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Risk-Return Incentives in Liberalised Electricity Markets

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Abstract: We employ Monte Carlo analysis to determine the distribution of returns for various electricity generation technologies. Costs and revenues for each technology are arrived by means of a sophisticated unit commitment and economic dispatch algorithm. The results show that small amounts of coal investment along with high investment in advanced CCGT can reduce the risk of baseload-only portfolios, while flexible generation technologies appear on the efficient frontier when all technology types are considered. Diversification incentives regarding operational considerations dominate over incentives to diversify between fuel types

JEL Classification: Q40

Key Words: Power generation, mean-variance portfolio

1 Introduction

The liberalisation of electricity markets has given rise to a new focus on investment incentives in electricity generation technologies. In the past, investment decisions were taken by government-owned utility companies whose notional mandate was to provide electricity generation, transmission and supply at least cost. Generation investments were therefore determined primarily based on the cost and availability of fuel Hobbs (1995) and the size of system demand. Concerns over climate change and energy security have led to a new focus on the environmental impacts of electricity generation, as well as a reluctance to depend heavily on energy imports. Thus the objectives of electricity generation have become multi-faceted. Given that the contributions of electricity generation mixes towards these objectives are largely no longer determined by a central planner, but instead are dependant on private investment decisions, it is prudent to examine the risks and returns of investment in various electricity generation plants. Such examination should account for uncertain fuel and carbon prices, with generator remuneration based on the marginal cost of electricity provision. Increasing amounts of variable renewable generation, which demand increased flexibility of operation from conventional generation, require that unit commitment and economic dispatch be employed in performing such analyses.

In determining optimal portfolios when accounting for both risk and return, we utilise the methodology of mean-variance portfolio (MVP) theory. MVP theory was initially developed to analyse diversification portfolios of financial securities (Markowitz, 1952) and has since been applied in many other areas, including electricity generation portfolios. The utilisation of MVP theory allows the methodologies and results of this paper to compare well with other work undertaken in this area.

1.1 Literature review

The majority of the literature in this area concentrates on determining the mean-variance efficient frontier from a system or social planner perspective. Historically this was appropriate due to the reasons outlined above but least-cost scheduling is now no longer sufficient as it ignores generator returns from a private investor's perspective. Bar-Lev and Katz (1976) apply MVP theory to the electric utility industry in the USA. They found that US electric utilities were sufficiently diversified but that their portfolios generally had high risks and high returns. They propose the 'cost-plus' regulatory regime, in which costs are always recovered, as the reason for the move towards high risk portfolios. Humphreys and McClain (1998) evaluated the energy consumption mix in the USA using MVP methods and found that the electric utility industry was operating at a position of low risk. They postulate that the move of the electric utility industry toward more efficient points of production since 1980 is due to the relative risk aversion of the industry, but that a desire for higher returns under liberalisation had given rise to a switch to gas in the 1990s.

Awerbuch (2000, 2004, 2005) uses MVP theory to examine the impact of adding renewable technologies to generation mixes. Awerbuch's approach maximises return on investment (MWh/€) for a given level of risk and finds that renewables can decrease portfolio cost and risk in spite of the fact that their stand-alone costs are high. These results are again arrived at from a focus on system returns and risks, rather than those of private investors. Jansen et al. (2006) analyse the efficiency of the Dutch generation mix under various scenarios by attempting to minimise cost for a given level of cost risk. Their focus is on the societal benefit from reduced cost risk and renewable generation peneration. Doherty et al. (2006) examine optimal electricity generation portfolios for higher levels of wind generation, again by minimising system costs while accounting for increased levels of cost risk. Roques et al. (2010) use MVP methods to identify the optimal wind power deployment portfolio across Europe from a cost minimisation perspective. Instead of cost level and risk, they examine the level and variability of wind generation under different wind capacity installations across Europe. They find that both the current and the planned renewable portfolios are not on the efficient frontier, and a coordinated approach across Europe for renewable deployment would result in a lower level of risk for the same wind capacity investment.

Delarue et al. (2011) use MVP theory, again from a system cost minimisation perspective, to identify the efficient frontier using quadratic constrained programming (QCP) to account for both investment and fuel costs. Thus the capacity factor for each type of generation is determined within the analysis. They find by taking capacity factor as an endogenous variable arising from the economic dispatch of the generation technologies available that changes are seen in the optimal portfolio. As QCP is used, however, economic dispatch only can be modelled with no way of including unit commitment and start costs. Such omissions become increasingly significant as renewable generation increases, as noted above. Furthermore there is no examination of electricity prices or the incentives generators will face in choosing their efficient portfolio for investment purposes.

Roques et al. (2008) use MVP theory to determine the optimal generation portfolio from a private investor's perspective, rather than from a system perspective. They use Monte Carlo analysis to obtain a distribution for the net present value per MW of three types of baseload generation (Combined Cycle Gas Turbine, nuclear and coal) and thus to find mean-variance efficient portfolios. They find that the level of correlation between fuel, carbon and electricity prices plays a significant role in the determination of the optimal portfolio. Their work does not calculate generator returns based on the economic dispatch of these generation technologies but instead assumes a fixed capacity factor for each generation type. This also means there is no meaningful way of calculating the electricity price and so the price is assumed to follow a normal distribution, along with fuel and carbon prices. As well as the obvious shortcomings that this methodology entails, it cannot be used to consider mid-merit and peaking technologies, and furthermore is unsuited to analysing systems with increasing penetrations of variable renewable generation.

This paper identifies the efficient frontier of electricity generation investments by simulating both unit commitment and economic dispatch from a least-cost system perspective rather than assuming a capacity factor, and then by using the dispatch arrived at to calculate the returns on each type of plant. This means that the analysis need not be restricted to baseload technologies. By simulating full unit commitment rather than economic dispatch alone, the generator schedule arrived at will prove robust even when the issues surrounding variability which can arise with wind generation are included. The hourly electricity price can also be calculated from the marginal cost of electricity provision at each hour, eliminating the need to obtain the electricity price by sampling from a distribution. In this way the returns of generators under least-cost dispatch and marginal-cost pricing can be determined for any given generation technology.

2 Methodology

The annual operational dispatch and costs are determined by a sub-model, a unit-commitment algorithm called *FAST*, which determines and quantifies the cost of an optimal schedule for each expansion combination. The FAST algorithm (described in Fig. 2) was originally designed to replicate the input-output relationship of a Mixed-Integer Program (MIP) that is outlined in Shortt et al. (2012). In this formulation, units whose size or cycling characteristics are such that a linear representation of their costs would not yield accurate schedules, have been given a mixed-integer formulation. The remaining units, which tend to be numerous, small and flexible, have linear variables to represent their production costs. This substantially reduces computation for the mixed-integer formulation, but the computation time still tends to be impractically high. The FAST algorithm is a response to this problem.

The logic of the algorithm is given in Fig. 2. At each hour, the algorithm will consider a start if the quantity of online inflexible plant is less than the *Net Capacity Demand* (NCD), which equals demand less wind, plus reserve. If this is the case, it will incrementally move forward in time, determining the cumulative saving and the cumulative profit from starting an inflexible unit of each type that has available offline units (if a unit does not start, the flexible plant must generate, at a higher cost). If the type with the largest positive cumulative profit is also the type with the largest cumulative save, or, there has been a type with a positive profit and consideration of further time-steps would not make sense, this type will be committed.

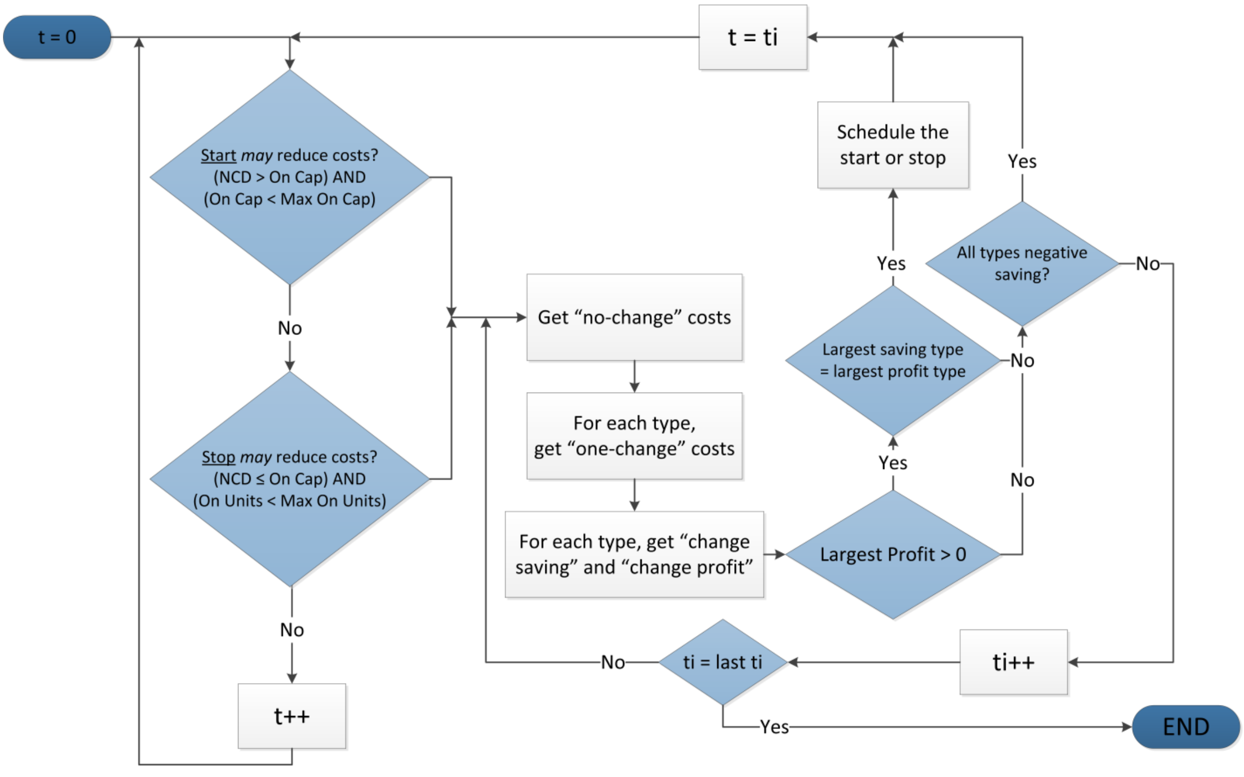

Figure 1: Logical structure of FAST algorithm, in somewhat simplified form.

Reciprocally, where the quantity of online inflexible plant is greater than the net-capacity demand, a similar set of calculations is performed to determine whether a unit stop would be cost-optimal or would be necessary (as where demand falls below the minimum collective output of the inflexible plant).

The FAST model, as described above, is run for a test system. The algorithm also computes the price of electricity as the marginal cost of electricity provision. In order to calculate the Net Present Value (NPV) of each type of investment under consideration over the lifetime of the investment, the simulation is run over thirty years. The legacy plant on the test system is disposed of according to a pre-determined retirement schedule; this mechanism along with an annual increase in demand necessitates the modelling of a capacity expansion. Capacity expansions occur only for those years where the capacity available in the given year proves insufficient to meet the demand for that year. The capacity expansion is determined based on the most profitable plant within a given year. Thus the algorithm assumes that other players in the market do not have perfect foresight and make their investments based on which plants are most profitable in the year under study.

Seven generation technologies are considered in this work. They are Sub-Critical Coal (SubC Coal), Super-Critical Coal (SupC Coal), Advanced Super-Critical Coal (ASupC Coal), Combined Cycle Gas Turbine (CCGT), Advanced Combined Cycle Gas Turbine (ACCGT), Aeroderivative Gas Turbine (ADGT) and Open Cycle Gas Turbine (OCGT). The annual returns for each plant can be calculated by multiplying the dispatch of each plant over the course of the year by the electricity price at each hour (for those hours which saw the plant dispatched). The annual fixed costs for each plant are given by the Weighted Annual Cost of Capital (WACC), as calculated according to the parameters in Table 1. The source of the plant characteristics and capital costs is NREL (2011). The annual variable costs are calculated based on fuel and carbon costs, as well as the plant's particular characteristics, such as efficiency. Thus the NPV of each plant type over the thirty years can be calculated as the sum of the stream of revenues minus costs.

	Build time	Efficiency	WACC	Start Cost	Max Output	Min Output	Plant Life
Units	years	%	/MW	€	MW	MW	years
SubC Coal	5	34	92,400	40,000	500	150	30
SupC Coal	4	40	115,600	40,000	500	150	30
ASupC Coal	5.5	46	138,700	40,000	500	150	30
CCGT	4.5	54	63,900	120,000	500	250	20
ACCGT	3.4	60	76,600	120,000	500	250	20
ADGT	2.5	43	50,400	0		0	20
OCGT	1	33	34,700	0		0	20

Table 1: Generation technology characteristics

Fuel and carbon prices are sampled from a lognormal distribution. A lognormal distribution was chosen as prices are assymmetrically distributed, due to the fact that they cannot be negative. Furthermore, an examination of historical gas, coal and carbon prices from the Energy Information Administration (EIA - www.eia.gov) found that they were well-approximated by a lognormal distribution. The mean values for carbon prices were based on the IEA's World Energy Outlook's price projections IEA (2011) while fuel prices were derived from various sources and the author's own estimates (Figure 2). The standard deviations and correlations of fuel and carbon prices were based on those found in Roques et al. (2008). This facilitates comparison between the results of this paper and those of Roques et al. (2008). These statistics are given in Table 2.

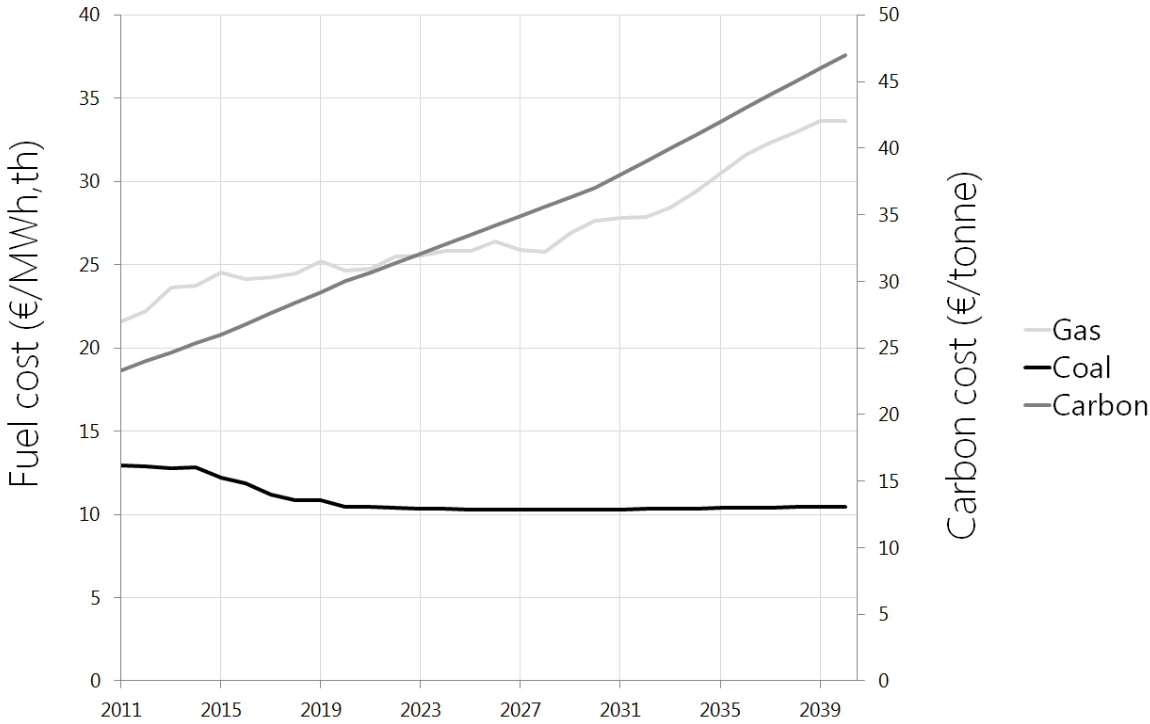

Figure 2 : Fuel and carbon price projections

Correlation coefficient	Gas price	Coal price	CO2 price
Gas price	1	0.56	0.73
Coal price		1	-0.46
CO2 price			1

Table 2: Price correlations

The test system chosen is the Irish electricity market which comprises electricity systems of the Republic of Ireland and Northern Ireland. The Irish system was chosen as it is a small island system with limited interconnection to other systems. For the purposes of this study the interconnection which does exist on the Irish system was ignored. This means that the returns on each of these plants can be calculated without reference to infeeds from another system, and the impact of wind generation on the operation of conventional generation could be captured, rather than seeing high exports at times of high wind. The initial generation portfolio used for this analysis is 1500MW of coal generation, 3500MW of CCGT and 3000MW of peaking generation. The peak demand of the system in the first year is 5000MW with demand increasing over time according to estimates from the system operator, EirGrid plc.

The projected growth in wind generation for the Irish system is also included. The installed wind capacity in the start year (2012) is 2000MW with installed wind capacity reaching 6000MW by the year 2020. No further wind expansion is modelled after 2020. The projected wind production values corresponding to the projected installed capacity figures are were also obtained from EirGrid plc.

The distributions of NPV of each technology which are obtained as described above are used to identify which portfolios lie on the mean-variance efficient frontier. Investors then choose the portfolio which suits them best according to their own preferences and risk aversion. The *portfolio return* $E(r_p)$ for each portfolio P is given by the average of the returns of each component i of the N components of the portfolio weighted by their proportion X_i in the portfolio:

$$E(r_p) = \sum_{i=1}^{N} X_i E(r_i) \tag{1}$$

The *portfolio risk* is given by its standard deviation σ_p:

$$\sigma_p = \sqrt{\sum_{i=1}^{N} X_i^2 \sigma_i^2 + \sum_{i=1}^{N} \sum_{j=1, i \neq j}^{N} X_i X_j \rho_{ij} \sigma_i \sigma_j} \tag{2}$$

where ρ_{ij} is the correlation between asset i and asset j. Thus the inclusion of two assets with negative correlation in any portfolio will decrease the overall risk for that portfolio.

3 Results and discussion

In order to study the returns of each of the generation technologies under study, the simulation is run seven times. Each time, 500MW of the generation technology under consideration is present in year one and remains (ie will not be retired) for the duration of the simulation. The rest of the portfolio evolves around this fixed generation block. While this means that some of the interactions between the various types of generation technologies may not be fully captured, as there is no guarantee that investment will occur in all seven technologies during each simulation, it avoids requiring 3500MW of generation capacity to remain fixed for the duration of the simulation, which would have an undue effect on the evolution of the rest of the generation capacity on the system.

3.1 Efficient baseload portfolios

The efficient frontier of all possible portfolios of inflexible baseload generation is first examined. The space of potential portfolios is searched by increasing the percentage of the portfolio which is made up by each baseload technology in increments of ten percentage points. Figure 2 illustrates the risk-return plot of all baseload portfolios, with the efficient frontier marked.

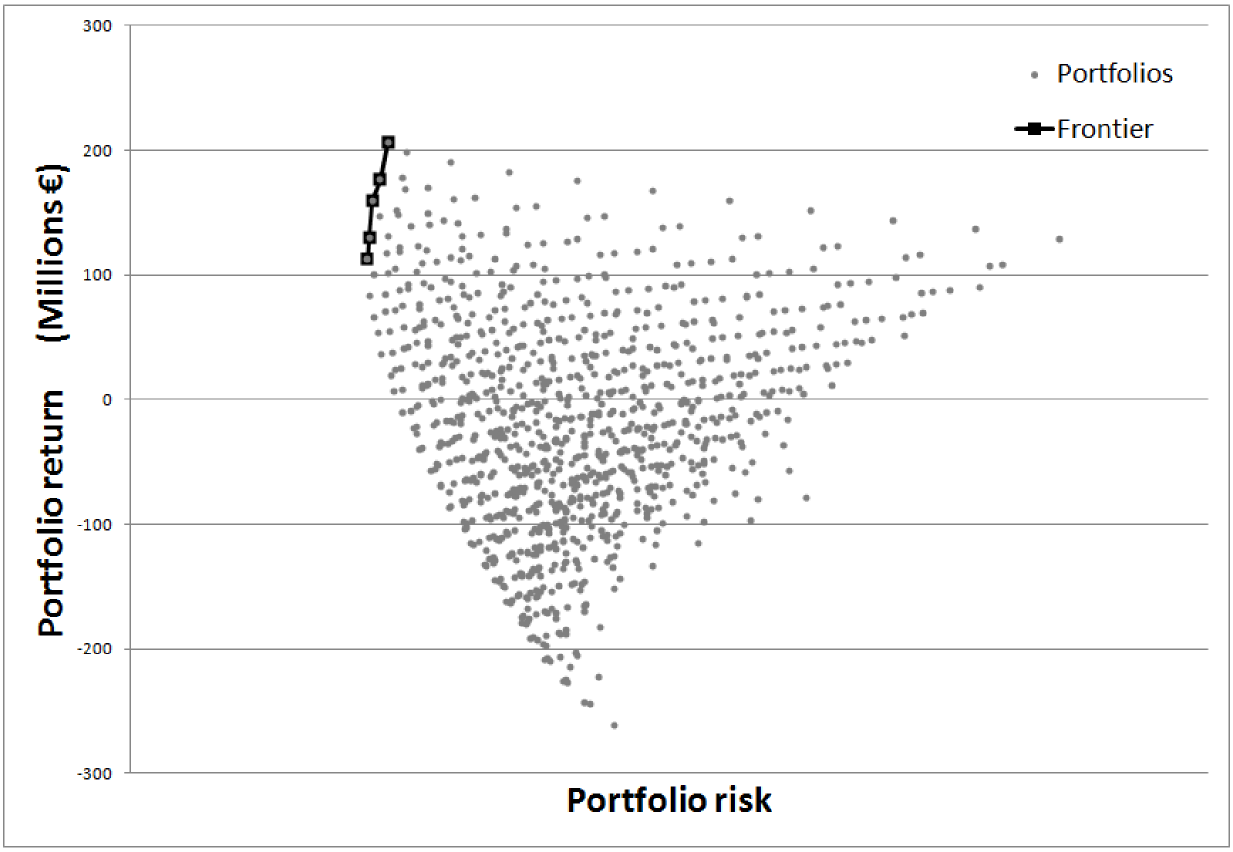

Figure 3: Risk-return plot of baseload portfolios

The composition of the baseload portfolios which appear on the efficient frontier appears in Figure 3. The efficient portfolio of highest risk (and therefore highest return) is that of full investment in advanced CCGT; this is unsurprising as advanced CCGT has the highest net present value on a stand-alone basis. However it appears that the inclusion of coal generation can reduce the risk of baseload-only portfolios. Sub-Critical coal plants do not feature at all, which is unsurprising due to their low efficiency; however Super- and Advanced Super-Critical coal appear in small quantities. This is due to the fact that the minimum generation of coal plants is thirty percent of total output, while the minimum production of CCGT plants is fifty percent. Thus coal units can part-load better than CCGT. Coal plants also have start costs which are significantly lower than those of CCGT plants. These factors combined mean that coal plants can vary their output in response to changes in net load, allowing CCGT units to remain at full operation as much as possible and thus to increase their returns. The increase of variable renewable generation will see such considerations increasing in importance as the increased renewable generation leads to higher variability in net load. Figure 3 does however illustrate that even the baseload portfolio of lowest risk consists of at least seventy per cent advanced CCGT. Thus the incentives to diversify away from gas are limited.

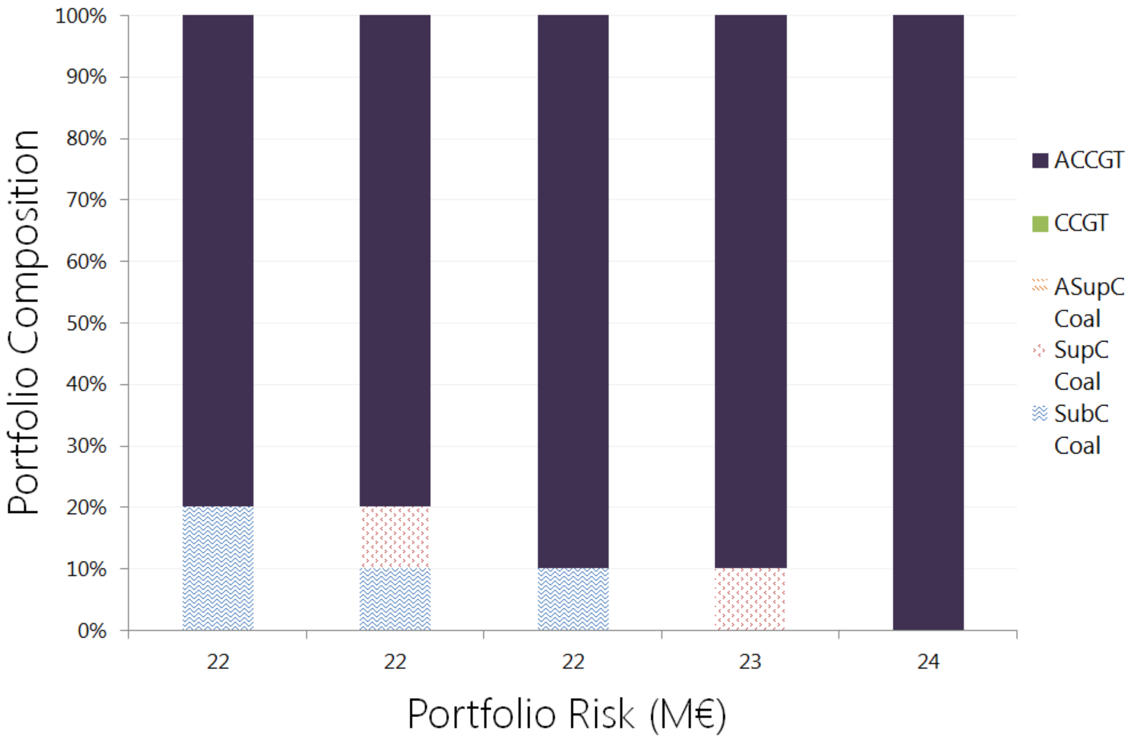

Figure 4: Composition of mean-variance efficient baseload portfolios

The fact that there is indeed a frontier of efficient baseload investments, rather than one optimal portfolio, is in contrast to Roques et al. (2008). They find there is only one efficient portfolio, that of full investment in CCGT. Thus it appears that the inclusion of unit commitment and endogenously determined dispatch can capture some variation which affects the profitability of pure baseload portfolios. This is unsurprising as the consideration of the risk-reducing effects outlined above, such as the ability of coal plants to part-load, cannot be captured by assuming a capacity factor and ignoring start costs as Roques et al. (2008) did. Furthermore, in order to further explore the source of the difference between our findings and those of Roques et al. (2008) we examine the electricity prices which arise from the FAST model. Taking a fixed data set for demand and wind, and a fixed generation portfolio, we run the FAST model one hundred times, taking fuel and carbon prices from lognormal distributions as described above. The electricity prices found are given in Figure 4. The prices have two clusters, one around the lower price seen when a baseload plant is the marginal unit, and another cluster around the higher prices seen when peaking plants are the marginal unit.

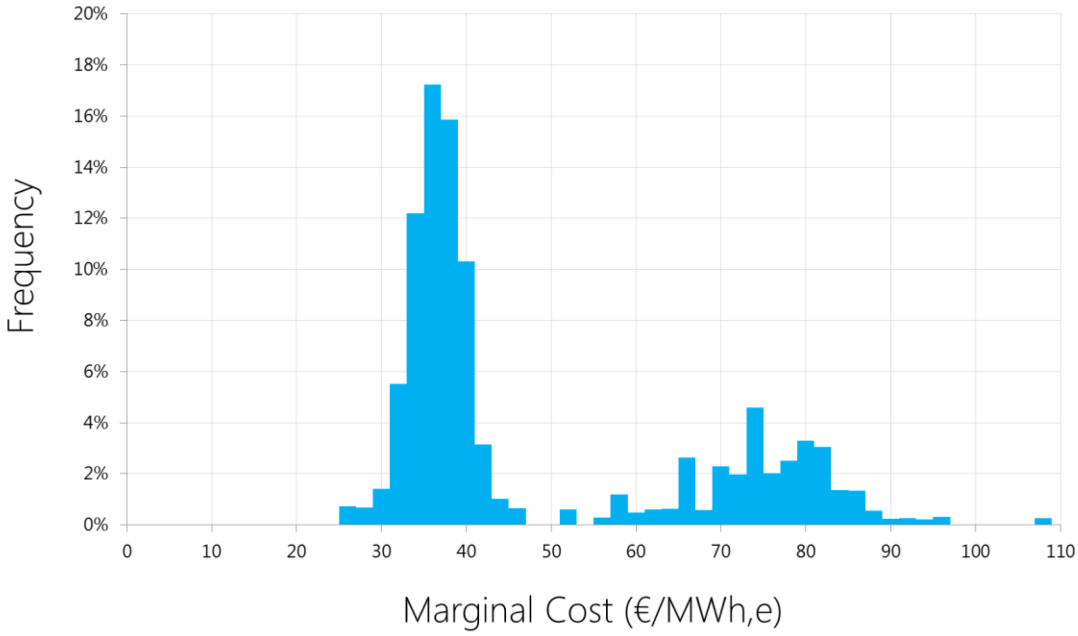

Figure 5: Electricity prices arrived at by the FAST model

Roques et al. (2008) used a unimodel distribution, rather than a bimodal one as in Figure 4. roques thus did not take account of the variation of prices during the course of the day due to the difference in marginal cost between baseload and peaking plant. This, along with the unit commitment and economic dispatch considerations outlined above, explain the observation of a frontier of efficient baseload portfolios rather than the single efficient point which was observed by Roques et al. (2008).

3.2 Efficient portfolios considering all generation technologies

The whole space of possible portfolios, including those with flexible peaking generation technologies, is then searched, also in increments of ten percentage points. The risk-return plot of each of these portfolios is given in Figure 5, with the mean-variance efficient frontier marked in.

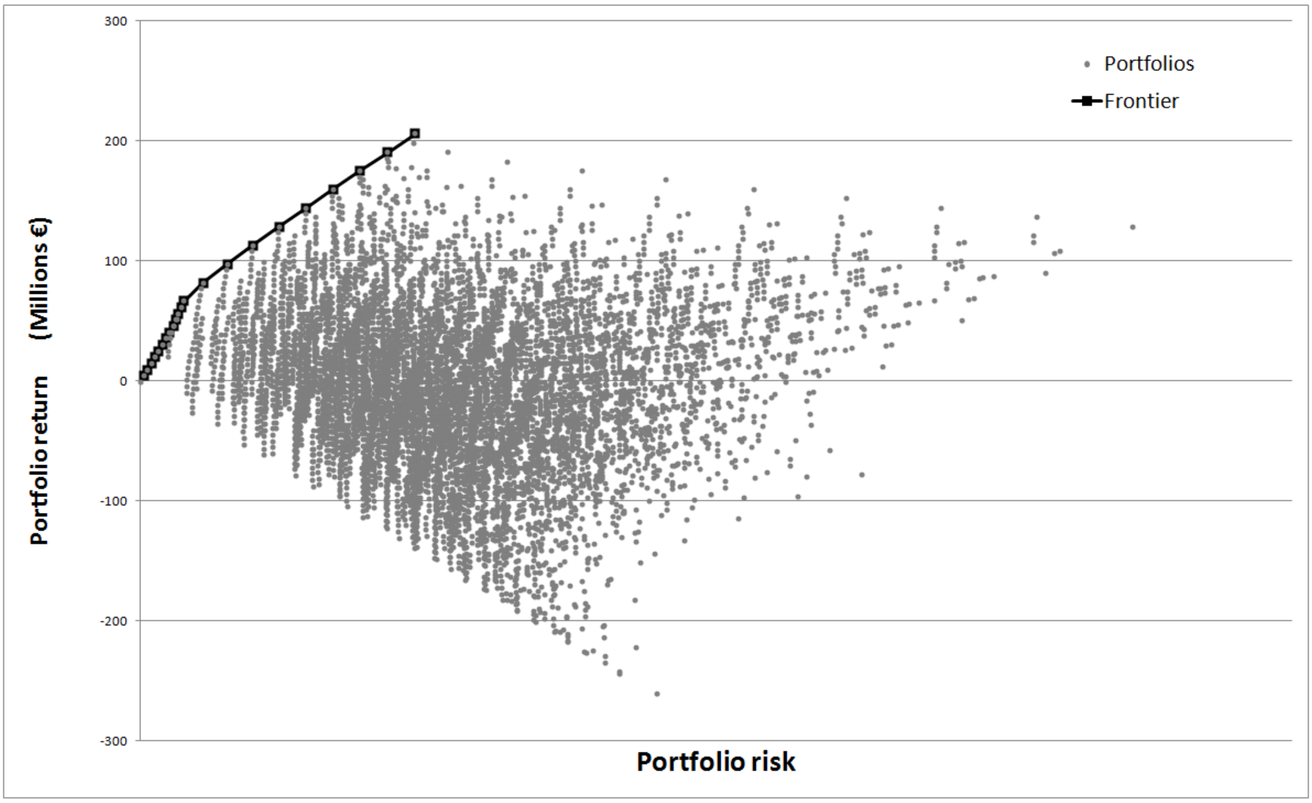

Figure 6: Risk-return plot of electricity generation portfolios

It is clear again that, in contrast to Roques et al. (2008), there is an efficient frontier of investment portfolios; thus there is no one portfolio that provides the best return for any level of risk. Figure 6 shows the composition of portfolios on the efficient frontier arranged according to portfolio risk. None of the coal technologies are to be found on the efficient frontier, and only advanced CCGT units are on the frontier. The portfolio of full investment in advanced CCGT remains the portfolio with the highest return but also the highest risk; the presence of other technologies on the frontier reduce risk.

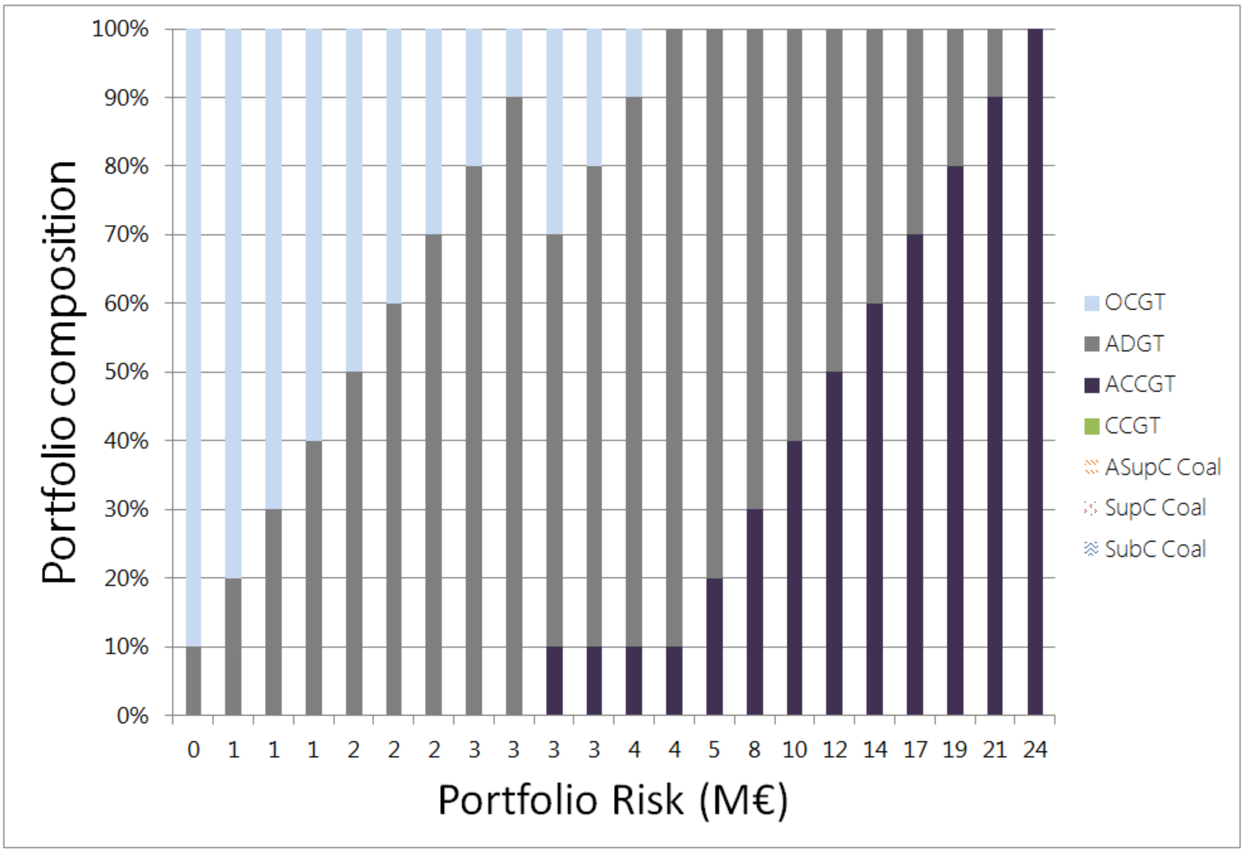

Figure 7: Composition of portfolios on the efficient frontier

ADGT investment features heavily in the efficient frontier as ADGT also has a positive net present value. This is due to its low start-up costs and the fact that OCGT has high marginal cost; thus when both ADGT and OCGT are online ADGT receives high infra-marginal rent. The fact that ADGT appears in lower risk portfolios which also include CCGT suggests that ADGT units decrease the risk of CCGT units. This is in spite of the fact that there is positive (but low) correlation between ADGT and CCGT units. This is most likely due to the fact that the expansion is run seven different times with a fixed block of a different generation type each time, and so some of the cross-benefits of different plant types may not be captured. The same can be said of OCGT investment, which features in many of the efficient portfolios in spite of the fact that on a stand-alone basis OCGT is always a loss-making plant under marginal-cost pricing.

Given that the baseload-only portfolios were dominated by investment in advanced CCGT, it is not surprising that the generation technologies which appear on the efficient frontier are more flexible technologies. The role which coal played in the efficient baseload portfolios (partloading and facilitating higher output from advanced CCGT units) is better performed by flexible units when investment in all technologies in considered. This is because the start costs and minimum production values, which are lower in the case of coal plants compared to those of CCGT, are negligible in the case of more flexible generation technologies such as ADGT and OCGT. Furthermore ADGT and OCGT have faster start times and also can ramp at faster rates than coal plants. Thus they can adapt to variable net load even better than coal plants can and can reduce variation in output from CCGT units more effectively.

Given that investment in coal technologies does not feature heavily in the optimal baseload portfolio or at all on the efficient frontier of all optimal portfolios, we can conclude that fuel price risk is not sufficient to justify fuel diversification. This is due to the fact that gas plants are nearly always the marginal unit, and so the electricity price is a function of the gas price. Therefore the risk the gas generator faces due to gas price risk is reflected in the return they make and the incentive to diversify between fuels is diminished. The benefits of diversification appear to be confined to diversifying between types of technology taking operational issues into account. The detailed nature of the FAST algorithm allows these effects to be incorporated when determining the schedule and thus the returns of each plant. Therefore the inclusion of unit commitment and detailed scheduling is necessary if the operational interactions between the various plant types is to be properly quantified.

The interaction between risk and return, and the efficient frontier which arises as a result, is significant. Figures 7 and 8 give the fifteen portfolios of highest return and lowest risk (with positive return) respectively. The composition of such portfolios differs greatly from those on the efficient frontier. It can be seen that those portfolios which yield the highest returns include some coal (both super-critical and advanced super-critical) and conventional CCGT. In fact each of these portfolios are at least eighty per cent inflexible baseload technologies. By contrast, those portfolios of lowest risk (with positive return) include at most ten per cent baseload technologies. The fact that the efficient frontier features a mix of both flexible and inflexible technologies suggests that there may be sufficient incentives when both risk and return are taken into account to ensure diversity in the electricity generation mix. This is significant as many systems are considering specific incentives to ensure sufficient flexibility in the generation mix (EirGrid, 2011; Abdul-Rahman et al., 2012). While considerations of generator returns alone may lead system operators and regulators to conclude that such incentives are necessary, the consideration of risk may mean that such incentives in fact prove unwarranted. A further examination of this possibility is recommended before any such policies are advanced.

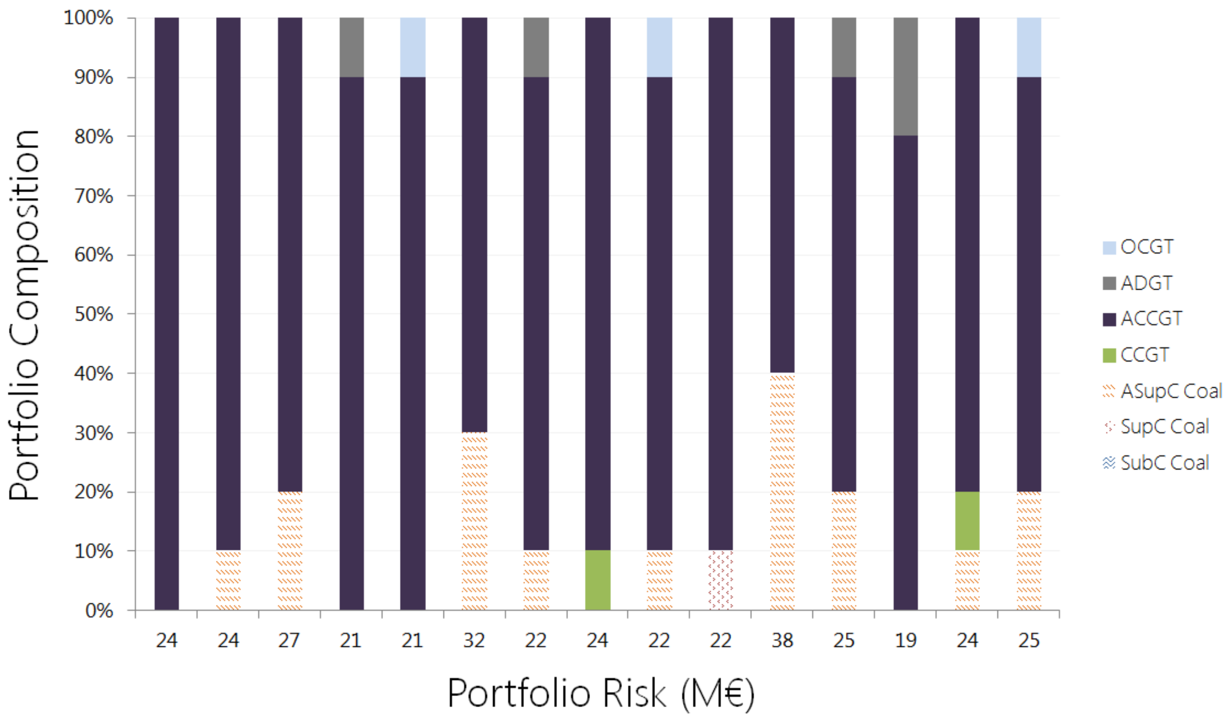

Figure 8: Composition of fifteen portfolios of highest return

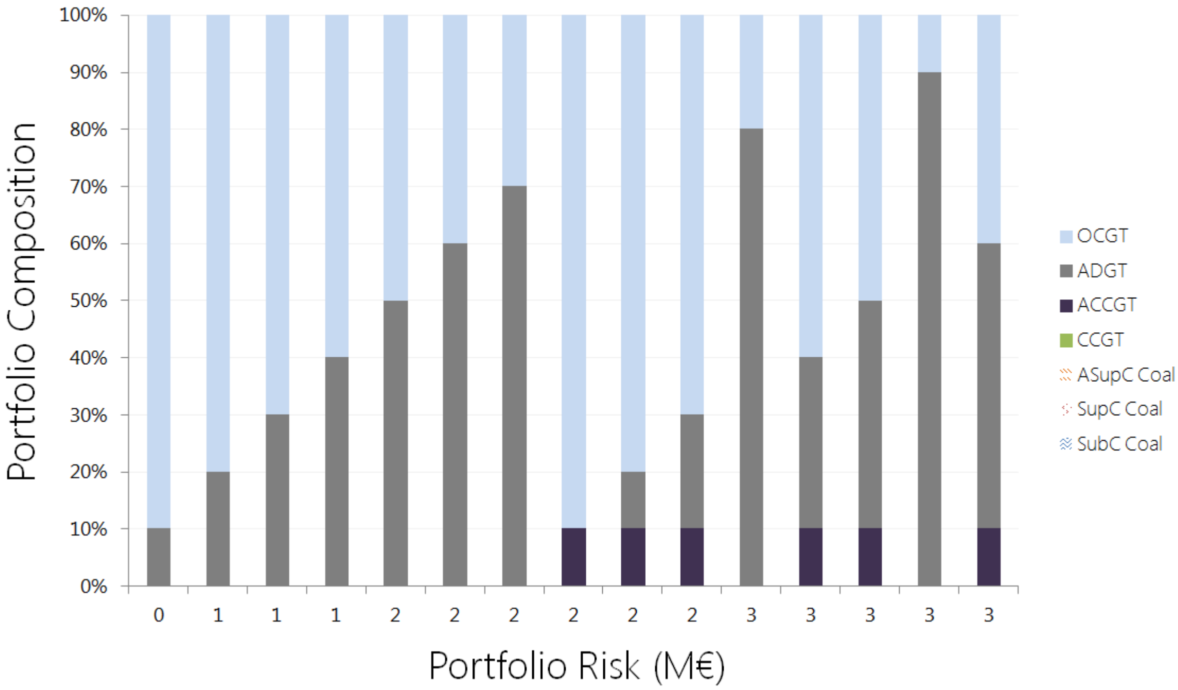

Figure 9: Composition of fifteen portfolios of lowest risk and positive return

The inclusion of a make-whole payment, by means of which a generator is guaranteed to recover their costs over a certain period of time, could have an effect on the results. This would remove the risk faced by baseload units regarding their start costs. The inclusion of a capacity-payment mechanism, which is a fixed payment received by generators based on their availability for generation, would change the average returns of each generation technology and therefore of each portfolio as well. Finally the consideration of interconnection to neighbouring systems, which can provide further diversification options to investors, could change the composition of the efficient frontier. We leave such considerations for further work.

4 Conclusion

This paper used a sophisticated scheduling algorithm to determine least-cost electricity generation schedules. The FAST algorithm avoids many of the pitfalls of similar modelling in this area by including start costs and no load costs. Thus the model can legitimately identify the least-cost schedule in the presence of variable generation, which gives rise to larger changes in net demand.

A Monte Carlo analysis was performed under varying fuel and carbon prices. The FAST algorithm determined the least-cost generation schedule and marginal pricing was used to calculate the returns for each generator. A distribution of the net present value of each type of electricity generation technology was attained and the mean-variance efficient frontier of generation investment portfolios was found.

The efficient portfolios for baseload generation saw high amounts of investment in advanced CCGT, with some investment in coal seen to reduce risk. When all types of generation technology were considered, efficient portfolios on the frontier consist of advanced CCGT, ADGT and OCGT, in varying quantities. Full investment in advanced CCGT provided the highest return, therefore ADGT and OCGT are incorporated to reduce the overall risk of the portfolio. This reduction in risk is due to a reduction in the number of costly starts that baseload units, including CCGT units, have to perform, and by increasing the online production capacity factor of advanced CCGT units. The consideration of the effect of make-whole payments, capacity payments and interconnection on the efficient frontier is proposed as an extension to this work. A more robust examination of the incentives faced by generators regarding investment in flexible generation technologies is also recommended.

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Appendix Distribution of NPV of each generation technology

The mean and standard deviation for the NPVs of the seven generation technologies under study, as well as their correlations, are given in Tables 3 and 4.

Generation technology	SubC Coal	SupC Coal	ASupC Coal	CCGT	ACCGT	ADGT	OCGT
Mean	-269	-95	116	-80	207	51	-1,042
Standard deviation	46	38	82	61	23	3	0

Table 3: Summary statistics of the NPV of each generation technology (M)

Generation technology	SubC Coal	SupC Coal	ASupC Coal	CCGT	ACCGT	ADGT
SubC Coal	1	0.19	0.06	0.07	-0.23	0.01
SupC Coal		1	0.89	0.52	-0.03	0.29
ASupC Coal			1	0.58	0.06	0.34
CCGT				1	-0.19	0.65
ACCGT					1	0.17
ADGT						1

Table 4: Correlation coefficients for the NPV of each generation technology

The zero standard deviation seen for OCGT plants is due to the fact that as the unit with the highest marginal cost, the OCGT plant will always set the electricity price, and always break even on energy costs. The return on an OCGT plant is therefore determined by its fixed costs on