Paper ID APEN-MIT-2019_121
Applied Energy Symposium: MIT A+B
May 22-24, 2019 • Boston, USA

Renewable support policy evaluation: The importance of uncertainty

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Abstract— Policy makers are tasked with selecting, designing, and implementing policies to support the transition to a sustainable power system. As part of the task they often turn to models to quantify and compare the options available to them. In this work we investigate the importance of representing a wide range of economic and physical sources of uncertainty in the modelling used to evaluate different decarbonization policies.

We investigate six different energy policies across three different methods for incorporating uncertainty into decision making models in a Portugal based case study. We find that the method for incorporating uncertainty into the model used to evaluate policies leads to differences in the resulting capacity expansion plan, in the ability to meet carbon intensity targets, and in the abatement costs of policies. Policies designed in a deterministic way can result in significant violations of the emission target and the expected costs be more than double those estimated in a deterministic way.

We also find that the six policies appear roughly equivalent when analysed by the deterministic model but perform very differently when uncertainty is considered potentially biasing decision makers that ignore uncertainty. Finally, we demonstrate that the simplified inclusion of uncertainty, such as scenario analysis, often underestimates the carbon reduction effect of policies and can over or under estimate costs.

Keywords— generation expansion planning, electricity market modelling, renewable energy policy, decarbonization

I. Introduction

The role of uncertainty in the energy sector is becoming increasingly important over both the long- and short-term planning horizons [1]. Both the number of areas where uncertainty is considered, and the degree of that uncertainty, are considered to be growing [2]. The policy maker, energy system planner, or utility is faced with making long term investment decisions, often for assets with a 30 year plus lifetime, where significant uncertainty exists over a number of important dimensions.

For a demonstration of the magnitude of these uncertainties consider the historical review of long term energy demand forecasts undertaken in [3]. The authors demonstrate that historical forecasts of energy demand were both systematically high and underestimated the level of uncertainty. The realized level of energy demand in the year 2000 was less than half the most optimistic forecasts and well below the average. For a more recent demonstration of the scope of uncertainty [4] reviews forecasts for levelized CCGT costs for the period to 2040. The authors find a near consensus in cost projections for forecasts generated before 2005 in the 20-40£/MWh range. However, forecasts created between 2005 and 2010 range in values between 60-160£/MWh. The representation of these large uncertainties is identified in [5] as one of the key challenges to the future of energy system modelling.

It is clear then that uncertainty is an important component of the future of the energy sector and this should then be an important input to the decision-making process. We focus on the problem faced by policy makers who are tasked with planning and encouraging the decarbonization of the energy sector. We specifically look at the models used in the evaluation of policy decisions and how they deal both with uncertainty, and the way the market responds to this uncertainty.

In [6] the authors review approaches for evaluating energy and renewable support policies and find that generation expansion planning (GEP) models are a common approach to evaluating these decisions. When we look at the literature for this class of model, we find evidence that uncertainty is often overlooked or excessively simplified for the purposes of modelling. In a recent review of the literature of GEP [7] of the 227 papers cited only 54 were classified as containing a stochastic element and only 17 included stochasticity in more than one input dimension.

In addition to the sources of uncertainty, the method of including it into the model is also an important dimension. Typical approaches range from simplistic treatments which involve multiple simulations of a deterministic model such as scenario analysis and Monte-Carlo simulation to more complex approaches such as stochastic or robust optimization, which include uncertainty within the model formulation itself.

In a review of the related field of energy storage expansion planning [8], the authors demonstrate that the inclusion of stochasticity in research increased drastically after the year 2000. However, the majority of this research deals with the more simplistic approaches of scenario modelling or Monte Carlo simulation. For papers published after 2010, still less than 20% feature the more sophisticated stochastic optimization approach to uncertainty modelling.

In this work we demonstrate the importance of the inclusion and careful treatment of uncertainty across all relevant dimensions when assessing renewable energy policies. In the context of a real-world generation expansion planning problem we:

- Compare the effectiveness of several different renewable support policies under different assumptions of uncertainty including an emission limit, carbon price, renewable generation subsidy, and renewable investment grant.
- Demonstrate the importance of inclusion of uncertainty into the model for policy assessment, with many policies designed in a deterministic model not achieving target levels of carbon reduction when real world uncertainty is considered in investment decisions.
- Demonstrate the importance of including uncertainty inside the model (through stochastic optimization).

II. Methodology

The aim of this paper is to compare different treatments of uncertainty in a GEP model for policy making. The methodology here covers the three important steps in this process. Firstly, the means for quantifying input uncertainty in a scenario generation and reduction process is outlined. Then we detail the GEP model formulation and outline the case study used in this analysis.

A. Scenario Treatment

We apply uncertainty to three key model inputs: fuel prices, energy demand, and renewable technology capital and operating costs. For fuel prices and demand it is reasonably common to consider these sources of uncertainty aleatoric and consider that a stochastic process can be considered a reasonable representation (as characterized in [2]). For these sources of uncertainty we follow a typical scenario generation and reduction approach, as discussed in [9] and detailed here in section 1.2.1.

For technology costs we take a different approach and apply equal weights (equal probabilities) to the high, medium, and low forecasts developed by the National Renewable Energy Laboratory (NREL) [10]. In this way the evolution of costs is uncertain but exogenous to the model (as opposed to endogenously determined, as in [11]). Technology costs can be considered to entail both epistemic and aleatoric uncertainty [2] and the application of expert judgement to define and assign a weighting to such scenarios for modelling is one potential approach, as in [12]. An alternative proposed approach is to fit a triangle distribution over the range of scenarios as in [13], however, this assumes the extreme scenarios represent the limits of potential values as opposed to probable potential scenarios. In this paper, we use the model to represent the decisions of actors in the market, and our treatment of technology costs should reflect how we believe they incorporate this information into their decisions. While the application of equal weights is an assumption, we believe this is a reasonable treatment for the question of estimating investors long term views.

B. Scenario Generation and Reduction

The basic process for scenario generation and reduction is:

1. Fit statistical model to historical data;
2. Generate a range of future scenarios based upon statistical model, and;
3. Reduce the scenario set with a fast forward selection methodology.

For load growth we fit a Geometric Brownian Motion (GBM) process as with [14] and for fuel prices we fit an Ornstein Uhlenbeck (OU) process typical for commodity prices [15]. After fitting the processes to the data, we generate 10000 random individual scenarios which provide a discrete approximation of the future realizations of each series.

To select a set of inputs for the model we then apply a scenario reduction methodology to pick four representative scenarios and their relative weights (relative probabilities in this case). We use the fast forward selection (FFS) [16] technique with the Euclidean norm set as the distance metric as often applied to generation expansion problems [9].

C. Uncertainty Representation

For the purpose of this study, we implement a mixed integer GEP model with a two stage stochastic optimization, a common tool for making energy policy related decisions [6]. As the purpose of this study is to include a detailed representation of uncertainty, which drastically increases problem size, we implement a model formulation designed to minimize the problem size in other areas while remaining representative.

We simulate the model under three different representations of uncertainty.

- **Deterministic (D):** A single deterministic scenario is optimized, where demand, fuel prices, and technology construction costs take a single value based on the expected value of the forecasts developed in the previous section.
- **Scenario Average (SA):** All possible combinations of fuel prices, demand forecasts, and construction costs forecasts are simulated as independent scenarios (48 in total). Scenario analysis or Monte Carlo analysis, where scenarios differ but are modelled independently, is the most common method to incorporate uncertainty [8]. The investment decisions made here reflect the model having perfect foresight for each scenario. When modelling a liberalized market or central utility for policy making this implies that market participants do not take risk or uncertainty into account when making investment decisions (as the model is optimized to a known future). To generate results for comparison from this approach the expected result is taken by multiplying

the results of each scenario by its probability of occurring.

- **Stochastic optimization (SO):** When running the model as a stochastic optimization problem we force it to make a single set of decisions that must be fixed over all potential futures for a selected set of years. This reflects real world decision making where investors must decide to make an investment without knowing what the future levels of demand, fuel prices, or construction costs will be. In such a situation we tend to see more conservative decisions (the investor cannot optimize aggressively to a given forecast as this is not certain to occur) and a preference to delay decisions for a time where more information is known. In [17] the authors show that under the assumption of perfect competition the actions of individual investors in a competitive market oftentimes can be modelled as a centralized least-cost generation expansion planning problem, including in the general case where investors are making decisions on the basis of a stochastic optimization over uncertainty.

It is important to be clear about the interpretation of the stochastic optimization here. One potential application of the GEP for the policy maker could be to find the decarbonization support policy that is optimal given uncertainty (see [18], for an example of optimizing policy decisions). Instead here we are investigating the question: given that investment decisions are made taking uncertainty into account (without the perfect knowledge of the future), what then is the expected effect of different decarbonization policies?

D. *Expansion Model*

In the remainder of this section we provide a high-level overview of the GEP model applied in this study. This model is an extension of the model used in [19] to accommodate multiple scenarios and non-anticipativity constraints.

Equation 1 presents a simplified view of the objective function of the optimization. Broadly the model attempts to minimise the expected value of the total system cost. The costs considered include build costs for new units c^{Build}, annual fixed costs for all units c^{Fixed}, variable costs $c^{Variable}$ which include fuel costs, variable operating and maintenance costs, unit start costs, and any carbon price costs. Finally, the model allows for penalty costs for violating constraints $c^{Penalty}$, which here includes the cost of unserved energy, cost of unserved spinning reserves, and costs to curtail renewable generation.

$$\min \sum_{s\in S} w_s^{Scenario} \cdot \sum_{y\in Y}\sum_{p\in P}\Bigg(DF_y \cdot c^{Build} + DF_y^{Step} \cdot \Big(c^{Fixed} + \sum_{d\in D} w_d^{Day} \cdot \sum_{t\in T}\left(c^{Variable} + c^{Penalty}\right)\Big)\Bigg) \quad (1)$$

Of note are the weights and discount factors used in this equation. For each scenario $s \in S$, a scenario weight $w_s^{Scenario}$ is applied, representing the probability of that scenario occurring (see section II B, for details).

The model is run with a limited set of representative days $d \in D$, each having a set of chronological time periods $t \in T$, and an associated weight w_d^{Day} (broadly the number of days the 'representative' days is representing) such that $\sum_{d\in D} w_d^{Day} = 365$. Representative days with chronological time periods have been shown to be important in modelling high levels of renewable penetration [20]. The rrepresentative days have been selected based upon the approach detailed in [19]. The model includes $p \in P$ power plants representing both the existing fleet and potential build candidates.

The discount factors DF_y and DF_y^{step} are used to discount future build and annual costs. In this model only every fifth year is included (as a set of representative days) but weighted to reflect that it is representing a 'step' of five operational years with the discount factor DF_y^{step}. If we assume an annual discount rate of df the annual DF_y and step DF_y^{step} discount factors are calculated as follows:

$$DF_y = (1 + df)^{-(y-1)} \quad (1)$$

$$DF_y^{step} = \sum_{i=y}^{y+4} DF_i \quad (2)$$

For full details of the model constraints, the reader is referred to [19]. However, the following features are of note:

- The model enforces integer build decisions to represent the fact that, particularly for large conventional units, power plants must be constructed in minimum economic or technical sizes.
- When the model is solved as a stochastic program, non-anticipativity constraints are enforced on the first year of build decisions, meaning the model selects the same build decisions across all scenarios. These constraints reflect the reality that some decisions must be made before the uncertainty in inputs is resolved. Effectively, planners must optimise their initial build decisions to be optimal against the uncertain inputs.
- In each scenario, in each model year, in each representative day, in each hour, the model must meet demand with generation (or incur highly penalised unserved energy or dump energy). The model enforces time period chronology to ensure power plant dynamics can be captured. Additionally, the model captures the provision of spinning reserves from conventional reserve capable power stations.
- Detailed power station dynamics are captured, including start costs and ramping restrictions for conventional units. For battery storage units daily energy storage constraints ensure that storages generate and charge in a feasible manner within each day (the storage of energy between days is prohibited due to the restrictions of using representative days).
- The model captures the emission of carbon from power station operations and can optionally enforce either a price on carbon emissions or a limit on annual carbon emissions.

TABLE 1 RENEWABLE SUPPORT POLICY DETAILS AND DESCRIPTION OF MODEL IMPLEMENTATION

Renewable support policy implementation	2023	2028	2033
Carbon limit - An annual limit on carbon intensity in each scenario, starting in the second simulation year 2028. The policy is implemented as a constraint on annual total emissions, the constrained value depends both on the intensity limit and on the realisation of demand in a given scenario.	None	250 g/kWh	240 g/kWh
Carbon price - A price for the emission of carbon borne by the generator. The price on carbon emissions is included in the objective function similar to other variable costs.	10 $/tonne	30 $/tonne	50 $/tonne
Renewable subsidy - A subsidy for renewable energy provided to the system (similar to additional returns from the sale of renewable obligation payments). This subsidy should be interpreted as additional to market revenue in a market environment (as opposed to a replacement payment such as a feed in tariff). The subsidy is implemented as a negative variable cost for new built renewable technologies.	25 $/MWh	25 $/MWh	25 $/MWh
Renewable grant – A grant towards the capital cost of new renewable technologies (alternatively the grant can be considered a tax incentive). This policy is implemented as a reduction in capital costs for renewable technologies.	450 $/kW		
Solar subsidy - A subsidy targeted to the provision of solar energy provided to the system. The subsidy is implemented as a negative variable cost for a new solar power plant.	80 $/MWh		
Solar grant – A grant towards the capital cost of a new solar power plant. This policy is implemented as a reduction in capital costs for new solar power plant.	1000 $/kW		

III. CASE STUDY

As previously discussed, including such a large number of scenarios in a single optimization creates major challenges.

We therefore select a case study where we can minimize the problem size while still drawing representative results. For this exercise we model the island of Terceira in Portugal which has several characteristics that are useful here. Firstly, it is a small isolated system (effectively a microgrid), however, energy demand is growing and future investment in generation capacity is required. The island also features a relatively high level of variable renewable penetration which currently results in occasional curtailment actions making it representative of the high renewable generation systems of the future. The model selects between four representative technologies in 5MW increments: small scale diesel engines, Li-ion storage, PV solar, and small-scale onshore wind.

A. *Decarbonization / Renewable Support Policies*

Here we include six different common decarbonization support policies for assessment under different assumptions about uncertainty, as detailed in Table 1. The values for the carbon policies are set in such a way as to achieve the same target carbon limit in the deterministic case for all policies. This provides an equal basis on which to compare policies under the inclusion of uncertainty.

IV. RESULTS

In Figure 1 we provide the expected capacity expansion plan selected by the GEP model without any decarbonization support policy under the three treatments of uncertainty (D, SA, and SO).

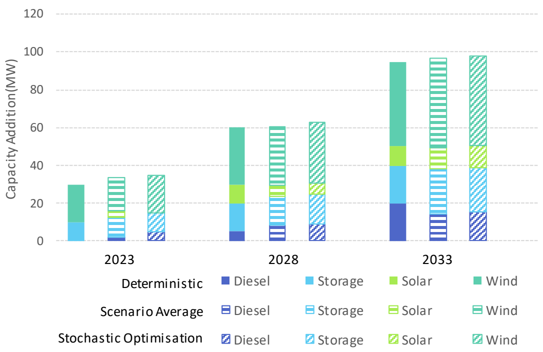


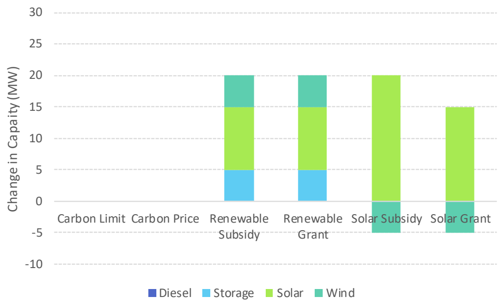
Figure 1 Base case new build results of GEP model under the deterministic scenario without the application of any renewable support policy.

Firstly, it is interesting to note that under all three treatments the expansion plans are relatively similar. The first year is of the most interest as this is the year where the stochastic optimization selects decisions under uncertainty (the non-anticipativity constrained year). When comparing the deterministic and scenario average results for this year, we see that diesel and solar power are selected in only a subset of scenarios, so that on average, the quantity is less than one full 5MW unit of either (if we were to round to the nearest unit, the scenario average result and the deterministic result would be the same here).

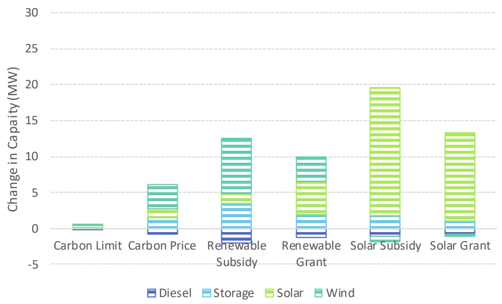
Comparing then to the stochastic optimization solution, we see that even though the diesel generator is only needed in a select few scenarios, we would expect that a centralised planner or a perfectly competitive market would build this generator if fully considering uncertainty as a stochastic optimisation. In practice, this means that the upside in the relatively few scenarios outweighs the downside in thee majority of others. This result demonstrates the first situation where a policy maker would incorrectly derive results from models that do not account for market participants taking into account uncertainty. Based on a deterministic, or scenario average, view of the market the policy maker may conclude that it is unlikely that any new conventional generation will be built, and perhaps delay decarbonization policy, where this does not reflect the view of the more sophisticated SO model.

Figure 2 demonstrates the change in expansion plan in the first model year (2023) for each decarbonization support policy, as assessed by the model under the three different treatments of uncertainty. The first difference to note is that the deterministic model does not result in the emission limit or emission price policies affecting any change in this first model year. In contrast, the stochastic optimization model finds that, in fact, these policies would increase the build of solar. A simplistic treatment of uncertainty as in the scenario average model is also unlikely to lead the policy maker to detect this effect, the SA results suggesting that instead wind capacity would be built. Here, the simplified treatment of uncertainty could lead the policy maker to underestimate the short-term effect of these policies (keeping in mind that the carbon reduction target is for the second model year 2028).

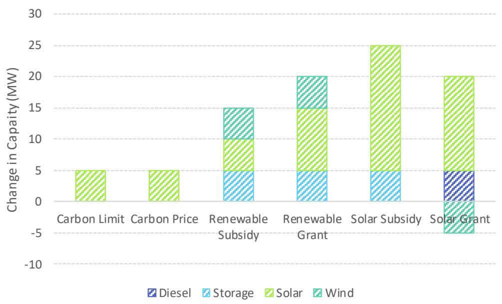
While results for the deterministic and stochastic optimization models are relatively similar for the renewable grant and subsidy policies, the scenario average differs



(a) Deterministic



(b) Scenario Average



(c) Scenario Optimisation

Figure 2 Change in build of new units in 2023 model year after the implementation of renewable support policies under different treatments of uncertainty.

significantly. In this case, improving the treatment of uncertainty, by running scenarios, but not including how the market responds to this uncertainty, reduces the policy makers' ability to evaluate policy, overestimating the build of wind over solar, and underestimating the required storage technology and additional capacity overall. Finally, focusing on the solar specific support policies, the deterministic and scenario average models both underestimate the requirement of storage (in some scenarios, without demand growth, if a large amount of solar is built, this storage is required (economic), a situation only capture by the SO model). This increased need for storage increases the build cost associated with these policies and could lead the policy maker to understate the cost of these policies overall.

Finally, in Figures 3 and 4 we present the effectiveness of the policies at reducing carbon emissions to reach the target carbon intensity level and the costs associated with doing so, respectively. While all policies achieve the target emission intensity level in the deterministic case of 250 g / kWh, when uncertainty is incorporated into the model, this is not necessarily the case.

The one policy that achieves the target (or close to it) is the carbon limit, which applies to all scenarios. In other words, investors make build decisions to meet this limit regardless of the outcomes of the uncertain inputs. With all the other policies the investors decisions depend on the costs and benefits of the different technologies (given decarbonization support), but in several scenarios this does not result in a strong enough incentive to reduce carbon emissions below the given limit. Even the expected carbon intensity (given that some scenarios will be over and some under) is not achieved by the policies designed in the deterministic model. In the worst case this results in an expected 6.1% violation of the emission target and 42% violation in the worst scenario.

The use of over simplified uncertainty in the form of the SA case leads to the overestimation of the degree to which this target is will not be met on average (and the maximum degree to which it is violated). This results from the build decisions demonstrated in Figure 2, where looking at scenarios individually the model perfectly optimizes to the known future, in many scenarios building less renewables compared to the stochastic optimization. The stochastic optimization reflects the result of market decisions made considering uncertainty where renewable investments are made, and exist in all scenarios, meaning more renewables persist into the future and lower carbon emissions in scenarios where they would nothave been built if the future was foreseeable (for example, low fuel costs and high renewable costs).

In Figure 4, we compare the expected costs of the policies under different model treatments of uncertainties. For the purpose of these comparisons, subsidy costs / carbon revenues are accounted for to ensure an applicable comparison. When looking at the deterministic results all policies not directly targeted at solar seem to have very similar costs, and only the subsidies limited to the solar technology have higher costs. However, when we

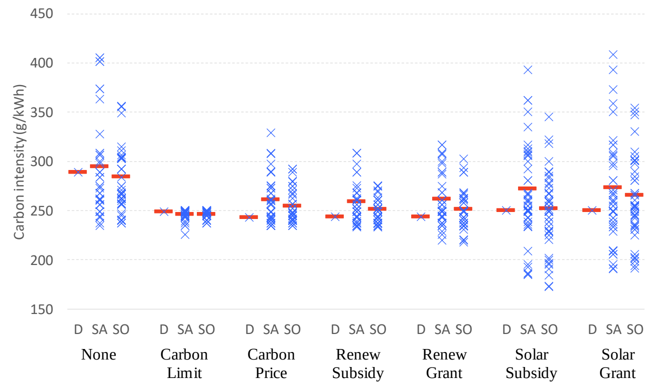


Figure 3 Carbon intensity levels in 2028 model year for all scenarios under different carbon support policies and treatments of uncertainty (D deterministic, SA scenario average, SO stochastic optimisation). Expected carbon intensity shown in red.

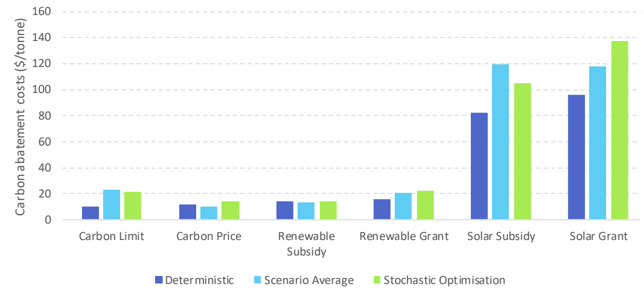


Figure 4 Carbon abatement costs (change in total system costs resulting from renewable support policy / reduction in emissions) for all renewable support policies and treatments of uncertainty.

incorporate uncertainty this result changes. In particular, the carbon limit is significantly more expensive, with costs over two times higher, as it enforces sufficient changes to meet the target over all scenarios, where the other renewable agnostic scenarios are relatively cheaper. These results reinforce the fact that a carbon limit provides greater certainty around emissions, where a carbon price produces greater certainty around costs. Additionally, only with the inclusion of uncertainty do we find differences between the subsidy and grant based renewable policies. For the model to gain the benefits of the subsidy, the renewable units need to be able to produce. This means that these policies result in a higher use of storage as opposed to diesel units. While this effect is not picked up in the deterministic case, it is found in some of the scenarios where different cost or demand conditions mean that there exists a difference between storage and diesel generation economic viability.

V. CONCLUSION

Investment decisions in the energy sector involve large sums of money and require return over long periods of time. Moreover, these decisions are complicated by the large amount of uncertainty inherent in the forecasts of inputs that are important to making these decisions. In this work we investigated the importance of representing uncertainty in the modelling used to evaluate different decarbonization policies.

We find that the six policies compared are roughly equivalent when evaluated with a deterministic model but the expansion plan, decarbonization, and cost, all differ significantly when uncertainty is included inside the model. The cost of the carbon limit policy, the most economical when assessed deterministically, more than doubles when uncertainty is taken into account.

We find that the five other policies considered; carbon price, renewable subsidy, renewable grant, solar subsidy, and solar grant, not only do not achieve the target carbon intensity level in all scenarios, but also not in expectation (the expected carbon intensity is greater than the target). Additionally, we find the renewable subsidy and grant policies to be roughly equivalent deterministically but different under more sophisticated treatments of uncertainty, with the grant policies being more expensive in carbon abatement terms than the subsidies.

Finally, we demonstrate that the simplified inclusion of uncertainty, such as scenario analysis or Monte Carlo simulation often overestimates the violation of policy targets and underestimates costs.

ACKNOWLEDGMENT

This work is supported by the Fundação para a Ciência e Tecnologia (FCT) through the MIT-Portugal Program and the FCT scholarship PD/BD/113715/2015 as well as the InnoEnergy PhD school. Thanks are also due to FCT through support from the IN+ Strategic Project UID/EEA/50009/2013. Finally, the authors would like to thank GUROBI for the supply of academic licenses.

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