IAN MICHAEL TROTTER

ESSAYS ON ENERGY AND CLIMATE CHANGE

Tese apresentada à Universidade Federal de Viçosa, como parte das exigências do Programa de Pós-Graduação em Economia Aplicada, para obtenção do título de *Doctor Scientiae*.

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APROVADA: 03 de agosto de 2016.

Viviani Silva Lirio

Delly Oliveira Filho

Amaro Olímipio Pereira Júnior

Lavinia Rocha de Hollanda
(Coorientadora)

José Gustavo Féres
(Orientador)

To Kari and Andreza

"Kom arbeidslyst og treng
deg på. Her skal du motstand
finne." (Solan Gundersen)

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TROTTER, Ian Michael, D.Sc., Universidade Federal de Viçosa, agosto de 2016. **Ensaios sobre energia e mudanças climáticas.** Orientador: José Gustavo Féres. Coorientadora: Lavinia Rocha de Hollanda.

Gestão de recursos energéticos é fundamental para a economia global e o bem-estar da população. Ao mesmo tempo, mudanças no sistema climático podem afetar profundamente a demanda por energia e o suprimento de energia. Primeiramente, é importante entender como os recursos existentes podem ser usados eficientemente. Por isso, o primeiro capítulo desta tese estuda a operação ótima de terminais de importação de gás natural liquefeito (GNL) com armazenamento. GNL é cada vez mais considerado uma forma de energia chave na transição de combustíveis fósseis às fontes renováveis. Os resultados principais sugerem que a operação de infraestrutura existente pode ser melhorada consideravelmente. Em segundo lugar, gostariamos saber mais sobre como funções vitais da sociedade poderiam ser afetadas por mudanças no clima. Nesse contexto, o segundo capítulo examina o impacto de mudanças climáticas na demanda de energia elétrica: esse capítulo desenvolve um método para incorporar incerteza meteorológica na geração de cénarios de demanda de energia elétrica sob um clima não-estacionária, e subsequentemente usa o método para estudar o caso do Brasil. Em resumo, o resultado principal sugere um aumento significativo na incerteza da demanda de energia elétrica devida às mudanças no clima. Finalmente, depois de investigar os impactos de mudanças climáticas, é natural perguntar o que pode ser feito para mitigar seus efeitos. Por isso, o terceiro capítulo apresenta uma análise exploratória de um dos esforços mais ambiciosos de mitigar mudanças climáticas – o Mecanismo de Desenvolvimento Limpo (MDL) – em que projetos em paises em desenvolvimento realizam medidas de redução de emissões de gáses de efeito estufa para ganhar créditos, que podem ser vendidos a entidades em paises desenvolvidos com metas de redução. O objetivo da pesquisa foi descobrir consequências intencionais e não-intencionais do mecanismo, e assim aprender lições valiosas que devem ser considerados para esforços futuros. Os resultados sugerem que projetos de mitigação nas regiões mais pobres são os mais sensíveis ao preço de créditos de carbono.

Abstract

TROTTER, Ian Michael, D.Sc., Universidade Federal de Viçosa, August, 2016. **Essays on Energy and Climate Change.** Advisor: José Gustavo Féres. Co-advisor: Lavinia Rocha de Hollanda.

Energy resource management is fundamental to the global economy and the well-being of its population. At the same time, changes in the climatic system threaten to deeply affect both the demand for energy and the energy supply. Firstly, it is important to understand how the existing resources can be used efficiently. Therefore, the first chapter of this thesis studies optimal operation a liquefied natural gas (LNG) importation terminal with storage, since LNG is increasingly being considered an key form of energy in the transition from fossil fuels to renewable energy sources. The main results suggest that the operation of existing infrastructure can be improved considerably. Secondly, we would like to know more about how vital societal functions could be affected by changes in the climate. In this respect, the second chapter investigates the impact of climate change on electricity demand: this chapter develops a method for incorporating weather uncertainty in electricity demand scenario generation under a non-stationary climate, then performs a case study using the method for the case of Brazil. In brief, the main results point to a significant increase in the uncertainty of electricity demand due to changes in the cliamte. Finally, after exploring the impact of climate change, it is natural to ask what can be done to mitigate the effects. The third chapter therefore performs an exploratory analysis on one of the most ambitious global efforts to mitigate climate change – the Clean Development Mechanism (CDM) – in which projects in developing countries implement greenhouse gas reduction measures to earn credits, which can be sold to entities in developed countries with reduction targets. The research aimed to uncover intended and unintended consequences of the mechanism, and thus learn valuable lessons which must be considered in future efforts. Mainly, the results suggest that mitigation projects in the poorest regions are the most sensitive to the price of carbon credits.

1 Introduction

It is difficult to overestimate the social and economic importance of energy, both for developed and emerging countries. The management of energy resources is fundamental to the global economy and the well-being of its population, and yearly investment and operation costs are on the order of hundreds of billions of dollars.

There are in particular two factors that add considerably to the complexity of efficient management of energy resources. Firstly, our technological capabilities are constantly evolving, and the energy infrastructure is in constant development. The consequences and impacts of each of these developments must be adequately explored and understood to ensure an efficient management of energy resources. Some current trends are developments in energy transportation technology and infrastructure such as liquefied natural gas, the emergence and proliferation wind power and photovoltaics, batteries for grid-level electricity storage, smart meters, and so forth. Secondly, efficient resource management involves addressing significant amounts of uncertainty along a number of dimensions. Not only uncertainty about future technological capabilities, but also about macroeconomic trends, as well as considerable weather and climate uncertainty.

This thesis presents three essays that deal with topics in energy and climate change. Each of the essays explores a single facet of the challenges posed by recent or expected future developments to the efficient management of energy resources, and they are a result of collaborative work with a number of dedicated professionals: José Gustavo Féres, Torjus Folsland Bolkesjø, Lavinia Hollanda, Marília Fernandes Maciel Gomes, Marcelo José Braga, Bjørn S. Brochmann, Ole Nikolai Lie and Dênis Antônio da Cunha.

The first essay treats an energy storage problem from the oil and gas industry: the optimal management of a liquefied natural gas (LNG) regasification plant with onsite storage. Although LNG technology has existed for several decades, the importance of LNG in the energy matrix of many countries has increased considerably the last decade. Representing a larger portion of the total energy supply, it is important to investigate how to adequately schedule the delivery of energy, and whether the infrastructure is used in an efficient manner. The essay therefore develops a mathematical model to describe the optimal operation of a LNG terminal with storage, and then performs a number of numerical simulations to investigate whether a handful of existing LNG terminals are currently operated in a manner consistent with the model. The intention of this essay is to contribute to our understanding of the efficient management of this particular type of resource, whose importance has been increasing recently. The results of this work were published in Energy, vol. 105, in June 2016, in collaboration with Marília Fernandes Maciel

Gomes, Marcelo José Braga, Bjørn Brochmann and Ole Nikolai Lie (TROTTER et al., 2016).

The second essay explores the incorporation of weather uncertainty in electricity demand forecasts when the climate is considered non-stationary, and subsequently investigates the possible effects of climate change on the demand for electric power in Brazil. The results reaffirm the seriousness of the impacts of climate change the energy demand, and further explores the uncertainty of the effects, which are important considerations for climate change policy issues, adaptation and mitigation efforts, as well as for investment planning. This work therefore contributes to our understanding of the potential social and economic impacts of climatic change. The results of this work were published in Energy, vol. 102, in May 2016, in conjunction with Torjus Folsland Bolkesjø, José Gustavo Féres and Lavinia Hollanda (TROTTER et al., 2016).

The final essay focuses on the consequences of a specific attempt at using policy to mitigate climate change, the Clean Development Mechanism (CDM) which was part of the Kyoto Protocol, in which greenhouse gas abatement projects in developing countries earn emissions credits, Certified Emissions Reductions (CER), which can be commercialised and applied towards the reduction targets of industrialised countries. The essay investigates how the market price of CERs has affected the characteristics of the projects applying for approval under the mechanism, and thereby investigates how market forces have affected the viability of greenhouse gas abatement projects of various types in different regions of the world. The results of this investigation was published in Ecological Economics, vol. 119, in November 2015, together with José Gustavo Féres and Dênis Antônio da Cunha (TROTTER; CUNHA; FÉRES, 2015).

The three essays share the common themes of energy resource management and climatic change. Furthermore, the ordering of the essays was chosen to reflect a logical development. In a very broad sense, the first essay discusses cause of climatic change (e.g. fossil fuels), the second essay discusses the effect (e.g. changes in electricity demand), whereas the third essay discusses a proposed solution (the CDM of the Kyoto Protocol). The first essay, which treats the operational efficiency of storage at LNG importation terminals, suggests that it may be possible to increase the operational efficiency of existing infrastructure by simply employing better mathematical modelling tools. Inefficient operation of the energy infrastructure not only contributes unduly to pollution, it also raises the social cost of energy provision. Therefore, increasing the operational efficiency the energy infrastructure is an important, simple and cheap step towards mitigating climate change, which in addition has a direct positive impact on welfare. Furthermore, LNG is considered to play a particularly important role in climate change mitigation as a *transition fuel*. That is, in the transition from fossil fuels to renewable energy sources. However, for the planning and design of the transition from fossil fuels to renewable sources, it is imperative to have access to reliable and detailed demand scenarios. This need is addressed by the second essay, whose main topic is the generation of electricity demand scenarios with a long time horizon and high temporal resolution, which takes into account a non-stationary climate. Having determined some of the possible effects of climate change, we turn our attention to climate change mitigation. The final essay brings up the subject of climate change mitigation, with a detailed analysis of one of the most ambitious global mitigation policies proposed by the Kyoto Protocol. Therefore, in a very abstract sense, the ordering of the essays represents a thematically logical progression through the causes, the effects and the solutions of climate change.

These three essays further our understanding of important issues concerning energy resource management and climate change. Combined, the essays will contribute to our ability to plan for the future, both by exploring the possible impacts of future events such as climate change, as well as developing a deeper understanding of efficient infrastructure operation and the design of appropriate public policies.

In the remainder of this thesis, a chapter is dedicated to each of the essays, in the same order as discussed above. Each of the essays is a self-contained piece of work, and they can be read individually or in any order. A final chapter offers some general concluding remarks.

2 Optimal LNG Regasification Scheduling for Import Terminals with Storage

Abstract

We describe a stochastic dynamic programming model for maximising the revenue generated by regasification of Liquefied Natural Gas (LNG) from storage tanks at importation terminals in relation to a natural gas spot market. We present three numerical resolution strategies: a posterior optimal strategy, a rolling intrinsic strategy and a full option strategy based on a least-squares Monte Carlo algorithm. We then compare model simulation results to the observed behaviour of three LNG importation terminals in the UK for the period April 2011 to April 2012, and find that there was low correlation between the observed regasification decisions of the operators and those suggested by the three simulated strategies. However, the actions suggested by the model simulations would have generated significantly higher revenues, suggesting that the facilities might have been operated sub-optimally. A further numerical experiment shows that increasing the storage and regasification capacities of a facility can significantly increase the achievable revenue, even without altering the amount of LNG received, by allowing operators more flexibility to defer regasification.

Keywords: LNG; Optimization Techniques; Empirical Analysis.

2.1 Introduction

Liquefied Natural Gas (LNG) is becoming an increasingly important source of energy for many countries. In the United Kingdom – with an annual natural gas consumption of around 900 TWh and once a significant exporter of natural gas – imports of LNG by ship have exceeded national gas production since 2009 (NATGRID, 2011). Other natural gas-dependent regions are also expected to follow the same pattern, with LNG imports by ship increasing as regional natural gas reserves are gradually depleted.

Natural gas consumption typically exhibits a seasonal pattern due to its use for heating, and changing meteorological conditions can cause large and rapid changes in consumption. Natural gas producers, however, have little flexibility to change their

Published in Energy, vol. 105, in June 2016, together with Marília Fernandes Maciel Gomes, Marcelo José Braga, Bjørn Brochmann and Ole Nikolai Lie (TROTTER et al., 2016).

deliveries on short notice and for this reason the integrity and safety of the natural gas pipeline network depends heavily on storage facilities that have the ability to react quickly to demand changes. Storage facilities therefore constitute a critical part of the natural gas infrastructure.

LNG importation terminals normally contain an array of onshore storage tanks into which the incoming LNG cargoes are unloaded. The tanks serve primarily as a buffer storage to compensate between the bulk offloading of LNG from ships and the gradual flow of natural gas to customers. The LNG is stored in the tanks until it is regasified and delivered to customers through a pipeline network. The storage tanks share some characteristics with traditional gas storage facilities, most importantly they often have the ability to rapidly change their deliveries to the pipeline network and can thus contribute significantly to the integrity and safety of the natural gas pipeline network. Due to the rapid response offered by LNG storages, many pipeline operators have constructed separate LNG storage facilities specifically for emergency situations.

In the context of a deregulated market, storage operators are faced with the problem of scheduling their withdrawals from storage in order to maximise their profit. Assuming that the market price of the gas to some degree reflects the excess or scarcity of gas, the traditional storage players buy and store gas during periods of excess, then sell and discharge gas during periods of relative scarcity, profiting on the price differences between the periods. Incidentally, this profit-seeking behaviour also provides increased supply security and price stability (NATGRID, 2011; EIA, 2004). Operators of LNG storage tanks at importation terminals are faced with a similar optimisation problem as operators of traditional storages, although the operational characteristics and constraints of these facilities differ from traditional gas storage facilities. Therefore, this study focuses on the optimisation of withdrawals from these increasingly important facilities with their distinct characteristics.

Lai et al. (2010) appear to be the first, and so far only, to specifically address the storage of LNG at importation terminals, although their model considers the storage component in the larger context of a full LNG value chain rather than in isolation. This treatment may be inappropriate in the case where the source of cargoes is not predetermined, for instance when individual cargoes are bought from various suppliers on shorter notice (e.g. "spot" cargoes). Furthermore, they find that the value of the real option to store LNG at a regasification terminal is largely insensitive to stochastic variability in the shipping process, which is an important result and implies that the model can be greatly simplified to consider only the storage component in isolation. In addition to isolating the modelling of LNG storage at the import terminal from the rest of the LNG value chain, we would also like to avoid the discretisation of the price process that is required by their model and is generally undesirable since natural gas spot prices tend to vary over a wide range.

Although there has been little research specifically on the optimisation of LNG storage tanks at import terminals, the problem is closely related to management of traditional natural gas storage facilities, such as depleted fields, aquifer and salt caverns. The management of these types of natural gas storage facilities has attracted significant research interest, mainly under the guise of gas storage valuation using real-option theory because modelling the optimal management is a necessary step for assessing the value of natural gas storage (MARAGOS; RONN, 2002). Weston & Ronn (2002) recognised gas storage valuation as a stochastic dynamic programming problem and proposed a solution that requires a discretisation of the inventory and price, of which the latter is a somewhat problematic requirement that is avoided in this study. Drawing on similarities with hydrothermal scheduling, Bringedal (2003) modelled the optimal operation of gas storage using the stochastic dynamic dual programming method developed by Pereira & Pinto (1991). Boogert & Jong (2008), as well as Carmona & Ludkovski (2010), proposed least-squares Monte Carlo approaches based on the options valuation framework of Longstaff & Schwartz (2001). Chen & Forsyth (2007) treat gas storage valuation as a stochastic control problem which results in a Hamilton-Jacobi-Bellman partial differential equation, and can be resolved numerically with a semi-Lagrangian discretisation method. Thompson, Davison & Rasmussen (2009) also propose an approach based on the numerical resolution of non-linear partial differential equations, with a particular emphasis on capturing the parabolic and hyperbolic nature of the natural gas storage operating characteristics. Lai, Margot & Secomandi (2010) proposed an approximate dynamic programming method to value the real option of storing natural gas, and found that sequentially optimising a deterministic model of the intrinsic value could provide a near-optimal policy at reasonable computational cost.

We propose a stochastic dynamic programming model specifically for maximising the revenue of LNG storage tanks at importation terminals in relation to a spot market. Although the model is based on the model developed by Boogert & Jong (2008), it extends this approach to include additional constraints that are characteristic to this specific type of storage: most importantly the absence of storage injection and the arrival of bulk shipments of LNG. Then we perform numerical simulations for three LNG importation terminals in the United Kingdom – Isle of Grain, South Hook and Dragon – based on real-world data from April 2011 to April 2012. We investigate whether or not the simulations match the observed regasification decisions, in order to discover if the operators really are maximising their revenues and if the model can be useful for forecasting purposes. Furthermore, we conduct a numerical experiment with counterfactual parameters for one of the facilities to illustrate how model simulations can be used to estimate the additional revenue resulting from a hypothetical increase in storage and regasification capacities.

Our research mainly differs from earlier efforts in two ways. Firstly, we focus in isolation on LNG storage tanks at importation terminals, which are becoming increasingly important parts of the supply infrastructure in many regions and we incorporate constraints and characteristics specific for this type of storage. Such a treatment does not, to our knowledge, exist in the current literature. Secondly, no earlier study appears to have compared the behaviour of a natural gas or LNG storage optimisation model to the observed behaviour of facility operators, although this could provide some very interesting insights into both the validity of such models and the behaviour of operators in practice.

There are four groups who might take a particular interest in this study. Firstly, the model may help investors and engineers assess how various technical properties of a facility affect the economic value. Secondly, the model and the numerical simulation strategies may help operators of LNG storage tanks at importation terminals improve their regasification decisions and increase their revenue. Thirdly, given the market impacts of such decisions, participants in gas and adjacent markets (other regions as well as other commodities) may be interested since the results will reveal operational characteristics of important participants and may help improve forecasting capabilities. Finally, those with a practical interest in market efficiency and consumer benefits, such as regulators and government agencies, may be interested in evaluating to what extent the market mechanisms are successfully achieving certain objectives.

A mathematical specification of a revenue-maximising model for LNG storage tanks at importation terminals follows in the next section. In the third section, parameter calibration and three numerical simulation strategies are discussed. The fourth section discusses the results of numerical simulations carried out for three LNG importation terminals in the UK based on data from the period April 2011 to March 2012 and a hypothetical capacity expansion. The fifth section outlines the main conclusions of this study in brief.

2.2 A Revenue-Optimising Model for Scheduling Regasification from LNG Storage Tanks at Importation Terminals

We assume that the operators of LNG storage tanks in the importation terminals daily select the quantity of gas to regasify, sell and discharge into the pipeline network in order to maximise their expected accumulated revenue over a given time horizon. In addition to the technical capacity restrictions of the facility, the available actions are constrained by the initial stock level, the schedule of arriving LNG cargoes and the prices for the natural gas offered in the spot market. This study intends to analyse only the operation of the LNG storage tanks, and for this reason the schedule for LNG deliveries by ship will be considered fixed and given. This model will also not consider the influence of the actions of the operators on the market prices, which will be considered exogenous to the model.

Assuming that the operators choose their daily deliveries at the start of each gas day and do not change their mind in the course of the day, we can consider their decision problem defined on a discrete and finite time horizon $t_i \in \{t_0, t_1, \ldots, t_T\}$ over which the optimisation will be performed, in which each element represents one day. Given a spot price for natural gas S_i on day t_i, we assume the revenue earned by an operator who chooses to sell and regasify a quantity a_i is given by:

$$R(a_i, S_i) = a_i S_i. \tag{2.1}$$

If we treat the LNG that is already in storage as a sunken cost, and we assume that the transaction and holding costs are independent of the decision a_i, then maximisation of the revenue will yield the exact same behaviour as maximisation of the profits. Although it may not be obvious at first, these assumptions are perfectly reasonably for this particular problem since we are only concerned with achieving the best regasification schedule vis-a-vis a natural gas spot market with a stochastic price. That is, we want to optimally distribute a fixed volume of natural gas over a fixed time horizon, and so we can assume that the costs are approximately equal for all regasification schedules and this allows us to focus on maximising the revenue rather than profit. Since the future spot price S_i is a stochastic variable, the objective of the LNG storage operator is to maximise the expected accumulated (discounted with a factor β) revenue over the time horizon:

$$\max_{\{a_i\}_{i=0}^{T}} \mathbb{E}_0 \left[\sum_{i=0}^{T} \beta^i a_i S_i \right]. \tag{2.2}$$

The inventory level, x_i, must be maintained within the technical limits of the installation, and furthermore we assume that operators avoid emptying the tanks entirely because of the high cost of re-cooling tanks that have been completely emptied. Therefore, we force the model to retain the inventory within certain limits, $x_i \in [\underline{x}, \overline{x}]$. If we represent the volume of gas unloaded from LNG ships into the storage tanks by $\{b_i\}_{i=0}^{T+1}$ and assume that no gas is lost or used in the regasification process, the inventory evolves according to:

$$x_{i+1} = x_i - a_i + b_i. \tag{2.3}$$

The volume regasified and sold, a_i, is considered the only variable under the direct control of the operators. The volume available for regasifying and selling each day is subject to four constraints: (1) the amount cannot exceed the regasification capacity of the facility, (2) the inventory must not be brought beyond its limits, (3) the remaining inventory cannot impede the unloading of any arriving ship, and (4) the final inventory must reach x_{T+1}. The upper limit, $\overline{a_i}$, is restricted by the regasification capacity a_{cap}, the current inventory compared to the minimum inventory $x_i - \underline{x}$, and the relationship between scheduled LNG ship arrivals and the final inventory $x_i - x_{T+1} + \sum_{j=i}^{T+1} b_j$, such that:

$$\overline{a_i} = \min \left\{ a_{cap}, \quad x_i - \underline{x}, \quad x_i - x_{T+1} + \sum_{j=i}^{T+1} b_j \right\}. \tag{2.4}$$

The lower limit, $\underline{a_i}$, can be either zero, restricted by the relationship between the current stock level and the number of days until the final stock level must be reached $x_i - x_{T+1} - (T - i) \times a_{cap}$, or could be restricted by the scheduled arrival and unloading of LNG ships if the following expression for $a_{F,i}$ is positive:

$$a_{F,i} = x_i - \overline{x} + \max \left\{ \left(\sum_{j}^{T+1} b_j \right) - (j - i) \times a_{cap}, \quad j = i, \ldots, T + 1 \right\}. \tag{2.5}$$

For this reason, the lower limit for discharge is given by the expression:

$$\underline{a_i} = \max \left\{ 0, \quad a_{F,i}, \quad x_i - x_{T+1} - (T - i) \times a_{cap} \right\}. \tag{2.6}$$

Note that our assumptions currently ignore boil-off, which is treated as negligible, although it could be taken into consideration quite easily by replacing the 0 in equation 2.6 with the boil-off rate.

The problem faced by the operator each day – choose the quantity of gas to regasify and sell, $\{a_i\}_{i=0}^{T}$, in order to maximise the expected discounted revenue over the entire time horizon subject to uncertainty in the spot price S_i, given starting stock level x_0, ending stock level x_{T+1} and a LNG ship unloading schedule $\{b_i\}_{i=0}^{T+1}$ – can be summarised by the following:

$$\max_{\{a_i\}_{i=0}^{T}} \mathbb{E}_0 \left[\sum_{i=0}^{T} \beta^i a_i S_i \right] \tag{2.7}$$

$$\text{s.t.} \quad a_i \in [\underline{a_i}, \overline{a_i}] \tag{2.8}$$

$$x_{i+1} = x_i - a_i + b_i \tag{2.9}$$

$$\{b_i\}_{i=0}^{T+1}, x_0, x_{T+1} \quad \text{given.} \tag{2.10}$$

According to Bellman's optimality principle, the objective function, equation 2.7, can be rewritten in the familiar recursive form:

$$V_i(x_i) = \max_{a_i} \left(a_i S_i + \beta \mathbb{E}_i \left[V_{i+1}(x_{i+1}) \right] \right). \tag{2.11}$$

The first term in this expression represents the immediate revenue, whereas the second term represents the value of the gas that is saved for the remainder of the time horizon. Although this formulation immediately appears more tractable due to decomposing the full decision problem into a series of single-step decision problems, the most interesting aspect of this problem is how to compute the expectation over the stochastic price S_i. The numerical resolution of this model is treated in the next section.

2.3 Numerical Resolution

We outline three different strategies for resolving the model numerically: (1) a perfect strategy which generates a strict upper bound for the revenue by using historical spot prices as if the operators have perfect foresight, (2) a rolling intrinsic strategy which considers the prices of futures contracts as perfect forecasts for future spot prices and adjusts the regasification schedule on a daily basis as new futures prices are realised in the market, and (3) a full option strategy which incorporates uncertainty through a least-squares Monte Carlo method similar to the natural gas storage valuation technique developed by Boogert & Jong (2008).

The strategies require determining the continuation value in all potential states, but to make the model computationally tractable we rely on discretising the inventory to a fine regular grid of a few hundred grid points. The discretisation is chosen so fine that it is unlikely to substantially impact the solution quality.

2.3.1 The Perfect Strategy

When historical spot prices are available, we can ignore the stochastic nature of the problem and solve the deterministic model by backwards induction. This generates an upper limit to the revenue, *the posterior bound*, that could have been generated with the facility over the time period if the operator had perfect foresight. In reality it is unlikely that the operators attain the revenue generated by such a strategy, but the behaviour and revenue generated by the model using this strategy will nonetheless serve as important points of reference as an absolute upper boundary.

2.3.2 Rolling Intrinsic Strategy

In the traditional intrinsic strategy, the operator commits to a full schedule at the start of the time horizon and can immediately lock in the profit by buying and selling forward/futures contracts. A *rolling* intrinsic strategy allows the operator to reassess the schedule every day based on updated market prices, rather than committing to a full schedule for the entire period at the start of the period.

For this operational strategy, we use the market prices of futures contracts as perfect forecasts for future spot prices, then solve the model by backwards induction and simulate the execution of the action suggested by the model for the current day. This is then repeated every day, as new prices are revealed in the market. In this study, we first apply a smoothing process to the curve of futures prices for the purpose of avoiding artificial sharp jumps in the spot price forecast at the change of contract periods – the smoothing process creates a more gradual transition in the spot price forecasts. The details of the smoothing process are treated in the next section. However, this small departure from the tradition implies that it may not be possible to perfectly hedge the position in the futures markets.

In addition to being computationally fast, this strategy is fairly unsophisticated and consists of simple procedures applied to information that is almost surely known to the operators. The strategy is also low-risk, as it allows operators to largely hedge their position in the futures market.

2.3.2.1 Maximum Smoothness Forward Curve

The forecasts for spot prices will be based on a smooth curve created from the prices of the futures contracts, according to the method outlined by Guan & Xiao (2002) and Benth, Benth & Koekebakker (2008), and summarised here.

Suppose that we have a list of m prices of futures contracts, each with price F_j and delivery period τ_j^i to τ_j^f, $j \in \{1, \ldots, m\}$:

$$F = \{(F_1, \tau_1^i, \tau_1^f), (F_2, \tau_2^i, \tau_2^f), \ldots, (F_m, \tau_m^i, \tau_m^f)\}. \tag{2.12}$$

We first construct a list of periods, $\{\tau_0, \tau_1, \ldots, \tau_n\}$, in which overlapping delivery periods have been split. The smooth price curve, $S(t)$ will be constructed by one polynomial of the fourth degree per interval:

$$S(t) = \begin{cases} a_1 t^4 + b_1 t^3 + c_1 t^2 + d_1 t + e_1, & t \in [\tau_0, \tau_1\rangle \\ a_2 t^4 + b_2 t^3 + c_2 t^2 + d_2 t + e_2, & t \in [\tau_1, \tau_2\rangle \\ \vdots \\ a_n t^4 + b_n t^3 + c_n t^2 + d_n t + e_n, & t \in [\tau_{n-1}, \tau_n]. \end{cases} \tag{2.13}$$

Firstly, the average of the smooth function $S(t)$ over the delivery period of any futures contract must be equal to the price of the contract:

$$F_j = \frac{1}{\tau_j^f - \tau_j^i} \int_{\tau_j^i}^{\tau_j^f} S(t) \mathrm{d}t, \quad j \in \{1, \ldots, m\}. \tag{2.14}$$

Secondly, we want $S(t)$ to be smooth, thus we construct $S(t)$ to have C^2 continuity by setting the two first derivatives of adjacent pieces equal, and we also add a boundary condition requiring that the derivative is zero at τ_n:

$$a_i {\tau_i}^4 + b_i {\tau_i}^3 + c_i {\tau_i}^2 + d_i \tau_i + e_i = a_{i+1} {\tau_i}^4 + b_{i+1} {\tau_i}^3 + c_{i+1} {\tau_i}^2 + d_{i+1} \tau_i + e_{i+1} \tag{2.15}$$

$$4 a_i {\tau_i}^3 + 3 b_i {\tau_i}^2 + 2 c_i \tau_i + d_i = 4 a_{i+1} {\tau_i}^3 + 3 b_{i+1} {\tau_i}^2 + 2 c_{i+1} \tau_i + d_{i+1} \tag{2.16}$$

$$12 a_i {\tau_i}^2 + 6 b_i \tau_i + 2 c_i = 12 a_{i+1} {\tau_i}^2 + 6 b_{i+1} \tau_i + 2 c_{i+1} \tag{2.17}$$

$$4 a_n \tau_n^3 + 3 b_n \tau_n^2 + 2 c_n \tau_n + d_n = 0. \tag{2.18}$$

Because these conditions are still not sufficient to uniquely determine all the free parameters of the function $S(t)$, a minimum curvature condition is introduced, which thereby ensures that $S(t)$ has maximum smoothness:

$$\min \int_{\tau_0}^{\tau_n} S''(t)\mathrm{d}t. \tag{2.19}$$

Resolving the system of linear equations resulting from the conditions 2.14-2.19, we are able to determine all the parameters of the function $S(t)$: the curve which covers the prices of all the futures contracts, with C^2 continuity and maximum smoothness. From this specification of $S(t)$, one can generate a price for each day in the time horizon:

$$S_i = \int_{t_i}^{t_{i+1}} S(t)\mathrm{d}t \quad i \in \{0, 1, \ldots, T-1\}. \tag{2.20}$$

The optimal regasification decision a_i for the rolling intrinsic strategy is calculated by backwards induction of the model using the maximum smoothness forward curve for a given day. The execution of the decision is then simulated, and the next day the procedure is repeated using updated prices of futures contracts.

2.3.3 Full Option Strategy

The third strategy is based on the storage valuation techniques developed by Boogert & Jong (2008), in which a Monte Carlo method is used to simulate n future spot price paths $\{\hat{S}_i^c\}_{c=1}^n$ and a least squares method is used to estimate the continuation value in each step of the resolution of the model by backwards induction, visiting all states at each step. This type of strategy is often called an extrinsic or option strategy, because it estimates the value of deferring decisions in the presence of uncertainty.

This method requires selecting and calibrating an appropriate process for simulating paths of future spot prices. Although any of a number of price processes can be chosen for this, we follow Boogert & Jong (2008) and choose an Ornstein-Uhlenbeck process, which is quite common in the context of energy markets:

$$\mathrm{d}S_i = \lambda(\mu_i - S_i)\mathrm{d}t + \sigma \mathrm{d}W_i. \tag{2.21}$$

This stochastic process exhibits reversion to the mean, μ_i, with velocity $\lambda > 0$. W_i represents standard brownian motion, and therefore $\mathrm{d}W_i \sim N(0, \sqrt{\mathrm{d}t})$. The volatility of the process is given by $\sigma > 0$. The mean reversion rate, λ, and the volatility, σ, can be calibrated using historical spot prices. The mean μ_i to which the price reverts is normally some assumed long-term mean price, but in this study we find it appropriate to interpret the prices generated from the maximum smoothness forward curve as forecasts for the mean spot price in the future μ_i.

The numerical resolution is performed by visiting each reachable inventory state in each step, starting from the final period, and for each path selecting the decision that maximises the sum of the immediate profit and an approximation of the continuation value constructed by a linear combination of k basis functions:

$$a_i^{*c} = \underset{a_i \in [\underline{a_i}, \overline{a_i}]}{\arg\max} \left\{ a_i \hat{S}_i^c + \sum_{j=1}^{k} \gamma_j^{a_i} \phi_j(\hat{S}_i^c) \right\}. \tag{2.22}$$

Since we are moving backward in time, we already have an estimate for the value of each inventory level in the next period $\{\hat{V}_{i+1}^c(x_i - a_i + b_i)\}_{c=1}^n$ for each price path. We can determine the coefficients $\{\gamma_j^{a_i}\}_{j=1}^k$ – one set of coefficients per next-period inventory level encountered by choosing a_i – by ordinary least squares regression of the discounted next-period value estimate against the basis functions evaluated in the current price:

$$\beta \hat{V}_{i+1}^c(x_i - a_i + b_i) \approx \sum_{j=1}^{k} \gamma_j^{a_i} \phi_j(\hat{S}_i^c), \quad c = 1, \ldots, n. \tag{2.23}$$

According to Boogert & Jong (2008), approximately 50 price paths is sufficient to achieve apparent convergence, and the power series up to the sixth order provides a set of basis functions that appears to behave relatively well.

The main advantage of this strategy is the more realistic and opportunistic treatment of uncertainty compared to the other two strategies, along with rapid convergence compared to other Monte Carlo based methods. It is expected that the profit from following this strategy will fall between the profit from the perfect strategy and the rolling intrinsic strategy.

2.4 Numerical Experiments

2.4.1 Simulations for Three Existing UK Facilities

We now perform numerical experiments for the purposes of illustrating and exploring the use of the model in a real-world context, thereby highlighting key features of the model whilst simultaneously investigating important operational characteristics of the facilities. One simulation of the model is performed for each of the three strategies – the perfect strategy, the intrinsic strategy and the full option strategy – using observed market data and the technical and operational characteristics of three LNG importation terminals in the United Kingdom: Dragon, Isle of Grain and South Hook. The period chosen for the simulations was the start of April 2011 to the end of March 2012, a period that represents one full *storage year*.

The behaviour generated by the model simulations will be compared to the observed behaviour of the facility operators. The technical characteristics of the facilities and the

Table 1 – Characteristics of the facilities and parameters used in the simulations*

	Dragon	**Isle of Grain**	**South Hook**
Max storage capacity (mcm)	192	582	465
Min storage capacity (mcm)	6	78	36
Regasification (mcm/d)	24	59	70
Starting stock 2011-04-01 (mcm)	70	328	253
Ending stock 2012-03-31 (mcm)	37	326	335
LNG received Apr 2011–Mar 2012 (mcm)	1 681	5 876	12 723

Source: Thomson Reuters.

* The volumes are measured in gaseous state at a temperature of 20°C and pressure 1 atm. The numbers are given in million cubic meters (mcm), assuming a calorific value of around 11 kWh/m^3.

parameters used in the simulations are summarised in table 1. All the simulations were performed using observed starting stock levels, ending stock levels and LNG refill schedule. Therefore, simulations for each facility differ only in the regasification schedule and not in the total volume of LNG sold on the market. Therefore the three simulations for each facility are considered to be comparable both to each other and to the observed behaviour.

This study assumes that the operators are remunerated according to the spot gas price on the National Balancing Point (NBP). The development of the NBP spot gas price during the period in consideration is shown in figure 1. The volatility of the price was considerable during the period in question, in particular showing large drops (and quick recoveries) during the summer and autumn, and a short-lived peak during the winter. The apparent temporary effect of the sharp movements suggests that a mean-reverting process is adequate, and supports the choice of an Ornstein-Uhlenbeck price process, at least superficially.

For the rolling intrinsic strategy, which uses the prices of futures contracts as a forecast for the spot price in the future, maximum smoothness forward curves were constructed for each day of the period in consideration. Figure 2 shows a single example of such a maximum smoothness forward curve, together with the prices of the futures contracts on which it is based. Note also that the prices of futures contracts with delivery period during the winter are higher than those with delivery period during the summer, mainly due to the higher gas consumption for heating purposes during the winter. The smooth forward curve was constructed such that the average price over each futures contract period equals the observed futures contract price, whilst exhibiting C^2 continuity such that sharp jumps are avoided at the change of contract periods. The maximum smoothness forward curve serves as the expected price for the rolling intrinsic strategy, and also as the mean for the mean-reverting price process used in the full option strategy.

The full option strategy uses an Ornstein-Uhlenbeck process to generate daily prices in the future, and figure 3 shows one example of a price path generated by this

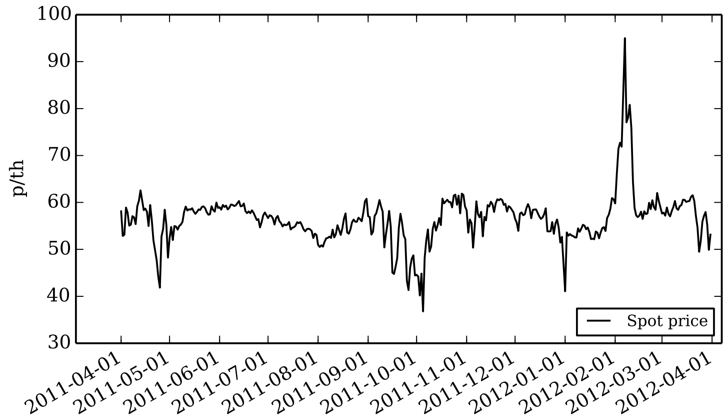

Figure 1 – Natural gas spot price (System Average Price, Actual Day) at the National Balancing Point in the United Kingdom, denoted in pence per therm. Source: Authors' elaboration based on data from (NATIONAL GRID, 2012).

process. The simulated price path remains relatively close to the maximum smoothness forward curve which is used as the mean price, but in addition exhibits volatility and mean reversion – characteristics which appear similar to how the spot price behaves in reality. Beyond these shallow observations, however, the appropriateness of this specific price process is uncertain, although a thorough discussion of this subject is beyond the scope of this study. For the simulations of the full option strategy, 50 price paths were created, a number sufficient to ensure convergence according to Boogert & Jong (2008). The volatility, σ, and the mean reversion rate, λ, for the Ornstein-Uhlenbeck process were estimated using NBP spot price from January 2007 to December 2011, following the ordinary least squares method detailed by Smith (2010) or Lund & Ollmar (2002).

Two aspects of the simulation results are of great interest in this study: the accumulated revenue that each of the strategies generated compared to the observed behaviour, and the correspondence between regasification decisions a_i made by each of the strategies and the observed decisions. These two aspects of the simulations are treated in detail in the two next sections.

2.4.1.1 Accumulated Revenue

The accumulated revenues of the facilities generated by the observed behaviour and the three simulated strategies are shown in table 2. All the simulations generated higher revenues than the observed behaviour. The revenues generated by the rolling intrinsic strategy simulation exceeded the revenues generated by the observed behaviour by GBP 6 million for Dragon, GBP 12 million for Isle of Grain, and GBP 16 million for South Hook. This is a somewhat surprising result because the rolling intrinsic strategy is considered to represent a rather unsophisticated and low risk strategy, and the revenues generated by

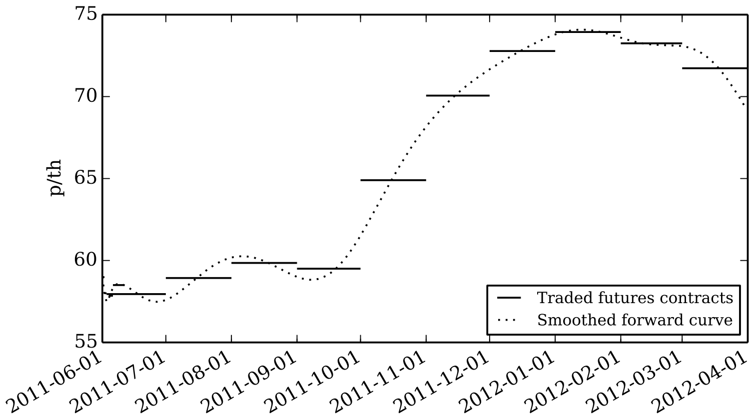

Figure 2 – Closing prices of UK Natural Gas futures contracts on June 1 2011, together with a smoothed price curve. Source: Authors' elaboration based on data from (INTERCONTINENTAL EXCHANGE, 2012) and research results.

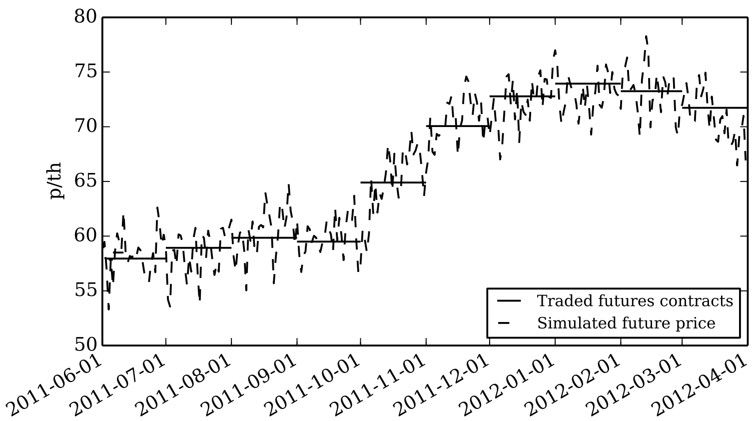

Figure 3 – Closing prices of UK Natural Gas futures contracts on June 1 2011, together with simulated futures prices generated by an Ornstein-Uhlenbeck process. Source: Authors' elaboration based on data from (INTERCONTINENTAL EXCHANGE, 2012) and research results.

Table 2 – Accumulated revenue between 2011-04-01 and 2012-03-31 (modelled), in millions of GBP

	Dragon	**Isle of Grain**	**South Hook**
Observed	364	1 272	2 666
Intrinsic	370	1 284	2 682
Full Option	372	1 283	2 682
Perfect	392	1 342	2 682

Source: Research results.

the observed behaviour were initially expected to exceed those generated by this strategy. In the case of South Hook, the accumulated revenues for all three simulations were equal, which might indicate that the terminal receives LNG cargoes so frequently compared to the storage and regasification capacities that it reduces the amount of time that regasification can be deferred. Table 2 suggests that facility operators could increase their revenue by adopting either of the operational strategies simulated by the model to optimise their regasification schedule.

The figures 4, 5 and 6 show the development of the accumulated revenues for the installations Dragon, Isle of Grain and South Hook for each of the simulated strategies and the observed behaviour over the selected time horizon. The accumulated revenues for each of the simulated strategies appear to remain relatively close. In the case of Dragon and Isle of Grain, the operators appear to prefer regasifying earlier than the model simulations, since the revenue of the observed regasification exceeds the model simulations earlier in the time horizon. However, since the revenues of the simulated strategies eventually ended up higher in every case, this shows that the additional revenue achieved by deferring regasification under price uncertainty can be significant and that LNG importation terminals can make significant gains from utilising their storage capacity more efficiently to optimise the regasification schedule.

2.4.1.2 Comparison between Simulated and Observed Regasification Decisions

The mean absolute relative error between the regasification decisions of the simulations of the different strategies, a_i, and the observed behaviour is summarised in table 3. The simulations for Dragon and Isle of Grain presented an error of between 110% and 130%, which suggests that the regasification decisions of the model simulations and the observed regasification decisions do not correspond well. The errors for the simulations for South Hook were slightly lower, but do not alter the conclusion.

From the scatter plots for each of the installations – figures 7, 8 and 9 – it is evident that the regasification decisions of the simulations and the observed regasification decisions are very different: the model simulations appear to prefer extreme actions, as the simulation

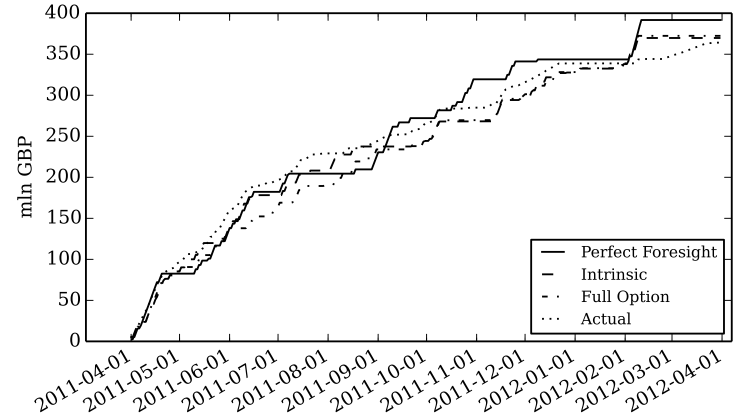

Figure 4 – Simulated accumulated revenue for the Dragon LNG Terminal in the United Kingdom. Source: Research results.

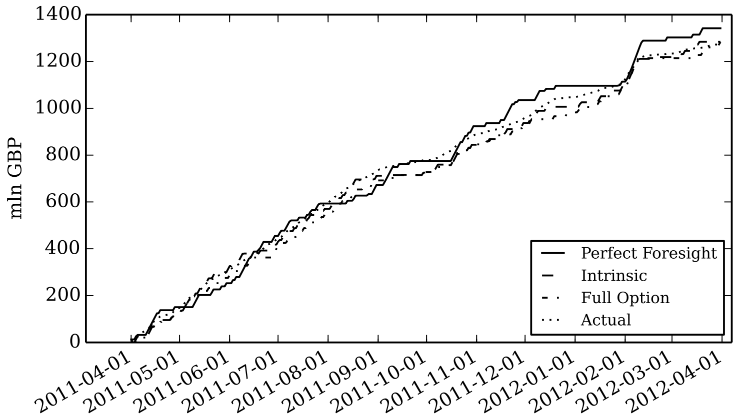

Figure 5 – Simulated accumulated revenue for the Isle of Grain LNG Terminal in the United Kingdom. Source: Research results.

Table 3 – Mean absolute relative error between simulated and observed regasification decisions

	Dragon	**Isle of Grain**	**South Hook**
Intrinsic	109.9%	111.3%	82.5%
Full Option	114.5%	118.3%	82.5%
Perfect	125.2%	121.9%	82.5%

Source: Research results.

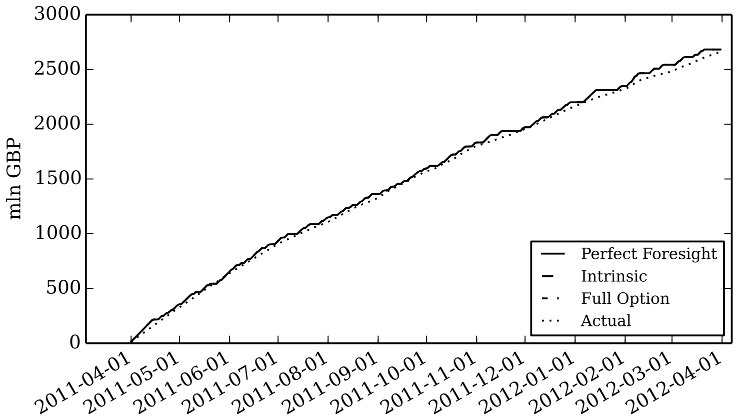

Figure 6 – Simulated accumulated revenue for the South Hook LNG Terminal in the United Kingdom. Source: Research results.

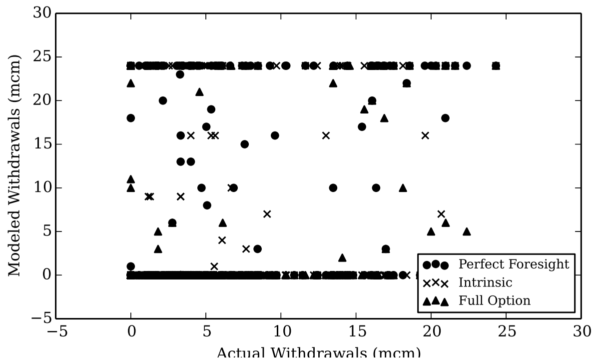

Figure 7 – Scatter plot – the observed regasification against the simulated regasification for the three strategies for Dragon. Source: Authors' elaboration based on data from (NATIONAL GRID, 2012) and research results.

decisions are clustered at the maximum or minimum regasification capacities, whereas the observed behaviour is much more moderate and appears to choose regasification quantities much more freely. In particular, figure 9 shows that the simulations for South Hook recommended regasification at the capacity of 70 mcm/d every single day, whereas the observed regasification rarely exceeded 60 mcm/d.

Table 4 shows the Spearman rank correlation coefficients between the recommended regasification from the simulations and the observed regasification decisions for each of the three installations and each of the three strategies. The correlation coefficient is between 25% and 42% for the simulations for Dragon and Isle of Grain, which we consider fairly low: a recommendation for high rate of regasification from the simulations is apparently not related to a high observed rate of regasification. For South Hook, the rank correlation coefficient was meaningless, because the recommended action was always to withdraw at

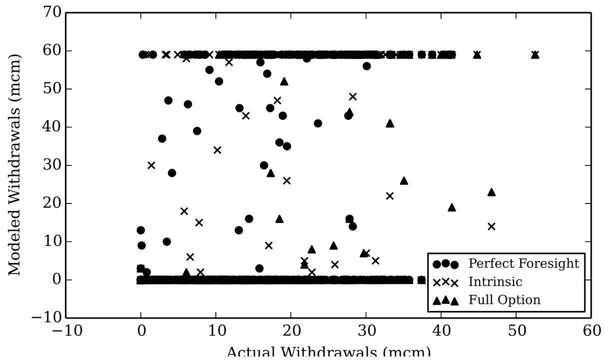

Figure 8 – Scatter plot – the observed regasification against the simulated regasification for the three strategies for Isle of Grain. Source: Authors' elaboration based on data from (NATIONAL GRID, 2012) and research results.

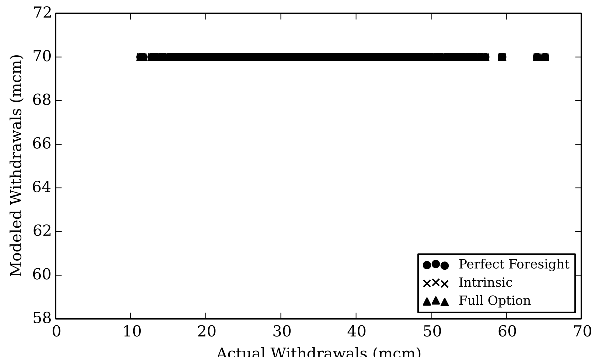

Figure 9 – Scatter plot – the observed regasification against the simulated regasification for the three strategies for South Hoook. Source: Authors' elaboration based on data from (NATIONAL GRID, 2012) and research results.

Table 4 – Spearman Rank Correlation Coefficient

	Dragon	**Isle of Grain**	**South Hook**
Intrinsic	25.4%	36.9%	N.S.
Full Option	30.9%	42.0%	N.S.
Perfect	29.4%	27.8%	N.S.

Source: Research results.

capacity and the recommendation can therefore not be ranked. Although these correlations are low, it is noteworthy that the full option strategy resulted in a higher correlation for Dragon and Isle of Grain and therefore appears closer to their employed strategy than the others. However, the low correlations suggest that observed actions and recommended actions from the simulations are unrelated, and so the model appears to be unsuitable for forecasting the regasification decisions of the facilities.

2.4.1.3 Discussion

It is possible that the discrepancy between the simulations and the observed behaviour is caused by additional technical, economical or contractual limitations that are not well represented in the model. However, many of the finer operational details of facilities are often considered confidential, so it can be difficult to obtain sufficient information to construct a more realistic model.

Furthermore, some technical details may have been oversimplified by the model. There could, for instance, be some loss of gas due to the operation of the facility and this may affect the regasification decisions. The simulations also disconsidered boil-off, which could be significant or could be reliquefied and returned to storage at an increase in the cost-of-carry. However, we expect that these factors only cause significant changes in the regasification schedule in marginal cases, and that the technical characteristics already captured by the model are overwhelmingly important in the determination of the schedule.

Another possible explanation for the discrepancy between the simulations and the observed behaviour is that the model assumes that the operators of the installations behave as if they were a single proprietor and capacity holder, whereas the observed behaviour could in reality be the combined result of many different actors with different positions because each installation has several capacity holders. If this is the case, however, the capacity holders could gain from cooperating, and the operation of the facilities is not (Pareto) optimal. A similar concern may arise if the operators have sold the gas in long-term contracts, but also if this is the case the operation is not optimal, and offsetting the long-term contracts against the spot market to optimise the value of the storage could provide significant gains.

One of the assumptions of the model was also that the actions of the operators do not affect market prices, which is obviously a bold assumption when the regasification capacities of the facilities are as high as in this case. This assumption permitted the model to act without considering the effect of its own actions on the price, a liberty that the operators may not have in reality. There are indications that the natural gas market in the UK behaves similar to a Cournot oligopoly, and a more sophisticated model might include the effect of its own actions on prices. A model that considers such an effect would conceivably show a more moderate behaviour that would be more in line with the observed behaviour.

Yet another simplification that was made in the model was that the LNG refill schedule for the entire time horizon was given in advance. In reality, the schedule is more likely to be at least partially uncertain and/or undetermined. It would be reasonable to believe that an operator faced with an uncertain schedule would prefer to save more gas than otherwise, since the schedule is more likely to be incomplete only in the distant future. The model can be expanded to take into account uncertainties in the delivery schedule, but it is excessively difficult for a retrospective study to take into account, as it would require knowing the expected delivery schedules of the operators at all times. A violation of this assumption would make the operator unable to optimise the discharges as the model recommends, leading to lower accumulated revenues over the time horizon.

The final explanation for the discrepancy between the simulation results and the observed behaviour is the possibility that the operators use less sophisticated means to select their daily regasification volumes than this model represents. If this should be the case, and the model presented in this study indeed offers a sufficiently accurate representation of their situation, then the facilities could be operating sub-optimally and the model presented here can be adopted by the operators to improve their regasification schedules.

2.4.2 The Value of a Hypothetical Expansion of the South Hook LNG Terminal

The model can also be used to estimate the additional revenue that can be generated with hypothetical capacity expansions. To illustrate such a usage, we examine in brief the hypothetical addition of extra storage and regasification capacity at the South Hook LNG importation terminal in the UK.

The simulations of all strategies for this facility in the previous section resulted in the same accumulated revenue, suggesting that South Hook might have received LNG shipments at such a high rate compared to the storage and regasification capacities that the operator had few possibilities to defer regasification. Therefore, we find it interesting to investigate what would happen if the facility had greater storage and regasification capacity, offering greater flexibility for the regasification schedule. This experiment highlights the value of increasing only the storage and regasification capacities, without altering the total amount of gas available to the facility. The additional revenue generated by the expanded facility in this counterfactual scenario is therefore only a result of allowing the operator to move gas between time periods more efficently.

The parameters used for the simulations of the hypothetical expanded South Hook terminal are shown in table 5. Note that the maximum storage and the regasification capacities have been doubled, whereas the remaining parameters are left unaltered – even the starting/ending inventory levels and the amount of LNG received in the period of interest.

The accumulated revenues of the simulations using all three strategies with the original and expanded facilities are shown in table 6. The revenue of the perfect strategy (posterior bound) in the selected one-year period was GBP 213 million greater for the hypothetical expanded facility than for the original installation, representing an increase

Table 5 – Characteristics of the facilities and parameters used in the simulations*

	South Hook	SH Expanded
Max storage capacity (mcm)	465	930
Min storage capacity (mcm)	36	36
Regasification (mcm/d)	70	140
Starting stock 2011-04-01 (mcm)	253	253
Ending stock 2012-03-31 (mcm)	335	335
LNG received Apr 2011–Mar 2012 (mcm)	12 723	12 723

Source: Thomson Reuters.

* The volumes are measured in gaseous state at a temperature of 20°C and pressure 1 atm. The numbers are given in million cubic meters (mcm), assuming a calorific value of around 11 kWh/m^3.

Table 6 – Accumulated revenue between 2011-04-01 and 2012-03-31 (modelled), in millions of GBP

	South Hook	SH Expanded	Increase (%)
Intrinsic	2 682	2 793	4.1%
Full Option	2 682	2 769	3.2%
Perfect	2 682	2 895	7.9%

Source: Research results.

of about 8%. The intrinsic and full option strategies showed increases of GBP 111 million and GBP 87 million, or approximately 4% and 3%, respectively. Since this increase in simulated revenue was achieved without altering the total amount of LNG, the simulations illustrate that the option value provided by increased storage and regasification capacities can be significant, and can have dramatic effects on the possible achievable revenue of an LNG importation terminal.

2.5 Conclusion

We outlined a stochastic dynamic programming model for the optimisation of revenue from storage and regasification of LNG at import terminals vis-a-vis a natural gas spot market, and showed how the resulting optimisation problem could be solved numerically utilising three different strategies: a perfect strategy that creates a posterior bound by using historical prices, a rolling intrinsic strategy which optimises regasification decisions each day considering the futures market as a perfect forecast for future spot price, and a full option strategy based on a least-squares Monte Carlo method that attempts to realise the option value of deferring regasification decisions under price uncertainty.

Numerical experiments showed that the revenue generated by simulations of all three strategies exceeded the revenue generated by the observed behaviour of the operators of three LNG importation terminals in the UK. Although the model simulations arrived at accumulated revenue relatively close to the observed accumulated revenue, the regasification decisions chosen by the simulations and the observed regasification decisions appeared unrelated. This suggests that either the operators could be facing additional constraints that are not well represented in the model, or that the facilities are not operated efficiently. Facility operators might be able to increase their revenues by adopting the model presented here. Positive side effects of increased operational efficiency would include an increase in economic surplus, a more stable price, increased supply security and a more predictable market.

In addition to being useful for operational decisions, our method can be used to estimate the value of planned or hypothetical capacity expansions for facilities. We illustrated this usage by investigating the value of increasing the storage and regasification capacities for one of the facilities in the simulation, whilst maintaining the total amount of LNG unaltered over the period. The accumulated revenue generated in the simulation increased substantially, showing that the option value of deferring regasification can be significant and that simulations of the model can be useful for estimating the value of such expansions.

3 Climate Change and Electricity Demand in Brazil: A Stochastic Approach

Abstract

We present a framework for incorporating weather uncertainty into electricity demand forecasting when weather patterns cannot be assumed to be stable, such as in climate change scenarios. This is done by first calibrating an econometric model for electricity demand on historical data, and subsequently applying the model to a large number of simulated weather paths, together with projections for the remaining determinants. Simulated weather paths are generated based on output from a global circulation model, using a method that preserves the trend and annual seasonality of the first and second moments, as well as the spatial and serial correlations. The application of the framework is demonstrated by creating long-term, probabilistic electricity demand forecasts for Brazil for the period 2016-2100 that incorporates weather uncertainty for three climate change scenarios. All three scenarios indicate steady growth in annual average electricity demand until reaching a peak of approximately 1071-1200 TWh in 2060, then subsequently a decline, largely reflecting the trajectory of the population projections. The weather uncertainty in all scenarios is significant, with up to 400 TWh separating the 10th and the 90th percentiles, or approximately ±17% relative to the mean.

Keywords: Long-term load forecast; Electricity demand; Climate change.

3.1 Introduction

Changes in the Earth's climatic system over the next several decades could have large direct and indirect consequences for electricity demand in many regions (IPCC, 2013). At the same time, effective energy planning requires projections with a long time horizon, high temporal resolution and a clear indication of the uncertainty of the projections – especially considering the long lead times and lifetimes of energy infrastructure, as well as the increasing proliferation of intermittent energy sources (e.g. wind and photovoltaic power generation).

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Weather variables have been used regularly for electricity demand forecasts since Dryar (1944) first noted that electric system load was influenced by weather conditions and “events of unusual attraction”. Electric system planning, production scheduling and daily operations of the power system now depend heavily on load forecasts that take consideration to weather conditions. Since its inception, load forecasting has been such a prolific topic that a thorough review of the literature is beyond the scope of this paper. However, a handful of studies have specifically addressed the subject of probabilistic, long-term and high-resolution load forecasts. We focus on a few works that can be considered the primary intellectual progenitors of this study. Although many earlier studies estimated certain parameters of the probability distribution of electricity demand (normally first and second moments), Veall (1987) first estimated the full probability distribution of future annual peak electricity demand using a nonparametric bootstrapping approach. Building on this approach, Adams, Allen & Morzuch (1991) included weather variables and investigated the probability distribution at a weekly and daily temporal resolution. To estimate the full probability density function of the peak load forecast, Belzer & Kellogg (1993) explored a Monte Carlo approach for fitting an extreme value distribution to the load forecasts, and Charytoniuk & Niebrzydowski (1998) used a product kernel to estimate the conditional multivariate probability density function of load. In a move to replace historical weather observations with forecasted weather, Taylor & Buizza (2003) incorporated weather uncertainty in load forecasts for the next ten days by using weather prediction ensembles. Using a simple multiple regression model calibrated on historical data, McSharry, Bouwman & Bloemhof (2005) generated weather simulations by the method of surrogates to estimate the probability density function of peak electricity demand one year ahead. In a similar fashion, Pezzulli et al. (2006) employed a climatological weather generator calibrated on historical weather to calculate density forecasts using a hierarchical Bayesian model. Acknowledging that future weather patterns may differ from historical patterns, Hor, Watson & Majithia (2006) used the output from a global circulation model to create daily load forecasts for the period from 2011 to 2100, and in addition incorporated model uncertainty by residual simulation. Hyndman & Fan (2010) developed a framework for forecasting the probability density of long-term peak electricity demand, based on calibrating a semi-parametric additive demand model on historical data and subsequently generating a large number of simulated realisations using temperature simulations, assumed future socio-economic variables and residual bootstrapping. Similarly, Ziser, Dong & Wong (2012) used a large number of synthetic weather scenarios generated by surrogate methods in order to incorporate weather uncertainty in demand forecasts, although the demand models were calibrated using machine learning techniques. In a less complicated approach, Hong, Wilson & Xie (2014) used 30 years of historical weather data and three socio-economic scenarios to create an ensemble of load forecasts from a multiple linear regression model for hourly load. Attempting to improve load forecasting by using weather forecasts rather than historical weather, Felice, Alessandri & Catalano (2015) examined the use of seasonal ensemble weather forecasts for creating probabilistic load forecasts up to four months ahead.

Common for nearly all of these earlier studies is that their period of interest is sufficiently short to allow them to legitimately disregard changes in the climate and assume that weather patterns will remain relatively stable over the forecast horizon. The exception is (HOR; WATSON; MAJITHIA, 2006), who incorporate the output from a global circulation model and create forecasts up to year 2100, although they incorporate uncertainty only by residual simulation rather than considering uncertainty in the input variables. For the explicit purpose of examining weather risk due to climate change, it is not correct to assume that the weather patterns are stable, nor only incorporate uncertainty by means of residual simulation.

Therefore, this study presents a framework for incorporating weather uncertainty in high-resolution electric system load forecasts by combining an econometric demand model and a large number of weather simulations. The weather simulations are based on the output from a global circulation model (GCM) and are designed to preserve the trend and seasonality of the first and second moments of the weather variables, as well as spatial and serial correlations present in the GCM output. This is useful for evaluating the electricity demand subject to weather risk under climate change scenarios. We demonstrate the application of this framework by creating a probabilistic forecast for Brazilian electricity demand for the period 2016-2100, with daily resolution and subject to weather uncertainty under climate change scenarios.

The method is presented in the context of a quantitative thought experiment on Brazilian electricity demand under climate change scenarios, and there are several reasons for this choice. In a review of the literature on the impacts of climate change on the eletricity market, Mideksa & Kallbekken (2010) noted specifically that more research was needed on the demand-side impacts in Latin America. Although Schaeffer et al. (2008) have previously studied the demand-side impacts of climate change on Brazilian electricity demand, our study improves upon this earlier study in two important ways. Firstly, it employs a stochastic approach that emphasises weather uncertainty and will provide an estimate of the probability distribution of demand, whereas Schaeffer et al. (2008) chose a deterministic approach. This is a very important aspect, as shown by Ferreira, Oliveira & Souza (2015), who have called for more research on stochastic modelling of the Brazilian Electric Power Sector. Secondly, this study takes advantage of more recent data – updated observations, models and discoveries – that were unavailable at the time of the earlier study. In light of recent advances in this research area, an updated assessment of the impact of climate change on the Brazilian electricity demand is sorely needed.

The main contributions of this study are therefore twofold. Firstly, we propose a new method for incorporating weather uncertainty in electricity demand forecasts when weather patterns cannot be assumed stable. This topic is presumably of great interest to a number of energy and climate change researchers worldwide. Secondly, the study satisfies an acute need for an updated appraisal of the impacts of climate change on Brazilian electricity demand in light of recent advances in this field of research. This is a topic of interest to policy makers, energy market participants and researchers with a particular interest in Brazil.

The remainder of this article is organised as follows: section 3.2 describes the calibration of an electricity demand model for Brazil with daily resolution. Section 3.3 demonstrates how the model is used for forecasting electricity demand, including how weather simulations are generated for creating probabilistic forecasts that incorporate weather uncertainty. The subsequent section, section 3.4, provides an overview of the main results and a detailed discussion. Finally, section 4.5 summarises the main findings of this study and suggests directions for future research.

3.2 Calibrating an Electricity Demand Model

3.2.1 Drivers of Electricity Demand and Modelling Framework

In order to create an econometric model for aggregated electricity demand, it is first necessary to identify the relevant variables that affect electricity demand and select an appropriate modelling framework. Fortunately, we need not start *ab initio*: we can rather draw heavily on the rich literature concerning this topic.

Two main considerations led to the choice of a daily temporal resolution for the electricity demand model, which is the highest temporal resolution afforded by the publicly available Brazilian electricity demand statistics. The first argument is that a higher resolution may offer a greater degree of accuracy for the model. Consider, for example, the possibility that high temperatures during the weekend have a slightly different impact on demand than high temperatures during working days. A model aggregated to monthly or annual scale might make it difficult to distinguish between these two cases, or similar interaction effects that might exist. Secondly, the highest possible temporal resolution is most useful for planning purposes. For instance, the peak instantaneous demand is often used as an important point of reference for supply planning purposes, since planners often want to ensure that maximum generation capacity is greater than peak instantaneous demand. The increasing share of renewable non-dispatchable energy sources also means that the timing of demand changes can have a great impact on expansion and dispatch planning, that is, whether high-demand periods coincide or not with high generation from non-dispatchable energy sources. In electric systems where the supply is dominated by hydroelectric generation, the order of events can also be of great importance to supply planning, for instance if a high-demand period precedes or succeeds a period of precipitation. A daily model is therefore much more useful for planning purposes than a monthly or annual model.

The choice of daily temporal resolution means that the model must both include factors that change quickly, from one day to the next, and factors that change slowly, in the course of years and decades.

Dryar (1944) noted – already in 1944 – that day-to-day changes in electricity demand were heavily influenced by weather conditions and extraordinary events, and ever since then weather variables and calendar variables have regularly been included in short-run electricity demand forecasts. It is therefore natural to include weather variables and calendar effects in the demand model in order to mainly capture day-to-day changes in electricity demand. Since this study explicitly focuses on climate change scenarios, the gradual change in the characteristics of the weather variables will also capture the direct effects climatic change on electricity demand. The effect of temperature on demand is often assumed to be non-linear (e.g. Hor, Watson & Majithia (2006), Hyndman & Fan (2010), Hong, Wilson & Xie (2014)), and this is most simply incorporated by replacing temperature by the number of degrees the temperature exceeds or falls below certain cut-off temperatures.

On a longer time-scale, factors that change more slowly are known to impact electricity demand, such as technology, demographics and economic activity (e.g. Stanton, Gupta & El-Abiad (1969), Uri (1977), Hor, Watson & Majithia (2006), Hyndman & Fan (2010)).

Technological change is an important determinant of electricity demand. However, the effect of new technology on electricity demand is ambiguous, as it may both increase and decrease electricity demand through creating new applications for electricity or replacing existing ones. In addition to the ambiguity, it is not easy to measure nor obtain credible forecasts of technological change. Therefore, we have chosen not to include technological change in the model.

Several demographical variables, such as population size, age composition, urbanisation rate and household size, can potentially influence electricity demand. We choose only to include population size in the model, because we expect the importance of this single demographic factor to greatly outweigh the others, and we have access to reasonably credible forecasts of population size for the entire forecast horizon. Including additional demographical variables might substantially complicate the model and the creation of forecasts from the model, whilst most likely only providing marginal benefits. If the results are sufficiently good, it should not be necessary to increase model complexity by introducing additional demographical variables.

Economic factors, such as national income, industrial production and income distribution, also affect electricity demand. Analogous to the choice of population size as the single demographic variable, we select national income as the only economic variable to include in the model: we expect the influence of national income to outweigh that of the remaining economic variables, credible forecasts are easily available, and including further economic variables would make the model more complex whilst presumably offering only marginal improvements. If the results of this choice are satisfactory, there is little incentive to increase the complexity of the model by including additional economic variables.

Price is generally considered one of the main determinants of demand. However, demand is a crucial component of the price formation, which means that it would be necessary to forecast demand in order to forecast price, but we would also need to forecast price to construct a demand forecast. This would lead to a circular problem, or at best a simultaneous problem, which we want to avoid in this particular study. Therefore, electricity price is not considered in the demand model. However, several studies on the household sector in Brazil assert that price elasticity of electricity demand in that particular sector is low, much lower than income elasticity (ANDRADE; LOBÃO, 1997; SCHMIDT; LIMA, 2004; MATTOS; LIMA, 2005), suggesting that this is of lower importance than factors already included, and may not be such a serious omission.

The demand model is constructed using a multiple linear regression framework. Although more complex modelling approaches have been widely explored in the literature, Hong, Wilson & Xie (2014) argue that multiple linear regression approaches often prove superior to machine learning approaches, and have the additional benefits of being simpler to operationalise and more defensible, in the sense that the influence of each factor is directly and explicitly quantified. This study involves extrapolating beyond the range of the observed data and into the remote future, so the transparency offered by a multiple linear regression framework is a particularly important consideration. Within the multiple linear regression framework, we apply logarithms to the electricity demand, the national income measure and the population size, in order to achieve constant elasticity of demand in those two factors. Since the estimation therefore is carried out in logarithm space, the remaining variables will represent multiplicative effects on electricity demand.

3.2.2 Data and Methodology

The demand model is calibrated using ten years of daily electricity demand data for the Brazilian Interconnected Power System, which serves 98.3% of Brazilian electricity demand (ONS, 2015). The data is split into a training sample consisting of the nine first years, which is used for the calibration of model parameters, and a validation sample consisting of the final year of data, which will be withheld for out-of-sample testing of the model.

Weather observations are available from the Integrated Surface Database (ISD) of the National Oceanic and Atmospheric Administration (NOAA), which contains 28 weather stations in Brazil with less than 10% missing hourly observations in the ten-year period (NOAA, 2015). We impute replacements for the missing temperature observations using a PCA-based method described by Josse & Husson (2011), which is believed to perform relatively well for this dataset due to a fairly low share of missing values and a substantial amount of both temporal and geographical regularity. We further reduce the number of included weather variables by applying the framework for weather station selection proposed by Hong, Wang & White (2015), which ranks individual weather variables by the goodness-of-fit of a simplified model that does not include the remaining weather variables, then selects the highest ranking weather variables such that the model error is minimised. We depart slightly from the framework by including all the weather terms explicitly in the model instead of calculating a composite weather variable. This procedure results in a selection of 18 weather terms pertaining to 13 different weather stations. Autoregressive and lagged terms of the weather variables are also included in order to account for inertia and accumulative weather effects, as discussed by Li et al. (2009). Based on a simple grid search using out-of-model error measures, we chose to include the 9-day moving average and one-day lagged weather terms.

Demographic and economic factors are also important for electricity demand, especially in the long term. Unadjusted quarterly GDP figures and projected monthly population numbers are included in the model (IBGE, 2015; IBGE, 2013). To include include the quarterly GDP figure in the daily resolution model, we apply the GDP figure in the relevant quarter to each day of the quarter. Since population numbers are given only at the start of each month, we perform a simple linear interpolation to obtain daily estimates for population.

Calendar effects are responsible for much of the day-to-day variation in electricity demand, and therefore we include dummy variables for each day of the week, major national and regional holidays, special events (such as FIFA World Cup matches in which Brazil plays), and for so-called bridge days, which are working days that fall between two non-working days. For some of the holidays, we distinguish between the case when it occurs on a weekday and when it occurs during the weekend, since these cases often impact demand differently. The number of daylight hours at four locations (Porto Alegre, São Paulo, Salvador and Fortaleza) was included in the model, to capture seasonality that may not be reflected well in the remaining variables.

Multiple linear regression is common for calibrating electricity demand models, and provides both transparency and excellent performance, even when compared to more sophisticated machine learning techniques (HONG; PINSON; FAN, 2014). Multiple linear regression was used to calibrate a model of the following functional form:

$$
\begin{aligned}
\ln(L_t) = & \sum_{i=1}^{p} \alpha_i \mathrm{HDD}_{t,i}^{T_H} + \sum_{i=1}^{q} \beta_i \mathrm{CDD}_{t,i}^{T_C} + \sum_{i=1}^{r} \gamma_i \mathrm{CDD}_{t,i}^{T_{CA}} \\
& + \sum_{i=1}^{p} \alpha_i' \mathrm{HDD}_{t-1,i}^{T_H} + \sum_{i=1}^{q} \beta_i' \mathrm{CDD}_{t-1,i}^{T_C} + \sum_{i=1}^{r} \gamma_i' \mathrm{CDD}_{t-1,i}^{T_{CA}} \\
& + \sum_{i=1}^{p} \alpha_i'' \sum_{j=1}^{9} \mathrm{HDD}_{t-j,i}^{T_H} + \sum_{i=1}^{q} \beta_i'' \sum_{j=1}^{9} \mathrm{CDD}_{t-j,i}^{T_C} + \sum_{i=1}^{r} \gamma_i'' \sum_{j=1}^{9} \mathrm{CDD}_{t-j,i}^{T_{CA}} \\
& + \theta_1 \ln(\mathrm{POP}_t) + \theta_2 \ln(\mathrm{GDP}_t) \\
& + \sum_{i=1}^{n} \kappa_i \mathrm{CAL}_{t,i} + \sum_{i=1}^{s} \lambda_i \mathrm{DH}_{t,i} \\
& + \eta_t
\end{aligned}
\tag{3.1}
$$

where

- L_t denotes the electric system load on day t;
- $\mathrm{HDD}_{t,i}^{T_H}$ (Heating Degree Days) denotes how many degrees below the base temperature T_H the daily average temperature (that is, daily maximum plus daily minimum divided by two) is at weather station $i \in \{1, \ldots, p\}$ on day t;
- $\mathrm{CDD}_{t,i}^{T_C}$ (Cooling Degree Days) denotes by how many degrees the daily average temperature at weather station $i \in \{1, \ldots, q\}$ exceeds the base temperature T_C on day t;
- $\mathrm{CDD}_{t,i}^{T_{CA}}$ (Cooling Degree Days Accelerated) denotes by how many degrees the daily average temperature at weather station $i \in \{1, \ldots, r\}$ exceeds the base temperature T_{CA} on day t;
- POP_t denotes the estimated population on day t;
- GDP_t denotes the gross domestic product in the quarter to which day t belongs;
- $\mathrm{CAL}_{t,i}$ is a set of dummies marking calendar effects;
- $\mathrm{DH}_{t,i}$ is the number of hours of daylight on day t at location $i \in \{1, \ldots, s\}$;
- η_t denotes the model error on day t, which could contain residual amounts of serial correlation.

The cut-off temperatures for degree day calculations were determined by performing a simple grid search using an out-of-sample error measure, which favoured the choices $T_H = 18°\mathrm{C}$, $T_C = 25°\mathrm{C}$ and $T_{CA} = 28°\mathrm{C}$.

Table 7 – Summary of the results of the model estimation for selected model parameters. The full details on the estimated model parameters can be found in Trotter et al. (2015).

Variable	**Estimate**	**Std. err.**	**P-Value**
$\ln(\text{GDP}_t)$	0.4751	0.0097	9.33e-07***
$\ln(\text{POP}_t)$	1.7086	0.3401	5.35e-07***
Daylight Hours Porto Alegre	-3.2164	1.3053	0.013786*
Daylight Hours São Paulo	8.0754	2.3586	0.000625***
Daylight Hours Salvador	-7.2021	1.4636	9.05e-07***
Dummy: Monday	-0.0277	0.0007	¡2.2e-16***
Dummy: Saturday	-0.0894	0.0010	¡2.2e-16***
Dummy: Sunday	-0.2030	0.0009	¡2.2e-16***
Dummy: Jan 01	-0.2579	0.0134	¡2.2e-16***
Dummy: Good Friday	-0.2113	0.0091	¡2.2e-16***
Dummy: Dec 25	-0.2845	0.0147	¡2.2e-16***
CDD^{25} (station 837460)	0.0058	0.0007	¡2.2e-16***
CDD^{25} (station 837800)	0.0031	0.0012	0.005483**
CDD^{25} (station 837680)	0.0034	0.0012	0.004058**
CDD^{25} (station 838270)	0.0029	0.0008	0.000155***

Significance codes: $^{***}p < 0.1\%$, $^{**}p < 1\%$, $^{*}p < 5\%$.

Since the specified model contains a large number of predictors, some of which may not be very relevant, backwards stepwise regression using the Bayesian Information Criterion was performed in order to select the final set of predictors. This provides a more parsimonious model with a minimal decrease in the forecasting performance.

3.2.3 Model Fit

Table 7 summarises the estimation results for a small subset of the model parameters. The in-sample mean absolute percentage error (MAPE) of the model on the training sample was 1.64%. The ex-post forecast on the validation sample (i.e. given the observed historical value of all the predictors) on the test sample is 1.93%. The magnitudes of the errors indicate a fairly good model fit, relatively close to those reported in similar studies (e.g. (MCSHARRY; BOUWMAN; BLOEMHOF, 2005; HOR; WATSON; MAJITHIA, 2006; ZISER; DONG; WONG, 2012; HONG; WILSON; XIE, 2014)). The small difference between the in-sample and out-of-sample error measures also suggests that overfitting is unlikely to be a significant problem.

The estimated coefficient of the term $\ln(\text{GDP}_t)$, $\theta_2 = 0.475$, corresponds to the income elasticity of electricity demand. The sensitivity of electricity demand to GDP in this model is therefore simple: a 1% increase in GDP is accompanied by a 0.475% increase in electricity demand. Earlier studies have estimated the income elasticity of electricity demand for various sectors or geographical regions of Brazil, but no study has reported the elasticity of the aggregate electricity demand. Table 8 compares our estimate of the

Table 8 – Estimated income elasticities of electricity demand in other studies.

Authors	Region	Sector	Est. Income Elasticity
Present study	All	All	0.475
(MATTOS; LIMA, 2005)	Minas Gerais	Residential	0.532
(SCHMIDT; LIMA, 2004)	All	Residential	0.539
(SCHMIDT; LIMA, 2004)	All	Commercial	0.636
(SCHMIDT; LIMA, 2004)	All	Industrial	1.920
(ANDRADE; LOBÃO, 1997)	All	Residential	0.213

Source: Mattos & Lima (2005), Schmidt & Lima (2004) and Andrade & Lobão (1997).

income elasticity of electricity demand with those obtained in other studies. Although our estimated income elasticity differs from earlier attempts, it appears to be well within reason, despite the radically different approach of the present study.

Based on these observations, we consider the model satisfactory for our purposes.

3.3 Probabilistic Forecasting of Electricity Demand for Climate Change Scenarios

We create forecasts for electricity demand by applying the model from the previous section to assumed future values of the explanatory variables.

Population and GDP scenarios until year 2100 have been developed by the Organisation for Economic Co-operation and Development (OECD) and are provided through the Shared Socioeconomic Pathways database (IIASA, 2015), intended to serve as a common starting point for climate change researchers (VUUREN et al., 2014; O'NEILL et al., 2014). For this study, we have selected three scenarios: SSP1 - Global Sustainable Development, SSP2 - Business as Usual, and SSP5 - Conventional Development/Economic Optimism. We perform an exponential interpolation on the raw decadal data in order to obtain daily estimates for the population, and an exponential interpolation to obtain annual GDP, to which we apply a simple seasonal profile in line with historical observations (Q1: 23.98%, Q2: 24.91%, Q3: 25.70%, Q4: 25.40%). The scenarios are then multiplied by a constant factor such that the scenario data matches a recent historical observation (January 2015 for the population and year 2014 for the GDP). Figure 10 shows the resulting population of Brazil for the three chosen scenarios, and figure 11 shows the corresponding annual GDP.

On the basis of daily downscaled climate projections from the MIROC5 global circulation model (WATANABE et al., 2010) for the Representative Concentration Pathways (RCP) 4.5 W/m^2 and 8.5 W/m^2 (VUUREN et al., 2011), provided by National Aeronautics and Space Administration (NASA, 2015), we simulate a large number of weather paths. This will enable us to analyse the impact of weather uncertainty on the

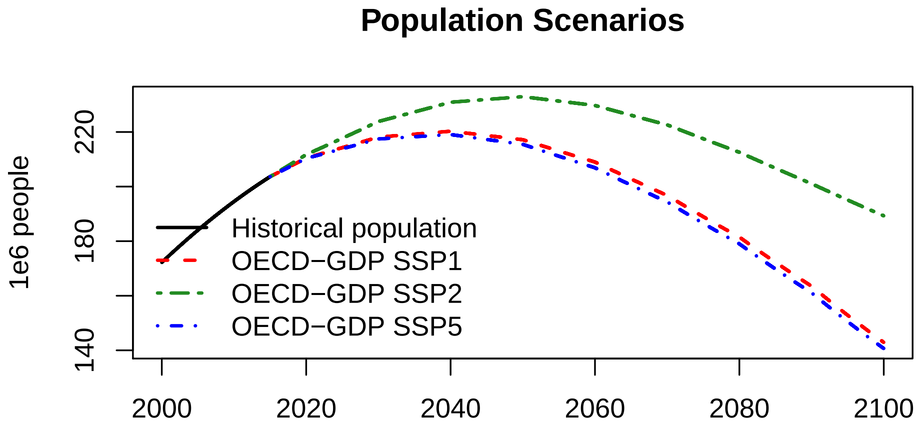

Figure 10 – Population of the Shared Socioeconomic Pathway scenarios.

Source: The Brazilian Institute of Geography and Statistics (IBGE, 2013), International Institute for Applied Systems Analysis (IIASA, 2015).

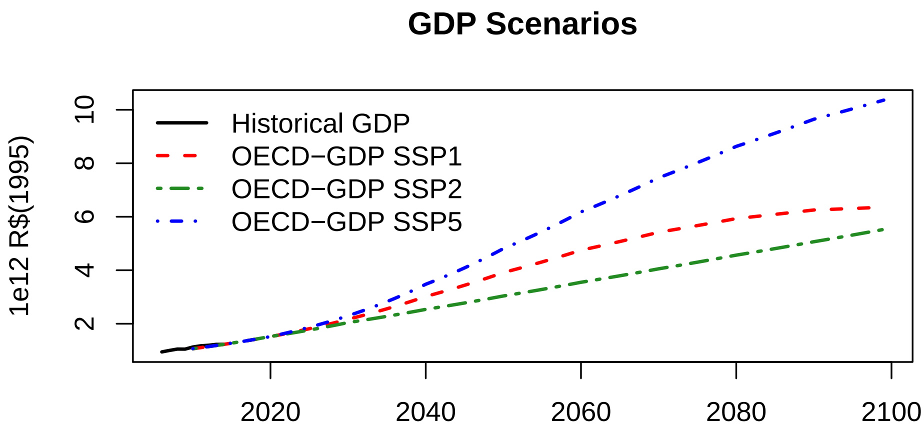

Figure 11 – GDP of the Shared Socioeconomic Pathway scenarios.

Source: The Brazilian Institute of Geography and Statistics (IBGE, 2015), International Institute for Applied Systems Analysis (IIASA, 2015).

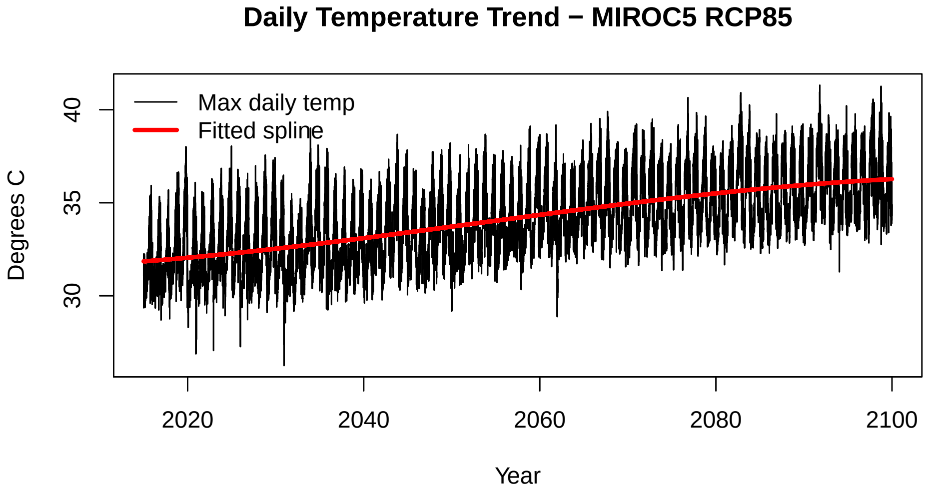

Figure 12 – Maximum daily temperature from a single weather station (820980), and a spline fitted to the data.

Source: National Aeronautics and Space Administration (NASA, 2015).

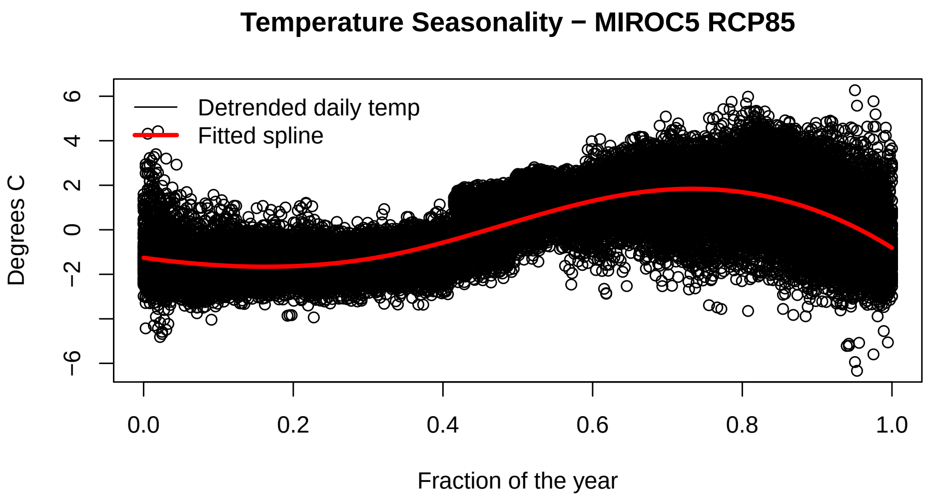

Figure 13 – Detrended maximum daily temperature from a single weather station (820980) at fractions of the year, and a spline fitted to the data.

electricity demand. A simulated weather path is created using the following procedure:

1. Trend and seasonal splines are fitted to each weather variable from each weather station, as illustrated in figures 12 and 13;

2. Trend and seasonal splines are fitted to the annual and daily standard deviations of the detrended and deseasonalised weather variable, as illustrated in figures 14 and 15;

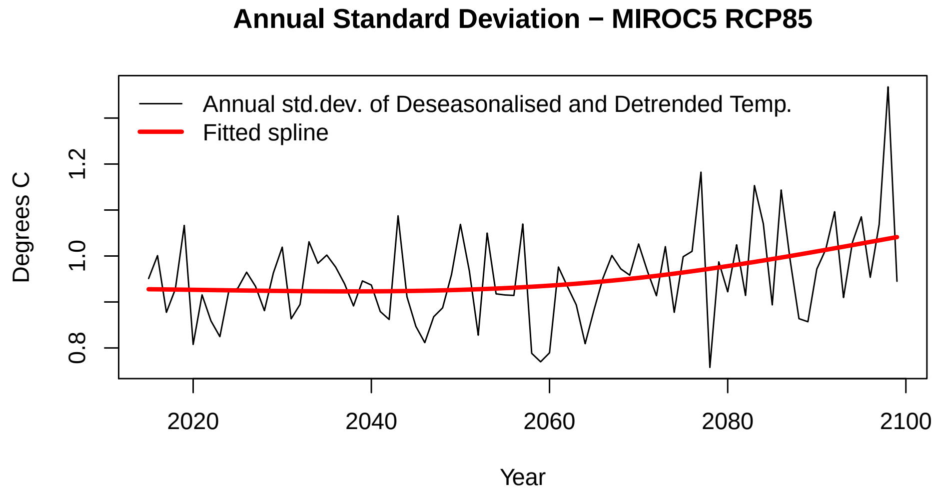

Figure 14 – Standard deviation of the detrended and deseasonalised maximum daily temperature from a single weather station (820980), and a spline fitted to the data.

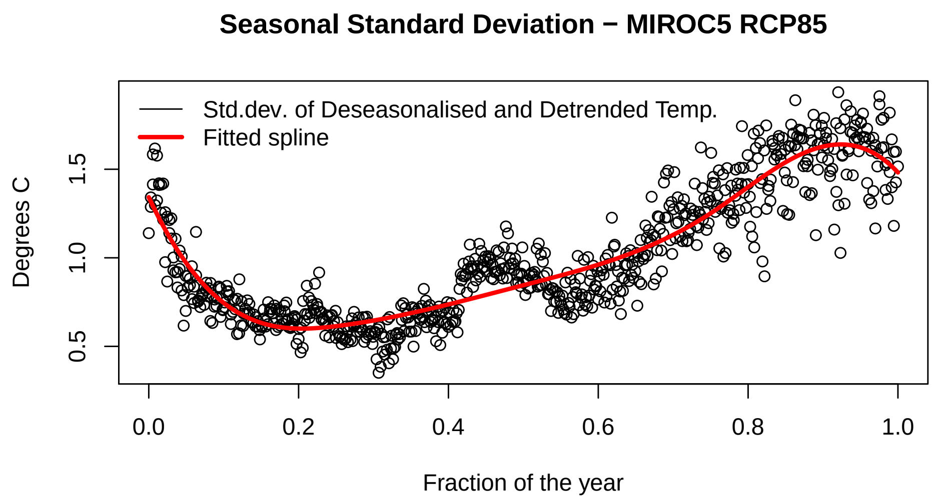

Figure 15 – Standard deviation of the detrended and deseasonalised maximum daily temperature from a single weather station (820980) throughout the year, and a spline fitted to the data.

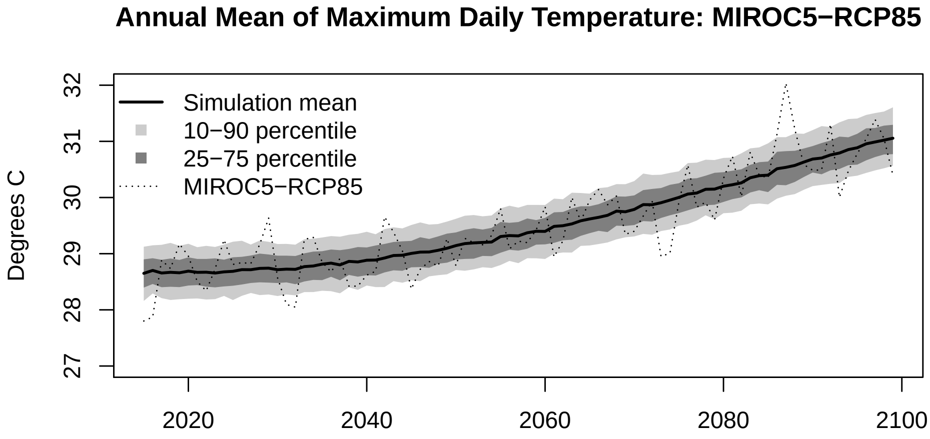

Figure 16 – Annual mean of the daily maximum temperature of the weather scenarios, based on the MIROC5 global circulation model run with the representative concentration pathway 8.5.

Source: National Aeronautics and Space Administration (NASA, 2015).

3. The weather variable is detrended by subtracting the splines for trend and seasonality, then normalised by dividing by the trend and seasonality of the standard deviation;

4. The residuals are resampled in blocks of an arbitrary number of days containing all weather variables;

5. The resulting residuals are de-normalised by multiplying by the trend and seasonality of the standard deviation, then retrended again by adding the splines for trend and seasonality.

This procedure should preserve trend and annual seasonality in the first and second moments of the data through detrending and normalisation, as well as serial and spatial correlation through the use of block resampling. By repeating steps 4 and 5 of this procedure, an arbitrary number of realistic weather paths can be created from a single weather path generated by a global circulation model (GCM).

In order to check that the simulated weather paths are reasonable, figure 16 illustrates the distribution of the annual mean of the maximum daily temperature for 500 paths generated on the basis of the temperature path of a single weather station from the RCP8.5 scenario of the MIROC5 global circulation model. The number of points from the GCM that falls within each band of the simulated distribution is very close to the expected number, and the distribution therefore appears to provide an excellent fit for the data.

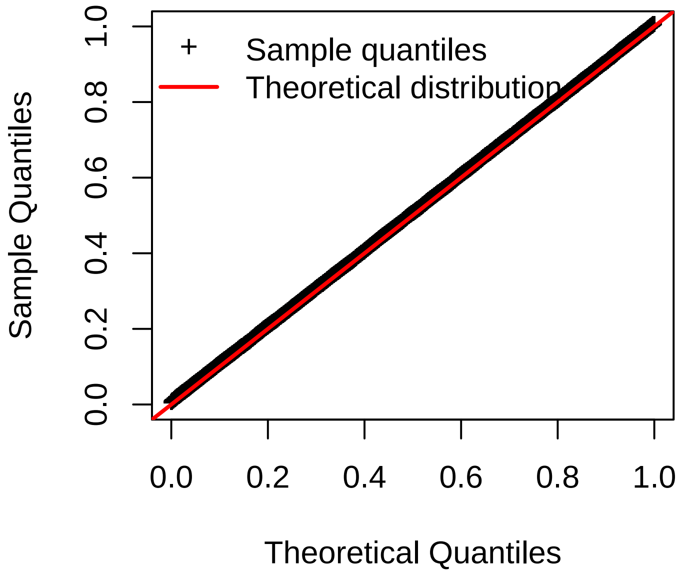

Figure 17 – Quantile plot showing the quantile of each daily maximum temperature from the RCP8.5 scenario of the global circulation model MIROC5 in relation to the 500 simulated daily maximum temperatures.

To further verify that the simulated weather paths are reasonable, we note that one would expect the proportion of GCM output values below a given quantile of the simulated distribution to be approximately equal to the quantile itself – for instance, 10% of the time we would expect the GCM output to be below the 10th percentile of the simulated distribution. The plot in figure 17 shows that the data conforms almost perfectly to this expectation: the simulated daily weather variables appear to be chosen from the same distribution as the daily weather variable provided by the GCM. In addition, table 9 shows selected quantiles of the distributions of the differences between correlations in the simulated weather variables and the GCM output. For all the tested correlations – spatial correlation and the autocorrelations of first, second and third order – the distributions of the differences between the correlations of the simulated weather and the GCM output were very tight and roughly centered around zero. The slight negative skew of the differences in the autocorrelations might be caused by the discontinuities at the block edges introduced by the block resampling process. However, given the small magnitude of the differences, we consider that the simulated weather variables adequately replicate the spatial and serial correlations of the GCM output. Given that the simulated weather variables appear to be drawn from the same disitribution as the GCM output and also accurately reproduce the spatial and serial correlations of the GCM output, we find the weather simulations suitable for our purposes.

Table 9 – Distributions of the differences between correlations in the simulated weather variables and the GCM output.

	10%	**25%**	**50%**	**75%**	**90%**
Spatial correlation	-0.027	-0.016	-0.006	0.002	0.013
Autocorrelation (1st order)	-0.009	-0.005	-0.002	0.002	0.007
Autocorrelation (2nd order)	-0.010	-0.006	-0.002	0.004	0.011
Autocorrelation (3rd order)	-0.011	-0.007	-0.002	0.005	0.011

The population and GDP scenarios are paired with appropriate climate scenarios to create three main scenarios: SSP1 and SSP2 are paired with RCP4.5 and SSP5 is paired with RCP8.5. Although the SSP and RCP scenarios are orthogonal in principle, the pairings were selected because they exhibit a certain degree of internal consistency and have been suggested as possible reference scenarios (VUUREN et al., 2014). The electricity demand model summarised in table 7 can then be calculated for each simulated weather path generated on the basis of the GCM output for the respective RCP, together with assumed values for population and GDP obtained from the accompanying socio-economic scenario. To capture serial correlation in the electricity demand beyond that captured by the demand model, we incorporate residual simulation: a SARIMA model is calibrated on the residual from the demand model on the training sample, and a simulation of the error term is paired with each weather simulation.

3.4 Results and Discussion

We calculated the load model for the period 2016 to 2100 using 500 simulated weather and residual paths for each of the three main scenarios SSP1/RCP4.5, SSP2/RCP4.5 and SSP5/RCP8.5. A summary of the resulting estimated distribution of annual electricity demand for key years is shown in table 10. Figures 18, 19 and 20 show the distribution of annual electricity demand in the three main scenarios, and for comparison includes official government projections (EPE-PDE, 2014; EPE-PNE, 2014) and earlier projections made by Schaeffer et al. (2008).

The electricity demand in all three scenarios increases until approximately year 2060, then subsequently decreases. This clearly mirrors the trajectory of the population growth in the three demographic scenarios, as shown in figure 10, and illustrates clearly that population growth was found to be a highly significant determinant of electricity demand during the model calibration. The uncertainty bands are also significant, with at most around 400 TWh separating the 10th and 90th percentile (approximately $\pm 17\%$ relative to the mean). This shows clearly that the impact of weather uncertainty on electricity demand is substantial.

Another obvious feature in the graphs, is that the official government projections

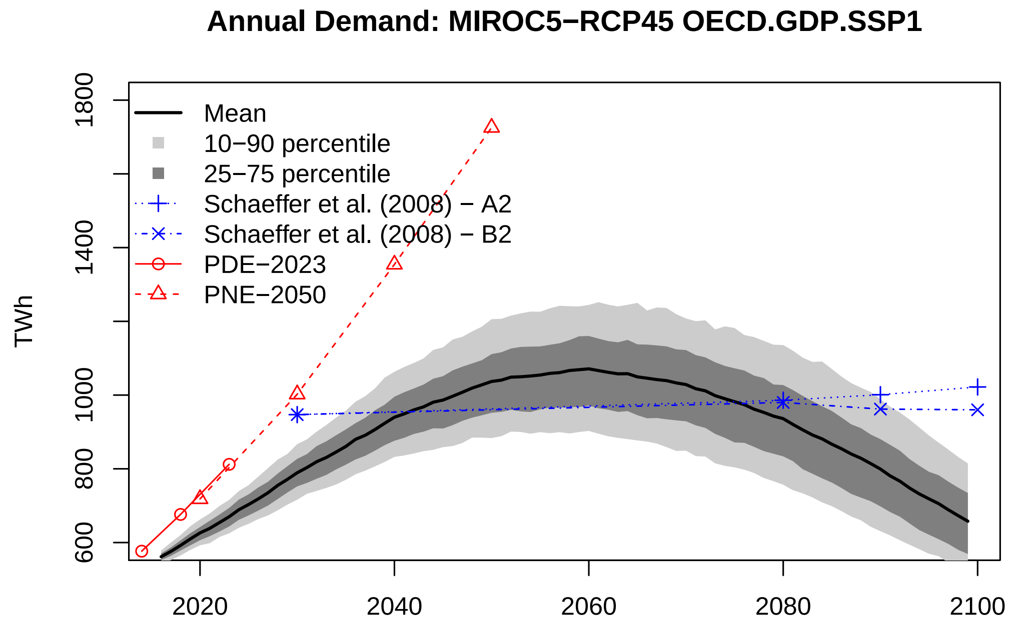

Figure 18 – Annual electricity demand in the SSP1/RCP4.5 scenario.

Source: Empresa de Pesquisa Energética (EPE-PDE, 2014, p. 41) (EPE-PNE, 2014, p. 150), (SCHAEFFER et al., 2008).

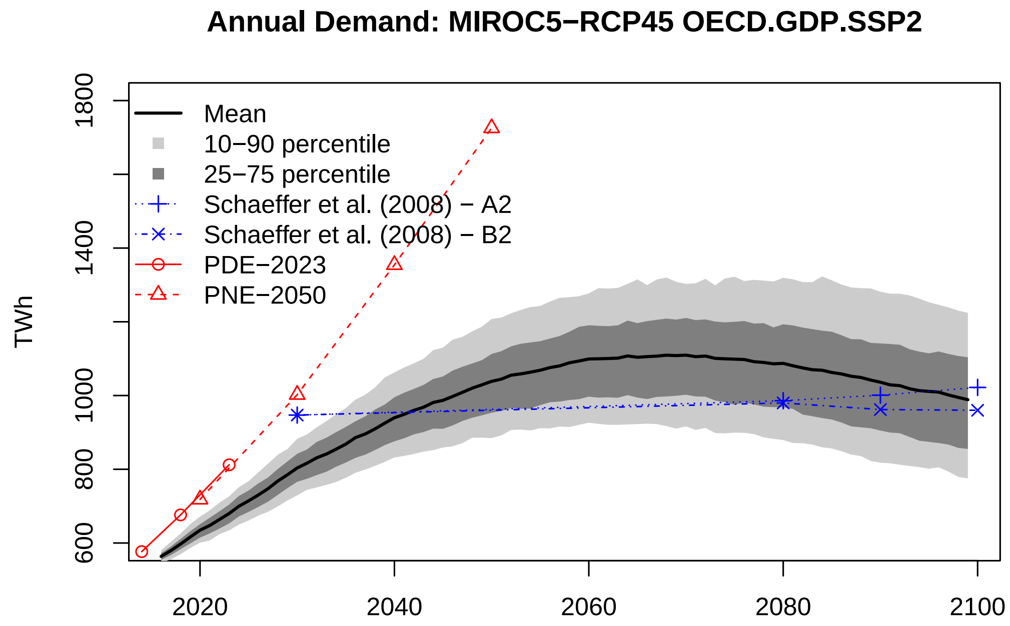

Figure 19 – Annual electricity demand in the SSP2/RCP4.5 scenario.

Source: Empresa de Pesquisa Energética (EPE-PDE, 2014, p. 41) (EPE-PNE, 2014, p. 150), (SCHAEFFER et al., 2008).

Table 10 – The mean and quartiles of the estimated probability distribution of annual electricity demand (TWh) for selected years in the three scenarios.

Scenario	Year	Mean	1st Quartile	2nd Quartile
SSP1-RCP4.5	2020	626.19	606.32	642.12
	2030	789.34	752.37	827.05
	2040	939.92	876.11	995.58
	2050	1036.97	952.03	1111.22
	2060	1071.18	971.65	1160.23
	2070	1028.56	928.95	1122.11
	2080	936.04	833.80	1027.20
	2090	799.39	698.15	880.53
	2099	657.84	569.06	734.49
SSP2-RCP4.5	2020	634.80	614.68	650.96
	2030	803.61	765.98	842.00
	2040	939.72	875.90	995.35
	2050	1038.44	953.39	1112.80
	2060	1099.15	997.03	1190.53
	2070	1109.56	1002.11	1210.47
	2080	1087.29	968.53	1193.18
	2090	1036.20	905.00	1141.36
	2099	988.65	855.23	1103.90
SSP5-RCP8.5	2020	625.60	606.82	642.52
	2030	808.86	771.40	847.31
	2040	999.74	934.05	1058.49
	2050	1134.25	1040.90	1215.05
	2060	1200.14	1088.05	1298.01
	2070	1181.04	1065.74	1282.36
	2080	1105.18	986.24	1214.25
	2090	973.55	851.78	1068.97
	2099	826.43	712.22	924.20

(EPE-PDE, 2014; EPE-PNE, 2014) are significantly higher than any of the results produced by our model. The official projections were developed using a bottom-up approach and based on explicit sector-wise forecasts provided by experts, as opposed to our top-down approach based on a calibrated econometric model. The great differences in the methodology makes it difficult to attribute the differences between the results to any particular source. On the other hand, the projections for the years 2080, 2090 and 2100 created by Schaeffer et al. (2008) are in general quite close to the projections produced by our approach.

To gain additional insight into the forecasts produced by this methodology, figure 21 shows the annual electricity demand of the SSP5/RCP8.5 scenario when each of the factors GDP, population and weather are allowed to vary whilst the remaining two factors are kept stationary. This decomposition shows clearly that the growth of the electricity demand is mainly associated with the increasing GDP, whereas the decrease in electricity demand beyond about 2060 is obviously related to the population decline that starts around 2040. The contribution of the weather variables to the overall path of electricity demand is

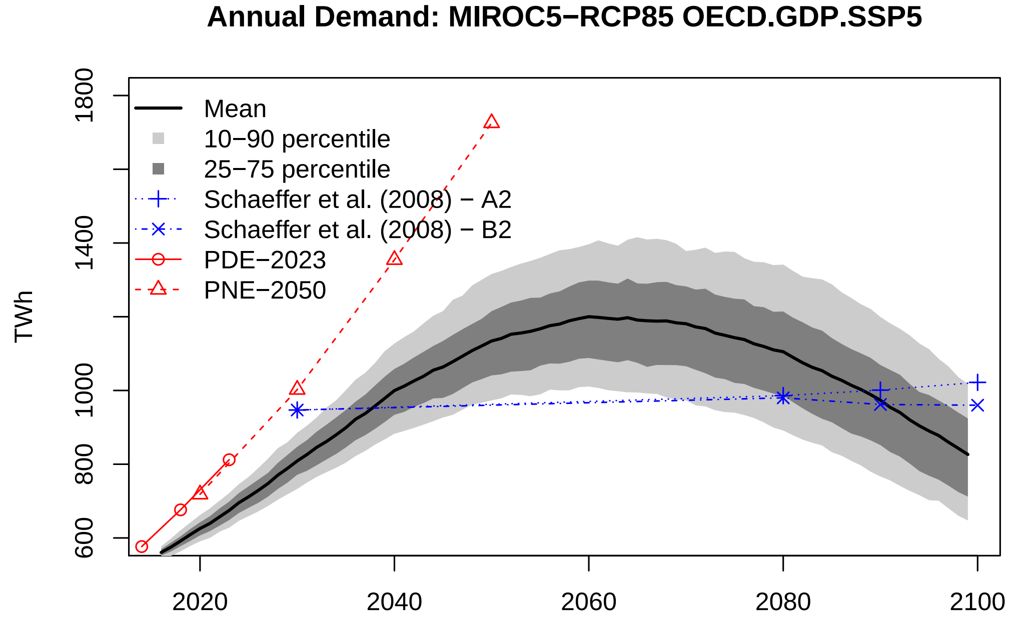

Figure 20 – Annual electricity demand in the SSP5/RCP8.5 scenario.

Source: Empresa de Pesquisa Energética (EPE-PDE, 2014, p. 41) (EPE-PNE, 2014, p. 150), (SCHAEFFER et al., 2008).

comparatively modest, but positive over the entire forecast period. The contribution of the weather to the uncertainty of electricity demand therefore appears more important than its contribution to the overall trend.

The impact of climate change on electricity demand has been studied in many regions throughout the world (see, for instance, Mideksa & Kallbekken (2010) and Schaeffer et al. (2012) for more comprehensive reviews of regional studies). Although a comparison of our results with all previous studies is beyond the scope of this study, it can be instructive to place our results in an international context. Figure 22 compares the demand of the SSP2/RCP4.5 scenario with the forecast for four different European countries – Finland, Germany, France and Spain – for the period 2015 to 2050, constructed using the A2 scenario and presented by Pilli-Sihvola et al. (2010). Germany and Finland are expected to experience lower growth rates in electricity demand than France and Spain, reflecting both more mature economic conditions and cooler climatic conditions. It is interesting to note that the trajectory of the electricity demand in Brazil most closely resembles the trajectory of Spain, which is more climatically and economically similar to Brazil than the remaining countries.

However, some limitations of our proposed framework must be taken into consideration. Firstly, some drivers of electricity demand have not been included in the model for

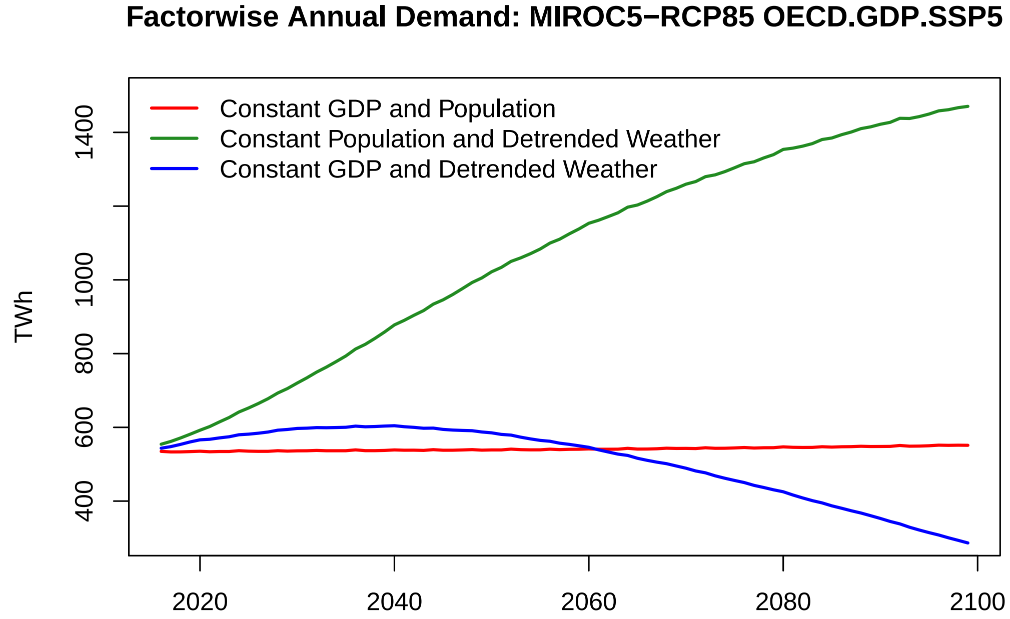

Figure 21 – Annual electricity demand in the SSP5/RCP8.5 scenario, when holding two of the three main factors GDP, population and weather stationary and letting the remaining factor evolve. This illustrates the contribution of each forecasted factor to the total demand.

practical reasons. This includes for instance the prices of electricity and substitutes, as well as additional demographic variables such as household size and urbanisation rates. Since the performance of the selected predictors is already acceptable, there is little incentive to increase the complexity of the model by including these variables, as the benefits would presumably only be marginal. Secondly, the framework makes no explicit allowance for structural or technological change, which could substantially alter the determinants of electricity demand in the long run – for instance inreasing use of electric vehicles, proliferation of air conditioning, and depletion of mineral reserves which could reduce industrial demand. The model will stop providing useful forecasts when the determinants of demand differ significantly from what they were during the calibration period. This might be a sudden and disruptive or a slow and gradual structural change in electricity demand. It may appear disingenuous to calibrate a model on ten years of historical data, then subsequently use the model to make projections for the next 85 years, whilst knowing that almost anything can change in the meantime. This applies, in essence, to all attempts at forecasting the remote future. In this respect, we present the projections as an interesting quantitative thought experiment, that can still provide useful and valuable information. Thirdly, we did not allow for uncertainty in the GDP and population projections. Although this could be easily incorporated in principle, our main focus has been on climatic risks and therefore

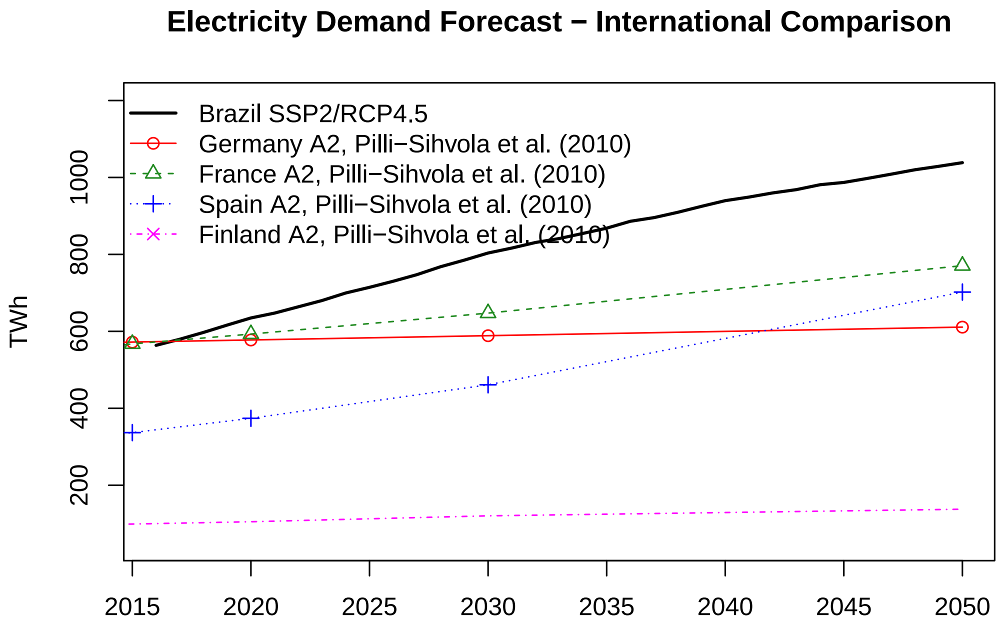

Figure 22 – Annual electricity demand in the SSP2/RCP4.5 scenario between 2016 and 2050, compared with electricity demand forecasts for Finland, Germany, France and Spain.

Source: (PILLI-SIHVOLA et al., 2010).

we concentrated on weather uncertainty. And finally, the projections disregard uncertainty in the model parameters. Although it is not realistic to assume that the calibrated model is absolutely accurate, this simplification again enabled us to focus on climate risk and weather uncertainty. None of these limitations entirely invalidate the methodology or the projections, but they represent shortcomings that deserve to be taken into consideration.

3.5 Conclusion

We have proposed, tested and illustrated an approach for incorporating weather uncertainty into long-term electricity demand forecasting in cases when the weather cannot be assumed stable. This is a development that is particularly important for climate change studies. The method is based on creating simulated weather paths from the output of a global circulation model, and is designed to preserve trends and annual seasonality in the first and second moments, as well as serial and spatial correlation. The method for creating simulated weather paths appears to perform suitably for the purposes of estimating the impact of weather uncertainty on future electricity demand.

The approach has been illustrated by creating an up-to-date stochastic electricity demand forecast for Brazil for the period 2016 to 2100, in light of the new climatic, demographic and macroeconomic simulations accompanying the IPCC AR5 report. This is also an important contribution: not only is there a definite need for more research on the impacts of climate change on electricity demand in Latin America (MIDEKSA; KALLBEKKEN, 2010), but there is also a need for studies that explicitly utilize a stochastic approach (FERREIRA; OLIVEIRA; SOUZA, 2015). By basing the stochastic projections on a daily electricity demand model, the framework developed in this study gives access to an unprecedented level of detail about possible future Brazilian electricity demand which can be very valuable for planning purposes.

A natural extension of the present study is to use the results to analyse the impact of weather uncertainty on the planning of electricity distribution and generation capacity in Brazil. However, this study only represents a small step in the direction of incorporating weather uncertainty into climate change studies. We hope that the method we have presented not only proves useful for studying the Brazilian electric sector, but that it will enable the incorporation of weather uncertainty in impact assessment, planning and adaptation studies in other areas and sectors that may also be greatly affected by climate change.

4 The Relationships Between CDM Project Characteristics and CER Market Prices

Abstract

This study explores the relationship between key characteristics of Clean Development Mechanism (CDM) projects and Certified Emission Reduction (CER) prices. Using multiple correspondence analysis, we show that the CER credit prices are likely to have had a greater influence than regional levels of economic development on the sectors, regions and sizes of CDM projects. There are comparatively few CDM projects in Sub-Saharan Africa (less South Africa) and the small-scale forestation projects that are characteristic for the region mainly entered the CDM pipeline when CER credit price levels were high. Latin America hosts a larger number of projects, and the small-scale methane, biofuel and hydro projects that are typical for this region generally also applied for validation under high CER price levels. The large industrial gas and energy efficiency projects typical for the Middle East/Northern Africa region appear to have been largely insensitive to CER price levels. The large number and variety of projects in Asia have applied for registration under a broad range of CER price levels.

Keywords: Clean Development Mechanism (CDM); Climate Policy; Development; Emission Credits; Environment; Multiple Correspondence Analysis.

4.1 Introduction

Mitigation of climate change is widely considered one of the biggest challenges currently facing humanity according to the United Nations' Intergovernmental Panel on Climate Change (IPCC, 2014). The Clean Development Mechanism (CDM) of the Kyoto Protocol, one of the most ambitious international political efforts for reducing greenhouse gas emissions, is an offset mechanism that allows emissions reduction projects in developing countries to earn Certified Emissions Reduction (CER) credits that can be traded and applied towards the emission reduction targets of industrialised countries (KYOTO PROTOCOL, 1997; CDM, 2013). The intention of this market-based mechanism is to allow market forces to control which and where emissions reduction measures are

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taken, under the assumption that emissions will be reduced in a cost-efficient manner (CDM, 2013). In addition to lowering the costs of fulfilling the reduction commitments of developed countries by allowing importation of credits from countries with lower abatement cost, the CDM was intended to attract investment to developing countries and to support the transfer of low-emissions tecnhologies to developing countries. This would promote economic growth whilst dampening the growth of greenhouse gas emissions – in other words, contribute to clean and sustainable development in developing countries (CDM, 2013).

The agreement came into force in 2005 and by December 2012 over 7500 projects were registered, representing projected reductions of about 3.5% of global annual greenhouse gas (GHG) emissions (CDM, 2013). The total number of issued CER credits until the end of the first abatement period in 2012 represented the equivalent of 1.16 billion tonnes (Gt) of CO_2 emissions, greatly exceeding early estimates of the total CER market size (MENSBRUGGHE, 1998; HAITES, 1998; ELLERMAN; DECAUX, 1998; MCKIBBIN et al., 1999; VROLIJK, 1999; EDMONDS et al., 2000; ZHANG, 2000). There is, however, some controversy concerning the reductions. Findings by Zhang & Wang (2011), as well as Zeng et al. (2013), suggest that many projects would have been implemented even in the absence of the mechanism, that is, they are not *additional*. Furthermore, Rosendahl & Strand (2011) found that even successful CDM projects may increase emissions elsewhere through indirect effects, so-called *leakage*. Schneider (2011), Strand (2011), Strand & Rosendahl (2012) and Hayashi & Michaelowa (2013) have recently raised the concern that the crediting rules of the mechanism may have created incentives to increase rather than reduce emissions, a problem often attributed to the counter-factual *baseline* from which the emissions reduction is calculated. Despite these difficulties, the delivery of emissions reductions is considered by many to be the most successful aspect of the CDM (RAHMAN; DINAR; LARSON, 2010; HUANG; BARKER, 2012; COLE, 2012; HUANG; BARKER, 2012; NEWELL, 2012; MICHAELOWA, 2013).

There is considerably less optimism about how well the mechanism has promoted sustainable development. Rive & Rübbelke (2010) show that CDM projects have the potential to achieve poverty alleviation, although Rindefjäll, Lund & Stripple (2011) argue that the national authorities disregard requirements for sustainable development in order to attract greater investments. In an early review of the available literature, Olsen (2007) found little support that CDM significantly contributes to sustainable development. Pearson (2007), Lövbrand, Rindefjäll & Nordqvist (2009) and Alexeew et al. (2010) even argue that the dual objectives of low-cost abatement and sustainable development are at least partially incompatible, and Ellis et al. (2007) note that the project portfolio was mainly shaped by the financial incentives of CER credits. Analysing 16 CDM projects, Sutter & Parreño (2007) found that less than 1% of the emissions reductions were expected to come from projects with a significant contribution to sustainable development. Studying other subsets of the CDM projects, Gupta et al. (2008), Wittman & Caron (2009) and Martinez & Bowen (2012) also report meagre contributions to sustainable development. In terms of poverty reduction, studies by Michaelowa & Michaelowa (2011), Martinez & Bowen (2012) and Crowe (2013) find that projects have not delivered significant pro-poor benefits.

When it comes to technology transfer, often considered a key component of promoting sustainable development, the picture is more divided. Before any empirical project data was available, Parson & Fisher-Vanden (1999) recognised that the crediting rules of the mechanism could favour retrofits over new investments. In an early analysis of 201 proposed CDM projects, Ellis & Gagnon-Lebrun (2004) noted that the emerging portfolio appeared to emphasise low-cost retrofits rather than projects with greater technology transfer benefits. In a later study, Haites, Duan & Seres (2006) found that roughly one third of all projects claim to involve technology transfer. Youngman et al. (2007) also concluded that CDM projects were facilitating technology transfer, although not sufficiently to allow the technologies to become commonplace in the host countries. Examining 63 registered CDM projects, Coninck, Haake & Linden (2007) found that 50% of the projects involved equipment transfer and in addition there was substantial knowledge transfer. A recent survey by Gandenberger et al. (2015) showed that about two thirds of CDM projects involve significant technology transfer.

Overall, the literature cited earlier therefore indicates that the projects are more successful at providing cost-effective emissions reductions than at promoting sustainable development, although one aspect of sustainable development – technology transfer – appears to be considered moderately succesful.

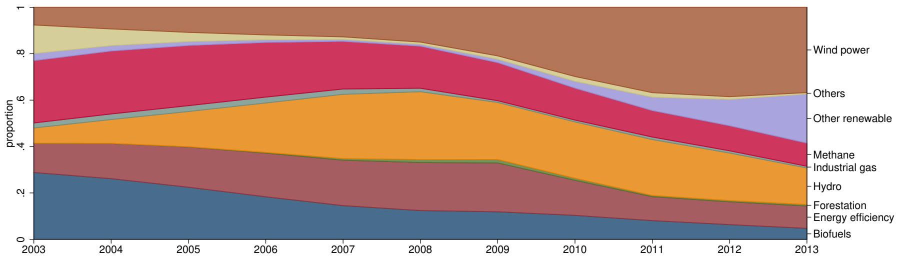
Beyond the ability of specific projects to contribute to sustainable development, there has been concern that the composition of the project portfolio is inadequate for providing substantial sustainable development benefits. Cosbey et al. (2005) noted that the emerging portfolio of projects favoured certain countries and project types, typically low-cost end-of-pipe projects in emerging market countries. The least developed countries were underrepresented as project hosts and project types considered to have greater potential to promote sustainable development represented only a small share of the total number of projects. Olsen (2006) attributed part of the geographical disparity to some LDCs being unable to prioritise climate issues politically. Byigero, Clancy & Skutsch (2010) argued that the low participation of Sub-Saharan Africa was a result of various endogenous barriers, such as an inadequate general investment climate, low level of industrialisation and lack of institutional infrastructure. Flues (2010) showed that the geographical distribution of the projects was positively related to economic growth and abatement potential, which tends to favour advanced developing countries as opposed to the least developed countries. These results were largely supported by Winkelman & Moore (2011), who explained the regional distribution of projects by higher carbon-intensity and growing markets for the co-products of the CDM projects (e.g. electricity). Kivyiro & Arminen (2013) also pointed to institutional factors and host country size as important determinants of project location, which again puts many least developed countries at a disadvantage. Although Zhu (2012) found that domestic and economic investment conditions were most important in an analysis of 2763 registered projects, Röttgers & Grote (2014) and Costantini & Sforna (2014) suggested that existing bilateral relationships also influence the geographical distribution of projects. Fay (2013) found awareness, capacity, eligibility and access to finance to be important determinants of the geographical distribution of projects.

The existing literature has largely focused on host country characteristics as the determinants for the composition of the project portfolio, and the CER market conditions appear to have received little attention in this respect – despite the fact that the CDM represents a market-based approach. Hultman et al. (2012) and Xie, Shen & Wang (2014) suggested that the anticipated revenue of the project developers plays a central role in the decision to pursue CDM investments, whereas Schneider, Schmidt & Hoffmann (2010) and Ervine (2014) showed further that the CER price directly affects the viability of some projects and the flow of private investment. This shows that CDM investment decisions are clearly influenced by the price of CER credits. This is a particularly interesting insight in light of the turbulent price of CER credits in the secondary market, and the price collapse in 2011/2012. Through affecting individual projects, the CER market conditions may therefore have profoundly influenced the composition of the project portfolio.

Within this context, the purpose of this study is to explore how the CER market conditions have influenced the composition of the CDM project portfolio, a subject that has received little attention in earlier literature. More specifically: how does the CER price during the project planning phase relate to the key project characteristics location, scale and sector? As investment decisions are guided by profitability considerations, the large changes in market conditions are likely to have exerted a profound influence on the CDM project portfolio in terms of the size, sectoral and regional distributions of CDM projects. In addition to providing a more complete understanding of the determinants of the sectoral and regional distributions of the projects, this analysis may also generate some insight about the costs of implementing various clean technologies in different regions and sectors. The results of this study will contribute to our understanding of how CER market conditions have influenced the composition of the CDM project portfolio, and could impart valuable lessons both to market participants and to policy makers.

The paper is organised as follows: the next section will present a brief narrative of the development of the CDM project portfolio and market conditions, highlighting certain key characteristics. Section 4.3 will establish the empirical framework used in this study and show how Multiple Correspondence Analysis (MCA) will be employed to provide a

Figure 23 – Development in the share of project types entering the CDM project pipeline



Source: Institute for Global Environmental Strategies (IGES, 2013)

high-level understanding of how project characteristics interrelate and how they relate to the CER price during the project planning period preceding the initiation of the CDM project cycle. Section 4.4 will discuss the principal stylised facts revealed by the analysis, and section 4.5 will summarise our main findings.

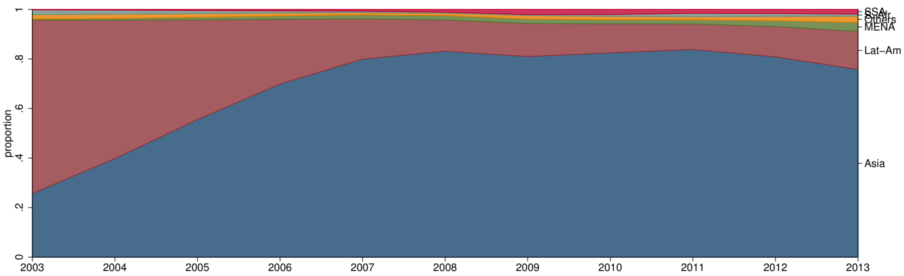
4.2 A Brief Review of the CDM Project Portfolio and the CER Market

Here we outline some of the basic characteristics of the distribution of CDM projects between sectors, locations and scales, as well as how these distributions have changed over time. This description is based on a database compiled from the Project Design Documents (PDD) of 11 954 CDM projects that have initiated the Global Stakeholder Process (GSP) as of March 2013, published by the Institute for Global Environmental Strategies (IGES, 2013).

Figure 23 shows the development of the proportion of various project types over the time period from 2003 to 2013. The most striking features of the figure are the increasing popularity of wind power projects since 2008, the decreasing popularity of biofuels projects throughout the period, and the recent surge in popularity of other renewables, which consist mainly of solar power projects.

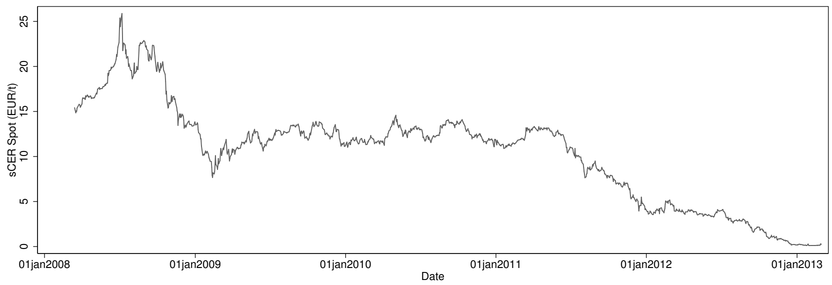
When investigating the proportion of projects hosted in each region, as shown in figure 24, the main development is the increasing proportion of projects located in Asia – mainly China – and the decreasing proportion of projects located in Latin America. In comparison, however, the participation of the remaining regions – South Africa (S. Afr.), the remaining Sub-Saharan Africa (SSA), Middle East/Northern Africa (MENA) and others – has been modest throughout the period. The projects were quite evenly divided between small and large scale until 2009, when the proportion of larger projects started increasing, hitting approximately three quarters of all projects applying for registration in early 2013.

Figure 24 – Development in the share of projects entering the CDM project pipeline



Source: Institute for Global Environmental Strategies (IGES, 2013)

Figure 25 – Daily CER spot price in the secondary market



Source: Thomson Reuters Point Carbon (TR-PCA, 2013)

The price of CER credits on the secondary market, as shown from early 2008 and onwards in figure 25, have generally dropped since 2008: after being traded at up to 25.88 EUR/t in 2008, the price dropped to a low of 0.11 EUR/t in late 2012. The dramatic drop in prices is often attributed to a combination of overallocation of emission allowances to countries, a greater than expected supply of certified emissions reductions, political uncertainty regarding the future of emissions trading, economic hardship following the 2007-2008 financial crisis and import restrictions on CER credits to the European Union, which is considered one of the main buyers of carbon credits (JOTZO; MICHAELOWA, 2002; NEUHOFF et al., 2006; MICHAELOWA, 2014).

A more advanced analysis of the composition of the CDM project portfolio is needed to discover how different project characteristics interrelate, and how they relate to the CER market prices. Considering the level and volatility of CER credit prices, in addition to the political uncertainty surrounding global emissions trading, exploring the interrelationships between various project characteristics and the price is of great interest to both market participants and policy makers.

4.3 Research Method and Approach

4.3.1 Multiple Correspondence Analysis

Dimensionality reduction techniques are useful for exploratory analysis, since they reduce a high-dimensional dataset to a small number of significant factors that capture the most important features of the dataset. The most common method is perhaps Principal Component Analysis (PCA), which calculates an ordered set of axes such that the projection of the data points along these axes maximise the variance. Since this analysis is intended to be of a more exploratory and descriptive nature, as opposed to for instance formal modeling or hypothesis testing, we consider a dimensionality reduction technique appropriate.

However, PCA is intended for continuous variables, whereas most of the variables that will be considered in this analysis – sectors, geographical regions and scale – are categorical. The related technique called Multiple Correspondence Analysis (MCA) is a dimensionality-reduction technique that is applied to categorical variables and is often used to create a map of the data which visualises the relationships between several categorical variables, thereby helping to reveal and understand key features of an underlying categorical dataset. Since the variables in this exploratory analysis are largely categorical, MCA is a suitable method.

MCA performs a singular value decomposition of the table containing the relative frequencies of all two-way crosstabulations of the categories in order to reveal the association structure of the underlying data. The projections of the categories along the directions corresponding to the two largest singular values are visualised in a two-dimensional map that preserves the most important features of the data, such that similar categories appear close to one another and dissimilar categories appear separated.

In the context of MCA, the concept of *inertia* is considered the categorical analogue to variance for continuous variables. The term *mass* refers to the relative frequency of data points pertaining to a given category. The main advantages of using MCA are that any number of categorical variables can be included, that it allows for the ordination of factors by importance to the distribution, and that it may bring out features in the data that may not initially be obvious. More details about the method can be found in Greenacre & Blasius (2006).

Finally, we will discuss some possible confounding factors and verify the robustness of our results with respect to the definitions of the categories applied to the CDM project data and the price used in the analysis.

4.3.2 Data

4.3.2.1 Project Region, Sector and Scale

In order to earn CER credits a project must be subjected to an elaborate approval process, and the documentation that accompanies the application is made available to the public. The Project Design Document (PDD) that accompanies the application contains both technical and financial details of the project, and these are publicly available on the internet (CDM, 2013).

The project data used in this analysis was preprocessed by the Institute for Global Environmental Strategies (IGES), who extract and systemise the data in the PDDs (IGES, 2013). IGES has collected data for 11 954 CDM projects that have initiated the first step of applying for registration – the Global Stakeholder Process – as of March 2013. The relevant attributes that will be considered in this analysis are the project sector, the region of the host country, and the scale of the project, all of which are availabe in the data from IGES.

The CDM projects are divided into nine sectors: biofuels, energy efficiency, forestation, hydropower, industrial gas, methane, wind power, other renewable energy and others. They are also divided into six regions: Asia, Latin America (Lat-Am), Middle East/Northern Africa (MENA), South Africa (S. Afr.), Sub-Saharan Africa (SSA) excluding South Africa, and others. The projects are further categorised as either large scale or small scale. Although these categories attempt to group together project types and countries that share important characteristics, a discussion on the robustness of our results with respect to this categorisation is also presented together with the results.

Table 11 summarises the categorisation and the data available from IGES in the form of a contingency table, detailing the number of projects categorised by sector, region and scale.

4.3.2.2 CER Price

In this analysis, we wish to examine the effect of CER prices on the composition of the CDM project portfolio. Since the sale of CER credits is presumably one of the main incentives for projects to incur the additional costs of applying to be registered in the CDM, it is reasonable to assume that the price of emissions credits is a decisive factor in the investment decisions for CDM projects and has therefore likely exerted a profound influence on the composition of the CDM project portfolio.

The interrelationships between the project characteristics and the price level of the CER credits are the focus of this study. Therefore, we include all projects that have initiated the CDM project cycle in our analysis – even those that have later been withdrawn or rejected – because the project developers have presumably responded to the

Table 11 – Number of CDM projects per project type, region and scale

	Asia	**Lat-Am**	**MENA**	**Others**	**S. Afr.**	**SSA**	**Total**
Large Scale							
Biofuels	405	170	2	0	3	14	594
Energy efficiency	933	78	47	19	20	20	1117
Forestation	19	21	0	4	0	14	58
Hydro	1174	259	2	17	0	10	1462
Industrial gas	110	25	16	7	5	1	164
Methane	548	279	42	27	13	18	927
Other renewable	153	23	9	2	5	5	197
Others	115	40	8	1	0	4	168
Wind power	1886	202	15	14	20	10	2147
Total	5343	1097	141	91	66	96	6834
Small Scale							
Biofuels	652	117	5	3	4	12	793
Energy efficiency	627	74	42	9	18	19	789
Forestation	15	5	0	0	0	14	34
Hydro	1211	188	1	20	5	9	1434
Industrial gas	4	1	0	0	0	0	5
Methane	665	291	11	27	7	6	1007
Other renewable	242	6	10	0	1	3	262
Others	21	5	0	0	0	0	26
Wind power	744	21	2	2	0	1	770
Total	4181	708	71	61	35	64	5120

Source: Institute for Global Environmental Strategies (IGES, 2013) promise of revenue from CER credit sales and acted by submitting a project with specific characteristics. The CER credit price we attach to each project is therefore considered sufficient to have triggered the initiation of the CDM project cycle.

Although some CDM project registration applications include a reference CER price which is used in the project's financial projections, such a reference price is unavailable for a large number of project applications and is often little more than a placeholder value in other project applications. In principle, it would be ideal to use this price since it presumably reveals the CER price expectations of the project developers, but due to the low availability and quality of the CER reference price used in the project applications, we chose not to base our analysis on this price.

The CER credit price the project has received in the primary market would be a reasonable substitute and would to a greater extent reflect the actual profitability of the project, but unfortunately this information is generally unavailable due to contract secrecy and furthermore may be unavailable for projects which have not yet received CER credits.

In this analysis, the CER credit price on the secondary market was used. One of the main shortcomings of basing the analysis on the secondary market price rather than the reference price or primary market price, is that it may not actually be a good proxy for the actual expectations of the project developers. The resulting analysis is not invalidated by this, however, due to the possibility that the secondary market price has influenced the expectations of the project developers. Zavodov (2012) claims that it is at least somewhat common practice to base primary market prices on the secondary market price together with a discount rate, similar to the methodology proposed by Ascui & Costa (2007). For many projects, the price in the secondary market therefore serves as a widely known reference point. Furthermore, the CER credit price in the secondary market is assumed to provide a reasonable measure of an unbiased consensus of the value of the carbon credits, in the sense that it is unaffected by specific factors that would affect the primary market price and the reference price, such as the negotiation skills or optimism of individual project developers. In addition, the secondary market price is more easily available, more reliably reported and more complete than the alternatives. For these reasons, we believe that the price of CER credits in the secondary market provides the most appropriate and consistent measure of the value of the carbon credits to apply in this study.

The question of specifically how to assign the CER price from the secondary market to each project is not entirely obvious. In this particular study, we wish to assign a price to each project that was sufficient to trigger the developers to apply for CDM project status. In order to represent the CER price at a critical time during the preparation of the business case of the project and the Project Design Document, we calculate the average CER price for the 365 days preceding the start of the Global Stakeholder Process. The Global Stakeholder Process occurs early in the project validation stage, and is a

30-day period in which the Project Design Document is first made available to the public and comments are accepted from observers. According to Magnusson (2014) this can be considered the date when the existence of the project becomes public knowledge. By using the average price of the 365 days preceding the start of this period, we aim to assign to each project a value that represents the prevailing CER price in the period corresponding to the finalisation of the project design documentation and the final decision to apply for CDM project status. As the choice of a 365-day averaging period is somewhat arbitrary, we will also discuss the possible implications of this choice on our results.

The daily spot price assessment for CER credits on the secondary market is available from Thomson Reuters Point Carbon, and was published daily from early 2008 and onwards (TR-PCA, 2013). For each project, we calculated the average price over the 365 days preceding the initiation of the Global Stakeholder Process. Since multiple correspondence analysis requires categorical variables, each price was subsequently classified as either low, medium or high based on whether it pertained to the lower, middle or upper third of the interval between the minimum and maximum price.

4.4 Results and Discussion

4.4.1 Model Adjustment

Table 12 summarises the adjustment quality of the multiple correspondence analysis. The first axis accounts for 40.58% of the total inertia (analogous to variance in the continuous case), whereas the second axis accounts for 11.69%. Together they account for 52.27% of the total inertia, suggesting that the two-dimensional representation of the data will be reasonably effective and convey significant amounts of information, although a relatively large proportion of the inertia, 47.73%, will not be represented in the map. Apart from the three subsequent principal axes representing 8.44%, 5.07% and 3.64% of the total inertia, respectively, the remaining proportion of the inertia is thinly spread out on the remaining principal axes, suggesting that the first few dimensions indeed capture most of the structure in the dataset.

Table 13 shows the projection of the categories along the two first principal directions, along with the square correlation between each category and each principal direction, and the contribution of each category to the directions' inertia.

4.4.2 Interpretation of the MCA dimensions

4.4.2.1 Interpretation of the first axis

There are nine categories whose contribution to the first axis is greater than the average (5.0%): the project types Biofuels, Methane and Wind power, the region Latin

Table 12 – Multiple Correspondence Analysis adjustment summary

		Number of obs.	11,954
		Total inertia	0.056031
		Number of axes	2
Dimension	**Principal Inertia**	**Percent**	**Cumul. percent**
dim 1	0.0227394	40.58	40.58
dim 2	0.0065483	11.69	52.27
dim 3	0.0047287	8.44	60.71
dim 4	0.0028403	5.07	65.78
dim 5	0.0020402	3.64	69.42
dim 6	0.0003168	0.57	69.99
dim 7	0.0000558	0.10	70.09
dim 8	0.0000005	0.01	70.10
Total	.0560308	100.00	

Source: Authors' elaboration

Table 13 – Projection of categories along the two first principal directions

		Overall			**Dimension 1**			**Dimension 2**	
Categories	mass	quality	%inert	coord	sqcorr	contrib	coord	sqcorr	contrib
Project Type									
Biofuels	0.029	0.682	0.038	1.433	0.644	0.060	0.645	0.038	0.012
Energy eff	0.040	0.064	0.038	0.233	0.023	0.002	-0.574	0.041	0.013
Forestation	0.002	0.509	0.078	1.549	0.024	0.005	-12.96	0.485	0.324
Hydro	0.061	0.535	0.018	0.366	0.181	0.008	0.951	0.354	0.055
Ind. gas	0.004	0.179	0.026	-0.348	0.007	0.000	-3.306	0.172	0.039
Methane	0.040	0.574	0.070	1.545	0.562	0.097	-0.414	0.012	0.007
Other renew.	0.010	0.275	0.062	-2.084	0.273	0.042	0.327	0.002	0.001
Others	0.004	0.234	0.012	-0.525	0.037	0.001	-2.247	0.196	0.020
Wind power	0.061	0.698	0.126	-1.886	0.698	0.217	0.097	0.001	0.001
Region									
Asia	0.199	0.629	0.020	-0.326	0.433	0.021	0.410	0.197	0.033
Lat-Am	0.038	0.600	0.077	1.704	0.576	0.110	-0.659	0.025	0.016
MENA	0.004	0.146	0.034	-0.267	0.004	0.000	-3.060	0.142	0.042
Others	0.003	0.195	0.011	0.489	0.028	0.001	-2.229	0.167	0.016
S Afr	0.002	0.171	0.009	-0.942	0.084	0.002	-1.784	0.087	0.007
SSA	0.003	0.474	0.079	0.689	0.008	0.002	-9.674	0.465	0.313
Scale									
LARGE	0.143	0.544	0.048	-0.602	0.441	0.052	-0.540	0.102	0.042
SMALL	0.107	0.544	0.064	0.803	0.441	0.069	0.721	0.102	0.056
Price									
Low Price	0.024	0.536	0.067	-1.921	0.530	0.088	-0.388	0.006	0.004
Medium Price	0.099	0.737	0.045	-0.908	0.735	0.081	0.090	0.002	0.001
High Price	0.128	0.738	0.079	1.060	0.738	0.143	0.003	0.000	0.000

Source: Authors' elaboration

America, the categories for large and small scale, and all three the price categories.

The contributions of the price categories to this axis are high, 31.2%. In addition, the low and high price categories are placed at opposite extremities of the first axis, and therefore we suspect that this axis is highly related to the CER credit prices. The Spearman rank correlation coefficient between CER price level and the projection of the individual projects along the first principal axis is $\rho = 0.6598$, which shows that there is a reasonably strong relationship between a project's placement along the first axis and the CER price level at project inception.

Since the price has been decreasing consistently throughout the period, there may be a confounding effect between the CER price level and time: CDM rules have evolved along the period, participants have learned from their experiences, institutional capacities have been gradually developed and the strategic positions of different regions or sectors have changed. The Spearman rank correlation coefficient between a simple trend variable and the projection of the individual projects along the first principal axis is $\rho = -0.6349$, which is almost as strong as that for the CER price level. Due to the high correlation between CER price level and a simple trend variable ($\rho = -0.8971$), it is difficult to disentangle the effects of these two factors on the project portfolio.

Coulon, Khazaei & Powell (2013) argue that the dynamics of environmental markets that depend highly on a fixed-date compliance event resemble binary options markets. Therefore, it is also possible that the market design itself could have induced a high correlation between time and price. The implication of this is that the time variable would be one of the main determinants of price, and explain at least part of the correlation between time and price, and thus also between time and the first principal axis. That is, the time trend could be a determinant of price rather than a confounding effect, and the high correlation between the trend variable and the price should be less worrying. The price also reflects the evolution of the market conditions over time: in some respects, price can be considered a synthesis of all available relevant information. The possibility of a confounding effect between CER price level and time therefore does not invalidate our interpretation, although unobserved variables that may affect both price and the project portfolio remain a cause for some concern.

The high correlation between the first principal axis and CER price level suggests that the influence of CER market conditions on the key project characteristics has been profound. Unless serious confounding factors are identified, the first principal axis can be interpreted as representing the *CER price level*.

4.4.2.2 Interpretation of the second axis

There are four categories whose contribution to the second axis exceeds the average (5.0%): forestry and hydro project types, the region Sub-Saharan Africa and the category for small projects. With respect to the regional categories, the second axis orders the regions in the following order: Asia, Latin America, South Africa, Others, Middle East/Northern Africa and Sub-Saharan Africa. This ordering is interesting, because it corresponds to the ordering of several economic and institutional indicators for these regions. This implies that the second axis may be related to the level of economic development.

To substantiate this suspicion, we calculated the Spearman rank correlation coefficient between the projection of CDM projects along the second axis and the Human Development Index (HDI) of the host country: $\rho = -0.2625$. The HDI is a composite index that intends to represent several facets of development using a single figure (ANAND; SEN, 1994; HDI, 2014). According to Costa, Rybski & Kropp (2011), the HDI has been extensively used by the United Nations Development Programme (UNDP) to compare social and economic development between countries and across time, and therefore we consider it an appropriate measure for verifying our interpretation. Although the moderate magnitude of the correlation by no means shows an outstandingly clear relationship, it can nonetheless be considered acceptable in the context of an exploratory analysis.

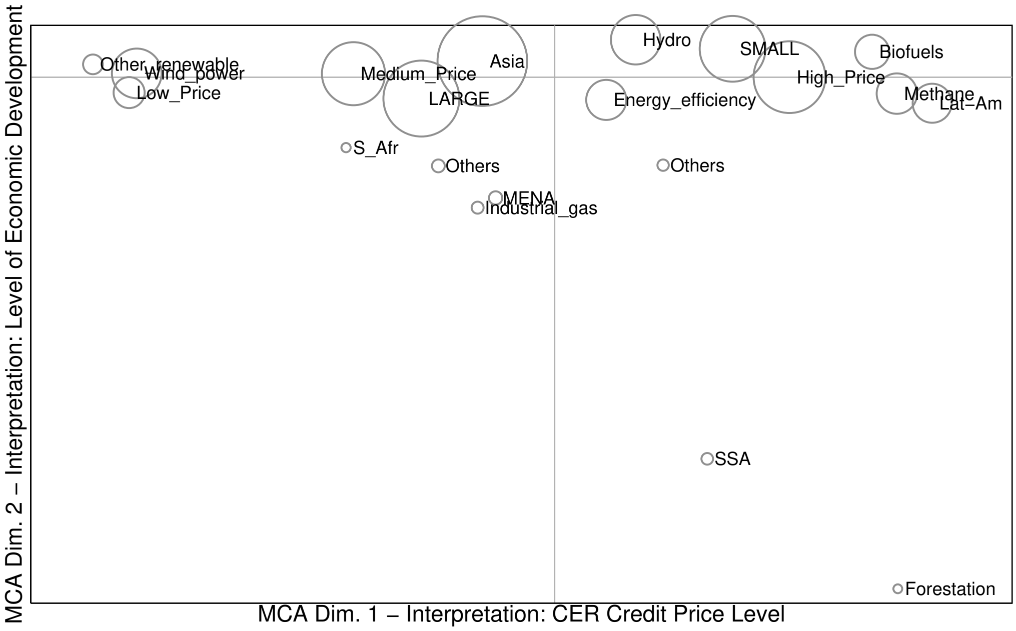
The interpretation of the second axis as the level of economic development and the concentration of projects in the higher end of the axis, would support earlier findings that project location and sector are greatly influenced by economic and institutional factors that favour more advanced developing countries (NONDEK; NIEDERBERGER, 2004; OLSEN, 2006; BYIGERO; CLANCY; SKUTSCH, 2010; FLUES, 2010; WINKELMAN; MOORE, 2011; ZHU, 2012; FAY, 2013; KIVYIRO; ARMINEN, 2013).

Therefore, although with due disclaimers, the second dimension can be considered to represent the *level of economic development*.

4.4.2.3 Main Determinants of Project Characteristics

Many earlier studies have focused on endogenous host country characteristics, such as institutional factors and level of economic development (e.g. Nondek & Niederberger (2004), Olsen (2006), Byigero, Clancy & Skutsch (2010), Flues (2010), Winkelman & Moore (2011), Zhu (2012), Fay (2013), Kivyiro & Arminen (2013)), as well as pre-existing bilateral relationships with other countries (e.g. Röttgers & Grote (2014), Costantini & Sforna (2014)), as significant determinants of CDM project locations and sectors. Assuming our analysis is not significantly affected by confounding factors, our analysis suggests that the CER market conditions may be a more important determinant for the project sector, location and scale than the level of economic development of the host country.

Figure 26 – Multiple Correspondence Analysis Biplot



Source: Author's elaboration

This is an important finding and supports our initial assumption that market conditions during the project planning phase influence the decision to apply for CDM project status. Although evidence of this in the context of individual projects has been reported in earlier literature (e.g. Schneider, Schmidt & Hoffmann (2010), Hultman et al. (2012), Xie, Shen & Wang (2014), Ervine (2014)), the current analysis suggests that CER market conditions might represent the most important individual factor – provided that confounding effects are relatively modest – and also allows us to examine the influence of market conditions on the entire CDM project portfolio.

4.4.3 General Tendencies of Project Characteristics

The most important result of multiple correspondence analysis is often the map of the categories projected along the first two principal directions, which reveals the most important underlying features of the dataset and allows us to explore general tendencies of the data.

Figure 26 shows the two-dimensional projection of the categories along these directions: the distance between points representing different categories measures how closely related the categories are, and the size of the circle marking each point reflects the category *mass* (i.e. the relative frequency of CDM projects belonging to the category). We can use this map to highlight some of the most interesting features of the dataset.

Asia is the region which accounts for the largest share of CDM projects, as evidenced by being the region represented by the largest circle. This is consistent with China being considered the country with the highest abatement potential, closely followed by the rest of developing Asia (NAUCLÉR; ENKVIST, 2009). The fact that Asia is situated very close to the origin in the map shows that the mix of projects in Asia is close to the overall average mix. As for project scales, Asia has a slight preference for larger projects. Preferred project types are renewable energy (primarily wind and hydro), industrial gas and energy efficiency. CDM projects in Asia appear to have been registered under a variety of market conditions, as it is situated close to the origin of the first principal axis.

Projects in Latin America are fewer than in Asia and generally applied for registration when CER credit prices were at a high level, since the marker is relatively small and located to the right in the map. Latin America appears to have a particular affinity for small scale projects, and biofuels, methane and hydro projects are characteristic. Considering that particularly Brazil has large abatement potential within forestation, it is a little surprising that this region does not associate more strongly with forestation (NAUCLÉR; ENKVIST, 2009).

The position of South Africa on the biplot is close to Asia, and also shows a preference for large scale projects. It is well-represented amongst industrial gas, wind and energy efficiency projects. Being positioned slightly to the left in the biplot means that most projects applied for CDM status when the CER price level was medium or low.

MENA is positioned very close to the marker for industrial gas projects, as MENA hosts almost 10% of the projects in this category. The region is also well-represented with energy efficiency projects. The projects in the region are predominantly of large scale, and the position of the marker between the medium and high price categories indicate that most projects applied for registration when CER price level was on the high side.

The small marker size for Sub-Saharan Africa indicates that it is host to few projects. Although biofuels, methane and energy efficiency projects are popular in the region, the region is particularly well represented in the forestation projects category. In fact, 30% of forestation projects are located in the SSA region, whereas the region accounts for only 1.3% of the total number of projects. This is a somewhat surprising observation, since this particular region is strongly affected by the land tenure problem (UNRUH, 2008). Being located to the right in the biplot indicates that most projects entered the CDM project cycle when the prices were high.

Table 14 shows a brief summary of the characterisations of the distribution of projects between regions, project types, scales and CER price level. The few general tendencies highlighted here seem to be the most apparent and important characterisations of the distribution of CDM projects of different scales between sectors and regions.

Table 14 – Summary of project characteristics

Region	**Project Types**	**Scale**	**Price**
Asia	Energy efficiency Renewables Industrial gas	Large	Medium
Latin America	Methane Biofuels Hydro	Small	High
South Africa	Industrial gas Wind Energy efficiency	Large	Medium Low
MENA	Industrial gas Energy efficiency	Large	High Medium
SSA	Forestation	Small	High

Source: Authors' elaboration

4.4.4 The Influence of CER Market Conditions

The identification of the first principal axis as representing the CER price level suggests that market conditions have had a profound effect on project characteristics. Here we will attempt to briefly describe the most salient features of the relationship between the CER price level and the project characteristics, and propose possible explanations for some of the observed features.

4.4.4.1 Project Sector

The analysis placed forestation, methane and biofuel projects at the extreme right of the first axis, meaning that these project types generally submitted applications when the CER price level was high. Considering that the viability of some biofuel projects depends on prices for competing petroleum products and that methane-related projects also often depend on the sale of an energy product (often gas or electricity), part of the explanation may be that the commercial viability of these projects dropped in the wake of the global economic slowdown, since energy prices and CER prices decreased in tandem. Although forestation projects have been estimated to be viable with a carbon price as low as USD 4.50 per tonne, it is possible that forestation projects have decreased in popularity over the period due to rule changes and uncertainties regarding the credits (OLSCHEWSKI; BENITEZ, 2005; PEDRONI, 2005; DUTSCHKE et al., 2005).

The project categories for hydropower and energy efficiency are placed slightly to the right of the center, which suggests that more hydropower and energy efficiency projects were registered at the high and medium price levels than at the low price level. Part of the appeal of these two project types, however, is normally related to associated products: the revenue stream from electricity sales, in the case of hydropower, and for energy efficiency projects it depends on the associated energy cost savings. In addition to low CER prices, it is possible that the general decrease in energy costs after 2008 has also contributed to making these project types less attractive.

The projects for industrial gas reduction are located almost equidistant from the three markers representing the price levels and close to the origin along the first principal axis, suggesting that these project types may be less sensitive to CER price levels. This may be explained by the fact that industrial gas reduction projects are often considered to have low cost and earn a large amount of credits, which makes them attractive at any price level and therefore insensitive to the price level.

Wind power and other renewable energy projects (e.g. solar) appear to have been registered at a low CER price level, indicated by their location far to the left hand side of the map. There are several possible explanations for this. Firstly, the low CER price level may simply coincide with the maturation of the wind power. That is, the timing of the capacity expansions just happened to coincide with a low CER price level, but without being materially affected by it. Secondly, the revenue from CER sales represent only a small share of the revenue stream of such projects – electricity sales represent a larger share – as such, these project types may be insensitive to CER price levels. Thirdly, renewable energy projects sometimes receive subsidies (in the form of feed-in tariffs, tax rebates, etc.), which would also help them remain viable regardless of the CER price. At the very least, it appears that the deployment of wind power and other renewable energy projects is not impeded by low CER price levels.

4.4.4.2 Host Region

There are two main ways through which the CER price level can relate to the host region of CDM projects. Firstly, the costs of developing projects vary between host countries, influenced by such factors as institutional quality and the costs of factors of production, and, secondly, the abatement potential varies greatly between regions – for example highly industrialised regions with high emissions naturally have higher abatement potential (ELLERMAN; DECAUX, 1998; CRIQUI; RUSS; DEYBE, 2006; NAUCLÉR; ENKVIST, 2009).

Latin America is placed to the right in the map, indicating that the projects in this region in general applied for registration when CER prices were at a high level. This may reflect both high costs of developing projects in the region and the predominance of biofuel and methane-related projects which may be more attractive at high energy prices (BARROS et al., 2006).

Projects in Sub-Saharan Africa also tend to have applied for registration when CER prices have been high, since the region is located to the right in the map. This may be related to the many forestation type projects developed in the region, which gradually became a less attractive project type (FORNER; JOTZO, 2002; SUBAK, 2003; LOCATELLI; PEDRONI, 2004; PEDRONI, 2005; DUTSCHKE et al., 2005; BOYD; CORBERA; ESTRADA, 2008). A low CER price level, together with increased uncertainty, makes such project types particularly unattractive. It is also possible that the lack of institutional capacity in this region means that a higher CER price level is required to justify a project application, that the low level of industrialisation entails that the abatement potential is limited in other sectors, and that the low level of economic development means that there is limited potential to profit from co-products of other project types (NAUCLÉR; ENKVIST, 2009).

Based on the central location of Asia in the map, projects hosted in Asia have predominantly requested registration at a medium CER credit price level. This is due to the large number and variety of projects hosted in the region, as this implies that the region hosts projects that are profitable at a range of price levels.

4.4.4.3 Project Scale

The placement of the project scale categories SMALL and LARGE on opposite sides of the first principal direction suggests that CDM projects achieve economies of scale. A higher share of small-scale projects were registered when CER credit prices were high, suggesting that the viability of these projects depends on a high CER price level. This observation supports findings by Fichtner, Graehl & Rentz (2003) and Rahman & Kirkman (2015), which have reported similar effects.

4.4.5 Robustness and Weaknesses

Here we will discuss three main sources of weaknesses for this analysis. Firstly, many of our observations may depend on the categorisation of the CDM projects, such that other definitions of regions or project types may produce different results. Secondly, the price we have chosen to use in this analysis may be inappropriate for some cases, and a different choice of price could lead to different conclusions. And, thirdly, the interpretation of the principal MCA directions is mostly an informal process and prone to confounding factors and errors.

The categorisation was chosen in order to group project types and countries that are thought to exhibit similar characteristics, but one can easily imagine alternative categorisations of project types and regions. However, when we ran the analysis on the ungrouped host countries and the completely disaggregated project types, the first two principal directions still displayed high correlations with CER price and HDI, respectively: the Spearman rank correlation between the projection along the first principal axis in the grouping used in this study and the projection along the first principal axis of the completely disaggregated analysis is $\rho = 0.68$. For the second axis, this number is $\rho = -0.39$ (the fact that the correlation is negative does not change the interpretation of the axis). This indicates that the categorisation chosen for this analysis is reasonable, and that the main results in this study are robust to the definition of categories.

There may also be alternative ways to treat the CER price. Our choice of a 1-year averaging period prior to the initiation of the Global Stakeholder Process rests on some assumptions that may be violated for some projects, that is, it may not be a very good proxy for the price expected by the project developers when the final decision to apply for CDM project status is made. However, since we eventually use only three categories for the CER price level in the final analysis (high, medium and low) and since CER prices have been decreasing almost monotonically throughout the period of analysis, we do not expect errors due to misclassification to be very influential. Repeated testing with alternative lag structures did not change the results materially, nor did tests with different numbers of price categories.

The most serious concern is confounding factors, which may influence the interpretation of the principal MCA directions. In particular, the movements in the price are so consistent – particularly the 1-year moving average – that it is almost indistinguishable from a (negative) time trend variable. Therefore there is a possibility that the first principal axis represents the evolution of the CDM or other developments over time, and not specifically the price level. On the other hand, however, the first axis correlates better with price than a trend variable – the difference is small, but statistically significant. In addition, the dynamics induced by the market design might mean that the simple passage of time is a fundamental driver of the CER price, in which case the high correlation between the first axis and a trend variable is natural and should not cause concern even if the effects of time and price cannot be entirely disentangled. Although the possibility of confounding effects is a reason to be cautious, it does not invalidate our analysis and we remain comfortable with interpreting the first principal axis as representing CER price level.

4.5 Concluding Remarks

The aim of this analysis was to explore the relationships between key characteristics of CDM projects and CER market conditions. In total, 11 954 CDM projects were included in this analysis. Multiple Correspondence Analysis showed that the two first principal directions account for 52.27% of the total inertia in the dataset, and the axes were interpreted as representing the CER price level in the year preceding the CDM validation phase and the level of economic development in the region, respectively. This establishes that the CER price level is a significant determinant of the location, sector and size of CDM projects – perhaps even *the most* significant determinant, unless significant confounding factors are present.

Our analysis revealed some interesting patterns in the geographical and sectoral distribution of projects: a concentration of projects in regions with higher levels of economic development, mainly Asia and Latin America representing energy-related projects (various forms of renewable energy, energy efficiency and methane-related projects), few projects and a disproportionately high share of forestation projects in Sub-Saharan Africa, and a preference for industrial gas and energy efficiency projects in Middle East/Northern Africa. This distribution roughly reflects innate characteristics and abatement potential of the regions. Increasing energy demand and existing technological capabilities/infrastructure in the more developed regions of Asia and Latin America means that a large portion of their abatement potential is within renewable energy or energy efficiency. The level of industrialisation of the Middle East/Northern Africa region makes it suitable for industrial gas and energy efficiency projects. Sub-Saharan Africa, with comparatively lower levels of industrialisation and institutional infrastructure, has focused on forestation projects which are less technologically intensive in comparison and represents a larger share of their abatement potential.

We observed that biofuels projects applied for registration mainly when CER prices were high, possibly due to the correlation between global energy and carbon prices. Forestation projects were also pursued mainly when CER prices were high, possibly reflecting greater cost or uncertainty surrounding this project type or the regions in which it occurs, especially Sub-Saharan Africa. Industrial gas emission reduction projects appeared to be less sensitive to CER price levels, whereas wind power projects were generally registered when CER credit prices were low. This might indicate that neither of these project types are very sensitive to the CER prices, and can remain profitable even at low CER price levels – possibly due to profitable co-products, subsidies or low deployment costs. The relationship between CER prices and host regions appears to be greatly affected by the types of projects that are pursued in each of the regions: the high CER credit price level of Latin American projects reflects the dominance of biofuels and methane-related projects in the region, the price insensitivity of Middle East/Northern Africa reflects the large share of industrial gas emission reduction projects, and the large variety of projects in Asia means that there is a mix of projects that applied for registration at all price levels. The analysis of project scale shows that a low CER price level is clearly associated with larger scale projects and vice versa.

Although market conditions have not received much attention in the existing literature, our exploratory analysis implies that the market conditions have exerted a profound influence on key project characteristics. A more complete understanding of the determinants of the sectoral and regional distribution of CDM projects can therefore be achieved by including the CER market conditions in the analysis. The observations presented in this study may have significant consequences for future policy developments, as these effects must be carefully taken into consideration in order to successfully achieve the dual objectives of sustainable development and efficient emission reductions.

The main results of this study appear robust to the categorisation of projects and countries, as well as to the definition of the CER price level. However, possible confounding effects that may affect the interpretation of the main determinants of the geographical and sectoral distribution, mainly due to the high correlation between time and the price level, are still a cause for concern, although we do not believe it invalidates our analysis.

The broad characterisations and patterns identified here can be very useful in a number of contexts, although it is important to note that they have not been formally and exhaustively tested. This study has only identified some possible patterns and the causes of these patterns have not yet been rigorously investigated and tested, altough some possible explanations for these patterns have been presented. Additional research is necessary to formally test the relationships identified in this study, to provide a deeper understanding of the underlying causes of these patterns, and to investigate possible confounding effects.

5 Concluding Remarks

The three essays presented in this thesis have thoroughly investigated three important issues in energy resource management and climate change. As a whole, the essays are intended explore the possible impacts of future events, develop a deeper understanding of the efficient operation of energy infrastructure and investigate the appropriate design of public policies, in order to contribute to our ability to plan for the future.

In the first essay – in which we compared numerical results of a mathematical optimisation model to the actual operation of a liquefied natural gas (LNG) regasification terminal – we discovered that existing energy infrastructure may be operated sub-optimally. This is an important insight, considering the negative financial and social impacts of inefficient energy provision, and suggests that there are still possibilities for increasing the operational efficiency of existing energy infrastructure.

On a longer time horizon, the efficient planning and operation of the energy system depends on high-quality forecasts. In this respect, the second essay presented a method for incorporating climate change effects in electricity demand forecasting. The method was used to generate an ensemble of electricity demand paths for Brazil between 2016 and 2100, under different population and economic growth assumptions. In general, the forecasts suggest that annual Brazilian electricity demand will peak in about 2060 at approximately twice the current annual demand, and thereafter decrease somewhat towards year 2100. This pattern of strong growth until 2060 is fuelled mainly by the prospects of economic growth, whereas the subsequent decline between 2060 and 2100 is caused mainly by the decrease in population forecasts. Weather, however, was considered an important driver of the electricity demand volatility and causes large variations in the electricity demand, which underlines the importance of considering climatic variations in electricity demand forecasting.

Continuing on the theme of climate change, the third essay closely examined one of the most ambitious climate change mitigation efforts introduced by the Kyoto Protocol: the Clean Development Mechanism (CDM), in which emissions credits earned by projects in developing countries could be commercialised and applied towards the emissions targets of developed countries. The study identified characteristics and patterns of the geographical and sectoral distribution of such projects, and identified the price of emissions credits on the secondary market as a significant driver for the geographical and sectoral distribution of such projects. This is an important insight and should prompt some serious deliberation and consideration as to whether the dual objectives of poverty reduction and low-cost climate change mitigation are compatible.

Given the social and economic significance of energy, together with the great uncertainties brought by the future, efficient energy resource management remains a topic of considerable importance. Although these three essays may answer a few questions, the research for each of the essays has revealed another (larger) layer of questions that are worth considering.

Firstly, the situation considered in the first essay was very restricted. A very valuable extension to the model might consider additional cases in which the assumptions of the model are relaxed – for example when there are storage costs, transaction costs, and when there is no natural gas spot market. Many LNG importation terminals have no onsite storage, and vessels must remain at the berth until they are emptied, which generates significant costs. In addition, some importation terminals are directly connected only to a natural gas power plant, whose dispatch is determined by the situation in the electric power grid. Given that cargo procurement has long lead-times, and that there could be significant uncertainty about the dispatch of the power plant due to for instance meteorological uncertainties, the resulting stochastic optimisation problem must be extended to include a large number of factors not considered in the model presented here. A generalisation of the model might therefore make it interesting to a much larger audience.

Another line of research within the operational efficiency of LNG terminals, is a comparison of several numerical resolution methodologies. Although the current LSMC approach appears to work relatively well, it would be interesting to investigate the use of the SDDP model or a direct linear programming model. There have also been some interesting attempts at applying techniques from machine learning to this type of problem (mainly reinforcement learning approaches, such as Q-learning, SARSA, etc.), which might represent a challenging and fruitful field of research.

The second essay glosses over many issues which merit further study. Some further research issues include the non-linearity of the demand response to temperature, the application of stochastic techniques such as Markov chains, techniques based on artificial intelligence, simultaneous modelling of the supply side, and the inclusion of the power price in the model. A rich comparison of several methodologies for demand scenario generation would be of great interest to a wide audience.

An obvious extension of the second essay would naturally be to apply techniques to real energy planning questions, in order to discover the significance of the results in a wider context. For instance, given the weather-based variation in electricity demand, what portfolio of generation capacity would be required to serve the demand, and what consequences does this have for the social cost of electricity generation?

Finally, the third essay explores a rich and rewarding topic, but the exploratory approach only serves to trace a vague outline of the effects of such mechanisms as the CDM. In this respoect, there is firstly a great need to establish more firmly the patterns discovered in the exploratory analysis and their suggested explanations. Although the CDM is at this moment considered a failure by many, such thorough *post-mortem* analyses and evaluations would serve to guide similar efforts in the future, such as the more specific mechanisms that are currently being proposed to replace it. In order to properly design good mechanisms to replace the CDM in spirit, it is vital to deeply examine and understand the results of the CDM experiment and subsequently apply the lessons to the new efforts. Even though the mechanism is perhaps currently politically out-of-favour, the social and economic importance of this topic appears only to be increasing. As such, the general topic of global mitigation efforts continues to have great relevance as the effects of global climatic changes continue to unfold and become more apparent. The potential of this type of mechanism to contribute to economic development and poverty alleviation also means that it merits a great deal of further research.

These three essays barely scratch the surface of this tremendously complex issue, but these modest contributions can hopefully still have a positive impact. However, there are still countless open questions to be investigated, plenty of unresolved issues, and plenty of work still to be done on the topics of energy and climate change.

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