Investigating the role of electric heat storage in increasing the capacity value of wind power

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# Table of Contents

LIST OF TABLES ................................................................................................. 5  
LIST OF FIGURES .......................................................................................... 5  
ABSTRACT ......................................................................................................... 7  
DECLARATION ................................................................................................. 8  
INTELLECTUAL PROPERTY STATEMENT ..................................................... 8  
ACKNOWLEDGMENTS .................................................................................... 9  

1. INTRODUCTION ........................................................................................... 10  
   1.1. BACKGROUND ......................................................................................... 10  
   1.2. SHAPE AND SCOPE ............................................................................... 12  
   1.3. STRUCTURE ............................................................................................ 12  

2. LITERATURE REVIEW .................................................................................. 13  
   2.1. POWER SYSTEM OPERATION .................................................................... 13  
      2.1.1. INTRODUCTION .................................................................................. 13  
      2.1.2. IMBALANCES ....................................................................................... 14  
      2.1.3. TREATING THE IMBALANCES ............................................................ 16  
         2.1.3.1. SYSTEM BALANCING ACTIONS FOR SHORT TERM IMBALANCES 17  
         2.1.3.2. SYSTEM PLANNING APPROACH FOR LONG TERM ADEQUACY 18  
            2.1.3.2.1. APPROACH 1: SYSTEM MARGIN .............................................. 18  
            2.1.3.2.2. APPROACH 2: CAPACITY VALUE OF GENERATION .......... 20  
   2.2. POWER SYSTEM LONG TERM PLANNING WITH WIND PENETRATION .... 22  
   2.3. DEMAND RESPONSE BY ELECTRIC STORAGE HEAT TECHNOLOGIES .... 25  
      2.3.1. ELECTRIC THERMAL STORAGE (ETS) ............................................... 26  
         2.3.1.1. NIGHT STORAGE HEATING FACILITY ........................................... 27  
      2.3.2. ETS AND WIND POWER .................................................................... 28  
      2.3.3. IMPACTS OF LOW WIND EVENTS ON HEAT STORAGE .................... 29  
      2.3.4. THERMAL LAG AND INSULATION ..................................................... 30  
      2.3.5. THERMAL LAG AND ENERGY STORAGE WITH PHASE-CHANGE-MATERIALS (PCM) . 32  
      2.3.6. THE AGGREGATED EFFECTS OF INSULATION AND 2CM PCM-LAYER ON THERMAL LAG 32  
      2.3.7. DEPLOYMENT POTENTIAL OF ETS ................................................. 33  

3. METHODOLOGY ........................................................................................... 37  
   3.1. CAPACITY VALUE .................................................................................... 37  
      3.1.1. LOLE .................................................................................................. 37  
         3.1.1.1. GENERATION MODEL .................................................................. 39  
         3.1.1.2. LOAD MODEL .............................................................................. 42  
            3.1.1.2.1. CURRENT LOAD .................................................................... 42  
            3.1.1.2.2. PROJECTED STORAGE ........................................................... 43  
               3.1.1.2.2.1. PROFILE DESCRIPTION .................................................... 44  
               3.1.1.2.2.2. ESTIMATING THE NEW LOAD PROFILE ............................. 46  
      3.1.2. PROJECTED RESISTIVE ..................................................................... 50  
         3.1.1.2.4. STORAGE & RESISTIVE ............................................................ 50
3.1.2. Generation and Load Models Ready to Calculate LOLE .................................. 51
3.1.3. Data Requirements ..................................................................................... 54
3.1.4. Wind Data .................................................................................................. 55
4. Results and Discussion ..................................................................................... 56
5. Conclusion ........................................................................................................ 63
Bibliography ......................................................................................................... 64
Annex 1: R Code .................................................................................................. 67
Annex 2: Methodology to Determine Wind Speed at Turbine Height and Wind Power Output ........................................................................................................ 71

Word count: 14994
List of Tables

Table 1: Operation actions to treat short term imbalances 16
Table 2: Planning approaches to ensure long term adequacy 17
Table 3: Capacity values for wind in the UK 23
Table 4: Storage material properties (average values) 27
Table 5: COPT example 40
Table 6: COPT of the actual power system (sample) 41
Table 7: Load model used 42
Table 8: Definition of seasons for electricity profiles 46
Table 9: LOLE sensitivity study results 58
Table 10: LOLE and capacity value results, for wind installed capacity=26 GW 59
Table 10: LOLE and capacity value results, for wind installed capacity=39 GW 59
Table 11: Capacity Value with Weibull density function as the wind model 62

List of figures

Figure 1: Daily and seasonal variations of the load 15
Figure 2: Imbalances resulting from the different fluctuations 15
Figure 3: Probability distribution of available system margin 20
Figure 4: The focus of this research is on Long Term Adequacy 21
Figure 5: Typical modern storage heater 26
Figure 6: ETS design 27
Figure 7: Maximum discharge times for standard heating systems 29
Figure 8: Space heating and temperature correlation 30
Figure 9: Thermal loss for walls with no insulation (left) and for walls with 12 cm insulation (right) 31
Figure 10: Different cooling behaviour of a wall depending on its conductivity and storage characteristics 33
Figure 11: Share of final energy consumption by end user 34
Investigating the role of electric heat storage in increasing the capacity value of wind power.

Figure 12: Domestic Energy consumption Breakdown
Figure 13: Fuel type used for domestic space heating data source
Figure 14: Frequency distribution of current load values
Figure 15: Adequacy evaluation steps
Figure 16: Frequency Distribution of current load values
Figure 17: Domestic load profile for Unrestricted and Economy 7 users
Figure 18: Domestic Economy 7 seasonal load profiles
Figure 19: Unrestricted demand user profile
Figure 20: Economy 7 demand user profile
Figure 21: Load minus 6 million unrestricted users
Figure 22: Projected new load incorporating electric heat storage
Figure 23: Storage load determination flowchart
Figure 24: Current vs Projected resistive Load
Figure 25: Current vs Storage & Resistive load
Figure 26: Cumulative Probability distribution function of the Current Load model
Figure 27: Frequency distribution of SEDG wind profile power output
Figure 28: Wind model based on Weibull density function
Investigating the role of electric heat storage in increasing the capacity value of wind power

Abstract

The aim of this research is to demonstrate how to increase the share of installed wind capacity that can displace conventional generation while maintaining demand and supply balanced at all times. Displacing more conventional generation could accelerate the shift to a low carbon energy system.

Currently, the ability of wind power to displace conventional capacity is limited. Wind power available varies over the time and this variation might not match the demand pattern over the same timescale. As a result there will be times when the installed wind capacity cannot supply enough power to meet the electricity demand. However, electricity is expected and should be available at all times. As a consequence, when wind energy is not available, the demand needs to be supplied by other methods mainly by conventional generation. Matching demand and supply at all times relate to system adequacy. In addition, the contribution that a given generator makes to generation system adequacy is its capacity value.

The working hypothesis of this study is that electric heat storage could increase the capacity value of wind. Electric heat storage is a flexible load that can be shifted to times when more wind is available.

A suitable methodology to calculate the capacity value of wind was identified. Supply and demand influence the capacity value calculation’s result. To test the research hypothesis, a demand model representing the storage heaters was developed. The methodology was modeled using statistical techniques and the code for the model was run on R platform. It was found that the increase in capacity value was not significant with the addition of heat storage. On the other hand, the capacity value increased when demand at peak time increased.
Declaration

No portion of the work referred to in the dissertation has been submitted in support of an application for another degree or qualification of this or any other university or other institute of learning;

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“And what is a man without energy? Nothing-nothing at all” (Twain, 1860)

1. Introduction

1.1. Background

Energy is vital for the operation of the society. However, our carbon intensive energy practices are causing a global climate disturbance that can dramatically shape our existence. In response, societies have started to slowly act to decarbonise the energy system.

A multitude of recent studies outlay how the world could obtain all the energy it needs from renewable sources (Jacobson and Delucchi, 2010, Singer, 2010). While their approaches are different, the conclusion is the same. Barriers do exist but with proper policies and willpower for change, it can be done.

Furthermore, a number of UK studies suggest that decarbonising the energy system can be carried out through the increased electrification of sectors such as domestic heating that currently use fossil fuels ((DECC), 2010, UKERC, 2009). To achieve carbon savings the electricity supply needs to be decarbonised; one low-carbon source is wind energy.

The UK plans to increase the contribution of renewable sources in the electricity sector by over 30% by 2020 up from 7% currently (DECC, 2011a, DECC, 2010). Wind generation will be the main contributor to achieve the electricity target, given the vast wind resource and its leading competitive position among renewable technologies ((DECC), 2010, Strbac et al., 2007, EEA, 2009). In addition to controlling emissions, increasing the share of wind power could increase the energy diversity and security of the electrical system (Grubb et al., 2006).
Wind generation may displace a significant amount of energy produced by large conventional plants. Assuming the annual electricity generation will be around 400 TWh\(^1\) in 2020, 120 TWh of electricity would be generated from wind if the 30% target is reached. With a capacity utilisation factor of 35%\(^2\), this should result in 39 GW\(^3\) of wind installed capacity. 120 TWh of electricity could be produced by wind instead of conventional plants; however, this does not mean that wind power can displace 39 GW of conventional capacity. Several studies mention that the ability of wind to displace conventional capacity is limited (Grubb et al., 2006, Strbac et al., 2007). This is because wind power output is variable\(^4\) and uncertain. The wind power available varies over the time and this variation might not match the demand pattern over the same timescale. As a result there will be times when the installed capacity cannot supply enough power to meet the demand (Delucchi and Jacobson, 2011) which will need to be supplied by other form of generation mainly conventional plants (Grubb et al., 2006).

Nonetheless, increasing the share of wind generation that can displace conventional capacity will contribute greatly to the successful transition to a less carbon intensive energy system. According to Delucchi and Jacobson (2011), there are ways to operate a power system with a significant share of variable generation like wind while ensuring that demand will be satisfied at all times and without the need for conventional sources. The methods include interconnecting geographically dispersed wind sites, using hydroelectricity to fill temporary gaps between demand and wind generation, demand-response management to shift flexible load to better match the availability of wind,

---

1. The majority of the pathways in the 2050 Pathways Analysis report of the Department of Energy and Climate Change forecasted an electricity generation around 400 TWh in 2020 (DECC, 2010).
2. A utilisation load factor = mean output in a period/rated capacity. (Strbac et al., 2007) assumed a wind utilisation capacity factor of 35% for the UK.
3. \(39 \times 0.35 \times 8760 = 120\) TWh. 8760 represents the number of hours in one year
4. Terminology differs between authors, and many analysts advocate the use of “variable” in preference to “intermittent”, noting that all power sources are interruptible; hence intermittent (Skea, 2008). This research uses “variable”.
1.2. **Shape and Scope**

The aim of this research is to demonstrate how to increase the share of installed wind capacity that can displace conventional generation while maintaining demand and supply balanced at all times.

The objective of the research is then, to investigate the role of demand response management in increasing the share of installed wind capacity that can displace conventional generation while maintaining demand and supply balanced at all times.

This research will focus on demand management by flexible loads that can be shifted to times when more wind is available. A flexible load does not require power in an immutable minute-by-minute pattern, but rather can be supplied in adjustable patterns over several hours (Delucchi and Jacobson, 2011). The working hypothesis of this study is that electric heat storage as an example of flexible load could increase the share of installed wind capacity that displaces conventional generation while maintaining demand and supply balanced at all times.

By investigating the role of electric heat storage in increasing the installed capacity of wind power, this research is trying to address both the challenges of the electrification of the heat sector as well as increasing the share of renewables simultaneously.

1.3. **Structure**

An understanding of power system operation, power system adequacy and the contribution that generators make to this adequacy (i.e. their capacity value) is necessary to demonstrate the hypothesis of this research. The literature review covers the previous topics and the electric storage heat technologies. The methodology
explains in details how to calculate the capacity value and how it could change with the introduction of heat storage. The results and discussion section expend on the findings.

2. Literature review

2.1. Power system operation

2.1.1. Introduction

The primary emphasis of power system operation and control is to supply electric energy to the customer in the most economic and reliable way (Billinton and Allan, 1996, Kirschen, 2002, Warne, 2003). The system consists of the generation plants that supply electricity to customers through transmission and distribution systems (Warne, 2003). Consumer demand in a power system is often called a load.

Power system reliability is divided into system security and system adequacy. Security is related to the ability of the system to respond to disturbances arising within that system (Billinton and Allan, 1996). A system is secure if it can withstand local or widespread losses of major generation and transmission facilities. On the other hand, generation system adequacy refers to whether there is sufficient facilities to meet the electric demand (Billinton and Allan, 1996, Keane et al., 2011). The facilities include the sufficient installed generation capacity and the associated transmission and distribution networks. In order to ensure adequacy, the demand of the loads plus losses must be balanced at all times by electricity supply (Kirschen, 2002, Warne, 2003).

If the balance is not maintained, the system collapses with considerable and sometimes catastrophic social and economic impacts. A total collapse of the system (blackout) means that an entire region or country may be without power for many hours,
especially as restoring the power system to normal operation is a complex and lengthy process (Kirschen, 2002, Kirschen et al., 2004).

### 2.1.2. Imbalances

The factors that introduce imbalance into the system include the continuous fluctuations in demand, an imprecise control of the output of the generators and the occasional sudden outages of generators or power lines due to a breakdown or a fault (Gross et al., 2006, Kirschen et al., 2004). The imbalances are divided into short term imbalances with a timeframe of seconds to a few days, and long term imbalances with a timeframe of several days to several years.

The demand varies from hour to hour, day to day and season to season (Gross et al., 2006, Kirschen et al., 2004, Warne, 2003). To illustrate these daily and seasonal variations in the UK, Figure 1 shows the load profiles for the third Wednesday of January and July in 2010. The load profiles show a demand peak surrounded by a period of lower demand. Furthermore, the winter load exhibits a sharp peak at 55 MW which is much higher than the system peak for summer at 42 MW. In addition, Figure 2 illustrates short term demand fluctuations and an outage in generation that causes a large deficit imbalance noticed in the middle of the fourth period.
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**Figure 1:** Daily and seasonal variations of the load  
*Data Source: European Network of Transmission System Operators for Electricity (ENTSO-E, 2011)*

**Figure 2:** Imbalances resulting from the different fluctuations (Kirschen et al., 2004).
2.1.3. Treating the imbalances

The power system operator must treat the imbalances to ensure an adequate supply of electricity. First, short term imbalances are considered as a system operation issue. They are treated with system balancing services. Second, long term imbalances are considered as a system planning issue. The power system operator plans in advance for a certain level of installed capacity that is supposed to provide a more general adequacy of the system (Gross et al., 2006, Kirschen et al., 2004). Several studies published details about operation actions and planning approaches to treat the imbalances. All the studies shared the same basic concepts of matching demand and supply (Gross et al., 2006, Kirschen et al., 2004, DENA, 2005, NERC, 2009). However, the terminology\(^5\) for the same concepts differed between the studies as illustrated in table 1 and table 2 below. The difference in terminology can create confusion for the reader and diminish their understanding of topic.

<table>
<thead>
<tr>
<th>Timeframe of imbalances</th>
<th>UKERC (Gross et al., 2006)</th>
<th>Dena (DENA, 2005)</th>
<th>NERC (NERC, 2009)</th>
<th>(Kirschen et al., 2004)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Instantaneous</td>
<td>Response</td>
<td>Primary control</td>
<td>Frequency and Tie-Line Regulation</td>
<td>Regulation</td>
</tr>
<tr>
<td>Seconds to minutes</td>
<td>NA</td>
<td>Secondary control</td>
<td>Load following</td>
<td>Load-following services</td>
</tr>
<tr>
<td>Few minutes</td>
<td>Fast reserve</td>
<td>Minute reserves</td>
<td>Unit commitment and day ahead scheduling</td>
<td>Spinning reserve</td>
</tr>
<tr>
<td>Several minutes</td>
<td>Standing reserve</td>
<td>Hourly reserves</td>
<td>NA</td>
<td>Supplemental reserve</td>
</tr>
</tbody>
</table>

Table 1: Different terminology used in the literature to identify the same operation actions to treat short term imbalances

\(^5\) This research adopted the terminology by (Kirschen et al., 2004) for the balancing services


<table>
<thead>
<tr>
<th>Timeframe of imbalances</th>
<th>UKERC (Gross et al., 2006)</th>
<th>NERC (NERC, 2009)</th>
<th>(Keane et al., 2011)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Long term</td>
<td>System Margin</td>
<td>Resource and capacity planning(capacity valuation and long-term load growth forecasting)</td>
<td>Capacity value of generation</td>
</tr>
</tbody>
</table>

*Table 2: Different terminology used in the literature to identify the same planning approaches to ensure long term adequacy*

The operation actions and planning approaches to maintain the overall balance, and hence the adequacy of the power system, are described in more details in the following sections.

**2.1.3.1. System balancing actions for short term imbalances**

*Regulation* is designed to handle rapid fluctuations in loads and small unintended changes in generation. This service helps maintain the frequency of the system at or close to its nominal value. It is provided by generation units that are connected to the grid that can increase or decrease their output quickly (Flexible generation). Moreover, *load-following services* handle slower fluctuations. This service is provided by units connected to the system that have the ability to respond to these changes in load. Regulation and Load-following involve small and predictable actions. (Kirschen et al., 2004). On the other hand, *Reserve services* handle large and unpredictable power deficits that can threaten the stability of the system. Reserve is classified into *spinning reserve* and *supplemental reserve*. Spinning reserve must start responding immediately to an imbalance (a change in frequency) and the amount of reserve capacity needed must be available very quickly. The supplemental reserve does not have to start responding immediately and the service may be provided by units that are not synchronized to the grid but that can be brought online quickly (Kirschen et al., 2004).
2.1.3.2. System planning approach for long term adequacy

This is different than the system balancing actions described above. Whilst balancing actions react to unexpected events quickly, system planning approaches ensure in advance that the supply system can withstand planned or unplanned outages, and meeting a peak demand that was higher than anticipated (Billinton and Allan, 1996). As showed in Table 2, the same concept differed between the studies reviewed. The following section will describe in more details two different approaches used for long term adequacy planning.

2.1.3.2.1. Approach 1: System Margin

Part of the literature evaluates long term adequacy through setting a value for a system margin. A system margin is defined as the capacity by which the total installed capacity of all the generating plant on the system exceeds the anticipated peak demand (Gross et al., 2006). For the pre-privatised electricity system, the central planner adopted a 24% margin to ensure adequacy (Gross et al., 2006, Strbac et al., 2007). Nowadays, with the shift to a market based electricity system operation, there is no set standard for the system margin. The system operator monitors but does not contract for a system margin. The system operator (National Grid) communicates to the market participants estimates of expected desired margin for several years to come in the Seven Year Statement and for several months to come just before the winter peak periods in the Winter Outlook Report (Gross et al., 2006). The national grid’s indicative level of adequate system margin is 20% above peak demand (Grid, 2010, Gross et al., 2006). By monitoring the system margin, the system operator can take a range of actions if the margin is not suitable to ensure reliability. The UK Energy Research Center, published a

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6 System margin is the current UK Grid Code term (Gross et al., 2006). The concept has been referred to historically as ‘capacity margin’ ‘system reserves’ or ‘plant margin’. In addition, the term reserves in “system reserves” do not include system balancing reserves related to the short term fluctuation services.
Document that reviewed more than two hundred international studies about the costs and impacts of integrating variable generation into the system (Gross et al., 2006). The system margin concept was used to evaluate the long term adequacy of the power system.

System margin is aimed at ensuring that a specific measure of adequacy is maintained. The measure of adequacy used in this approach is the Loss of Load Probability (LOLP). LOLP is the probability that the load will exceed the available generation at a given time. To maintain an adequate system, LOLP should be kept small (Gross et al., 2006). The relationship between system margin and the measure of adequacy (LOLP) can be quantified using statistical principles. LOLP and system margin are directly related and the LOLP can be determined from the system margin distribution (Gross et al., 2006).

The system margin is a statistical quantity, and follows an approximately normal distribution when thermal plants dominate supply capacity. The spread of the distribution of the system margin is measured by its standard deviation\(^7\):

\[ \delta m \]

Demand and supply will affect the system margin. As a consequence, the statistical relationship between the standard deviation of the system margin and the standard deviations of variations in demand (relative to expected demand) and plant availability (failure rate), denoted by \( \delta d \) and \( \delta s \) respectively is

\[ \delta m^2 = \delta d^2 + \delta s^2. \]

The figure below represents the probability of any particular level of plant margin for a given system, which depends on the probabilities of plant failure and load levels.

---

\(^7\) Standard deviation is a measure that tells how tightly clustered a set of values are around the mean value of a set of data. When the standard deviation is small the ‘bell curve’ depicted above is steep and narrow. When it is large the curve broadens and flattens out.
The area when the available margin is negative provides a measure of the loss of load probability (LOLP).

2.1.3.2.2. **Approach 2: Capacity Value of generation**

Another part of the literature does not quantify the adequacy in terms of a margin. A key metric for generation system adequacy is the capacity value of generation. The capacity value of a generator is the contribution that a given generator makes to generation system adequacy (Keane et al., 2011). System adequacy can be evaluated using several risk indices. These include the Loss of Load Probability (LOLP) mentioned in the previous section and the Loss of Load Expectation (LOLE). LOLE is the expected number of hours or days, during which the load will not be met over a defined time period. The methodology to determine LOLP and LOLE will be detailed later and it is different than the one mentioned previously involving the distribution function of the system margin.
The capacity value approach is more straightforward than the system margin approach in determining long term system adequacy. As a consequence, the capacity value approach will be used in this research. It will be explained in more details in the methodology section.

The impacts of wind power on the system operation will be detailed in the following section. However, only the impacts on long term planning will be considered for this research. The power system operation focus of this research will be only on long term adequacy and system planning. A reason for this is that some studies found that even with large amounts of wind power, the system balancing requirements needed would have very low costs (Delucchi and Jacobson, 2011). In addition, Ortega-Vazquez and Kirschen (2009) estimated system balancing requirements, focusing on spinning reserves in systems with significant wind power penetration and found that an increased wind power penetration does not necessarily require larger amounts of spinning reserves.

The following sections will describe the effects introduced by wind on the system operation in relation only to long term planning and how an adequate system can be evaluated using the capacity value approach.

Figure 4: The Focus of this research is on Long Term Adequacy
2.2. Power system long term planning with wind penetration

The significant increase in the share of wind power into the electricity system will impact system operation because wind will introduce:

- **Variability:** The power output of wind is variable. It changes according to the availability of wind resulting in fluctuations in the plant output on all time scales. This could introduce a new factor of imbalance by making the supply more variable (Gross et al., 2006, NERC, 2009).
- **Uncertainty:** The magnitude and timing of variable generation output is less predictable than for conventional generation. This could make it harder to control wind output by the system operator (Gross et al., 2006, NERC, 2009).

Power systems are planned such that they have adequate generation capacity to meet the load, according to a defined reliability target (Billinton and Allan, 1996, Keane et al., 2011). As stated previously, a key metric for generation system adequacy is the capacity value of generation. Moreover, the capacity value of a generator is the contribution that a given generator makes to generation system adequacy (Aguirre et al., 2009, Keane et al., 2011).

The wind power available varies over the time and this variation might not match the demand pattern over the same timescale. As a result there will be times when the installed capacity cannot supply enough power to meet the demand (Delucchi and Jacobson, 2011). The capacity value of wind will determine its contribution to generation adequacy.

Several studies determined the capacity value for wind at different penetration levels into the system and for different power systems (Grubb et al., 2006, Keane et al., 2011, 2011).
Investigating the role of electric heat storage in increasing the capacity value of wind power (Milborrow, 2007, Smith et al., 2007). Table 3 below shows the relevant studies for the UK. The UK Energy Research Center, published a document that reviewed more than two hundred international studies about the costs and impacts of integrating variable generation into the system (Gross et al., 2006). The entry in the table represent the relevant findings for the UK.

In addition, the Wind Power Coordination Committee and Power Systems Analysis, Computing and Economics committee of the IEEE Power and Energy Society (PES) set up a Taskforce on Capacity Value of Wind (herin Tasforce). The Taskforce overall objective was to survey the range of different capacity value methods presented in the literature and report on best practice (Keane et al., 2011). The second entry in the table represent the calculation of capacity value of wind for the UK using the prefered methodology by the Taskforce.

Capacity value can be expressed in several ways (Gross et al., 2006). It is expressed mainly as a percentage of the installed wind capacity at a given level of penetration of wind into the system (Gross et al., 2006, Keane et al., 2011). The penetration level can be expressed as the percentage of total system electricity provided from wind generation (Gross et al., 2006), or as the wind generation capacity as a percentage of peak system load (Keane et al., 2011).

<table>
<thead>
<tr>
<th>Studies</th>
<th>Level of wind penetration</th>
<th>Capacity Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>UKERC (Gross et al., 2006)</td>
<td>Up to 20% of electricity supply</td>
<td>22%</td>
</tr>
<tr>
<td>Taskforce (Keane et al., 2011)</td>
<td>44% of peak load</td>
<td>8%</td>
</tr>
</tbody>
</table>

Table 3: Capacity values for wind in the UK
The total electricity supply for the UK is 400 TWh/year (DECC, 2010, Strbac et al., 2007). A penetration level of 20% of electricity supply from wind for the UK means that 80TWh could be supplied from wind. This corresponds to 26 GW\(^8\) of wind installed capacity. A capacity value of 22% (Gross et al., 2006), means that 5.7 GW of the installed wind capacity contribute to system adequacy.

Likewise, the peak system load is 59 GW (National Grid, 2010). A penetration level of 44% of peak system load for the UK corresponds to 26 GW. A capacity value of 8% (Keane et al., 2011), means that 2.1 GW of the installed wind capacity contribute to system adequacy.

It can be noted that the two approaches result in very different outcomes. Gross et al. (2006) and the Taskforce use different methodologies to calculate the capacity value. The Taskforce define the capacity value as the *extra demand* which an additional generator can support without increasing the value of a chosen risk index (Dent et al., Keane et al., 2011).

Gross et al. (2006) define it as the *conventional capacity* which can be displaced without increasing the risk index. Gross et al. (2006) determined the capacity value of wind by comparing the system margin without variable penetration and the system margin with variable penetration. In this approach, the risk index is determined from the system margin probability distribution.

This research will use the preferred methodology as defined by the Taskforce. One reason for this is that it was more straightforward and clear. Aguire et al. (2009) find that the approach which compares with a conventional plant has a major disadvantage. This is because the approach requires properties of the conventional plant to be defined which could be arbitrary due to the variation in availability properties and unit sizes.

---

\(^8\) Same calculation method used in the introduction
between technologies. Whereas, (Dent et al., 2010, Keane et al., 2011) state that the Taskforce method requires fewer parameter choices to define the calculation.

The details of the capacity value methodology used in this research (Taskforce) and the determination of the loss of load indices will be described in more details in the methodology section.

This section showed that the capacity value of wind power using the Taskforce methodology is 8% of the total installed wind capacity. Then, for example when installing 26 GW of wind power, only 2 GW contribute to adequacy which means only 2 GW ensure that demand and supply are balanced all the time.

The working hypothesis of this study is that electric storage heaters as a form of demand response could increase the capacity value of wind, in other words, the share of wind power that can meet the demand at all times. Demand response and electric storage heaters technologies are described next.

2.3. Demand response by electric storage heat technologies

Demand response is purported as one of the methods available to address the variability of wind energy and ensure that the power supply will meet the electric demand (Delucchi and Jacobson, 2011, Stadler, 2008, Strbac, 2008). The authors state that demand response shifts flexible loads to better match available wind generation. As mentioned previously, a flexible load does not require power in an immutable minute-by-minute pattern, but rather can be supplied in adjustable patterns over several hours (Delucchi and Jacobson, 2011). Lighting for example is an inflexible load. However, heating can become a flexible load if it is accompanied with storage. The basic idea is to use radio-teleswitching to provide electricity for the heaters when wind power supply is high (Strbac, 2008).
Savage et al. (2008) and Stadler (2008) studied the role of demand side technologies, however, they looked at their role on balancing services. In addition, Hughes (2010) demonstrated that up to 500 households in the Prince Edward Island in Canada could have over 95% of their space heating demand from the output of a 5.15 MW wind farm. His study focused on the characteristics of the heat storage and the charging times rather on power system adequacy. This research is looking at the role of residential electrical heat storage technologies in increasing the capacity value of wind.

### 2.3.1. Electric Thermal Storage (ETS)

ETS technology is an electric heating device with storage. The storage heater system consists of an insulated core that is mostly built of magnesite, due to its high specific heat capacity and temperature stability up to 650°C (Sievers, 2007, Stadler, 2008). Electricity charges the core unit to high temperatures, and then the heat is stored and discharged at a later time when needed.

Figure 5 shows a typical modern type storage heater that can be installed in one room (ETS manufacturers: Stibel Eltron, Steffes)

![Figure 5: typical modern storage heater (Sievers, 2007)](image.png)

The functioning of an ETS is detailed in figure 6 below. The electric resistor (b) is the heating element responsible for the conversion of electricity into heat. The heat store (a) is the magnesite core. The uncontrolled static heat transfer to the room is reduced by
insulating the storage. The controlled dynamic heat release of modern ETS is done by a ventilator (d) that transports air through the hot storage and a bypass. The hot air is delivered via the hot air opening (f) where it is mixed with ambient temperature air.

![Diagram of ETS design](image)

**Figure 6: ETS design (Sievers, 2007)**

A high density and heat capacity (storing) and a high conductivity (heat release) constitute the requirements of thermal storage materials. Table 4 shows different storage material properties. Sievers (2007) argues that Magnesite is best suited for thermal storage.

<table>
<thead>
<tr>
<th>Material</th>
<th>Useable temperature range in °C</th>
<th>Useable temperature difference in °C</th>
<th>specific heat capacity $C_v$ in Wh/kgK</th>
<th>Density $\rho$ in kg/dm³</th>
<th>Volume specific heat capacity $\rho c$ in Wh/dm³</th>
</tr>
</thead>
<tbody>
<tr>
<td>Olivine</td>
<td>600-100</td>
<td>500</td>
<td>0.29</td>
<td>2.6</td>
<td>0.75</td>
</tr>
<tr>
<td>Alucrodon</td>
<td>600-100</td>
<td>500</td>
<td>0.28</td>
<td>2.9</td>
<td>0.81</td>
</tr>
<tr>
<td>Magnesite</td>
<td>650-80</td>
<td>570</td>
<td>0.31</td>
<td>2.95</td>
<td>0.91</td>
</tr>
</tbody>
</table>

*Table 4: Storage material properties (average values) (Sievers, 2007)*

### 2.3.1.1. Night Storage Heating Facility

A common example of ETS is the Night Storage Heating Facility (NSHF). In the UK Economy Seven tariffs were developed to support night-time storage heaters. The
electricity is provided at low cost during the night because the demand is low at this period and it is supplied from base-load plant that operates with lower marginal costs. The heat stored will be released during the day (Savage et al., 2008, Strbac, 2008, Sievers, 2007). The electricity suppliers control the operation of the heaters. Control commands are transmitted by the supplier via the electricity grid to the receivers of the electrical appliances (Sievers, 2007).

2.3.2. ETS and wind power

Night-time storage heaters operation as described above, suggest a possible synergy with wind power output as well instead of night-time supply only. Storage heating systems will be charged at night preferably from wind output, furthermore they will be charged during excess wind power output. In other words, the heat will be stored whenever there is sufficient electricity from the wind. By storing at night, the demand is shifted to periods of low demand which removes load from peak periods. Similar to the night-time storage, modern broadband communications allows the remote control of the loads with a minimal cost and intrusion in the home (Savage et al., 2008). The addition is that the heaters will be switched on at times of excess wind output. In this way, more wind energy could be absorbed and would therefore reduce the fuel burned (Strbac, 2008).

It is important to mention that heating is not a time-flexible load. The wellbeing of the households remains more important than any other consideration. However, the storage technologies enable this demand flexibility of the heat load.
2.3.3. Impacts of low wind events on heat storage

The ETS should be able to store heat for more than one day in the event of low wind conditions. Figure 7 below shows the maximum possible discharge time with respect to the ambient temperature for a standard heating system, shown in blue and for a flat heating system, shown in red. The curves are based on relatively recent designs (Stadler, 2008). The flat storage heating system is better suited for integration into rooms however they have a higher self discharge due to the relation between surface and volume (Stadler, 2008).

If the ambient temperature is relatively high, the heat capacity in the storage system will be maintained for up to two days. However, temperatures will decrease in winter. When the outside temperature is lower than the inside temperature, heat is released to the outside. This increases the heating requirement to maintain the household temperature at the required level. Consequently, the storage will be discharged faster.
Figure 8 plotted below using space heating demand data and outside winter temperatures from DUKES (DECC, 2011b) shows how space heating requirements increases when the temperature decreases. It could be assumed that the housing insulation level is low in GB because heat demand and external temperature correlate perfectly. When temperature decrease, the heat demand increase. It would be expected that in an insulated housing stock, the inside temperature (hence the heat demand) would be more or less constant or at least not this closely correlated with the outside temperature.

![Space heating demand (TWh) and winter external temperature in GB](image)

**Figure 8: Space heating and temperature correlation**

**Data source:** (DECC, 2011b)

### 2.3.4. Thermal lag and insulation

Thermal lag is a delay in the release of heat from a mass after heat has been absorbed. For example, the thermal lag of metals is minimal because of their high thermal conductivity (Wulfinghoff, 1999). In this case, the mass relates to the household. Since it...
is desirable to bottle up the heat within the household, insulation should be used (Wulfinghoff, 1999).

Heat is lost from buildings through the fabric of the building itself and through infiltration of cold air through holes and gaps (Boardman et al., 2005). The fabric consists of roofs, walls, floors, windows and doors. The losses from fabric can be reduced with insulation materials. Holes and gaps can be reduced with an airtight construction. Therefore, increasing the thermal lag of the households by insulating its fabric will reduce heat losses. Reducing the losses will decrease the discharge rate of the storage heater.

A German case study investigated the thermal storage ability of buildings. The figures below show the simulation results for an outside temperature of 0 °C while the heating system is turned off. Figure 9 represents walls with no insulation on the left and walls with 12 cm insulation on the right. The different coloured curves in the figures represent the different types of outside walls found in Germany. The initial room temperature is 20 degrees. The figure on the left shows that the cooling down process from 20 to 18 degrees only took several minutes for the non-insulated walls, while the figure on the right shows that it took several hours in the case of insulated walls.

![Figure 9: Thermal loss for walls with no insulation (left) and for walls with 12 cm insulation (right) (Sievers, 2007)](image-url)
2.3.5. Thermal lag and energy storage with Phase-Change-Materials (PCM)

In the events of low wind, the stored heat in the household and consequently in the storage heater should be maintained as long as possible. The previous paragraph showed the importance of insulation in minimizing those losses. This paragraph explains how Phase-Change Materials (PCM) will further minimize the heat transfer to the outside by storing the energy in the household’s fabric (Khudhair and Farid, 2004). PCM is different than insulation because it will not affect the conductivity of the fabric. Yet, when encapsulated with the fabric, it will store energy. As such PCM elements work as an energy storage device (Khudhair and Farid, 2004, Sievers, 2007). The energy is stored without losses within the PCM materials until the temperature drops under the melting point of the material (which is at ambient temperature) and the heat is provided back to the room. According to (Sievers, 2007) PCM can store large amounts of energy for space heating.

2.3.6. The aggregated effects of insulation and 2cm PCM-layer on thermal lag

Figure 10 shows the simulation results of the cooling-down behavior for one wall type after the heat system is turned off and for an outside temperature of 0 degrees (Sievers, 2007). It can be seen that the cooling-down time is longer for an insulated wall than for a wall with PCM only. As mentioned previously, the heat conductivity does not really change with adding PCM. At the beginning the temperature remains the same for a certain period of time, but this is while the PCM is finishing the phase change (in this case at 20 degrees). After finishing the phase change, the temperature drops quickly. However, as shown in figure 10, when aggregating insulation and PCM, the cooling-down time is much longer, as PCM increases the storage capacity.
In conclusion, to minimize the discharge rate of the heat storage and increase the period before it needs to be charged again, the cooling-off time of the household temperature should be increased. This can be achieved if the household fabric is insulated, which will lower its heat conductivity and if it gained a heat storage characteristic by encapsulating its fabric with PCM.

![Figure 10: Different cooling behaviour of a wall depending on its conductivity and storage characteristics. (Sievers, 2007)](image)

### 2.3.7. Deployment potential of ETS

The domestic sector is the second largest energy consumer in the UK with 30% of the total energy consumption after the transport sector with 38% (Figure 11). Furthermore, the breakdown of the domestic energy consumption shows that space heating accounts for almost 60% of this energy consumed (as shown in figure 12).
According to DECC (2011), 94% of the fuel used for domestic space heating is fossil fuel, primarily gas with 83% of the share (Figure 13 below). Hence, reducing emissions and meeting the GHG reduction targets by at least 80%\(^9\) by 2050 in the UK necessitates the phasing out the use of fossil energy for heating. Accordingly, the electrification of the heat sector and generating the associated electricity from renewable sources plays a major role in the shift to a less carbon intensive society in the years to come.

\(^9\) Relative to 1990 levels
There has been a radical technology shift in the heat sector in the UK since the 1970’s ((DECC), 2010). Gas boilers became the dominant technology after rising from a low market share 40 years ago. This is illustrated in Figure 14 showing that over 20 million households used gas for heating by the end of 2006, having risen from 7 million in 1970.
The estimated total number of households in Great Britain was 25.3 million in 2006 (ONS, 2011). The Domestic Energy Fact file published by the Building Research Establishment (Utley and Shorrock, 2008), shows that 2.5 million households used electric heating, 1.8 million used solid fuel and oil and nearly 21 million used gas for heating at the end of 2006 (Utley and Shorrock, 2008). Almost half of the electric heating is storage heaters, which leaves up to 24 million households that can be retrofitted to a low carbon heating technology.

The 2050 Pathways Analysis Report (herein Pathways) ((DECC), 2010) forecasted in the future scenarios different combinations and proportions of electric heat versus bio heat technologies (community scale biomass or biogas CHP, stirling engine micro CHP, individual building scale boiler). This research assumes that half of the households will switch to biogas and biomass fueled technologies and the other half will switch to electric heat. This results in 12 million household using electric heat. It is also assumed that half will use electric heat storage and the other half will use heat pumps. Therefore 6 million households could be retrofitted with electric storage heaters.

The literature review has demonstrated that the share of installed wind capacity that contributes to generation system adequacy is limited because of its variable and uncertain output. Generation system adequacy refers to the issue of whether there is sufficient installed capacity to meet the electric load (Billinton and Allan, 1996, Keane et al., 2011). The contribution of wind generation to system adequacy is assessed by the notion of capacity value. A suitable methodology to calculate the capacity value of wind was determined, it will be detailed in the following section. Moreover, the review suggests that demand response in particular electric storage heaters could contribute in the increase of capacity value. To test this hypothesis, a load model that incorporates the new electric heating technologies will be developed. Then it will be used in the capacity value calculations.
3. Methodology

3.1. Capacity Value

The methodology is based on the Taskforce preferred approach as mentioned in the literature review. The method is based directly on the definition of capacity value as the amount of additional load that can be served due to the addition of the generator, while maintaining the existing levels of reliability (Billinton and Allan, 1996, Keane et al., 2011). The level of reliability could be evaluated by several risk indices, the most commonly used is the Loss of Load Expectation (LOLE)

1. Calculation of the value of $\text{LOLE}_{\text{ref}}$ of the risk index before the additional generation (i.e. wind) is introduced.
2. Introduction of the additional generation to the risk calculation.
3. The capacity value of the additional generation is the additional demand which returns the risk index to its original value $\text{LOLE}_{\text{ref}}$.

The next step is to determine the Loss of Load Expectation (LOLE)

3.1.1. LOLE

There is no absolute guarantee in any electricity system that all demands can be met at all times (Gross et al., 2006). Probability techniques exist to quantify this risk; they are divided into analytical techniques and simulation techniques. The analytical techniques include the loss of load method and the frequency and duration approach. The simulation techniques are described by the Monte Carlo simulation. The technique used in this research will be the Loss of load. According to (Billinton and Allan, 1996) this method is the most widely used probabilistic technique for evaluating the adequacy of a given generation configuration.
The loss of load risk index can be defined as the Loss of Load Probability (LOLP) which is the probability that the load will exceed the available generation at a given time. Furthermore, the risk index can also be defined as the Loss of Load Expectation (LOLE) which is the expected number of hours or days during which the load will not be met over a defined time period (Billinton and Allan, 1996, Keane et al.).

The Loss of load risk index is determined as follows: the Generation and Load models are convolved to result in the Risk model that reflects the overall adequacy of the generation system. The models are described by probability distributions.

![Figure 15: Adequacy evaluation steps (Billinton and Allan, 1996)](image)

In an adequate power system the LOLP and LOLE should be kept very small (Gross et al., 2006). The pre-privatized electricity system required a LOLP\textsuperscript{10} value of 9% (Gross et al., 2006, Strbac et al., 2007). It is important to note the loss of load indices does not provide any indication of the frequency, duration and the severity of potential shortage (Billinton and Allan, 1996, Strbac et al., 2007). The following steps then are determining the generation model and the load model.

\textsuperscript{10} The LOLP is expressed as a percentage that is the maximum number of years per century in which load shedding may occur. 9%LOLP means 9 winters per century when the load will be lost.
3.1.1.1. Generation Model

The power system in theory may be running at full capacity with no failure of the individual units, zero capacity because of the failure of all the individual units, or at some intermediary capacity because of the failure of some of the individual units (Billinton and Allan, 1992). The probability distribution for the available conventional (or unavailable) generating capacity is derived through a Capacity Outage Probability Table (COPT) method.

The COPT can be determined using different methods. The simplest is using the binomial distribution that could represent the system if the units on the system had identical capacities, unavailabilities and the unit outages are independent and random (Billinton and Allan, 1992, Billinton and Allan, 1996). The binomial distribution is expressed as:

\[(p+q)^n\]

Where
\[n=\text{number of units}\]
\[p=\text{probability of an available unit}\]
\[q=\text{probability of an unavailable unit (FOR)}\]

In addition,

\[(p+q)^n = \sum_{r=0}^{n} nCr \cdot p^r \cdot q^{n-r} = 1\]

Where
\[r=\text{Number of available units}\]
\[n-r=\text{Number of unavailable units}\]
\[nCr=\text{The number of Combinations of } r \text{ available units from the total number of units } n\]

\[= \frac{n!}{r!(n-r)!}\]

\[\text{Where factorial of a number } x \text{ is denoted by } x! = 1*2*3*\ldots\ldots* (x-1)*x\]
To illustrate the equations above, the COPT is deduced for a system consisting of 3 units of 5 MW each and the probability of a unit failing is the same for all units and equal to 0.02.

<table>
<thead>
<tr>
<th>Units available ($r$)</th>
<th>Capacity available (MW)</th>
<th>Capacity out (MW)</th>
<th>Individual Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>15</td>
<td>$3C_0^* (0.98)^0 \times (0.02)^3 = (0.02)^3$</td>
</tr>
<tr>
<td>1</td>
<td>5</td>
<td>10</td>
<td>0.001176</td>
</tr>
<tr>
<td>2</td>
<td>10</td>
<td>5</td>
<td>0.057624</td>
</tr>
<tr>
<td>3</td>
<td>15</td>
<td>0</td>
<td>0.941192</td>
</tr>
</tbody>
</table>

**Total Probability** = $(p+q)^n = 1$

*Table 5: COPT example*

To be able to use the binomial distribution to determine the COPT of the actual power system, all the units are assumed identical with a capacity of 500 MW each, and characterized by a probability of unavailability or Forced Outage Rate (FOR) of 0.15. Strbac et al., (2007) used these assumptions in one of their studies to deduce the COPT that was part of a model that calculated the capacity value of wind in the UK.

The National Grid Seven Year Statement, lists information about the generating units including the effective unit capacity data of all the power plants (Grid, 2010). The conventional units’ capacity range from 7.5 MW Open Cycle Gas Turbines units at West Burton to 685 MW oil fired units at Littlebrook. Assuming that all generating units are identical is far from the actual situation, however determining the COPT of the system from a more complex methodology where an assumption is not necessary can be left for future follow up of this research. One method uses the principle of the binomial distribution in conjunction with other rules of probability to form a recursive technique that could be used when the components are not identical. Another technique is based on a Fourier transform method. However, for simplification purposes and since it was
used by other studies, the units on the system are assumed to be identical and the binomial distribution is used.

The operational generation capability at the start of winter 2010/2011 was 75.2 GW excluding wind capacity (National Grid, 2010). Wind power cannot be modeled by its capacity and FOR value because the wind availability is a matter of resource rather than mechanical availability (Dent et al., Keane et al., 2011). The wind then will be modeled as negative load. More details about this step will be described in the Load model section.

Back the COPT calculation of the conventional power system, assuming 500 MW per unit, will result in 150 identical units in the system with each unit having a force outage rate (FOR) of 0.15. So, to determine the Capacity Outage Probability Table (COPT) of the system or in other words, to determine the generation model of the system necessary for the calculation of the reliability index, a table similar to the table above is deduced, describing all the possible capacity levels of the system.

<table>
<thead>
<tr>
<th>Units available (r)</th>
<th>Capacity available (MW)</th>
<th>Capacity out (MW)</th>
<th>Individual Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>75000</td>
<td>1.3124E-127</td>
</tr>
<tr>
<td>1</td>
<td>500</td>
<td>74500</td>
<td>1.1453E-124</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>116</td>
<td>58000</td>
<td>17000</td>
<td>0.000555739</td>
</tr>
<tr>
<td>119</td>
<td>59500</td>
<td>15500</td>
<td>0.003115495</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>150</td>
<td>75000</td>
<td>0</td>
<td>1.35056E-11</td>
</tr>
</tbody>
</table>

*Table 6: COPT of the actual power system (sample)*
3.1.1.2. Load model

The load models used in this methodology are time series of hourly values of load for 1 year for Great Britain [28/03/2010-27/03/2011]. The data is downloaded from the European Network of Transmission System Operators for Electricity data portal (ENTSO-E, 2011). Different load models will be used; the details of how they are determined will be described in the following sections. Each of the load models will be convolved with the generation model described above (COPT) to result in the Loss of Load Expectation specific of the load model used. The LOLE value gives an indication about the adequacy of the power system. Low values of LOLE indicate an adequate system. Table 7 lists details about the different load models used.

<table>
<thead>
<tr>
<th>Load model name</th>
<th>details</th>
<th>Max load (MW)</th>
<th>Min Load (MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CurrentLoad</td>
<td>Actual time series of hourly load values</td>
<td>58,824</td>
<td>19,425</td>
</tr>
<tr>
<td>ProjectedStorage</td>
<td>Projected time series of hourly load values incorporating 6 million storage heaters</td>
<td>59,304</td>
<td>21,045</td>
</tr>
<tr>
<td>ProjectedResistive</td>
<td>Projected time series of hourly load values incorporating 6 million resistive heaters</td>
<td>70,824</td>
<td>19,425</td>
</tr>
<tr>
<td>Storage&amp;Resistive</td>
<td>Projected time series of hourly load values incorporating 6 million storage heaters and 6 million resistive heaters</td>
<td>71,304</td>
<td>21,045</td>
</tr>
</tbody>
</table>

Table 7: Load model used

3.1.1.2.1. Current Load

The current load values for Great Britain for one year are loaded into R. Figure 16 below shows the histogram of the values. It can be seen that 40,000MW is the most occurring value, and with no values under 20,000 MW or over 60,000 MW.
The methodology used to quantify the change introduced by the new electric heat storage load will be explained next. The Department of Energy and Climate Change, 2050 Pathways analysis ((DECC), 2010) (herein Pathways) state that the demand for electricity will increase due to significant electrification of some sectors including the residential heat sector. In order to emphasize the role of residential electric heat storage, electricity demand for the other sectors is assumed to be the same in this research. As a consequence, the projected demand load profile will show the change introduced from the residential heat sector only. Moreover, it is assumed that the number of households is constant, the domestic
internal temperature (comfort level) and thermal efficiency (level of insulation, airtightness) are the same as current levels.

It was demonstrated in the literature review that up to 6 million households could install electric storage heaters. The following step then is to determine how the 6 million households will change the total load profile of the UK. It is assumed that these users will have a similar electricity demand to the Domestic Economy 7 users that use night time storage heaters. However, as mentioned previously, the storage heaters will charge during night time and whenever there will be wind. In the following, only the effect of night time storage will be captured. Therefore, 6 million users are assumed to have a load profile similar to the Economy 7 users which does not take into account times of high wind output during the day for example.

The UKERC Energy Data Centre published average demand load profile data for Domestic Unrestricted users and the Domestic Economy 7 users (UKERC, 1997a). These two types of profiles will be used to change the current total load profile which will result in the projected load profile. The profiles will be explained first, and then the approach used to estimate the new load will be detailed.

3.1.1.2.2.1. Profile description

Figure 17 below shows the daily pattern of demand for the average domestic Unrestricted and Economy 7 customers respectively, during a winter Wednesday. The Economy 7 peak is at 2.5 kW and it takes place over night, this illustrates the charging time of the heater. The Unrestricted user has a lower electricity demand. However it is important to note that this does not mean that the overall energy consumption of the Unrestricted user is lower because evidently his load profile does not account for his fossil fuel consumption for heating.
Investigating the role of electric heat storage in increasing the capacity value of wind power

Figure 17: Domestic load profile for Unrestricted and Economy 7 users (UKERC, 1997b)

The Economy 7 load profile changes over the seasons to reflect the change in heat demand. Figure 18 illustrates the profiles for autumn, winter, spring, summer and high summer. This seasonal division is defined by UKERC as explained in table 1 below.

Figure 18: Domestic Economy 7 seasonal load profiles (UKERC, 1997b)
### Seasons Definition of seasons

<table>
<thead>
<tr>
<th>Seasons</th>
<th>Definition of seasons</th>
</tr>
</thead>
<tbody>
<tr>
<td>Summer (Smr)</td>
<td>Defined as the ten-week period, preceding High Summer, starting on the sixteenth Saturday before the August bank Holiday. [15/05/10-23/07/10]</td>
</tr>
<tr>
<td>High Summer (Hsr)</td>
<td>Defined as the period of six weeks and two days from the sixth Saturday before August Bank Holiday up to and including the Sunday following August Bank Holiday.[24/7/10 – 29/08/10]</td>
</tr>
<tr>
<td>Autumn (Aut)</td>
<td>Defined as the period from the Monday following the August Bank Holiday, up to and including the day preceding the clock change from BST to GMT in October.[30/08/10 – 31/10/10]</td>
</tr>
<tr>
<td>Winter (Wtr)</td>
<td>Defined as the period from the day of clock change from British Summer Time (BST) to Greenwich Mean Time (GMT) in October, up to and including the day preceding the clock change from GMT to BST in March.[1/11/10 – 27/3/11]</td>
</tr>
<tr>
<td>Spring (Spr)</td>
<td>Defined as the period from the day of clock change from GMT to BST in March up to and including the Friday preceding the start of the summer period.[28/3/11 – 13/5/11]</td>
</tr>
</tbody>
</table>

*Table 8: Definition of seasons according to UKERC (1997b)*

3.1.1.2.2.2. Estimating the new load profile

First, the Economy 7 and unrestricted load profiles will be multiplied by 6 million which will result in the total change that will be introduced by all the electric storage heat users. Figure 19 and 20 illustrate respectively the multiplied profile for the winter period of Unrestricted and Economy 7 users. Figure 20 shows up to 15 GW of demand that can be controlled and it is supposed to be supplied all from wind. Second, the Unrestricted total load profile will be subtracted from the ENTSO-E winter period data (Figure 21). The figures below represent one day in December. The same procedure of subtraction will be repeated for all 365 days.
Investigating the role of electric heat storage in increasing the capacity value of wind power

Figure 19: Unrestricted demand user profile

Figure 20: Economy 7 demand user profile

Figure 21: Load minus 6 million unrestricted users
Finally, the projected load will be obtained by adding 6 million Economy 7 users to the intermediate load (Figure 22).

The projected load profile shows the increase in electric demand estimated by the pathways due to the electrification of heat. While the current peak did not change, using controllable electric storage heaters prevented a new peak to occur since all the load was added at night time, when demand is low.

In conclusion, the same procedure will be applied 365 times and the new 8760 hourly values of the projected load will be used in the calculation of the adequacy index that will be used to determine the capacity value of wind. Figure 23 below lay out the general steps taken to determine the new seasonal profiles and then combine them to form the new yearly load profile.
Another two load profiles, Projected resistive and Storage&Resistive described below, were identified to be able to compare the results of capacity value of wind for different load models.
3.1.1.2.3. Projected Resistive

6 million resistive heaters of 2kw each are added to the current load during the winter season from 5pm until 10pm. Figure 24 illustrate the change for a winter day.

![Current vs Projected resistive Load](image)

Figure 24: Current vs Projected resistive Load

3.1.1.2.4. Storage & Resistive

6 million resistive heaters are added for the winter period during 5pm and 10 pm to the Projected Storage load profile. Figure 25 illustrate the change for a winter day.

![Current load and load integrating storage and resistive heaters for GB-Winter day](image)

Figure 25: Current vs Storage & Resistive load
3.1.2. Generation and Load models ready to calculate LOLE

Now that the generation model and the load models are determined, the next step will be to determine the Loss of Load Expectation. It is important to note that capacity outage mentioned in the generation model is different than loss of load. Capacity outage indicates a loss of generation which may or may not result in a loss of load. The loss of load depends on the generation capacity reserve margin and the system load level (Billinton and Allan, 1996). A loss of load will occur only when the capability of the generating capacity remaining in service is exceeded by the system load level (Billinton and Allan, 1996). Outages of capacity in excess of the reserve will result in varying numbers of time units during which loss of load could occur (Billinton and Allan, 1996). Expressed mathematically, the contribution to the system LOLE made by capacity outage $O_k$

$$= pk \times tk \text{ time units}$$

Where $pk$ is the individual probability of the capacity outage $O_k$

The Loss of Load Expectation for the study interval is described in the expression below.

$$LOLE = \sum_{k=1}^{n} pk \times tk \text{ hours/year}^{12}$$

Where

- $pk$= Probability of existence of the $k$ capacity outage
- $tk$= time units in the study interval that loss of load will occur if the $k$ capacity outage were to exist

In other words, this means that a particular capacity outage level $k$ will contribute to the system LOLE by an amount equal to the product of $pk$ and $tk$ (Billinton and Allan, 1996).

---

12 The unit is in hours/duration of the study if individual hourly load values are used (Billinton and Allan, 1996)
The following paragraph presents detailed calculations to illustrate the expressions above. Figure 26 shows the cumulative probability distribution function (CDF)\(^\text{13}\) of the total current load values in Great Britain for one year. The CDF indicates the probability of a random variable being less than or equal to some predefined value. Taking for example 40,000MW as one value of the load (random variable), the corresponding probability is 0.68. This means that 68% of the time (time=one year in this case), the load is less than or equal to 40,000 MW. This means that 32% of the time, the load is more than 40,000 MW. It can then be concluded that if a capacity outage of 40000 MW occurs, there will be a loss of load for 32% of the time.

![Distribution function of Current Load](image)

**Figure 26: Cumulative Probability distribution function of the Current Load model**

\(^{13}\)The CDF is obtained by ordering the values of the random variable (i.e. Load) in ascending or descending order (ascending in this case) and, by starting with the probability of occurrence of the smallest or largest value (smallest in this case), sequentially summate, i.e., cumulate, the probabilities of occurrence of each value until all such values have been cumulated. The cumulative distribution function increases from zero to unity as the random variable increases from its smallest to its largest value. (Billinton and Allan, 1992)
In this case

\[ t_k = 0.32 \times 8760 \]

and \( p_k = p(40,000) \text{ from } C0PT = 9.54881E-27 \)

As a result, this will contribute to the overall LOLE of the system by

\[ 9.54881E-27 \times 0.32 \times 8760 = 2.67672E-23 \text{ hours/year}. \]

This number is negligible which makes sense because the probability that 40 GW or 57\% of the generating units will be unavailable is almost impossible. Billinton and Allan (1996) neglect probability values less than \( 10^{-6} \). The LOLE is then the summation of all the outages that contribute to the loss of load. Annex 1 show the code in R that allows a fast computation of LOLE. The result section will present the LOLE of the four different systems corresponding to four different load models and their respective cumulative distribution function.

What was described in the previous sections consisted of the first step in the three-point algorithm described at the beginning of the methodology section:

1. Calculation of the value of \( \text{LOLE}_{\text{ref}} \) of the risk index before the additional generation (i.e. wind) is introduced.
2. Introduction of the additional generation to the risk calculation.
3. The capacity value of the additional generation is the additional demand which returns the risk index to its original value \( \text{LOLE}_{\text{ref}} \).

As mentioned before, wind power cannot be modeled by its capacity and FOR as wind availability is more a matter of resource availability than mechanical availability (Dent et al., Keane et al., 2011). Therefore the time series of wind power output will be treated as a negative load rather than additional generation. So instead of adding wind to the
Investigating the role of electric heat storage in increasing the capacity value of wind power

COPT table, it is combined with the load time series, resulting in a load time series net of wind power (Keane et al., 2011). Then, step 2 becomes introduction of wind power output as a negative load to the risk calculation. After that, in the same manner as step 1, the same generation model will be convolved with the new model net of wind power to obtain LOLE which will be lower than the \( \text{LOLE}_{\text{ref}} \). Evidently, \( \text{LOLE} \) will be lower because the generation system stayed the same while the load decreased.

The capacity value of the additional generation, wind in this case, equals the additional demand which returns the new \( \text{LOLE} \) to \( \text{LOLE}_{\text{ref}} \). This is done by an iterative process that increases the load data by a constant across all hours and the \( \text{LOLE} \) is recalculated at each step until the target \( \text{LOLE} \) is reached (Keane et al., 2011). The result section will show the capacity values obtained for all the systems.

3.1.3. Data requirements

The results of the capacity value calculation are dependent on the input data. In order to obtain good results, spatial and temporal data requirements are necessary. Temporal requirements relate to wind and load. The requirements include the length of the period of the study and the temporal resolution of the data. Spatial requirements relate to wind. They include the geographic distribution of the metering stations to ensure that the wind time series profile is representative of the whole country. The calculation should be based on hourly data for accurate results. Moreover, the calculated capacity value depends strongly on the correlation of wind and load (Hasche et al., Keane et al.), wind and load data need to be correlated. For example, hourly load data of one year should be used in conjunction of the hourly wind power output for the country for the same period. Moreover, according to (Hasche et al.) calculations based only on one year of data show large variations. It is important to base the calculation on more than one
year of data to capture the inter-annual variability of wind (Ela et al., 2010, Hasche et al., Keane et al., 2011).

The final section in the methodology describes the wind data.

3.1.4.  Wind data

Wind power output is a commercially sensitive information so it is hard to find especially for the whole country (Aguirre et al., 2009). The alternative is to derive it for the whole UK by using the Met Office measurement data of wind speed and transform it into wind power output using the power curve of the respective wind turbine types provided by the manufacturer. However, the wind speed is measured at 10m and wind speed at turbine height needs to be derived from the 10 m dataset. An applicable methodology from the EEA (2009) to determine wind speed at hub height is detailed in Annex 2. Nevertheless, some data will further need to be determined such as the roughness $Z_0$ of the land cover that affects wind speed at higher altitudes and calculating this information will be a lengthy process. This means an alternative dataset is preferable for this research.

The Sustainable Electricity Distributed Generation (SEDG) center made publically available half-hourly wind profile for one year (UKGDS, 2004). The wind profile is normalized i.e. it has a peak of 1. So to find the actual wind output in GW from a wind power plant of a given capacity, the normalized value should be multiplied by the wind plant capacity. Two wind profiles are calculated for 26 GW$^{14}$ and 39 GW installed capacity. These numbers represent a 20% and 30% electricity generation from wind respectively. The code for this algorithm (Annex 1) will be run in R platform, giving the LOLE and the capacity value.

$^{14}$ According to Strbac et al. (2007), the capacity utilisation factor of wind is 35% and the total electricity demand is 400 TWh. $0.2\times400=8760\times0.35\times X$, $X=26 \text{ GW}$ and $0.3\times400=8760\times0.35\times Y$, $Y=39 \text{ GW}$
4. Results and Discussion

“The future will be all electric” (Sebastian De Ferranti, 1910).

According to the 2050 Pathways Analysis report (2010), published by the Secretary of State for Energy and Climate Change, a range of different routes exist to successfully shift to a low carbon economy. The different pathways which are emphasized in the Carbon Plan include the need to substantially electrify the heat sector (DECC, 2011a, (DECC), 2010). By investigating the role of 6 million households using electric heating in increasing the capacity value of wind, this research assumes a contribution to the new radical technology shift that should take place in the heat sector.

Another common message from the 2050 Pathways Analysis report is that electricity supply would increase to meet the demand of new electric applications including heat ((DECC), 2010). Evidently the electricity will need to be decarbonised. Wind power will have a large contribution in the 2050 supply mix given the vast wind resource in the UK and its leading competitive position among other technologies ((DECC), 2010, Strbac et al., 2007, EEA, 2009). Nevertheless, the variable and uncertain nature of the wind means that it cannot be relied on at all times to meet the demand. As a consequence, and as demonstrated by several studies, the share of installed wind capacity that contributes to generation system adequacy is limited (Gross et al., 2006, Keane et al., 2011, Strbac et al., 2007). Generation system adequacy refers to the issue of whether there is sufficient installed capacity to meet the electric load (Billinton and Allan, 1996, Keane et al., 2011).

The aim of this research is to demonstrate how to increase the share of installed wind capacity that can displace conventional generation while maintaining demand and
supply balanced at all times. If this could be achieved, renewable power can displace more conventional generation and contribute to the shift to a low carbon energy system.

The working hypothesis of this study is that electric heat storage as an example of flexible load could increase the share of installed wind capacity that displaces conventional generation while maintaining demand and supply balanced at all times.

The contribution of wind to system adequacy is assessed by the notion of capacity value. A suitable methodology to calculate the capacity value of wind was identified. To test the research hypothesis, a load model representing the storage heaters was developed which will be used for the capacity value calculation. The methodology was modeled using statistical techniques and the code for the algorithm was run on R platform. The results will be detailed in the following sections.

According to Keane et al. (2011) study, the LOLE of the power system in GB was 0.061 hours/year before adding wind generation. The LOLE calculated before adding wind generation in this research for GB, is 0.013 hours/year which shows that the power system is even more reliable than what Keane et al. (2011) demonstrated. Furthermore, since this research used actual load data, the difference between the two LOLE values could be because a simplified generation model was used in this research.

Keane et al. (2011) mentioned that there is not a formal LOLE target in Great Britain\(^{15}\). A sensitivity study was conducted; the results (Table 9) show the variation in risk (LOLE) as a function of the unit size. As a consequence, the unit size in the model was changed from 500 to 460 MW to obtain the same LOLE as Keane et al. (2011). 

---

\(^{15}\) For example the LOLE standard in Ireland is 8 hours/year

Table 9: LOLE sensitivity study results.

Table 10 shows the results LOLE calculations for the system with the different load models used and the related capacity value. It can be noticed that including 6 million electric storage heaters does not affect the overall adequacy of the system. LOLE stayed very small. Evidently, this is because the storage load was added at night when demand was low. However, it was argued in this research that adding electric heat storage as a form of flexible demand would increase the capacity value of wind. The calculations proved this hypothesis wrong. The increase in capacity value is not significant with only 0.2%.

On the other hand, the capacity value increased to 16.5% when the load model was adjusted to incorporate resistive heaters consuming electricity at time of peak. 6 million resistive heaters were added in the winter season from 5pm till 10 pm. Evidently, the Loss of Load Expectation became very high because the generation capacity could not meet this high demand. Paradoxically the capacity value of wind increased. This can be surprising at first, however when looking closely to how the capacity value is calculated, the outcome makes sense.

The third point in the capacity value methodology algorithm expresses the capacity value as the additional demand which returns the risk index to its original value. According to this requirement then, the risk needs to return from 78 to 199 in
comparison to returning from 0.051 to 0.11. It is now evident why the capacity value is much higher when demand increases. It can be concluded then, that in risky systems where demand is very high and might not be supplied, the risk index will increase. The increase of the index will result in a high amount of capacity value. Keane et al.(2011) state that the capacity credit result increases as demand is increased.

**Wind installed capacity: 26 GW**

<table>
<thead>
<tr>
<th>Load model</th>
<th>LOLE w/o wind (hour/year)</th>
<th>LOLE with wind (hour/year)</th>
<th>Capacity value (MW)</th>
<th>% of installed capacity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Current Load</td>
<td>0.063</td>
<td>0.029</td>
<td>590.8</td>
<td>2.3%</td>
</tr>
<tr>
<td>Projected Storage</td>
<td>0.1128</td>
<td>0.051</td>
<td>667</td>
<td>2.5%</td>
</tr>
<tr>
<td>Projected Resistive</td>
<td>175.11</td>
<td>68.26</td>
<td>4287.8</td>
<td>16.5%</td>
</tr>
<tr>
<td>Storage and Resistive</td>
<td>199.37</td>
<td>78.57</td>
<td>4518.8</td>
<td>17.4%</td>
</tr>
</tbody>
</table>

*Table 10: LOLE and capacity value results for different load models and installed wind capacity=26GW*

Table 11 below, shows the results of LOLE and capacity value calculations for the four models, however with a 39 GW installed capacity that corresponds to 30% electricity demand supplied from wind.

**Wind installed capacity: 39 GW**

<table>
<thead>
<tr>
<th>Load model</th>
<th>LOLE w/o wind (hour/year)</th>
<th>LOLE with wind (hour/year)</th>
<th>Capacity value (MW)</th>
<th>% of installed capacity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Current Load</td>
<td>0.063</td>
<td>0.028</td>
<td>674.5</td>
<td>1.7%</td>
</tr>
<tr>
<td>Projected Storage</td>
<td>0.1128</td>
<td>0.049</td>
<td>702.3</td>
<td>1.8%</td>
</tr>
<tr>
<td>Projected Resistive</td>
<td>175.11</td>
<td>63.33</td>
<td>5063.4</td>
<td>13%</td>
</tr>
<tr>
<td>Storage and Resistive</td>
<td>199.37</td>
<td>72.37</td>
<td>5403</td>
<td>21%</td>
</tr>
</tbody>
</table>

*Table 11: LOLE and capacity value results for different load models and installed wind capacity=39GW*

The same observations as above, apply in this case. In addition, it can be noted that while the MW of capacity value is increasing the % of installed capacity is decreasing. It can be concluded that capacity value as a percentage of installed wind capacity
decreases with increasing wind capacity. This was highlighted in several studies (Gross et al., 2006, Keane et al., 2011, Strbac et al., 2007). Moreover, Keane et al., (2011) mention that this is because at higher wind capacities the possibility of very low output becomes more important on a system scale.

The capacity value of wind power obtained in this research for the current load is 2.3% of installed wind capacity, when wind penetration level is 20% of the total electricity demand. This number is lower than the capacity value determined by the Taskforce on the capacity value of wind power (Keane et al., 2011). This could be because of the different wind and generation models used.

The results of the capacity value calculation are dependent on the input data as shown by the sensitivity studies above. The SEDG wind profile includes a five-day period with 0 wind output, another period of 3 days with 0 wind output, and several shorter periods of 24 hours or less with a 0 wind power output. The majority of this 0 output occurrences took place in winter which coincides with high electricity demand. Consequently, this will decrease the capacity value of wind. The frequency distribution of wind output is illustrated in Figure 27 below. As mentioned, the majority of values are near zero.

Sinden (2007) investigated the characteristics of the UK wind resource long term patterns and its relationship to electricity demand. The author analyzed wind data for a time period of 30 years and examined the occurrence of extreme low and high wind speed events in the UK wind record, including periods during which wind power output would be curtailed. Sinden (2007) found that there is a slight increase in both average and maximum areas affected by low wind speed conditions during hours of high electricity demand, however the impact of these events is modest. A trend of increasing energy production from wind power during high electricity demand periods
was identified which increases the value of wind in meeting peak electricity demand. Moreover, the authors states that calm conditions persisting for one day are extremely rare and when they occur they cover a small fraction of the UK. According to Sinden (2007), the most widespread occurrence of calm conditions for one day impacted just 6% of the UK and the likelihood of this occurring is one day every 10 years. In addition high wind speed events are extremely rare and no hours were identified where electricity production from wind power throughout the UK was curtailed due to extreme events of low or high wind speeds.

![SEDG wind profile for 26 GW installed capacity](image)

*Figure 27: Frequency distribution of SEDG wind profile power output*

Furthermore, connecting wind farms over a large geographical area will greatly reduce the variability output of wind (Archer and Jacobson, 2007, Sinden, 2007). If one location is experiencing low wind regime, a geographic dispersion of the farms makes the probability that the same wind regime is experienced at another site low. Moreover the interconnection ensures that a low wind regime at one area will not affect the output of the whole system. In conclusion, wind speed data based on actual measurements in
geographically diverse locations in the UK should not present zero wind output based on Sinden’s (2007) observations above. If new measurement data is used, the resulting capacity value could be higher.

The Weibull probability density function is often used in wind energy engineering to describe wind speeds (RETSCREEN, 2001). It will be used to illustrate the effect of input data. The distribution has less 0 values then the SEDG profile (Figure 28). Using the same generation and load models, Table 26 shows that the capacity value of wind is higher when a Weibull density function is used as the wind model.

![Wind profile random Weibull Distribution](image)

**Figure 28: Wind model based on Weibull density function**

<table>
<thead>
<tr>
<th>Load model</th>
<th>Random installed wind capacity (GW)</th>
<th>Capacity value (MW)</th>
<th>% of installed wind capacity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Current Load</td>
<td>31</td>
<td>4785</td>
<td>15%</td>
</tr>
<tr>
<td>Projected Storage</td>
<td>28</td>
<td>5080</td>
<td>18%</td>
</tr>
<tr>
<td>Projected Resistive</td>
<td>31</td>
<td>7449</td>
<td>24%</td>
</tr>
</tbody>
</table>

*Table 11: Capacity Value with Weibull density function as the wind model*
5. Conclusion

The aim of this research was to demonstrate how to increase the share of installed wind capacity that contributes to system adequacy. Increasing this share while maintaining the levels of system adequacy means that conventional capacity is displaced which could accelerate the shift to a low carbon energy system.

However wind is variable and its contribution is low. Several studies mentioned methods to increase the role of wind in displacing conventional capacity. These methods include large scale storage or hydro electricity to fill the gaps between supply and demand. This research argued that residential electric heat storage could play a role in increasing the role of wind in displacing conventional capacity. However, the results obtained showed that it doesn’t. The capacity value of wind did not increase because of residential storage, quite the opposite it only increased in risky systems where demand exceeded the supply. It is likely that another methodology should be identified that could capture better the importance of residential storage heat on the capacity value of wind. It was mentioned in the literature that several indices can be used in the capacity value calculation beside LOLE, it would be worth to check if these indices could be more suitable for this case.

The results should not underestimate the role that Electric Storage heaters could play in decarbonising the energy system. The introduction of 6 million heaters maintained the same level of system adequacy. Moreover, their role in displacing gas heating contributes in meeting the GHG targets and increases the energy security of the country.
Investigating the role of electric heat storage in increasing the capacity value of wind power

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Investigating the role of electric heat storage in increasing the capacity value of wind power


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Annex 1: R code

LOLE Sensitivity analysis

Load
cdfL=load
sysC=75200
unitC=460
FOR=0.15
unitN=floor(sysC/unitC)
timeL=1-cdfL(sysC-seq(from=0,to=sysC-unitC,length.out=unitN))
cotp=dbinom(0:(unitN-1),unitN,FOR)
LOLE=sum(cotp*timeL)*8760
LOLE

Data Preparation of load and wind profiles.

Current Load values:
#Load the current load values contained in the spreadsheet: “Current.csv” into R
Current=read.csv(“C:/Users/HP/Documents/Current.csv”)
#The spreadsheet data is in a compact format that for one row, gives the hour followed by all the observations for that hour (i.e. each row contains 365 observations for a certain hour). However, R’s modeling functions need the observations in a single list (i.e. the table should be transformed into one list containing consecutive 8760 values. This is done by the function “Stack” )
CurrentStacked=stack(Current)

#output the stacked values from R into a new spreadsheet CurrentStacked.csv. Everything but the 8760 values will be kept in the spreadsheet
write.csv(CurrentStacked,”C:/Users/HP/Documents/CurrentStacked.csv”)

#Load the CurrentStacked.csv spreadsheet into R after deleting the unnecessary columns.
CurrentStacked=read.csv(“C:/Users/HP/Documents/CurrentStacked.csv”, header=FALSE)

#Create a numeric vector out of the values for further analysis
CurrentLoad=as.numeric(CurrentStacked)

#Histogram: tells us how many times each load value occured
hist(CurrentLoad, xlab=“Current Load values in GB for one year (MW)”,col=“blue”)

#Cumulative load distribution of the current load values

cdfCurrent=ecdf(CurrentLoad)
plot(cdfCurrent, xlab=“Current Load Values in GB for one year (MW)”)

Projected Load values:

#Load the projected load values contained in the spreadsheet: “Projected.csv” into R
Projected=read.csv("C:/Users/HP/Documents/Projected.csv")
ProjectedStacked=stack(Projected)

#output the stacked values from R into a new spreadsheet ProjectedStacked.csv for further data manipulation. Everything but the 8760 values will be kept in the spreadsheet
write.csv(ProjectedStacked,"C:/Users/HP/Documents/ProjectedStacked.csv")

#Load the ProjectedStacked.csv spreadsheet into R after deleting the unnecessary columns.
ProjectedStacked=read.csv("C:/Users/HP/Documents/ProjectedStacked.csv", header=FALSE)
#Create a numeric vector out of the values for further analysis
ProjectedLoad=as.numeric(ProjectedStacked)

#Histogram: tells us how many times each load value occurred
hist(ProjectedLoad, xlab="Projected Load values for one year (MW)",col="red")

#Cumulative load distribution of the projected load values

cdfProjected=ecdf(ProjectedLoad)
plot(cdfProjected, xlab="Projected Load Values (MW)")

Resistive Load

#Load the projectedPeak load values contained in the spreadsheet: “ProjectedPeak.csv” into R
ProjectedPeak=read.csv("C:/Users/HP/Documents/ProjectedPeak.csv")

ProjectedPeakStacked=stack(ProjectedPeak)

#output the stacked values from R into a new spreadsheet ProjectedStacked.csv for further data manipulation. Everything but the 8760 values will be kept in the spreadsheet
write.csv(ProjectedPeakStacked,"C:/Users/HP/Documents/ProjectedPeakStacked.csv")

#Load the ProjectedStacked.csv spreadsheet into R after deleting the unnecessary columns.
ProjectedPeakStacked=read.csv("C:/Users/HP/Documents/ProjectedPeakStacked.csv", header=FALSE)

#Create a numeric vector out of the values for further analysis
ProjectedPeakLoad=as.numeric(ProjectedPeakStacked)

#Histogram: tells us how many times each load value occurred
hist(ProjectedPeakLoad, xlab="Projected Load values for one year (MW) including resistive electric peak",col="purple")
Investigating the role of electric heat storage in increasing the capacity value of wind power

**Storage & Resistive**

# Load the Storage & Resistive load values contained in the spreadsheet: “SandR.csv” into R

```r
SandR0 = read.csv("C:/Users/HP/Documents/SandR0.csv")
```

```r
SandR0 = stack(SandR0)
```

```r
write.csv(SandR0,"C:/Users/HP/Documents/SandR.csv")
```

# Load the ProjectedStacked.csv spreadsheet into R after deleting the unnecessary columns.

```r
SandR = read.csv("C:/Users/HP/Documents/SandR.csv", header=FALSE)
```

# Create a numeric vector out of the values for further analysis

```r
SandR = as.numeric(SandR)
```

# Histogram: tells us how many times each load value occurred

```r
hist(SandR, xlab="Load incorporating storage and resistive heaters for one year (MW)", col="magenta")
```

**Wind Preparation**

# Preliminary preparation: First, the half hourly SEDG wind profile is transformed into hourly wind profile. Then the profile is multiplied by 26,000 MW. (or by 39,000 for the case of 39GW installed capacity)

# Loading the 26000MW wind profile into R.

```r
wind = read.csv("C:/Users/HP/Documents/WindProfile26000MW.csv", header=FALSE)
```

# Create a numeric vector out of the values for further analysis

```r
wind = as.numeric(wind)
```

# Histogram of the wind profile values

```r
hist(wind, xlab="wind profile values for 26GW installed capacity", col="green")
```

# Random Weibull distribution

```r
wind = rweibull(8760, shape=2, scale=10000)
```
Capacity Value

load = ProjectedLoad

wind = read.csv("C:/Users/HP/Documents/WindProfile26000MW.csv", header=FALSE)
wind = as.numeric(wind)
capacityValue = function(capVal, sysC = 75200, unitC = 460, FOR = 0.15) {
  # Number of conventional generating units (integer)
  unitN = floor(sysC/unitC)

  findLOLE = function(netLoad) {
    # Cumulative load distribution
    cdfl = ecdf(netLoad)
    # Cumulative probability of given load values.
    timeL = 1 - cdfl(sysC - seq(from = 0, to = sysC-unitC, length.out = unitN))

    # Capacity outage probability, given constant FOR.
    coptP = dbinom(0:(unitN-1), unitN, FOR)

    # Calculate LOLE
    LOLE = sum(coptP * timeL * 8760)
    return(LOLE)
  }

  adiff = abs(findLOLE(load) - findLOLE(load-wind+capVal))
  return(adiff)
}

result = optimize(capacityValue, interval = c(0, max(wind)))
result$minimum

paste("The rated capacity of wind is ", round(max(wind), 1), ", but the capacity value is only ", round(result$minimum, 1), sep=""")

---------
Annex 2: Methodology to determine wind speed at turbine height and wind power output

According to the European Environment Agency (2009), wind power can be produced for wind speeds > 4 m/s. The flow chart below presents an applicable methodology from the EEA to determine wind speed data. The wind speed data is measured at 10 m, so wind speed at turbine hub height needs to be derived from 10 m data. For onshore projects height is assumed to be 80 m (EEA 2009). However, the topography of the terrain strongly influences the wind from 0 to 200 m and this need to be taken into consideration when determining the wind speed. The 2 categories of the topography effects affecting wind speed are roughness and orography (EEA 2009). The roughness length $z_0$ expressed in meters is determined using land cover data. $z_0$ is then used to determine the wind speed at hub height. As for orography (i.e., wind speed up near a hill, cliff or a ridge and decelerate in a valley), elevation datasets are needed to determine it.
The power output is determined following a formula by Jenkins et al (2009) shown in the box below. For now the turbine size can be assumed to be 2 MW, the same size used by EEA for onshore and up to 2030 and five, 2MW turbines can be sited in 1 km² (EEA 2009).

Determining the **Power** available at the Wind Turbine.

Wind turbine size: TBD

\[ P_{\text{wind turbine}} = C_p \times (0.5 \times \rho \times A \times V^2) \]

with \( \rho = \text{air density (approximately } 1.225 \text{ km}^{-3} \)\)

\( A = \text{swept area of rotor, m}^2 \) TBD, dependent of turbine size

\( V = \text{Wind speed m/s} \)