Integrated Electricity and Gas Market Modeling – Effects of Gas Demand Uncertainty

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Abstract — **This paper develops an integrated fundamental investment model which considers both the gas and electricity sector. Furthermore, we adopt the theory of stochastic programming with recourse in the combined model to account for uncertainty in the gas market. This approach enables us to analyze how uncertain gas demand in other sectors affects decisions to invest in electricity generation capacities. We find an overall decrease and a reallocation of investments in gas-fired power plants. We also quantify the expected costs of ignoring uncertainty.**

Index Terms--Electricity market, Integrated energy system modeling, Natural gas market, Stochastic modeling

I. Introduction

A considerable amount of research has been oriented to the economic modeling of European energy markets. The large stream of model-based studies, however, focuses on single energy sectors, such as gas (e.g. [1] and [2]) or electricity (e.g. [3] and [4]). Consequently, many market models applied to a variety of research questions (e.g. market design, infrastructure expansion or policy analysis) neglect or at least do not endogenously consider interdependencies between markets.

As a contribution to the literature we include uncertainty in a large-scale integrated electricity and gas market model with empirical data. This paper focuses on the effects of gas demand uncertainty (in other sectors) on investments in electricity generation capacities. Non-electricity sectors have uncertain gas demand, which induces gas prices that vary with time and location. The magnitude of temporal and spatial changes of gas price is determined endogenously by a set of constraints in the gas-related sector of our model. Given that natural gas prices are an input in electricity market models, their variations affect both dispatch and investment decisions in generation capacity – which in turn have repercussions on the gas price.

To date, relatively few studies have highlighted the importance of accounting for the interdependencies between electricity and gas markets using an integrated modeling approach. [5] investigates both the temporal and spatial effects of model integration. The authors show that modeling practices which do not consider linkages between the markets lead to results with systematic deviations from an integrated modeling approach. [6] tests interactions between investments in natural gas and electricity infrastructure based upon a stylized representation of European markets. In a subsequent paper, the authors focus on the long-term effects of gas infrastructure development on power plant investments, as well as on the short-term supply shock scenarios to capture feedback effects on the electricity market [7]. [8] examines a number of supply disruption scenarios and their impacts on power system operation using an integrated model with a high temporal resolution.

Aiming to account for uncertainty, numerous studies use energy system models applying stochastic programming with recourse. [9] argues that a stochastic representation of intermittent RES can be advantageous for long-term investment planning. [10] shows how uncertainty in wind feed-in affects the electricity price's volatility in the long-term market equilibrium. [11] analyzes the effect of uncertainty in the daily wind feed-in on dispatch decisions in the short-term electricity market. The impact of uncertain gas demand on gas infrastructure decisions is studied in [4]. [12] applies a stochastic multi-horizon equilibrium model with both long-term and short-term uncertainties for a stylized example of a multi-energy system.

We continue this paper with four sections. In section II, we describe the methodology and familiarize the reader with the use of an integrated market model and the implementation of an uncertain gas demand. In section III, we report and compare deterministic and stochastic solutions. This is followed by analysis of the impact of uncertainty on the integrated energy system. Section IV concludes.

II. Methodology

In the following, we describe the integrated energy system model we applied, which considers the natural gas and electricity markets. In addition, we show and explain the objective function of our model.

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A. *Nomenclature*

Sets

$t \in T$	hours
$m \in M$	months
$y \in Y$	years
$n, nn \in N$	system nodes
$i \in I$	power generation technologies
$G \subseteq I$	gas-fired power generation technologies
$p \in P$	gas production facilities[1]
$s \in S$	scenarios

Variables

$COST$	total system costs [€]
$G_{i,t,y,s}$	power generation [MWh/h]
$INV_{i,n,y}$	investment in power generation capacity [MW]
$PR_{p,m,y,s}$	gas production [bcm]
$ST^{in/out}_{m,y,n,s}$	gas storage injection/withdrawal [bcm]
$TR_{p,m,y,n,nn,s}$	transport of natural gas (via pipeline or LNG route) LNG [bcm/km]

Parameters

$c^{CO2}_{i,y}$	CO_2 costs [€/MWh$_{el}$]
df_y	discounting factor
$fc_{i,y}$	fuel costs [€/MWh$_{el}$]
$ic_{i,y}$	annualized investment costs for power generation capacity [€/(MW*a)]
pc_p	production costs of gas supply [€/bcm]
sc^{in}, sc^{out}	storage costs [€/bcm]
$tc_{n,nn}$	transport costs of gas pipelines or LNG shipping [€/(bcm*km]
ρ_s	probability factor for each scenario

B. *Model Description*

In this paper, we create an integrated dynamic model concerning the power generation and gas sectors which has the ability to determine optimal investment in the electricity sector and operational decisions in both sectors. The model includes all relevant production and infrastructure elements for the EU-28. Furthermore, we include Switzerland, Norway, Russia, Algeria, Libya, Qatar and Nigeria.[2] Countries are represented as single nodes that are connected by gas and electricity infrastructure.[3] Model simulations are performed for representative periods up to the year 2030. In the context of this paper, we analyze the years 2020, 2025 and 2030. The gas market components have a time resolution of 12 months, and the electricity market components have a time resolution of 350 representative hours.[4] As they strongly depend on political actions, the development of renewable generation capacities is implemented exogenously.

We implement a set of natural gas demand scenarios based on uncertainty in the non-electricity sector. As a result, we generate monthly natural gas prices, which differ in location, time and scenario. The uncertainty in gas demand affects both investment and operational decisions in the electricity sector. We perform two model runs to quantify the impact of uncertainty. First, we run the deterministic "naïve" scenario, neglecting any uncertainty in gas demand: gas demand in the years 2020, 2025 and 2030 is assumed to be constant. Second, uncertainty is added. In this model run, we simultaneously optimize three demand scenarios: gas demand in the non-electricity sector varies from + 15 % (scenario 1) to – 15 % (scenario 3) in the years 2025 and 2030.[5] In scenario 2, there is no variation in gas demand (i.e. ± 0%). The resulting scenario tree is shown in Fig. 1.[6]

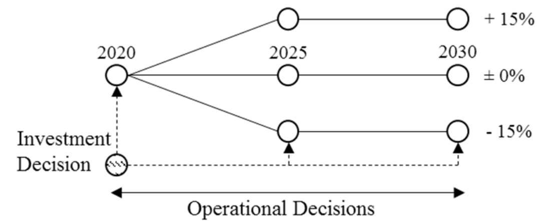

Fig. 1: Scenario tree

The probability of the appearance of each scenario (ρ_s) is assumed to be equal (1/3 for each scenario branch). The investment decision in the stochastic model run has to hold for all three scenario variations. It defines which amount of a technology will be installed in which year. Once a generation capacity is built, it has to stay in the market and cannot be decommissioned.

Our methodology utilizes a linear programming formulation (LP) of a global cost-minimization problem. The objective of our model is to minimize the expected discounted value of the total costs of electricity and gas production, transport and investments. The objective function is shown in (1).

$$\begin{aligned} COST = \sum_{n,t,y,s} \rho_s * df_y * \Bigg(& \sum_{i \in I \setminus G} (fc_{i,y} + c^{CO2}_{i,y}) * G_{i,n,t,y,s} \\ & + \sum_{g \in G} G_{g,n,t,y,s} * c^{CO2}_{g,y} \Bigg) + \sum_{i,n,y} df_y * INV_{i,n,y} * ic_{i,y} \\ & + \sum_{m,y,s} \rho_s * df_y * \Bigg(\sum_{p,n} pc_{p,n} * PR_{p,n,m,y,s} \\ & + \sum_{n} \left(sc^{in} * ST^{in}_{m,y,n,s} + sc^{out} * ST^{out}_{m,y,n,s} \right) \\ & + \sum_{p,n,nn} tc_{n,nn} * TR_{p,m,y,n,nn,s} \Bigg) \end{aligned} \quad (1)$$

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[1] Elements of set P come from linear piecewise approximation of the logarithmic production cost function per production node.

[2] The model dataset excludes Iceland, Ireland, Cyprus and Malta.

[3] Countries Spain and Portugal, as well as Lithuania, Estonia and Latvia, Norway, Sweden and Finland and Bulgaria, Slovenia, Serbia, Croatia and Greece are grouped by the nodes 'Iberia', 'Baltic', 'Scand' and 'Balkan'.

[4] We use an approach of each 25th hour of a year based on [15].

[5] We assume that the year 2020 is not subject to uncertainty.

[6] Note that the expected gas demand in the non-electricity sectors is the same in both model runs.

Due to the integration of the electricity and gas sector via a fuel linkage. Gas-fired power plants create a demand for gas, which has to be produced (as part of $PR_{p,m,y,s}$) and transported (as part of $TR_{p,m,y,n,nn,s}$) and, thereby, creates costs for the system. Both the electricity sector's gas demand and the costs of gas-fired electricity generation (which are based on the gas price in the respective country) are modeled as endogenous variables that provide us with reliable marginal costs estimators. Furthermore, by implementing a set of uncertain gas demand scenarios, the magnitude of temporal and spatial changes in gas price is determined endogenously by a set of relevant constraints in the gas market model. Hence, electricity generators investing and utilizing gas-fired power plants face expected values for the gas price depending on time and location.

C. Data

Hourly electricity demand and hourly renewable production data are taken from [13] and [14]. Electricity consumption is assumed to be constant until 2030. Our assumptions for future fuel costs come from [15] and [16]. Investment costs are taken from [17]. CO_2-prices are assumed to follow the *new policy scenario* in [18]. Existing national power generation capacities as well as their technology specific parameters and decommission pathways come from [19], [20] and [15]. We apply net transfer capacities (NTC) provided by [21] which restrict cross-border transmission flows. We assume no limitations on electricity flow within countries. With the aim of accounting for country-specific CHP utilization schemes, we implement temperature-dependent must-run conditions to meet the annual production volumes of CHP plants based on [22].

Data for the existing gas pipeline infrastructure connecting countries is based on [23]. Data for LNG liquefaction and regasification terminals was acquired from [24] and [25]. Storage data is based on [26]. We again use [21] to collect data for projections of European countries' annual gas demand. A monthly gas demand structure for each country is calculated as a historical average value based on [22]. Our model incorporates exogenous capacity expansions of natural gas infrastructure (including transmission network, storage facilities and LNG terminals). The structure of the system's development is harmonized with [21]. We analyzed numerous public information portals and relevant academic papers to devise the structure of gas production, transport and storage costs utilized for this research (e.g. [27], [2], [28] and [29]).

III. Results

In the following, we present the results of the model mentioned above focusing on how an uncertain gas demand affects the integrated system. We compare output from the two alternative settings: (i) a deterministic benchmark problem, where it is assumed that scenario 2 will happen with 100 % probability (referenced later as 'DP'), and (ii) a stochastic problem ('SP'). This is followed by analysis of the impact of uncertainty on the integrated system.

A. Effects of gas demand uncertainty on power generation investments

In this paper, we focus on endogenous decisions to invest in electricity generation capacities. We assume that existing generation capacities are subject to an age-dependent decommission pathway while electricity demand is constant. Furthermore, we implement several technical and political constraints restricting possible investments. As a result, it is not possible to invest in new nuclear power plants in numerous European countries. Lignite plants can only be built in regions where lignite reserves exist. Due to political restrictions, no additional lignite power plants can be constructed in Germany. In addition, a coal phase-out in several countries, such as Austria, France, Italy and UK, is taken into account.

In the following, we focus on the question of how uncertainty in natural gas demand affects optimal investment decisions. We compare the results of the DP and SP and highlight the deviations between them with respect to the extent of investment in the electricity market. Fig. 2 depicts investments in new electricity generation capacities and their allocation in Europe aggregated until 2030. Note that most of this investment is triggered by capacity needs resulting from age-dependent decommissioning of other stations (see above). Investments in gas-fired technologies (i.e. both OCGT and CCGT) are aggregated to simplify the graph.

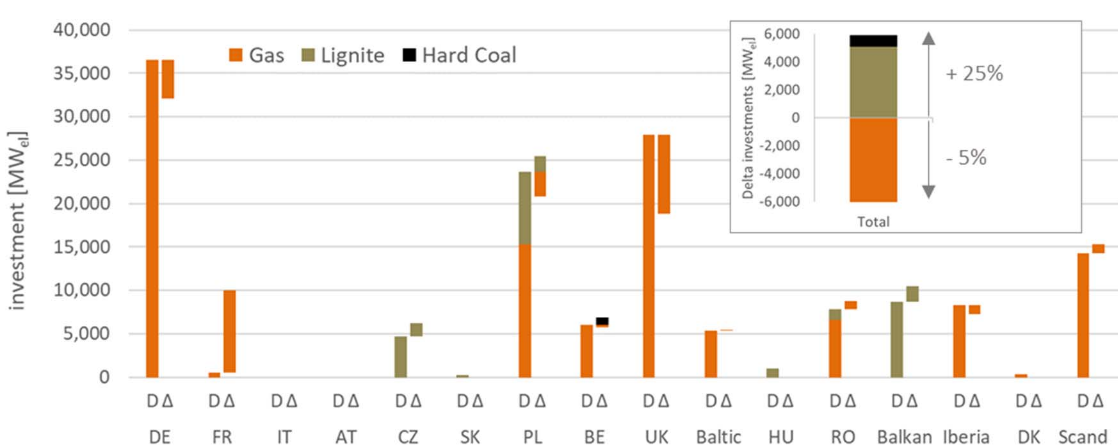

Fig. 2: Investments in power generation capacities over the modeling horizon: Deterministic benchmark (left column marked by D) and change in stochastic approach in comparison with the benchmark (right column marked by Δ)

The left column of each country shows the result of the DP, the right column states the difference between DP and SP. If, in the SP, a region invests more in a technology, the right bar rises above the DP and if a region invests a lower amount, the right bar "falls" down. In addition, the inserted graph shows the overall European investment deviation in the SP.

Fig. 2 demonstrates the effect of uncertainty on gas power plant investments. In particular, we see an overall decrease in gas power plant investments (- 5 % compared to the investment volume in the DP) while there is an overall increase in investment in lignite and hard coal power plants (combined + 25 % compared to the investment volume in the DP). Nuclear and oil technologies are not being invested in, both in the DP and in the SP. Additionally, we observe a shift in the allocation of gas investments in Europe.

The main driver for the overall decrease of gas investments is a general increase in the gas prices in the SP. After implementing scenarios with a higher and lower gas demand, we observe an increase in the average expected European gas price of 1.47 €/MWh_{th}. This increase can be explained by the incremental slope of the logarithmic gas production cost function (as proposed by [30]).[7] Gas producers face uncertain development of gas demand, while right-hand marginal production costs (i.e. costs of producing one unit more), on average, are higher than left-hand marginal costs (i.e. savings from producing one unit less). Hence, the expected costs to produce in an uncertain environment are higher than in the deterministic case. As a result, the competiveness of gas generation technologies diminishes and thus, investment volumes decrease.

The allocation differences in investments between the DP and SP are mainly driven by different developments of gas prices in each country. As we explained above, we observe an overall price increase. However, as each European region has a specific production and transport cost structure, they react differently to the implementation of uncertainty in gas demand.

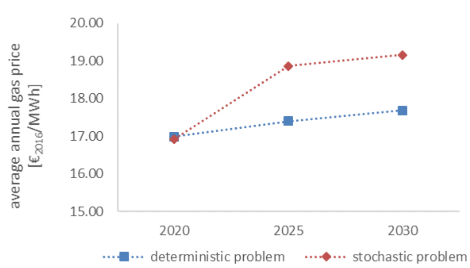

Fig. 3: Development of the average annual gas price in Europe for the deterministic and stochastic case.

B. *The impact of uncertainty on the integrated system*

We conduct the following calculations to analyze the impact of gas demand uncertainty on the integrated energy system. The methodology follows the approaches used in [2], [9], [31] and [32].

First, we calculate the Value of Stochastic Solution (VSS), which is also referred in the literature as the expected costs of ignoring uncertainty ([31], [33]). The VSS is calculated as follows: (i) we find the optimal investment decisions $INV_{i,n,y}$ in the "naïve" deterministic benchmark model, (ii) the stochastic model is solved with the vector $INV_{i,n,y}$ fixed, and (iii) we calculate the increase in expected cost of the stochastic model when it is solved with fixed investments from the deterministic model. The model set-up results in a non-negative VSS value because the optimal SP solution takes into account the minimization of the expected system costs over all scenarios simultaneously.[8] Table I illustrates the results.

TABLE I. VALUE OF STOCHASTIC SOLUTION

	Total costs	Expected costs of ignoring uncertainty
Stochastic	€ 247,078 M	
Stochastic*	€ 247,143 M	
VSS		€ 65 M
VSS (% of total costs)		0.026 %

*Stochastic model is solved with fixed investments from deterministic model

The VSS measures the value of considering the range of uncertainties in a stochastic model, rather than using a less realistic deterministic approach. As Table I shows, the obtained VSS is 0.026 % of the total system costs in the stochastic solution. Hence, the value of considering the uncertain gas demand for the power generation investment planning seems, at first glance, rather small. However, [2] analyzes the value of considering gas demand uncertainty for the gas transmission grid planning using a stand-alone gas market investment model, and reports a VSS value below 0.01 %. This finding suggests that there is value in considering uncertainty *across the integrated system*.

A second metric that can be derived from the modeling results is the Expected Value of Perfect Information (EVPI). The EVPI quantifies the reduction in system costs if a "central planner" knows in advance which realization of gas demand scenarios will happen. In order to calculate EVPI, we first solve each of the demand scenarios separately using a deterministic approach. Then, we take the difference between the expected costs of the stochastic solution and the probability-weighted average of the separate scenarios' costs (see Table II).

TABLE II. EXPECTED COSTS OF IGNORING UNCERTAINTY

	Total costs	Saving resulting from a perfect information
Stochastic	€ 247,078 M	
Deterministic		
Scenario 1	€ 223,432 M	€ 23,646 M
Scenario 2	€ 245,533 M	€ 1,545 M
Scenario 3	€ 271,125 M	- € 24,047 M
EVPI		€ 381 M
EVPI (% of total costs)		0.154%

[7] In order to keep the model formulation linear, we use a linear piecewise approximation of the logarithmic production cost function.

[8] [32] illustrates, however, that VSS can be negative for some of the agents on the market in multi-agent game theoretic problems.

The EVPI can be viewed as the added value to society of having perfect information about the future. [31] also defines it as an '*upper bound to the amount that should be paid for improved forecasts*'. We find that the EVPI is 0.154 % of the total system costs. This value is lower than reported by [9], where the authors modeled stochastic wind power generation within the stand-alone electricity investment model, but higher than in [2] (see above). This observation supports our hypothesis that the economic impact of uncertainty should be evaluated using an integrated modeling approach.

IV. Conclusion

In this paper, we have applied an integrated stochastic electricity and gas market model to assess how gas demand uncertainty in other sectors, such as heating, effects the electricity sector. In particular, we analyzed electricity generation capacities. Our results show that uncertainty of gas demand causes spatial and temporal changes of natural gas prices. Due to the strong impact of gas price on the profitability of gas-fired power plants, we observe an overall drop in investment volumes within Europe. The analysis of the VSS and the EVPI metrics highlighted the importance of recognizing the effects of uncertainty across the integrated energy system.

Further research should be conducted to fully understand the impact of uncertain demand (as well as other drivers of uncertainty) on all the planning decisions across the integrated energy system.

References

[1] F. Holz and C. v. Hirschhausen, "The Infrastructure Implications of the Energy Transformation in Europe until 2050: Lessons from the EMF28 Modeling Exercise," *Climate Change Economics*, vol. 04, 2013.

[2] M. Fodstad, R. Egging, K. Midthun, and A. Tomasgard, "Stochastic Modeling of Natural Gas Infrastructure Development in Europe under Demand Uncertainty," *The Energy Journal*, vol. 37, no. Sustainable Infrastructure Development and Cross-Border Coordination, 2016.

[3] W.-P. Schill and A. Zerrahn, "Long-run power storage requirements for high shares of renewables: Results and sensitivities," *Renewable and Sustainable Energy Reviews*, vol. 83, pp. 156–171, 2018.

[4] F. Müsgens, "Quantifying Market Power in the German Wholesale Electricity Market Using a Dynamic Multi-Regional Dispatch Model," *The Journal of Industrial Economics*, vol. 54, no. 4, pp. 471–498, 2006.

[5] M. Lienert and S. Lochner, "The importance of market interdependencies in modeling energy systems – The case of the European electricity generation market," *International Journal of Electrical Power & Energy Systems*, vol. 34, Issue 1, pp. 99–113, 2012.

[6] H. Weigt and J. Abrell, "Investments in a Combined Energy Network Model: Substitution between Natural Gas And Electricity?," CER-ETH – Center of Economic Research at ETH Zurich, Working Paper 16/237, 100540, 2014.

[7] J. Abrell and H. Weigt, "The Short and Long Term Impact of Europe's Natural Gas Market on Electricity Markets until 2050," *The Energy Journal*, vol. 37, 2016.

[8] J. P. Deane, M.Ó. Ciaráin, and B. P. Ó. Gallachóir, "An integrated gas and electricity model of the EU energy system to examine supply interruptions," *Applied Energy*, vol. 193, pp. 479–490, 2017.

[9] P. Seljom and A. Tomasgard, "Short-term uncertainty in long-term energy system models - A case study of wind power in Denmark," *Energy Economics*, vol. 49, no. 0, pp. 157–167, 2015.

[10] T. Möbius and F. Müsgens, "Electricity market equilibria and intermittent renewables — A stochastic approach," *IEEE Conference Proceedings (EEM 2017)*, pp. 1–5, Jun. 2017.

[11] F. Müsgens and K. Neuhoff, "Modelling Dynamic Constraints in Electricity Markets and the Costs of Uncertain Wind Output.," *EPRG Working Paper 05/14, University of Cambridge*, 2005.

[12] Z. Su, R. Egging, D. Huppmann, and D. Tomasgard, "A Multi-stage Multi-Horizon Stochastic Equilibrium Model of Multi-Fuel Energy Markets," *CenSES Working paper*, vol. 2/2015, 2015.

[13] Open Power System Data. Data Package Time Series. Version 2017-07-09, Link: https://data.open-power-system-data.org/time_series/, Accessed on 14.12.2017.

[14] ENTSOE, "Hourly load values for all countries for a specific month (in MW)," 2017.

[15] C. Gerbaulet and C. Lorenz, "dynELMOD: A Dynamic Investment and Dispatch Model for the Future European Electricity Market," DIW Berlin, 2017.

[16] VDK, "Marktinformationen," Verein der Kohleimporteure e.V., 2017.

[17] A. Schröder, F. Kunz, J. Meiss, R. Mendelevitsch, and C. v. Hirschhausen, "Current and prospective costs of electricity generation until 2050," *DIW Data Documentation*, vol. 68, 2013.

[18] IEA, "World Energy Outlook 2015," International Energy Agency, 2015.

[19] European Commission, "EU Reference Scenario 2016 – Energy, transport and GHG emissions - Trends to 2050," 2016.

[20] Open Power System Data. Data Package National Generation Capacity. Version 2017-07-07, Link: https://data.open-power-system-data.org/national_generation_capacity/, Accessed on 14.12.2017. 2017.

[21] TYNDP, "Ten-Year Network Development Plan," European Network of Transmission System Operators for Electricity (ENTSOE) and Gas (ENTSOG), 2017.

[22] Eurostat, "Environment and energy statistics," 2017. Link: http://ec.europa.eu/eurostat/data/database.

[23] ENTSOG Capacity map 2017, Link: https://www.entsog.eu/maps/transmission-capacity-map/2017.

[24] Gas InfrastruFcture Europe, Link: https://www.gie.eu/index.php/maps-data.

[25] GIIGNL, "The annual report on the LNG industry," The International Group of Liquefied Natural Gas Importers, 2016.

[26] AGSI+ storage transparency platform, Link: https://agsi.gie.eu.

[27] C. K. Chyong and B. F. Hobbs, "Strategic Eurasian natural gas model for energy Security and Policy Analysis," University of Cambridge, Faculty of Economics, 2011.

[28] European Comission, "The role of gas storage in internal market and in ensuring security of supply," General for Energy and Internal Energy Market Directorates, 2015. Link: http://ec.europa.eu/energy/en/studies/

[29] TIMERA ENERGY, "Deconstructing LNG shipping costs, Link: https://www.timera-energy.com/deconstructing-lng-shipping-costs." 2018.

[30] R. Golombek, E. Gjelsvik, and K. E. Rosendahl, "Effects of liberalizing the natural gas markets in Western Europe," *The Energy Journal*, pp. 85–111, 1995.

[31] A. H. van der Weijde and B. F. Hobbs, "The economics of planning electricity transmission to accommodate renewables: Using two-stage optimisation to evaluate flexibility and the cost of disregarding uncertainty," *Energy Economics*, vol. 34, no. 6, pp. 2089–2101, 2012.

[32] T. Baltensperger and R. Egging, "Stochastic modeling of imperfect markets," *Nova Science Publishers, Inc.*, 2017.

[33] J. R. Birge and F. Louveaux, *Introduction to Stochastic Programming*. Springer, 1997.