year). The total annual system cost increases by 17%.

5.2 Conclusions

It is found that wind power variability leads to an increase of the capacity installed of peak units and a decrease in the actual capacity factor of those units. Therefore it is argued that dispatchable natural gas-fired units serve as "back-up". Peakers are operating as reserve units to cope with load and wind resource variability over time. There is thus a back-up cost associated with wind varying widely across regions. The optimal penetration rate of wind power in the U.S. varies with substantial variations across regions

A key factor influencing the optimal wind power integration rate is the correlation between wind resource and load profiles, which are found to be negatively correlated in most U.S. regions. An increase in fossil fuel cost leads to an increase in the optimal integration level of wind. Adding a carbon tax mainly penalizes coal technology and increases the optimal integration level of wind power. Introducing a CO_2 tax increases the optimal penetration rate of wind and increases the total annual system cost.

5.3 Limitations and Future work

An immediate extension of the present work is to include a representation of other renewable energy sources, such as offshore wind, photovoltaic, solar thermal, geothermal, etc. The correlation between load and solar resource may be positive. Indeed, solar irradiation is higher during midday and summer when the electricity demand is high. The effect of introducing solar power may be an offset of wind variability.

A deterministic model was developed in the present thesis. Uncertainty is a critical issue for future exploration. Indeed, modeling uncertainty is likely to increase the back-up cost and to reduce the optimal penetration rate. Intermittency could be modeled by introducing a probabilistic representation of the wind resource in the model.

One of the biggest challenges for the large-scale deployment of wind power in the U.S. is the extension of the grid. Transmission is not modeled in the present thesis and could be added in future work. The transmission cost of wind power integration in the system will be dependent of the distance between the wind resource and the load.

To assess the economic and the environmental impacts of GHG mitigation policies, Computable General Equilibrium (CGE) models are commonly used. This type of models captures effects between different sectors of the economy. Prices and demand are endogenous in these models. However CGE models lack a detailed representation of the electric sector. Indeed, in economy-wide models, or 'top-down' models, aggregated production functions poorly represent the different electric generation technologies. In particular renewable energy technologies characteristics such as variability and intermittency are only partially represented. One approach to capture the non-dispatchable nature of renewable is to consider an equivalent technology of wind with back-up (Morris et. al. 2010). On the contrary, technology-rich engineering models, 'bottom-up' models provide a detailed representation of electricity generating technologies and grid transmission reliability issues. But these models are only partial equilibrium as they represent only the electricity sector, or more broadly the energy sector. They typically lack the representation of interactions among the various economic sectors. A future extension of the present work is to inform economic models in the representation of renewables. Finally the optimal generation mix also depends on the amount of storage capacity, interconnection and demand response in the power systems. All these components could be added in the CAPEW model in future exploration.

A wide variety of climate policy tools have been designed to reduce GHGs emissions. One policy approach tested by the CAPEW model is a carbon tax. The tax paid is equal to the marginal damages (Baumol 1972). Taxing conventional electricity generation technologies can be justified by two main reasons; the need to offset environmental externalities, and the need to create a competitive advantage to encourage the learning process for new clean technologies. But designing and implementing this tool raises several issues, such as political feasibility, timing, and complexity. As a tax would increase prices and might be difficult to agree on, a second approach to maintain prices difference between carbon-intensive and clean technologies is to apply lower tax on fossil-fuel technologies, or no tax, associated with a subsidy for renewable energy technologies. Future work may include testing other policy tools, such as a Feed-in-Tariff or Renewable Portfolio Standard (RPS).

Finally, most policy tools implemented are not taking into account the "integration externality". The unpredictable nature of renewables creates a negative externality associated with the integration of renewables into the existing grid, due to costs of transmission lines extension, back-up units built, peakers units operated as reserves, etc. They are thus likely to poorly evaluate wind power value in power systems. Consequently it is suggested that a policy design including wind power capacity and back-up costs would improve future power system planning.

6 APPENDIX

1. Generation cost

In the CAPEW model, technologies are represented with a variable and a fixed cost. "Overnight" capital costs, fixed O&M costs, variable O&M costs and heat rate are inputs from EIA Annual Energy Outlook 2010 (EIA 2011). The total capital requirement depends of the construction time d. It is calculated by

$$[2]= [1]+([1]*0.4*d)$$

where d is the construction time in years. I assume that d is 4 years for coal, 2 for NGCC, 5 for IGCC with CCS, 3 for NGCC with CCS, 5 for nuclear, 2 for wind, and finally 4 for biomass. For nuclear I add an additional cost of decommissioning of 20 % of the overnight capital cost. The project life is estimated at 20 years for all units. The capacity factors are inputs from standard assumptions. Finally, the fuel costs hypotheses are taken from the EIA Annual Energy Outlook 2011 (EIA 2011a and EIA 2011b) and varies in different scenarios (S1 and S2). The total annualized fixed cost is the sum of the total capital requirements and the fixed O&M costs, divided by the project life. The total variable cost is the sum of the variable O&M costs and the fuel costs. Below are represented the generation costs in the four scenario analyzed in the thesis.

Table 12 generation costs, scenario S1 "under current fuel costs with wind"

		Units	Pulverized Coal	NGCC	NGCC with CCS	IGCC with CCS	Advanced Nuclear	Wind	Biomass
1	"Overnight" Capital Cost	$/kW	3167	978	2060	5348	5335	2438	3860
2	Total Capital Requirement	$/kW	3674	1056	2307	6418	7469	2633	4478
3	Fixed O&M	$/kW	36.0	14.4	30.3	69.3	88.8	28.1	100.5
4	Variable O&M	$/kWh	0.0043	0.0034	0.0065	0.0080	0.0020	0.0000	0.0050
5	Project Life	years	20	20	20	20	20	20	20
6	**Capacity Factor**	**%**	**85%**	**85%**	**80%**	**80%**	**85%**	**32-46%**	**80%**
7	Operating Hours	hours	7446	7446	7008	7008	7446	3066	7008
8	Heat Rate	BTU/kWh	8800	7050	7525	10700	10488	0	13500
9	Fuel Cost	$/MMBTU	1.40	6.08	6.08	1.40	0.63	0.00	1.03
10	Fuel Cost per kWh	$/kWh	0.0123	0.0429	0.0458	0.0150	0.0066	0.0000	0.0140
11	**total annualized fixed costs**	$/MW-yr	**185,485**	**53,532**	**116,873**	**324,345**	**377,888**	**133,056**	**228,905**
12	**total variable costs**	$/MWh	**17**	**46**	**52**	**23**	**9**	**0**	**19**

Figure 30 generation costs, scenario S3 "under projected fuel costs"

	Units	Pulverized Coal	NGCC	NGCC with CCS	IGCC with CCS	Advanced Nuclear	Wind	Biomass
"Overnight" Capital Cost	$/kW	3167	978	2060	5348	5335	2438	3860
Total Capital Requirement	$/kW	3674	1056	2307	6418	7469	2633	4478
Fixed O&M	$/kW	36.0	14.4	30.3	69.3	88.8	28.1	100.5
Variable O&M	$/kWh	0.0043	0.0034	0.0065	0.0080	0.0020	0.0000	0.0050
Project Life	years	20	20	20	20	20	20	20
Capacity Factor	**%**	**85%**	**85%**	**80%**	**80%**	**85%**	**32-46%**	**80%**
Operating Hours	hours	7446	7446	7008	7008	7446	3066	7008
Heat Rate	BTU/kWh	8800	7050	7525	10700	10488	0	13500
Fuel Cost	$/MMBTU	**2.36**	**6.45**	**6.45**	**2.36**	0.63	0.00	1.03
Fuel Cost per kWh	$/kWh	0.0208	0.0455	0.0485	0.0253	0.0066	0.0000	0.0140
total annualized fixed costs	$/MW-yr	**185,485**	**53,532**	**116,873**	**324,345**	**377,888**	**133,056**	**228,905**
total variable costs	$/MWh	**25**	**49**	**55**	**33**	**9**	**0**	**19**

Table 13 generation cost, scenario S4 "under current fuel costs with CO2 tax"

c_tax	Units	Pulverized Coal	NGCC	NGCC with CCS	IGCC with CCS	Advanced Nuclear	Wind	Biomass
"Overnight" Capital Cost	$/kW	3167	978	2060	5348	5335	2438	3860
Total Capital Requirement	$/kW	3674	1056	2307	6418	7469	2633	4478
Fixed O&M	$/kW	36.0	14.4	30.3	69.3	88.8	28.1	100.5
Variable O&M	$/kWh	0.0043	0.0034	0.0065	0.0080	0.0020	0.0000	0.0050
Project Life	years	20	20	20	20	20	20	20
Capacity Factor	**%**	**85%**	**85%**	**80%**	**80%**	**85%**	**32-46%**	**80%**
Operating Hours	hours	7446	7446	7008	7008	7446	3066	7008
Heat Rate	BTU/kWh	8800	7050	7525	10700	10488	0	13500
Fuel Cost	$/MMBTU	**1.40**	**6.08**	**6.08**	**1.40**	0.63	0.00	1.03
Fuel Cost per kWh	$/kWh	0.0123	0.0429	0.0458	0.0150	0.0066	0.0000	0.0140
emissions	g/kWh	800	300	200	700	60	0	60
tax	$/MWh	0.012	0.0045	0.003	0.0105	0.0009	0	0.0009
total annualized fixed costs	$/MW-yr	**185,485**	**53,532**	**116,873**	**324,345**	**377,888**	**133,056**	**228,905**
total variable costs	$/MWh	**29**	**51**	**55**	**34**	**10**	**0**	**20**

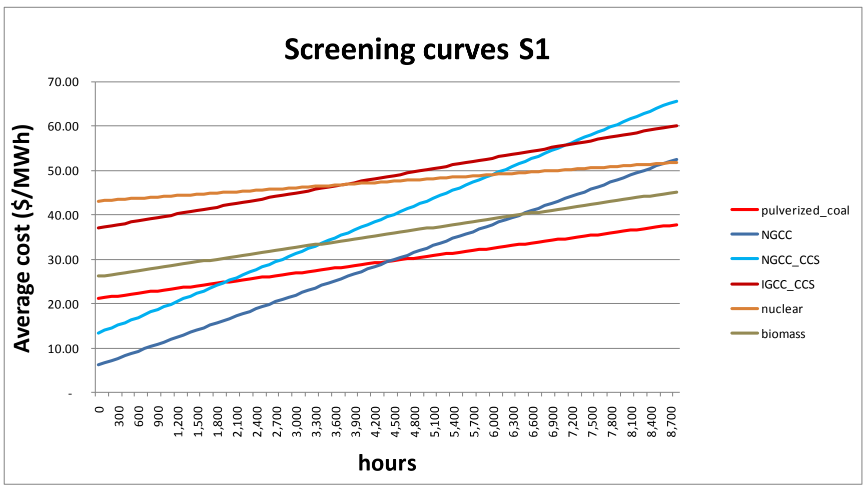
Table 14 generation costs, scenario S5 "under projected fuel costs with CO2 tax"

c_tax	Units	Pulverized Coal	NGCC	NGCC with CCS	IGCC with CCS	Advanced Nuclear	Wind	Biomass
"Overnight" Capital Cost	$/kW	3167	978	2060	5348	5335	2438	3860
Total Capital Requirement	$/kW	3674	1056	2307	6418	7469	2633	4478
Fixed O&M	$/kW	36.0	14.4	30.3	69.3	88.8	28.1	100.5
Variable O&M	$/kWh	0.0043	0.0034	0.0065	0.0080	0.0020	0.0000	0.0050
Project Life	years	20	20	20	20	20	20	20
Capacity Factor	**%**	**85%**	**85%**	**80%**	**80%**	**85%**	**32-46%**	**80%**
Operating Hours	hours	7446	7446	7008	7008	7446	3066	7008
Heat Rate	BTU/kWh	8800	7050	7525	10700	10488	0	13500
Fuel Cost	$/MMBTU	**2.36**	**6.45**	**6.45**	**2.36**	0.63	0.00	1.03
Fuel Cost per kWh	$/kWh	0.0208	0.0455	0.0485	0.0253	0.0066	0.0000	0.0140
emissions	g/kWh	800	300	200	700	60	0	60
tax	$/MWh	12	4.5	3	10.5	0.9	0	0.9
total annualized fixed costs	$/MW-yr	**185,485**	**53,532**	**116,873**	**324,345**	**377,888**	**133,056**	**228,905**
total variable costs	$/MWh	**37**	**53**	**58**	**44**	**10**	**0**	**20**

6.1 Screening curve illustration of different scenarios

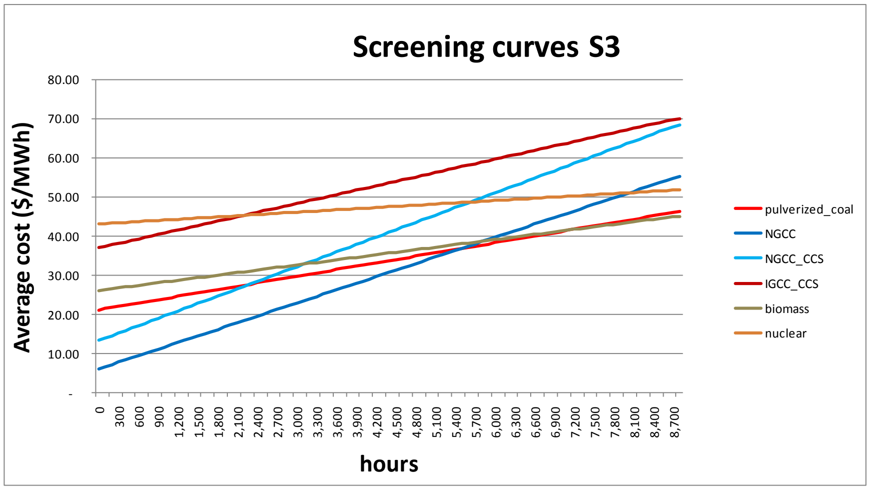
The screening curves below allow us to determine the optimal generation mix of dispatchable generation technologies. The first graph (Figure 31 screening curves, conventional technologies, S1) results from the hypothesis of fossil fuel costs (coal at 1.4$/mmBtu and gas 6.08$/mmBtu). Coal-fired technology is the cheapest technology for base-load units that are producing more than 4500 hours during the year. Natural Gas Combined Cycle plants are then the cheapest technology to meet shoulder and peak demand, corresponding to a production inferior to 4500 hours during the year.

Figure 31 screening curves, conventional technologies, S1 "under current fuel costs with wind"



In the scenario S3 "under projected fuel costs", the fuel cost of coal is set at $2.36/mmBtu and the fuel cost of gas is $6.45/mmBtu. Those numbers are averages of projections from 2015 to 2035 (EIA 2011). The average cost of coal has increased relative to the average cost of NGCC in this scenario compared to the reference scenario. The screening curve below illustrates that coal-fired technology is the cheaper option for units operating more than 6100 hours per year. Biomass technology also appears to be cheaper than coal technology for base load hours. However biomass technology is subjected to regional supply limitations. Therefore biomass is only an imperfect substitute to other conventional technologies and the result of the screening curves in the sensitivity analysis should be interpreted with reserves concerning biomass technology.

Figure 32. Screening curves, conventional technologies, S3 "under projected fuel costs"



Adding a carbon tax of 15$/ton of CO_2 modifies the variable cost of generation technologies. Coal technology appears to be more expensive than biomass as illustrated by the screening curves below. As highlighted in the previous paragraph, the relative cost of technologies should also include dispatchability features and has to be interpreted carefully for biomass technology.

Figure 33. Screening curves, conventional technologies, S4 "under current fuel costs with CO2 tax"

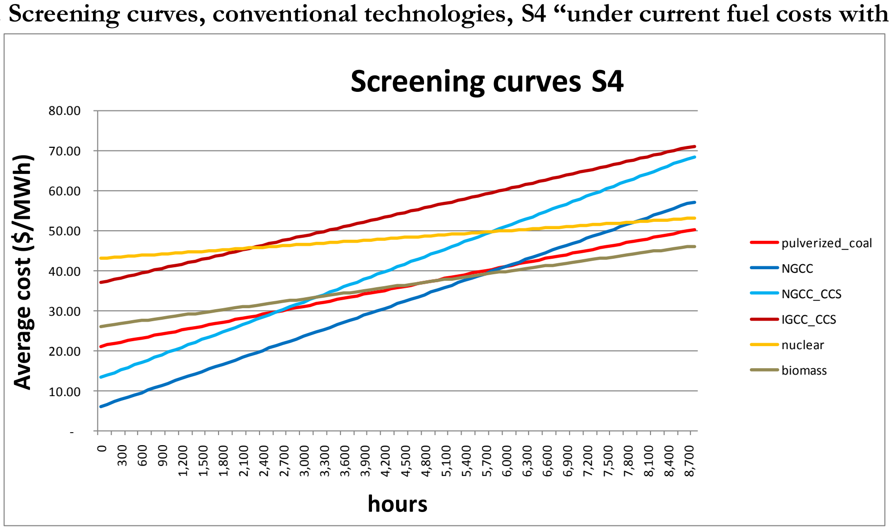
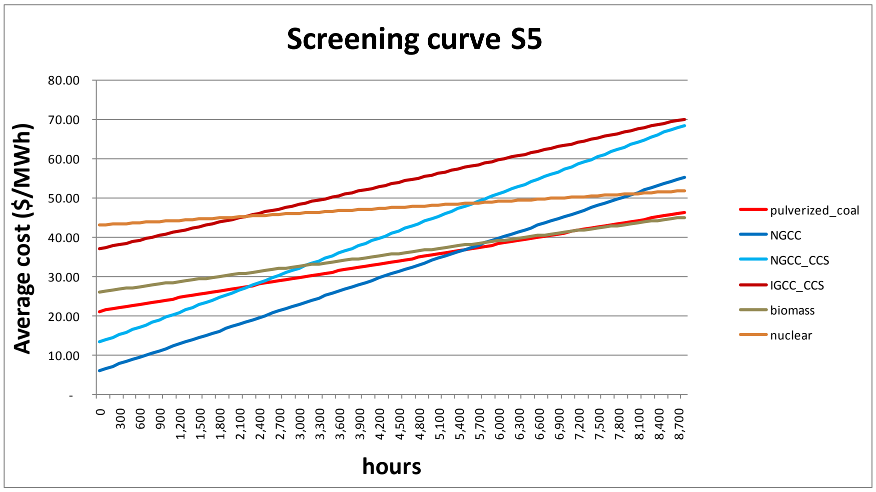


Figure 34. Screening curves, conventional technologies, S5 "under projected fuel costs with CO2 tax"



The conclusion from the scenario with a carbon tax is that a carbon tax mainly penalizes coal technology.

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