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Impact of Variable Generation in Generation Resource Planning Models

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Abstract—Long-term power system planning is beset by a trade-off between detail and scope: The chosen approach usually lies somewhere between modeling a great many generation portfolios coarsely and very few in a more detailed manner. This paper seeks to argue that the performance of generation portfolios is influenced by a sufficiently large number of variables, of varying uncertainties, such that the long-term investment problem can only be effectively tackled with very many runs of computationally light models that capture the most essential features of the problem. Taking a linear optimization program as the intended computational core, this paper describes two algorithms to build constraints for the linear program which capture many of the effects that are difficult or impossible to capture directly in non-chronological models, namely: unit starts, unit ramping, unit average output and adequate total system capacity. An application of these methods is also presented.

Index Terms—Power Generation Planning, Power Generation Reliability, Power System Maintenance, Wind Power Generation

I. INTRODUCTION

INVESTMENTS in power generation tend to be expensive and the plant invested in takes many years to build, often remaining in service for several decades. It can be expected then that a plant commencing service today will operate through a great deal of fuel price surges, regulatory reconfigurations, technology breakthroughs and much else. It is therefore necessary to have some rational means of comparing potential investment pathways. Generation Resource Planning (GRP) models are such a means.

Generation Resource Planning (GRP) models are primarily used to determine optimal future generation plant mixes given diverse sets of inputs, such as fuel prices, construction costs and system load data [1].

An initial consideration is to decide what it is that makes a portfolio optimal. It could be sought e.g. to minimize carbon dioxide emissions with a constraint for maximum total system cost. More typically CO₂ emissions are treated by taxing emissions in the model and minimizing total costs instead. The objective function is then a sum of costs, including a term for CO₂ costs.

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It has been recognized that a number of the inputs to these models are subject to significant amounts of uncertainty. The forecast price of emissions allowances could be said, for example, to be subject to significant uncertainty. In a GRP model that only considers cost, two portfolios with equal expected costs, but vastly different emissions could not be differentiated. If the price of emissions allowances was the largest source of cost uncertainty amongst the inputs, the lower-risk, lower emissions portfolio would surely be preferable. This trade-off between cost and risk in power generation portfolios has been noted and investigated by many authors [2]–[4]. These efforts have concentrated on uncertainty associated with the forecasting of model inputs, particularly fuel prices. This paper seeks to model an element of cost uncertainty that is particularly relevant to systems with large amounts of variable generation, namely the cycling of thermal generation. Cycling refers to the variation of the output of individual generators in response to system demand. Of particular relevance are large, rapid changes in output i.e. ramping; unit stops and starts; and part load operation. It has been estimated that the costs associated with cycling are large in many instances but are specific to, for example, the particular plant design and its operational history [5]. Of particular relevance are the costs of cycling units which were not designed for cycling operation, i.e. base-load units such as combined cycle gas turbines, nuclear fission reactors of all kinds and large coal-fired units [8].

It cannot be easily inferred what the cycling costs of units will be over their lifetime, especially where new generation technologies are being used. In planning studies, it is proposed here that estimates be made of the quantity of the cycling operations that would result in a cost, and penalties be assigned to these operations, defined by probability distributions rather than single values. This paper describes an algorithm—herein referred to as the *Cycling Module*—that can be used to estimate the quantity of cycling behavior. This is particularly relevant for systems that have, or are considering the integration of large quantities of variable and uncertain generation such as wind power or solar energy. The variability of these resources induces start/stop behavior and large, sudden ramps, while the uncertainty increases the part-load operation by increasing the need for operational reserves. This algorithm will be described in Section II.

Another particular impact of variable generation on GRP models is in the estimation of a suitable amount of total generation capacity on the system. Even in the absence of variable generation, a satisfactory estimate of adequate total installed capacity is subject to significant uncertainty. The

peak system load, for example, can only be known within large bounds of error, while unit and transmission outages can only reasonably be treated as random events. It is therefore preferable to make use of probabilistic methods [6]. It is then possible to determine an amount of total capacity that meets a defined system adequacy constraint, such as Loss Of Load Expectation—the number of hours where the load exceeds available capacity—or Expected Unserved Energy, the quantity of energy that could not be met during these hours.

It is proposed here that adequate capacity calculation methodologies need to be improved to take full account of variable generation. In particular the way in which maintenance schedules are produced needs to be modified. Generating units are typically subject to one significant scheduled service outage a year and so it has been typical to schedule this maintenance for times of low system load. Electricity demand often has a seasonal aspect to it, owing to e.g. winter lighting loads in countries towards the earth’s poles, or summer air conditioning loads in equatorial climates. Therefore, the majority of units in a system are often scheduled out during a particular period of the year.

However, variable generation also exhibits seasonal trends. This isn’t particularly important for systems where there is a poor correlation between system load and variable generation, as is the case for wind power generation in the United States [7]; but in certain regions, such as Northern Europe, the correlation of system load and variable generation is such that with increasing penetrations of variable generation, the notion of “maintenance seasons” is diluting. Small amounts of variable generation have little impact on the results of these calculations, so for most situations this has not been a problem. However, where large amounts of variable generation has been introduced, the outcome can be substantially different.

The second algorithm presented in this paper determines the quantity of conventional generation capacity, given a desired level of system adequacy and an installed capacity of wind power generation. A test case is presented where this algorithm is used to schedule maintenance for a system with a large installed capacity of wind power and a strong seasonal correlation between load and wind. For this system, a methodology that does not consider the seasonality of the wind generation will yield a maintenance schedule biased strongly towards the summer, while the method presented in this paper schedules units in a much more uniform manner across the year. The outcome is an installed capacity that comes a lot closer to actually providing the desired level of system adequacy.

The two algorithms discussed are being used as part of a generation resource planning model called SIFT that is currently in development. This model will be detailed in future work.

The capacity calculation algorithm is described in Section III, while the algorithm for estimating the quantity of cycling operations is discussed in Section II.

II. CYCLING MODULE

The accurate determination of the amount of cycling operations that a particular set of generating units is likely

to undergo is best achieved by use of a stochastic, mixed-integer, rolling unit commitment and dispatch tool such as the WILMAR planning tool [8]–[10]. However, the length of time it takes to schedule even a moderately sized system with a tool such as this renders this approach impractical given that in planning studies, it is usual to consider large numbers of inputs and portfolio combinations.

The following approach seeks to approximate the schedules of these full scheduling tools by emulating the observed systematic behavior of groups of units in them. Modeling the behavior of units indirectly in this way may not be suitable for every plant mix configuration but it is hypothesized that the information gained through approaches such as this should be relatively robust. Additionally, while preliminary testing of the outputs of this module has been favorable, for studies that make use of it, the outputs of the module can be compared against those of full scheduling tools.

A. Algorithm

It is observed that the units in a system can be roughly separated into two distinct *unit groups*. The first group consists of the units with some combination of high thermal efficiencies and high startup costs. These units will avoid going off-line, partly because the cost of restarting them is high, but also because a high thermal efficiency makes them less costly as a source of operating reserve. In simulated and real schedules it can be seen that these units tend to go through daily cycles of full output during high-load periods and reduced output during low-load periods. An important feature is that the least-cost solution is observed to be a proportional reduction in the output of the units. An illustration of this is shown in Figure 1 where the darkly shaded units reduce their outputs proportionally for the night valley and increase them again for the morning rise.

The remainder of units form another discernable group. These units are too costly to provide reserve and they also tend to have reduced startup costs and so only the unit at the bottom of the order of merit varies its output, while all the units higher up the merit order—i.e. with lower operating costs—remain online at their rated output.

Defining the output of the unit groups in this way allows for the rapid solution of the output of each unit. The only possible operational states are listed in Table I.

TABLE I
POSSIBLE UNIT STATES IN CYCLING ALGORITHM

Avoid Starts Group	Max Output Group
Fully Off	Fully Off
Group Output	Fully On
	Incremental Unit Output

It should be noted that the labels applied to the two groups have been chosen to avoid ambiguity. The *Avoid Starts* group is an attempt to characterize base-load *operation*, though the units have not been labeled as such. This is because the *Max Output* group contain units that would typically be

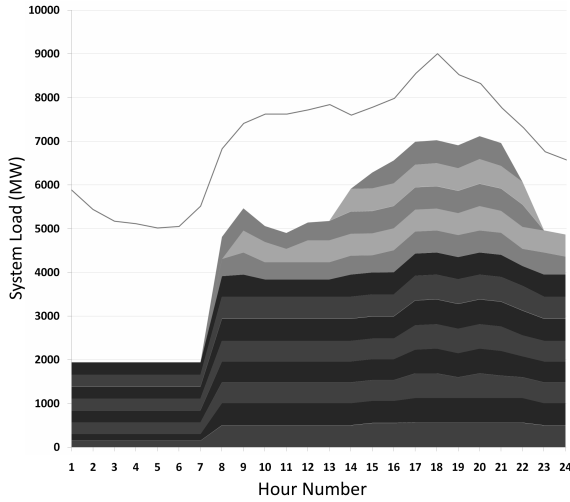


Fig. 1. An actual WILMAR unit schedule, with system load curve, for Irish test system July 1st 2020. Includes only large units that were not forced or scheduled out during that day.

characterized as base-load units, but are not operating in a base-load manner.

The general procedure is outlined in pseudo-code in Algorithm 1. The first step, performed by `getMarginalGroup()`, is to determine which *group* of units is marginal with respect to the system load. Given that the *Avoid Starts* group is first in the merit order, this group will be marginal when the system load (less wind) is less than the capacity of this group. The *Max Output* group will be marginal at all other times.

Once the marginal group has been determined, `setSuperMarginalGroupsFullyOFF()` sets groups lower in the merit order to be fully off while groups higher in the merit order are set fully on by `setSubMarginalGroupsFullyON()`.

The next function is illustrated graphically in Figure 2. Given the merit ordering of groups, and that each unit has a range of possible outputs, for any level of total generation there will be a range of the number of units that could be online.

When the *Avoid Starts* group is the marginal group, the maximum number of online units is selected, as choosing any less would induce startups. When the *Max Output* group is marginal, it is sought to have the minimum possible number of units online, maximizing the thermal efficiency of the group as a whole.

Algorithm 1 Cycling Module Algorithm

```

for each hour do
  getMarginalGroup()
  setSuperMarginalGroupsFullyOFF()
  setSubMarginalGroupsFullyON()
  getMarginalGroupOnlineUnits()
  setOutputValues()
  setRampingValues()
  countStarts()
end for
return results

```

B. Results

Taking system load, wind and generator data from the All Island Grid Study Portfolio 5 test system [11] and an extensive wind capacity factor data set, the capacity module was run and results are presented herein. A description of the data set used is given in the Appendix.

1) *Average Output*: It is seen that, consistent with the principle of the method, the average output of online units and all units in the *Avoid Starts* group is similar. This implies that very few units are ever taken offline in the *Avoid Starts* group.

The *Max Output* group shows a high average output for online units, consistent with its design. The average output of all units in the group is very low, implying that these units are used far less often than the *Avoid Starts* group. This is consistent with the group's lower position in the merit order.

2) *Unit Starts & Unit Ramping*: Referring to Figure 4 it can be seen that the *Avoid Starts* group has a greater number of total starts over the year than the *Max Output* group. This might initially seem surprising but it must be noted, referring to Table II, that the *Avoid Starts* is most often the marginal group, reflected in the residual load duration curve (Figure 5), where residual load is defined as the remaining load once variable generation has been subtracted from it. It should also be noted that while the residual load duration curve runs into negative values, the module always schedules a defined minimum of generation to maintain system inertia. This minimum was set to 1000 MW here, equal to the sum of minimum outputs of the 5 largest units on the test system.

The sum of absolute ramps, i.e. the sum of the absolute values of the derivative of the unit group output series, is a great deal larger for the *Avoid Starts* group. This is explained by the same reasoning as the increased starts.

TABLE II
PORTION OF HOURS AS MARGINAL GROUP (%)

Avoid Starts Group	Max Output Group
88.24%	11.76%

III. CAPACITY MODULE

This module determines the quantity of thermal generation capacity that is required on a system to meet a particular level of system adequacy. It is designed primarily for systems with significant amounts of variable generation such as wind or solar power. With the use of sufficient quantities of (preferably real) variable generation data and some basic thermal generator data, this module can provide an accurate estimate of adequate capacity and also a cost-optimal maintenance schedule for the thermal units on the system.

The general procedure for generation adequacy algorithms is as follows:

- 1) Choose a portfolio of units.
- 2) Choose an adequacy target (LOLE, EUE, etc.).
- 3) Take a load series for year (daily peaks or hourly values).
- 4) Schedule units out at times of low load.

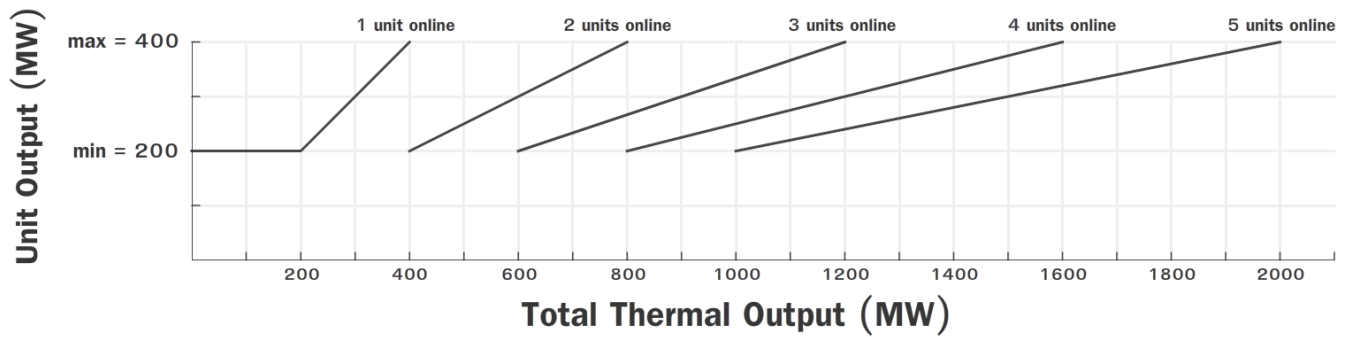


Fig. 2. Number of Units Online for any Given System Load

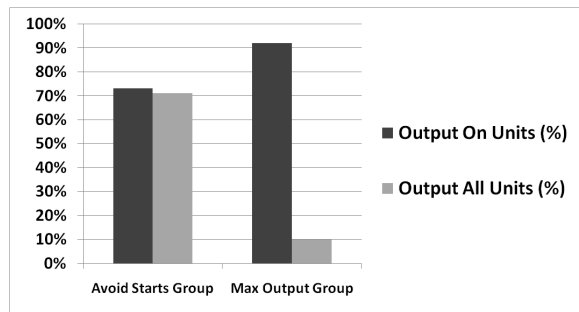


Fig. 3. Average Hourly Output of Units by Group.

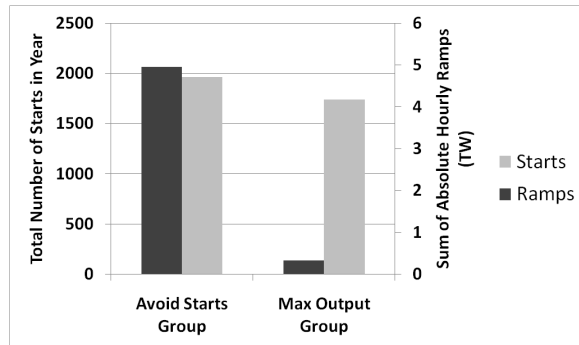


Fig. 4. Annual Starts & Ramps by Unit Group.

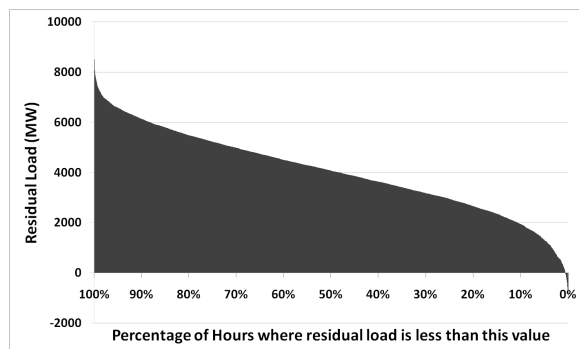


Fig. 5. Residual Load Duration Curve for test case.

- 5) Probabilistically determine a forced outage series.
- 6) Count the number of hours where the load exceeds available generation.
- 7) Adjust the initial portfolio to move closer to the chosen

adequacy target.

- 8) Repeat steps until the portfolio comes satisfactorily close to meeting the system adequacy constraint.

This procedure is limited for two particular applications.

Scheduling units for maintenance at times of low load takes no account of variable generation. As explained in Section I, where there is a significant installed capacity of variable generation, the maintenance schedule may become driven to an increasing extent by the variable generation profile. Where this is the case, these schedules effectively reduce the capacity value of the variable generation, and a system that employs the schedule will have to either over-build capacity or suffer reduced system reliability.

Another limitation is that the initial guess at the portfolio size has a strong impact on computation time. For models designed to be used by non-specialists it is not feasible to expect a "good" guess, neither is determining a good guess straightforward programmatically. For studies where the capacity of variable generation is a variable, the problem becomes even more challenging. For multi-stage models, which may not have any user interaction between stages, an uncertain computation time can be problematic when e.g. data is being passed between different programmatic environments in the execution of the model.

A. Algorithm

To account for the seasonal character of variable generation output, this module splits the year in to time periods. In this case, a 15-minute resolution data-set of system wind output between 1999 and 2008 for the Republic of Ireland was taken and split into 12 equal time periods, roughly equivalent to each month. There was therefore 10 years of data for each of the time periods, or about 350,000 values per period. The module samples these periods, so a choice has to be made as to whether the raw data should be sampled or a suitable distribution be created to match the data and the distribution be sample instead. The advantage of the latter option is that once the distributions for each periods have been created, the module only needs a set of parameters to characterize the wind output for the whole year. Sampling the raw data requires that the raw data be loaded to memory before it can be sampled. For large data-sets, this can take a significant length of time, which may not be suitable for certain modeling approaches.

There is therefore a trade-off here between the correctness of the samples and the execution time of the model.

The module can run in several modes to accommodate this. For the purposes of this paper, the raw data was sampled but for the larger planning model SIFT, of which this is just an element, suitable parameters for Weibull distributions have been determined so that the execution time of this model is not excessive.

The execution procedure the module undergoes is summarized in algorithm 2.

Algorithm 2 Capacity Module Algorithm

```

Build an approximate portfolio
Read in system load, residual load, wind data set
for each month wind data set do
  for each hour in month do
    Take a random sample
    Subtract it from load series
    Place result in Expected Residual Load (ERL) series
  end for
end for
for each unit do
  convolve maintenance period with ERL series
  schedule unit for maintenance at minimum
  add unit's capacity here to offline capacity series
end for
for each unit do
  determine length of "forced outage cycle"
  randomly place unit outage in this interval
  add unit's capacity here to offline capacity series
end for
for each hour do
  requiredCapacity(hour) = residualLoad(hour) + offlineCapacity(hour)
end for
sort requiredCapacity series
select requiredCapacity(hour) where hour = LOLE + 1
return this value

```

The portfolio selection step need only be approximate. This is the unit set that is scheduled for maintenance and subject to outages. If the initial amount of capacity is very different to the resulting adequate capacity, the portfolio can be changed and the module run again.

The *Expected Residual Load* (ERL) time-series is created by subtracting a random sample from the relevant monthly wind distribution, for each hour of the load time-series.

Then, for each unit, the ERL series is convolved with a vector of ones of length equal to the the number of hours the unit is offline during a maintenance period. For any particular hour of the resultant convolved series, each value is equal to the amount of residual load that the unit would be offline for, if it were to commence maintenance on that hour. The minimum of this series is therefore a suitable time to go out on maintenance, and so the units rated capacity is added to the *offline capacity series*, a series of length equal to the number of hours in the year.

Forced outages must then be applied to each unit. Each unit has a *Forced Outage Rate* (FOR), which gives the percentage of time that a unit is expected to be offline due to unscheduled outages. Each unit also has a *Mean Time to Repair* (MTTR), usually of the order of 50 hours. Any repair period could have started in the previous year, could be contained in the current year or might begin in the current year but end in the following year. The number of possible Repair Period Start Combinations (RPSC) is given in Equation 1, where *hours* is the number of hours in the study year.

$$RPSC = \text{hours} + MTTR - 1 \quad (1)$$

Units can then be placed on outage at random start hours until the forced outage rate has been reached. The outage hours that fall within the year are added to the offline capacity series.

The offline capacity series is then added to the residual load (load minus wind) series. This new series can be thought of as the amount of available thermal generation capacity that is required at each hour.

This series is then sorted in descending order, and finally the value at the r th hour is selected as the adequate generation capacity.

$$r = LOLE + 1 \quad (2)$$

It should be noted that the ERL time-series used in this algorithm is highly erratic and so could not be used as a simulated residual load series. It can however be used for these purposes, as the thermal units are out on maintenance for many hundreds of hours which results in the high frequency variation being smoothed entirely in the convolved series.

B. Results

Referring to Figure 6, it can be seen that there is a relatively large variation between runs, consistent with the uncertainty pertaining to wind output and forced outages. This is the expected outcome. The standard deviation was taken of the completed runs for every run and it can be seen that the standard deviation converges over greater numbers of runs. The adequate capacity results and the standard deviation of these results have been plotted on different scales. This has been done to demonstrate the trend in the standard deviation values.

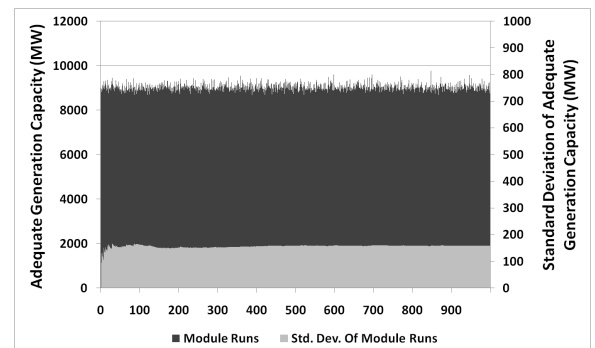


Fig. 6. Results of 1000 runs of the capacity module.

IV. CONCLUSION

With the advent of increasing capacities of variable generation on some systems, the traditional methods of generation resource planning have to be changed.

Units that have previously been characterized as base-load units will be subject to increasing amounts of cycling operation. If the costs of cycling are accounted for in long-term planning models, then more optimal decisions can be made with respect to generation investment. It may be found that portfolios that appeared to be low-cost may in fact be a great deal more costly, and that the composition of future generation fleets will have to adjust to take account of cycling.

As well as the price of fuel, emissions permits and other typical uncertain inputs, portfolio optimization models must also consider the cost uncertainty associated with operational risks such as cycling. In this way, the variance in the expected cost of cycling, as well as the expected cost of cycling can be included in planning studies. This will be pursued as part of future work.

Variable generation also modifies the generation adequacy problem. The seasonality of variable generation output has a strong impact on the scheduling of unit maintenance. This is especially important where there is a strong positive correlation between system load and variable generation output.

The scope of potentially viable power generation portfolios has increased. In generation resource planning models, it will be necessary to test very many portfolios. Additionally, the uncertainty in many of the inputs has to be accounted for, so that portfolios are characterized by not only their expected cost, but also their expected cost risk.

The modules described are part of a larger generation resource planning model, SIFT, which is being developed with the objective of accounting for the aforementioned impacts of variable generation.

APPENDIX

All-Island Grid Study data set

The data used in this paper is drawn primarily from workstream 2A of the All Island Grid Study [11]. The simulated system load time-series is an extrapolation of the real hourly system load from 2003, grown at 3% per year until 2020. The simulated system wind profile is based on real hourly system wind grown in such a manner as to model the effects and limits of geographical diversity on the all-island system. Unit rated output, minimum stable output, forced outage rates, mean time to repair and duration of maintenance periods were taken directly from the study, which were derived from a number of sources.

The study is available for download from <http://dcenr.gov.ie/>

Wind Power Distributions

Wind power capacity factor distributions for each month were derived from a data set provided by the Irish transmission system operator, EirGrid. It consists of energy meter readings at 15 minute intervals from 77 wind farms starting on 1/1/1999 and ending on the 31/12/2008. The capacity and location of each site is given in the data set.

REFERENCES

- [1] Hobbs, B.F., *Optimization Methods for Electric Utility Resource Planning*, European Journal of Operational Research 83, 1995.
- [2] Awerbuch, S., *Portfolio-based Electricity Generation Planning Policy Implications for Renewables and Energy Security*, Mitigation and Adaptation Strategies for Global Change, 2006.
- [3] Roques, F., *Fuel Mix Diversification Incentives in liberalized Markets: A Mean-Variance Portfolio Theory Approach*, Energy Economics, 2007.
- [4] Doherty, R., Outhred, H., O'Malley, M., *Establishing the Role that Wind Generators may have in Future Generation Portfolios*, IEEE Transactions on Power Systems, 2006.
- [5] EPRI, *Damage to Power Plants Due to Cycling*, 1001507 Palo Alto, CA, 2001.
- [6] Billinton, R. and Li, W., *Reliability assessment of electric power systems using Monte Carlo methods*, Plenum Publishing Corporation, 1994.
- [7] North American Electric Reliability Corporation, *Accommodating High Levels of Variable Generation*, Special Report, April 2009.
- [8] Troy, N., Denny, E., O'Malley, M.J., *Base-load cycling on a system with significant wind penetration*, IEEE Transactions on Power Systems, To be published.
- [9] Tuohy, A., Meibom, P., Denny, E., O'Malley, M.J., *Unit commitment for systems with significant installed wind capacity*, IEEE Transactions on Power Systems, May 2009.
- [10] Weber, C., Meibom, P., Barth, R., Brand, H., *WILMAR: A Stochastic Programming Tool to Analyze the Large-Scale Integration of Wind Energy*, Optimization in the Energy Industry, 2009.
- [11] All-Island Renewable Grid Study - Workstream 2A, *High Level Assessment of Suitable Generation Portfolios for the All-Island System in 2020*, 2006. Available from <http://www.dcenr.gov.ie/>



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