Regret analysis of investment decisions under uncertainty in an integrated energy system

Thomas Möbius*, Iegor Riepin
Chair of Energy Economics
Brandenburg University of Technology Cottbus-Senftenberg
Cottbus, Germany
*thomas.moebius[at]b-tu.de

Abstract — **As energy markets underlie significant uncertainties, predictions regarding future developments are difficult and ex-post often proven wrong. In this paper, we develop a two-stage stochastic cost-minimization model of integrated European electricity and gas markets. The model identifies optimal investment decisions in power generation capacity and the scenario-specific optimal dispatch for assets in electricity and gas sectors. The paper presents a regret matrix that examines the performance of first-stage investment decisions under the later realization of considered scenarios. We find that the chance of high regrets strongly depends on the scenario the investment decision is based on. Furthermore, we analyze the impact of each uncertain parameter on the expected regret. We find that neglecting uncertainties with regard to electricity demand levels and CO_2 prices in particular, result in a high regret. Furthermore, we quantify the value of perfect information.**

Index Terms — Integrated Energy System Modeling, Regret Analysis, Stochastic Modeling, Uncertainty

I. INTRODUCTION

Uncertainty is challenging for decision-makers in most economic sectors, including the energy sector. Observations from the past show that predictions of future developments in the energy system, e.g. deployment of renewables, end-consumer demand or fuel and CO_2 prices, are difficult and ex-post often proven wrong. This causes difficulties, in particular for long-term investment planning of infrastructure elements, such as power stations which can be characterized by long construction, amortization and lifetimes. Hence, accounting for the uncertainty is pivotal to achieve robust decisions regarding necessary infrastructure projects.

Numerous studies use energy system models applying stochastic programming to address uncertainty. [1] for example, focus on a stochastic representation of intermittent renewable energy sources (RES) and argue for its importance in long-term investment planning. The impact of the daily wind feed-in on dispatch decisions in the short-term electricity market is highlighted by [2]. [3], on the other hand, apply a stochastic market model to show how uncertain wind feed-in affects the long-term market equilibrium. Focusing on long-term planning as well, [4] account for uncertain renewable energy deployment paths and find significant effects on the optimal investment decisions. [5] highlight that ignoring risk in transmission planning for renewables and applying traditional deterministic planning methods has quantifiable economic consequences as the consideration of uncertainty can identify decisions that lead to lower expected costs. However, also uncertainty of other factors than RES need to be considered. With accounting for uncertainty of CO_2 and natural gas prices, [6] examine the choice for power plant technologies and the optimal timing for investments.

Furthermore, the rapid transition of the energy system leads to a further interconnection of energy sectors, such as the electricity and gas sector, and therefore requires a better consideration and understanding of multiple interdependencies between these sectors [7]. Following that need, [8] investigate temporal and spatial effects applying an integrated electricity and gas market model. The authors compare their results with modeling approaches that neglect the linkages between the two sectors and find systematic deviations. [7] focus on power plant investments and investigate how these are affected by long-term gas infrastructure developments.

This paper contributes to the literature by investigating the regret of investment decisions for electricity generation capacities that are made under the presence of multiple uncertain parameters within an integrated energy system. To account for uncertainty and interdependencies between energy sectors, we develop and apply a two-stage cost-minimization model of integrated European electricity and gas markets. Considering different sources of uncertainty, we investigate the effect of individual key model parameters on regret terms. Finally, we evaluate the value of improved information for these parameters.

The remaining part of the paper proceeds as follows: in section II we present the methodology where we familiarize the reader with the model set-up and define the metrics used in this study. In section III, we report and discuss our results. Section IV concludes.

978-1-7281-6919-4/20/$31.00 ©2020 IEEE

II. METHODOLOGY

The following section is structured into five parts. First, we describe the integrated energy system model and familiarize the reader with the scenario assumptions. Following that, we introduce the stochastic problem and formalize the terms regret and value of perfect information. Finally, we describe the data we implemented in our model.

A. Integrated market model and scenarios

In this paper, we present an analysis which is derived by the development and application of an integrated market model covering the electricity and gas sector. Both sectors are connected via a fuel linkage. Hence, gas-fired power plants create a demand for natural gas, which has to be produced and transported and, thereby, creates costs. The model includes all relevant production and infrastructure elements for the EU 27, the United Kingdom, Switzerland, Norway, Russia, Algeria, Libya, Qatar and Nigeria.[1] A more detailed description of the model can be found in [9].

The optimization model is formulated as a linear program (LP) and determines optimal investment decisions in the electricity sector in the first-stage and optimal operational decisions in both sectors in the second-stage under the premise of minimizing the overall system costs. As depicted in Figure 1, the model determines (i) the optimal investments decision that has to hold for all possible scenarios and (ii) the scenario-dependent optimal dispatch decisions of all assets for both electricity and gas components.

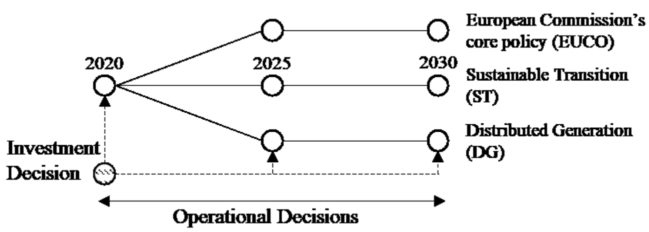

Figure 1: TYNDP scenarios for 2020-2030

We consider parametric uncertainty ranges for five selected model inputs: electricity demand, non-power-sector demand, fuel prices, CO_2 prices and RES deployment. The development of these parameters depends on the scenario paths depicted in Figure 1. Scenario data is based on consistent assumptions developed for the Ten Year Network Development Plan 2018 (TYNDP 2018) that is provided as a coordinated work by ENTSO-E and ENTSO-G. In that framework, EUCO represents the European Commission's core policy scenario to achieve the 2030 climate and energy targets. It can be characterized with the highest prices for lignite (8.3 €/MWh_{th} in 2030) and hard coal (15.5 €/MWh_{th} in 2030), as well as with the lowest price for CO_2 certificates (27 €/t in 2030). ST assumes a sustainable reduction of CO_2 emissions by replacing coal and lignite by gas power stations. Among the three scenarios, it shows the highest demand for natural gas and the highest price for CO_2 certificates (84 €/t in 2030). DG represents a decentralized development of the energy system with a focus on end-user technologies. It assumes the highest demand for electricity and the highest amount of installed RES capacity. A more detailed description of the scenario assumptions can be found in [10]. We assume the probability for each scenario path to appear to be equally likely (1/3 for each scenario branch). Note that the year 2020 is not subject to parametric uncertainty and is represented by data derived from the *best estimate* scenario provided by [10].

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

B. Stochastic problem

(1) defines a two-stage stochastic problem used in this paper. x represents the vector of the first-stage investment decisions and c^T the investment costs of the respective decision. With regard to the possible scenario realizations in the second-stage, the expected value E_ω for operational costs Q is computed. Q depends on the vector ω_i which represents the uncertain data (i.e. the vector of possible scenarios) and the vector x that has to hold for all possible scenario realizations. The resulting (expected) solution $E_\omega z$ is denoted as Stochastic Solution (SS):

$$SS := \min_x c^T x + E_\omega[Q(x, \omega_i)] = E_\omega z(x, \omega_i) \quad (1)$$

C. Regret Analysis

Referring to decision theory, regret is usually defined as the difference between the payoff of a given strategy and the payoff of the best strategy under the same state of nature [11]. Thus, regret is the cost of a wrong decision. In a context of our analysis, regret analysis can highlight how particular choices of reference scenario can lead to investments that have a risk of an extremely bad outcome (i.e. a high regret). Methodologically this section follows the work of [5] and [12].

The regret analysis is based on a payoff matrix. For that, we first determine a set of first-stage investments, (optimal either for the stochastic problem or for one of the considered scenarios) and then we evaluate how this set performs under all scenarios that can realize. Consider the optimal objective value $\varphi(\bar{x}(\omega_i), \omega_i)$ and corresponding investment decision $\bar{x}(\omega_i)$ for a scenario $i \in I$. We impose $\bar{x}(\omega_i)$ into the optimization problem as a fixed decision and examine how this set of investments performs, given that a different scenario $j \in I$ realizes. The resulting objective $\varphi(\bar{x}(\omega_i), \omega_j)$ is necessarily higher (or equal to) because of a poor match of investments with system needs in the second-stage. Thus, regret matrix $R_{i,j}$ can be computed as follows:

$$R_{i,j} = \varphi(\bar{x}(\omega_i), \omega_j) - \varphi(\bar{x}(\omega_i), \omega_i) \quad \forall i, j \in I \quad (2)$$

Further, we analyze how the optimal investments from a stochastic problem (x) perform relative to other possible first-stage investments. This adds one additional row to the regret matrix $(R_{s,j})$:

$$R_{s,j} = \varphi(x, \omega_j) - \varphi(\bar{x}(\omega_j), \omega_j) \quad \forall j \in I \quad (3)$$

D. Expected Value of Perfect Information

The Expected Value of Perfect Information (EVPI) shows the added value of improved information about the future. In addition to solving the stochastic problem, we solve a deterministic problem for each scenario, in which the total system costs are minimized. It is known in the literature as the *wait-and-see* solution [13]:

$$WS := E_\omega \left[\min_x \varphi(x, \omega_i)\right] = E_\omega \varphi(\bar{x}(\omega_i), \omega_i) \quad (4)$$

Then we can compare the *wait-and-see* solution to the *here-and-now* solution corresponding to the stochastic solution defined in (1). EVPI is calculated as the difference between the expected costs of the stochastic solution and the probability-weighted average of the scenarios' deterministic costs.

$$EVPI = SS - WS = E_\omega z(x, \omega_i) - E_\omega \varphi(\bar{x}(\omega_i), \omega_i) \quad (5)$$

The EVPI is useful because it shows how much the expected system costs could be reduced if a planner in the first-stage knows exactly which scenario would happen. Thus, in the context of our analysis, the EVPI shows how much society would be willing to pay to eliminate uncertainty [5].

E. Data

All scenario-specific data are taken from [10] and [14]. This covers hourly electricity demand, non-power-sector gas demand, installed renewable capacities, such as wind onshore, wind offshore and PV, fuel prices for lignite, hard coal and oil-fired power plants, as well as CO_2 prices. Fuel prices for nuclear power plants are stated in [15], prices for natural gas are endogenously computed by the model. As the electricity production from intermittent renewable capacities depends on meteorological conditions, hourly production factors for each installed Megawatt are determined using country-specific aggregated hourly feed-in volumes taken from [16]. We assume hourly production patterns not to vary over the years that are subject to the model horizon. Existing national thermal and hydro generation capacities as well as their technology-specific parameters and decommission pathways are derived from [15], [17], [18] and [19]. Investment costs for power stations are taken from [15]. In order to restrict cross-border transmission flows, we apply net transfer capacities provided by [14]. Limitations on electricity flow within countries are neglected in this study. Load shedding activities which are driven by a scarcity of power plant capacities are penalized with a country-specific value of lack of adequacy that is provided by [20]. To account for country-specific CHP utilization schemes for gas-fired units, we implement temperature-dependent must-run conditions, to meet the annual production volumes of CHP plants based on [21].

Data for the existing gas pipeline infrastructure are based on the [22]. Data for LNG infrastructure are based on [23] and [24]. Data about national storage capacities are based on [23]. Strategic storage requirements are based on [25]. The model incorporates exogenous capacity expansions of gas infrastructure. The structure of the system's development is harmonized with the [10]. Only units with final investment decision status are included in the dataset. Gas supply potentials available to the European market are also based on [10]. We also consider long-term contracts on an annual level based on [26] to facilitate realistic representation of gas market fundamentals. To account for seasonality of non-power sector gas demand, the annual gas demand levels are broken down to a monthly structure for each node. Monthly demand profiles are based on historical average monthly gas consumption data [21]. We used numerous public information portals and relevant academic literature to parameterize the cost structure of gas production [27], transmission [27], [28], [29] and storage [25].

III. Results

The results section starts with the regret analysis. We then go on to discussing the expected regrets of ignoring uncertainty individually for five key parameters. The third subsection is concerned with the EVPI analysis. Note that all money terms are presented in million €$_{2015}$.

A. Regret analysis

The matrix in Table 1 illustrates the regret terms resulting from combinations of a system planner's assumption on future (rows) and actual realizations of uncertain data (columns). We determine five alternative scenarios a system planner can base the investment decision on. Three scenarios are defined in TYNDP (EUCO, ST, DG), the expected value problem (EVP)[2] or the stochastic problem as defined in (1). The set of scenarios, which finally can realize, includes the three considered TYNDP scenarios.

Each entry of the $R_{i,j}$ matrix in Table 1 consists of two numbers: the objective value of a respective optimization problem and regret term in brackets. Note that regret is zero if the scenario planned for is the same as the one that actually plays out. An interesting observation is that the stochastic model's first-stage decision is not optimal for any individual scenario (i.e. all regrets in the last row are positive). However, the stochastic solution has the lowest expected regret (€ 565 M). It is explained by the fact that the stochastic problem, by definition, minimizes the expected regret [5], [30]. What also stands out in Table 1 is that if we assume the stochastic solution is not available and we rely only on first-stage investment plans from deterministic solutions, the EUCO scenario results in the lowest expected regret. In contrast, investment decisions based on ST and DG scenarios seem risky, as they result in very high regret in case EUCO scenario plays out.

[2] A problem wherein the uncertain parameters are replaced by their expected values.

Table 1: Regret matrix

		Actual second-stage scenario realization						Expected Value	
		EUCO		ST		DG			
Deterministic scenario ω_i used to derive first-stage decision $\bar{x}$	EUCO	€ 191,890 M	(0)	€ 220,756 M	(2,405)	€ 201,157 M	(2,199)	€ 204,601 M	(1,535)
	ST	€ 198,744 M	(6,854)	€ 218,351 M	(0)	€ 200,667 M	(1,710)	€ 205,921 M	(2,855)
	DG	€ 199,218 M	(7,329)	€ 220,249 M	(1,897)	€ 198,958 M	(0)	€ 206,142 M	(3,075)
	EVP	€ 195,809 M	(3,919)	€ 219,078 M	(727)	€ 199,571 M	(613)	€ 204,819 M	(1,753)
First-stage decision x derived from stochastic problem		€ 192,330 M	(440)	€ 219,395 M	(1,044)	€ 199,168 M	(211)	€ 203,631 M	(565)

B. *Effect of individual parameters*

In this section, we aim to provide further insights into regret analysis by investigating the effect of individual parameters. This represents a situation when a system planner either does not have information regarding the true distribution of an uncertain parameter when an investment decision is made or the information is ignored. For that, we adjust the stochastic problem by neglecting the uncertainty of a selected parameter and setting its value successively to each of scenario ω_j, while keeping distributions for other parameters. Thus, we receive four sets of investment decisions x (one each for EUCO, ST, DG and EVP) and compute the regrets following the procedure in section A. The expected values for all parameter-specific regrets are shown in Table 2.

Table 2 Expected regrets of ignoring uncertainty of key parameters

		Expected value of regret	Delta to Stochastic Solution	MIN Regret	MAX Regret
	Stochastic Solution	€ 565 M	-	€ 211 M	€ 1,044 M
Ignoring uncertainty of	Gas demand	€ 588 M	€ 23 M	€ 170 M	€ 1,287 M
	Electricity demand	€ 1,239 M	€ 674 M	€ 253 M	€ 3,070 M
	RES capacity	€ 760 M	€ 196 M	€ 201 M	€ 1,479 M
	Fuel price	€ 610 M	€ 45 M	€ 94 M	€ 1,553 M
	CO_2 price	€ 879 M	€ 314 M	€ 115 M	€ 3,641 M

Having said that the stochastic solution per definition reveals the set of investments x that results in the lowest possible expected regret, we apply this as a benchmark and compare it with the expected regrets when ignoring the uncertainty of an individual parameter. We observe that the impact, which the individual parameters have, strongly varies. Ignoring the uncertainty for electricity demand or CO_2 price results in investment decisions causing significantly increased expected regrets (increase by € 674 M and € 314 M respectively). In the case of electricity demand, the high regret can be explained by high shedding costs when underestimating the peak demand and over-investments, when overestimating the demand levels. Ignoring the CO_2 price uncertainty results in a sub-optimal investment mix regarding the CO_2 intensity of generation technologies. Ignoring fuel price or gas demand uncertainty, on the other hand, does not lead to a significant increase in the expected regret. In particular, the impact of gas demand is small, which can be explained by results derived in [9]. The authors observe reallocations of generation capacity investments, but the impact of gas demand uncertainty on the resulting gas prices is rather low. The uncertainty regarding the RES capacity has a moderate impact. Similarly, to the electricity demand, it affects the residual load. However, until 2030 it has a lower impact.

Additionally, Table 2 shows the minimum and maximum regret observed for each parameter. It stands out, that ignoring the CO2 price uncertainty, results in the largest range for the realized regrets – from € 115 M to € 3,641 M, even though the expected regret is lower than for ignoring electricity demand uncertainty. Thus, we observe the worst possible outcome when neglecting the uncertainty of future CO2 prices, which might be interesting, especially for risk-averse system planning.

C. *Value of perfect information*

Table 3 depicts the results for the EVPI calculation. The table contains the objective value of the stochastic solution $E_\omega z(x, \omega_i)$ which is compared to the objectives of all wait-and-see problems $\varphi(\bar{x}(\omega_i), \omega_i)$. The differences represent the savings, which result from perfect information about the future. As shown in (5), the EVPI defines by how much the expected system costs could be reduced if a planner knows which scenario will play out.

An interesting observation is that the EVPI value (€ 565 M) is equal to the expected regret of the stochastic solution shown in the last row of Table 1. This might become intuitive when considering the economic interpretation of the two metrics used in our discussion. On the one hand, the expected regret of a stochastic solution can be seen as the average penalty a system planer faces when an investment decision is based on a problem with imperfect information. On the other hand, the EVPI states the upper bound to the amount a risk-neutral system planner should pay for perfect information.

Table 3: EVPI

	Total costs	Savings resulting from perfect information
Stochastic Solution	€ 203,631 M	
EUCO	€ 191,890 M	€ 11,741 M
ST	€ 218,351 M	–€ 14,720 M
DG	€ 198,958 M	€ 4,673 M
EVPI		€ 565 M

Note that the resulting EVPI value should be seen in the perspective of the model's time horizon containing three representative years. For comparison though, this value is equal to 6 % of all investment costs in power generation in the stochastic solution. This finding reveals an order of magnitude for the maximum return of having perfect information.

IV. Conclusion

In this paper, we develop and apply an integrated two-stage stochastic model that accounts for interdependencies between the electricity and gas markets. We focus our discussion on regrets resulting from combinations of a system planner's assumption on future developments of uncertain parameters and actual realizations of uncertain data. We find that the chance of very bad outcomes, strongly depends on the scenario the investment decision is based on. In particular, investment decisions derived from ST and DG scenario assumptions seem risky. We highlight that even though the stochastic problem is not optimal for any individual scenario, it has the lowest expected regret. Further, we individually account for uncertainty of five key parameters and evaluate the impact on the regret terms. We find that ignoring uncertainty for electricity demand or CO_2 price, results in investment decisions leading to high expected costs. Finally, we quantify the value of perfect information to the system planner which we find to be at 6 % regarding all investment costs in power stations.

We believe that our findings will be interesting for system planners and energy modelers. The results highlight assumptions on future developments that lead to low (or high) expected costs. Overall, our analysis confirms the importance of recognizing the effects of uncertainty for long-term system planning. Further modelling work might explore a larger time horizon capturing European policy after 2030. Also, further research might investigate the impact of endogenous decision making for renewable investments.

V. Acknowledgement

The authors acknowledge the financial support by the Federal Ministry of Economic Affairs and Energy of Germany as part of the 6th energy research program 'research for an environmentally friendly, reliable and affordable energy supply'.

References

[1] K. B. Lindberg, P. Seljom, H. Madsen, D. Fischer, and M. Korpås, "Long-term electricity load forecasting: Current and future trends," *Util. Policy*, 2019, doi: 10.1016/j.jup.2019.04.001.

[2] F. Müsgens and K. Neuhoff, "Modelling Dynamic Constraints in Electricity Markets and the Costs of Uncertain Wind Output," 2006.

[3] T. Möbius and F. Müsgens, "Electricity market equilibria and intermittent renewables - A stochastic approach," in *International Conference on the European Energy Market, EEM*, 2017, doi: 10.1109/EEM.2017.7981988.

[4] M. Fürsch, S. Nagl, and D. Lindenberger, "Optimization of power plant investments under uncertain renewable energy development paths-A multistage stochastic programming approach," 12/08, 2012.

[5] 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 Econ.*, vol. 34, no. 6, pp. 2089–2101, 2012, doi: 10.1016/j.eneco.2012.02.015.

[6] P. S. Reinelt and D. W. Keith, "Carbon capture retrofits and the cost of regulatory uncertainty," *Energy J.*, vol. 28, no. 4, pp. 101–127, 2007, doi: 10.5547/ISSN0195-6574-EJ-Vol28-No4-5.

[7] J. Abrell and H. Weigt, "The short and long term impact of Europe's natural gas market on electricity markets until 2050," *Energy J.*, vol. 37, no. SpecialIssue3, pp. 125–146, 2016, doi: 10.5547/01956574.37.SI3.jabr.

[8] M. Lienert and S. Lochner, "The importance of market interdependencies in modeling energy systems - The case of the European electricity generation market," *Int. J. Electr. Power Energy Syst.*, vol. 34, no. 1, pp. 99–113, 2012, doi: 10.1016/j.ijepes.2011.09.010.

[9] I. Riepin, T. Möbius, and F. Müsgens, "Integrated electricity and gas market modeling - Effects of gas demand uncertainty," in *International Conference on the European Energy Market, EEM*, 2018, vol. 2018-June, doi: 10.1109/EEM.2018.8469790.

[10] ENTSOs, "TYNDP 2018 Scenario Report," 2018.

[11] D. Salvatore, *Managerial economics: principles and worldwide applications*. Oxford University Press, 2012.

[12] A. Motamedi, H. Zareipour, M. O. Buygi, and W. D. Rosehart, "A transmission planning framework considering future generation expansions in electricity markets," *IEEE Trans. Power Syst.*, vol. 25, no. 4, pp. 1987–1995, Nov. 2010, doi: 10.1109/TPWRS.2010.2046684.

[13] A. Madansky, "Inequalities for Stochastic Linear Programming Problems," *Manage. Sci.*, vol. 6, no. 2, pp. 197–204, 1960, doi: 10.1287/mnsc.6.2.197.

[14] TYNDP, "Maps & Data," 2018. [Online]. Available: https://tyndp.entsoe.eu/maps-data. [Accessed: 02-Mar-2020].

[15] A. Schröder, F. Kunz, J. Meiss, R. Mendelevitch, and C. von Hirschhausen, "Current and Prospective Costs of Electricity Generation until 2050," *DIW Data Doc.*, vol. 68, pp. 2002–2003, 2013.

[16] ENTSO-E. Transparency Platform, "Actual Generation per Production Type," 2020. [Online]. Available: https://transparency.entsoe.eu/.

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

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

[19] Open Power System Data, "Data Package National Generation Capacity. Version Version 2019-12-02," 2020. [Online]. Available: https://doi.org/10.25832/national_generation_capacity/2019-12-02. [Accessed: 02-Mar-2020].

[20] Cambridge Economic Policy Associates, "Study on the estimation of the Value of Lost Load of electricity supply in Europe," 2018.

[21] Eurostat, "Environment and energy statistics," 2019. [Online]. Available: http://ec.europa.eu/eurostat/data/database. [Accessed: 12-Apr-2019].

[22] ENTSOG, "Capacity Map," 2017. [Online]. Available: https://www.entsog.eu/maps/transmission-capacity-map/2017.

[23] Gas Infrastructure Europe, "Data transparency platform.," 2019. [Online]. Available: https://www.gie.eu/.

[24] GIIGNL, "The annual report on the LNG industry.," *The International Group of Liquefied Natural Gas Importers.*, 2016. [Online]. Available: https://giignl.org/publications.

[25] European Commission, "The role of gas storage in internal market and in ensuring security of supply.," *EU Publ.*, 2015, doi: 10.2832/568590.

[26] A. Neumann, S. Rüster, and C. von Hirschhausen, "Long-term contracts in the natural gas industry: Literature survey and data on 426 contracts (1965-2014)," *Data Doc. DIW.*, 2015.

[27] C. K. Chyong and B. F. Hobbs, "Strategic Eurasian natural gas market model for energy security and policy analysis: Formulation and application to South Stream," *Energy Econ.*, vol. 44, pp. 198–211, Jul. 2014, doi: 10.1016/j.eneco.2014.04.006.

[28] ACER, "Gas Transmission Tariffs in South and Central East Europe," *ECRB (The Energy Community Regul. Board) Rep.*, 2018.

[29] H. Rogers, "The LNG Shipping Forecast: costs rebounding , outlook uncertain," *Oxford Inst. Energy Stud. Energy Insight.*, vol. 27, 2018.

[30] D. Bunn, *Applied decision analysis*. London Business School, McGraw-Hill, New York, 1984.