Generation Expansion Planning under Uncertainty: An Application of Stochastic Methods to the German Electricity System

Mario Kendziorski*, Mona Setje-Eilers†, Friedrich Kunz‡

Abstract—**Renewable energies are expected to be the main electricity generation source. However, the variability of renewable energy supply poses challenges to the generation expansion modelling as uncertainty of hourly generation need to be adequately taken into account. This paper analyzes the implications of different approaches to optimization under uncertainty, ranging from stochastic to robust optimization. We apply these specific approaches to the German electricity system in 2035 and compare them to a deterministic optimization for each realization of the uncertainty. We consider the availability of wind and solar generation as explicit uncertainties affecting the second-stage dispatch level. The deterministic generation expansion problem shows significant variations of optimal capacity mixes depending on the underlying assumptions on hourly renewable feed-in. Moreover, these capacitiy mixes are hardly robust to unexpected situations. Contrarily, stochastic as well as robust approaches provide a consistent and robust capacity mix at only slightly higher total costs.**

Index Terms—**Electricity, renewable energy sources, optimization under uncertainty, stochastic optimization, robust optimization, Germany**

I. Introduction

THE traditional generation expansion problem aims at minimizing investment and operational costs of an electricity system from a regulated utilities' perspective. Throughout the last decades the traditional perspective became more complex through, inter alia, the development of new generation and demand technologies, the deregulation and restructuring of electricity markets, the stronger interaction with other resources, and an increasing incorporation of environmental goals. As a consequence of these new complexities, a wide range of generation expansion models and techniques evolved with different goals and perspectives on the long-term generation planning. Among others, ambitious climate targets and the corresponding political measures to decarbonize national energy sectors initiated the substantial growth of renewable energy sources in particular in the electricity sector.

Renewable energies are expected to be the main electricity generation source. However, the specific characteristics of renewable energy sources, i.e. the weather-dependent generation pattern of wind and solar, generally raise questions how much capacities and which technology mix are required to ensure the efficient balance of the system. The answer to these questions strongly depends on the general perspective and the underlying attitude towards risk. From a business perspective, renewable feed-in uncertainties might be expected to balance out each other over a longer time horizon of several years. Thus, stochastic or even deterministic optimization approaches are valid options for this perspective on long-term planning. From a political perspective, the focus might be more on extreme situations, i.e. situations with low renewable generation, driven by a stronger aversion towards risks. Thus, robust planning approaches are of more interest to identify worst-case situations or scenarios, and the associated capacity needs.

From a methodological perspective, most long-term planning applications abstract from uncertainties as they pose additional challenges to generation expansion modelling. As such, uncertainties can be incorporated in different ways through stochastic and robust optimization concepts in generation expansion models. In this paper, we compare different methodological concepts of handling uncertainties in long-term generation planning models. We limit our analysis to uncertainties arising from weather-dependent renewable generation[1] and consider different historical years as uncertainties through scenarios.[2]

The remainder of the paper is structured as follows: Section II provide as a literature review of relevant concepts and methods. Section III describes the general generation investment model as well as the different stochastic and robust methods. The results are presented and discussed in Section IV. Section V provides the conclusions.

II. Literature review

In the following, we review existing methods and concepts to account for uncertainties in generation planning models. Stochastic programming is a well-known concept in which uncertainties are reflected by their possible realizations accounted with specified probabilities of occurrence. Hence, a large body

*DIW Berlin, Department of Energy, Transportation, Environment, Mohrenstraße 58, 10117 Berlin, mkendziorski@diw.de.
‡DIW Berlin, Department of Energy, Transportation, Environment, Mohrenstraße 58, 10117 Berlin, fkunz@diw.de.
†DIW Berlin, Department of Energy, Transportation, Environment, Mohrenstraße 58, 10117 Berlin, msetjeeilers@diw.de.

[1] Among others, the increasing sectoral coupling of the electricity sector with other sectors, e.g. mobility or heat, could induce further relevant uncertainties to the generation expansion problem.

[2] This approach is mainly reasoned by the wide-spread use of historical weather years in long-term applications to determine hourly feed-in from renewable energy sources. Alternatively, the creation of feed-in time series could be done through stochastic processes or random sampling approaches.

978-1-5090-5499-2/17/$31.00

of academic literature on stochastic generation expansion planning exists, ranging from stochastic applications to real-world systems to methodological advances in solving stochastic programs. A broad overview on stochastic programming models in electricity and other energy sectors is given in Wallace and Fleten [18] and Möst and Keles [11]. In the following, we are rather interested in a general outline of the different approaches to stochastic generation expansion planning than providing a comprehensive review of the existing literature.

In the context of generation expansion, two-stage problems mostly account for short-term uncertainties which primarily affect the generation dispatch, e.g. uncertainties about load, availability of conventional generation units or the availability of renewable resources. Murphy et al. [14] develop a two-stage stochastic program with the generation type and capacity decision as first-stage variable and the allocation of installed capacities to segments of two different load duration curves as second-stage decision. The objective function minimizes the system costs composed of investment and expected generation cost including costs for unserved load. Load uncertainty is represented by two distinct scenarios for the load duration curve. Similarily, Lucas and Papaconstantinou [9] analyze the implications of uncertain electricity demand on the generation capacity mix and show that the solution to the stochastic program departs from the deterministic solution. Bloom [2] introduces the generalized Benders decomposition to the generation expansion problem to incorporate a probabilistic generation cost simulation in the subproblem. Nagl et al. [15] apply a two-stage stochastic optimization problem to the generation planning in 2050 for the European electricity system. The short-term uncertainty about the infeed of renewable sources, wind and solar, is taken into account in the long-term generation planning and compared to a deterministic application. The results show a significant impact of uncertain renewable generation patterns on overall generation capacities and associated costs as the value of uncertain renewable generation decreases. Zou et al. [20] address the problem of solving multi-stage stochastic problems. In contrast to a two-stage setting, the multi-stage setting allows for an adaption of investment decision to the evolution of long-term uncertainties. A particular difficulty is the solvability of these problems and the authors propose a solution technique to combine the tractability of the two-stage problem and adaptivity of decisions in the multi-stage setting.

Another approach is robust optimization which does not require probability distributions of the specified uncertainties and can be used for different objectives such as regret minimization or worst-case optimization. An extensive overview on robust optimization is given in [1]. Malcolm and Zenios [10] extend the two-stage stochastic model formulation of the generation expansion problem in Murphy et al. [14] by accounting for the variance of expected costs. This yields a solution which is robust in all considered scenarios and is less dependent to the characteristics of the uncertain parameters. Whereas total expected costs are higher, the variance of scenario specific costs as well as the amount of excess capacity is lower. Li et al. [8] use robust optimization on the generation expansion problem under future climate policy scenarios. A different approach on robust optimization using Benders decomposition can be found in [6]. Mulvey et al. [12] as well as Takriti and Ahmed [17] provide a more general view on robust optimization with exemplary applications to various problems.

The literature review illustrates the two general streams of uncertainty methods: stochastic and robust optimization approaches. While stochastic optimization requires assumptions on probability distributions, robust optimization focuses on worst-case realizations of uncertainties without an explicit specification of probabilities. In this paper, we compare the two general uncertainty approaches with different specifications to the commonly applied deterministic optimization. In doing so, we apply these approaches to the generation expansion problem of a realistic model of the German electricity system and compare optimal capacity investments as well as the robustness of the determined capacity mix. We limit our analysis to uncertainties arising from renewable generation feed-in and electrical load which directly affect the dispatch of installed capacities at the second stage.

III. Methods

We use the deterministic generation investment model DIETER [19] and extend this by different approaches to optimization under uncertainty. The model is a cost-minimizing system planning model and optimizes the future generation portfolio in a greenfield setting.[3] It accounts for investment options in different conventional and renewable generation technologies. Generation technologies are differentiated by investment and operational costs as well as their operational flexibility. Contrary to conventional technologies, the renewable technologies solar PV and wind are considered as non-dispatchable energy sources and are characterized by an hourly weather-dependent generation pattern. Moreover, different storage options, e.g. pumped-storage or battery, are considered to allow for an inter-temporal shift of load or generation, respectively. The model accounts for an hourly dispatch covering an entire year with 8,760 hours. The complete model description can be found in [19].[4]

We include exogenous conventional capacities reflecting the year 2035 which were derived from existing capacities in Germany and are assumed to be in operation in 2035 considering their technical lifetime. The data of existing generation capacities is based on Open Power System Data [16] and technical lifetimes are taken from [3, p. 110].

We extend the model by stochastic as well as robust optimization approaches and focus our analysis on incorporating short-term uncertainties[5] which directly take effect at the dispatch level. An example of this short-term uncertainty is the generation pattern of renewable energy sources or the hourly load pattern. Given these uncertainties, we firstly

[3] The current model is static with respect to investments and considers one investment period.

[4] For transparency and replicability, DIETER is an open-source model available under www.diw.de/DIETER.

[5] We define uncertainties affecting the dispatch level (second stage) as short-term uncertainties. In contrast, uncertainties which directly impact the first-stage decisions, i.e. the investment of installed capacity (e.g. uncertain investment costs) are considered as long-term uncertainties.

implement a stochastic programming approach which accounts for different hourly renewable generation patterns and their probability of occurrence. Secondly, we extend the stochastic programming approach by introducing a risk measure, i.e. valuing the volatility of cost variations of different realizations. This enables us to investigate, for instance, the impact of risk-averse planning on generation portfolio and generation mix. Finally, we extend the model by a robust optimization that does not require probability distributions. We end up with two different variants of generation expansion under uncertainty, a stochastic and a robust variant, and a deterministic model.

Formally, we consider time series of renewable energy feed-in and load from several years as scenario set Ω. One scenario $s \in \Omega$ consists of the load, PV, onshore and offshore wind generation time series for one year. An occurrence probability $\pi(s)$ is associated with each scenario s. The investment decisions have to be made before the scenario realization is known. Given the invested capacities, the model determines the cost optimal dispatch for each scenario. The objective function of the deterministic problem is to minimize the sum of investment and dispatch costs. For the sake of simplicity, we denote the investment costs as IC, depending on the capacity investments, and the scenario-dependent dispatch or operating costs as $DC(s)$ which depend on the dispatch or utilization of installed generation capacities. A full mathematical description of the model can be found in [19]. To ensure feasibility in all scenarios we include a variable for unserved load in the dispatch which is penalized in the objective function with cost of 5,000 EUR/MWh.

A. Deterministic Optimization

The initial model formulation as well as many applications of the generation expansion problem apply a deterministic optimization approach. Herein, the uncertainty defined by the scenario set Ω cannot be explicitly taken into account in the optimization of the capacity mix as a single realization of the uncertainty set needs to be selected as input. A commonly applied approach is to make use of a sensitivity analysis by changing the input data to evaluate their impact on model results. Consequently, the deterministic approach provides a capacity mix depending on the selected scenario s with the following objective function for each scenario s:

$$\min\ IC(s) + DC(s) \qquad \forall s \in \Omega \qquad \text{(Deterministic)}$$

B. Stochastic Optimization

Stochastic optimization is a possible approach to deal with the aforementioned uncertainty. Stochastic programming models include a probability distribution of the uncertain data over its uncertainty set or interval.

To overcome the infinite characteristic of continious probability distributions, scenario trees are used with discretized probability distributions. The classical two-stage stochastic programming approach optimizes the sum of first-stage costs and the expected second-stage costs over all scenarios. The objective function in our model is:

$$\min\ IC + \sum_{s\in\Omega} \pi(s) \cdot DC(s) \qquad \text{(Mean value)}$$

This objective function is inappropriate for high-risk decisions under uncertainty, i.e. if there exist scenarios with small probability of occurrence but very high costs. To overcome this issue, stochastic programming approaches are extended in the literature by specific risk measures, e.g. Conditional Value at Risk (CVaR), to account for different underlying risk preferences with respect to cost variations in different uncertainty realizations. The CVaR is widely used as it can be linearized. For a discrete cost distribution, α-CVaR is the expected cost of the worst α-percentile of scenarios [4]. The smallest meaningful value for α is $1/|\Omega|$, while typical values for α are close to 5% [13]. For computational reasons we included only five scenarios and therefore have to set $\alpha = 20\%$. The CVaR is the result of the following linear program [13]:

$$\begin{aligned} &\min\ c_{var} \\ &\text{s.t. } u + \frac{1}{1-\alpha} \sum_{s\in\Omega} \pi(s) \cdot \mu(s) \leq c_{var} \\ &\quad DC(s) - u - \mu(s) \leq 0 \qquad \forall s \in \Omega \end{aligned}$$

Here $u \in \mathbb{R}$ and $\mu(s) \in \mathbb{R}, s \in \Omega$ denote auxiliary variables. Let u^* be the optimal value of u, this is the smallest value such that the probability that the cost exceeds or equals u^* is less than or equal to $1-\alpha$ (Value at Risk). The optimal value of μ_s is the difference between the cost of scenario s and u^* [4].

When using the CVaR as risk measure, the objective function and additional constraints are

$$\begin{aligned} &\min\ IC + (1-\lambda) \sum_{s\in\Omega} \pi(s) \cdot DC(s) + \lambda c_{var} \qquad \text{(CVaR)} \\ &\text{s.t. } u + \frac{1}{1-\alpha} \sum_{s\in\Omega} \pi(s) \cdot \mu(s) \leq c_{var} \\ &\quad DC(s) - u - \mu(s) \leq 0 \qquad \forall s \in \Omega \end{aligned}$$

where $\lambda \in [0, 1]$ is used to trade-off risk and expected value.

C. Robust Optimization

Robust optimization has the advantage that no probability information is required. The classical approach described in [1] is to minimize the worst case costs:

$$\min(IC + \max_{s\in\Omega} DC(s)) \qquad (1)$$

This approach has the disadvantage that the operational costs in all scenarios s will be close to the worst-case costs and thus different from the cost-minimal scenario-specific solution, except for the worst-case scenario. This can be resolved by a min-max-min objective, which however requires sophisticated methods such as Benders decomposition for solving the nested optimization problem (see [6] for further information). We therefore recalculate the dispatch costs for each scenario with the optimal min-max capacity solution and do not employ Benders decomposition. The min-max objective can be easily linearised as follows using the auxiliary variable $m_{robust} \in \mathbb{R}$:

$$\begin{aligned} &\min\ m_{robust} \qquad \text{(MinMax)} \\ &\text{s.t. } (IC + DC(s)) \leq m_{robust} \qquad \forall s \in \Omega \end{aligned}$$

Another robust optimization method is regret minimization. Regret describes the cost difference between a compromise solution, where the scenario realization is unknown and the deterministic solution, where one scenario occurs with certainty. The objective is to minimize the maximum regret of any scenario [8]. Let $DS^*(s)$ denote the deterministic solution, then the objective function is as follows

$$\min(IC + \max_{s\in\Omega}(DC(s) - DS^*(s))) \qquad (2)$$

which can be linearized by introducing the auxiliary variable $m_{regret} \in \mathbb{R}$ yielding the following objective function and additional constraints:

$$\begin{aligned} \min\ & m_{regret} && \text{(Regret)} \\ \text{s.t. } & IC + DC(s) - DS^*(s) \leq m_{regret} && \forall s \in \Omega \end{aligned}$$

IV. Results

The aforementioned modeling approaches are applied to the German power system in 2035 with a renewable generation target of 60%. Existing conventional generation capacities total to 42.7 GW. Moreover, we consider historical renewable infeed and load time series of the years 2011-2015 as scenarios with an equal probability of occurence ($\pi(s) = 0.2$). Table I shows the general characteristics of renewable feed-in and system load for the considered years.

Year	Wind onshore [h]	Wind offshore [h][6]	PV [h]	Avg. load [MW]
2011	1,708	3,085	916	55,345
2012	1,634	2,956	970	53,494
2013	1,566	3,003	894	52,891
2014	1,499	2,941	878	57,553
2015	1,879	3,262	906	57,524

TABLE I
FULL LOAD HOURS OF RENEWABLE GENERATION TECHNOLOGIES

We are firstly interested in the value of stochastic programming by comparing stochastic and deterministic model versions with respect to the optimized capacity mix. Secondly, we analyse the robustness of the generation planning and compare it to the robust optimization approaches. Moreover, we analyze the implications of the different modelling approaches in terms of the resulting generation mix, total system cost as well as dispatch pattern.

A. Capacity mix

In all considered approaches, additional generation capacities are built of which the majority are renewable generation technologies to fulfill the renewable generation target. A minor share of the capacity additions comprises gas-fired CCGT capacities as well as storage capacities. However, both the total amount of installed capacities and their technological mix is affected by the optimization approach (Figure 1). As the deterministic approaches optimize the capacity mix for a single scenario, the level of total capacity as well as the technological mix are consequently sensitive to the corresponding load and renewable time series. Total capacity requirements range between 247 GW (Deterministic 2013) and 307 GW (Deterministic 2014). Similar effects are observed on a technological level with significant absolute variations for all generation technologies (CCGT [8.7 GW, 21.5 GW]; PV [82.3 GW, 125.6 GW]; Wind onshore [69.7 GW, 115.1 GW]; Wind offshore [0 GW, 26.2 GW]).

In contrast, optimization approaches under uncertainty directly account for these variations as uncertainties, which use different concepts, and determine a single capacity mix valid in all considered scenarios. The stochastic mean value approach –297 GW total capacity– and its extension by the CVaR –302 GW– show capacity levels between the extreme deterministic solutions as a consequence of the assigned scenario probabilities. Hence, changing the probabilities of scenarios would drive the results towards the most likely deterministic solution. Moreover, as the CVaR approach additionally accounts for variations in operational costs to reflect a risk-averse planning approach, costlier scenarios are more pronounced leading to increased capacity levels in our setting.

The highest total capacity among the uncertainty approaches is observed in the robust minmax approach –307 GW total capacity– reasoned by focus on the deterministic scenario with the highest operational costs ('Deterministic 2014' in our setting) due to low renewable feed-in and high average load (Table I). Finally, the regret approach, which minimizes the difference to the operational costs of the deterministic cases, shows a rather mixed technology portfolio and a lower total capacity of 279 GW compared to other uncertainty approaches. As the worst case in regret approach is defined by the cost difference to the deterministic solution, the capacity mix tends towards deterministic scenarios with low operational costs, e.g. the determinstc 2013 case with wind offshore and rather low new-built CCGT, as long as the capacity mix is robust in the remaining scenarios. With respect to the different technologies, significant absolute capacity variations are observed for non-dispatchable renewable technologies wind onshore and solar, whereas for other technologies, new-built CCGT and storages, absolute variations are somewhat lower. Finally, the optimized capacitiy mix is considerably affected by the underlying data assumptions, foremost the renewable generation profiles. Accounting for these variations as explicit uncertainties yields somewhat higher capacity requirements in most cases or a more diversified technology mix in one case, as highlighted by the regret approach.

B. Robustness

To evaluate the robustness of the different capacity portfolios, we analyse the hourly dispatch with repect to unserved load, firstly for the five considered scenarios and secondly for each possible combination of the five renewable and load years. Hence, the dispatch is evaluated for 25 different scenarios[7] using the optimized capacities of the aforementioned five deterministic and four uncertainty approaches. Thus, we end

[6]Due to a lack of consistent feed-in time series for German wind offshore sites, we employ hourly profile factors for the Netherlands based on [7].

[7]We combine the renewable time series of the years 2011-2015 with load time series of the same five years. A further combination of individual renewable time series is not performed due to likely inconsistency with respect to the underlying weather year.

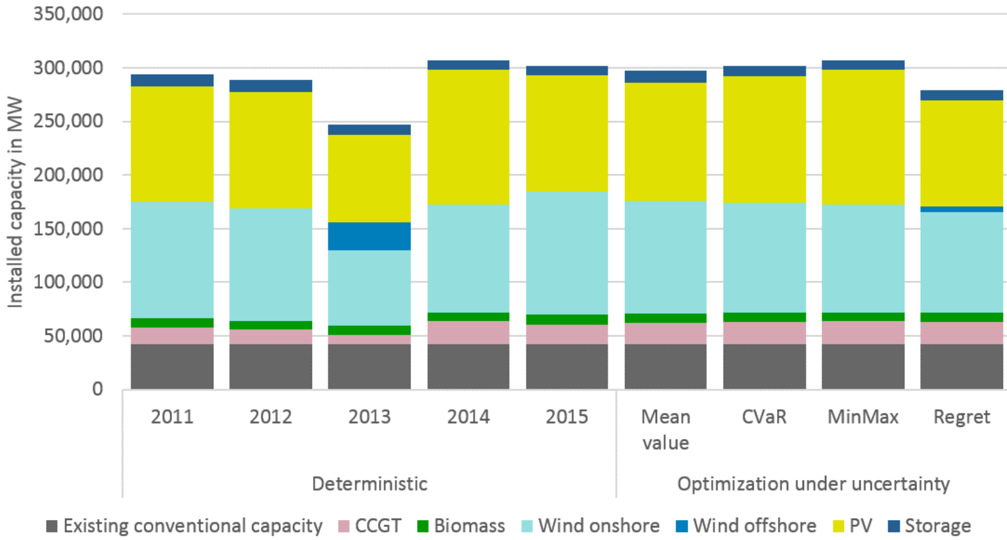

Fig. 1. Generation capacities by type for the considered approaches

up with 24 unexpected realizations (meaning renewable/load combinations not considered in the optimization of installed capacities) in deterministic settings and 20 unexpected realizations in the uncertainty approaches.

Model	No. critical scenarios	Avg. critical hours [h]	Avg. unserved load [MW]
2011 (deterministic)	7	17.4	3,858
2012 (deterministic)	14	19.8	4,282
2013 (deterministic)	24	77.4	5,210
2014 (deterministic)	0	0	0
2015 (deterministic)	2	6.5	2,843
Mean value	0	0	0
CVaR	0	0	0
MinMax	0	0	0
Regret	1	1	66

TABLE II
ROBUSTNESS RESULTS WITH RESPECT TO UNSERVED LOAD

As the uncertainty approaches directly account for uncertainties in the renewable and load time series, capacities are almost sufficient to meet the energy balance at every instant of time in the expected as well as in the unexpected scenarios (Table II). It is important to note that the assumptions on the value of unserved load (here: 5,000 EUR/MWh) as well as the weighting of scenarios in the stochastic optimization cases stongly determine the capacitiy mix and finally the level of unmatched demand. Thus, placing different weights on scenarios increases the likelihood for unserved load in expected and unexpected scenarios. An exception within the set of uncertainty approaches is the regret approach, which shows a small level of unserved load in only one of the scenarios. On the other hand, unserved load is observed in specific scenarios in almost all deterministic approaches with at most 1.4 TWh of unserved load (0.28% of total load) in the 2014 scenario with the capacity portfolio of 'Deterministic 2013'. In particular, the deterministic approaches based on the year 2013 shows the lowest robustness with unserved load in all unexpected scenarios, followed by the other deterministic approaches (Table II). An exception represents the 'Deterministic 2014' case which shows a feasible dispatch in other scenarios without any occurence of unserved load.

C. System cost

Subsequently, we compare the different approaches with respect to investment and operational costs. To allow for a comparison of deterministic and stochastic approaches, operational costs describe the average costs of the five years with the optimized capacity mix. Similar to the insights on installed capacities, Figure 2 shows that investment costs and, to a lower extent, also operational costs vary considerably among the different deterministic cases, whereas relatively stable costs are observed among the approaches under uncertainty.

Lowest investment costs are found in the deterministic case for 2012 and highest in the same case for 2013, mainly driven by the availability of variable renewable generation. The opposite can be observed for operational costs as renewables feature negligible operational costs and rather high investment costs. Thus, the variations of total costs are rather small due to the opposing impacts on investment and operational costs. Total costs increase by at most 3.5% between the deterministic 2011 and 2013 case. Among the uncertainty approaches, the cost differences are considerably smaller with at most 0.7% (0.44%) cost increase between the mean value and the regret (minmax) approach. Compared to the deterministic cases, the mean value approach comes at only 0.17% higher costs than the cheapest deterministic case for 2011. It is important to note that we exclude the costs for unserved load in the total costs, which occur in all deterministic cases except for 2014, as they considerably drive the total costs depending on the valuation of unserved load. Finally, based on our model setting and the underlying assumptions the comparison of costs highlights that the incorporation of uncertainties either through stochastic or robust methods does not lead to an escalation of system costs, but rather a modest increase in particular of investment costs. Moreover, with incorporation of uncertainties in an explicit manner, the capacity mix is robust to expected and a high number of unexpected developments, which reduces the risk of critical situations or escalating operational costs through unserved load.

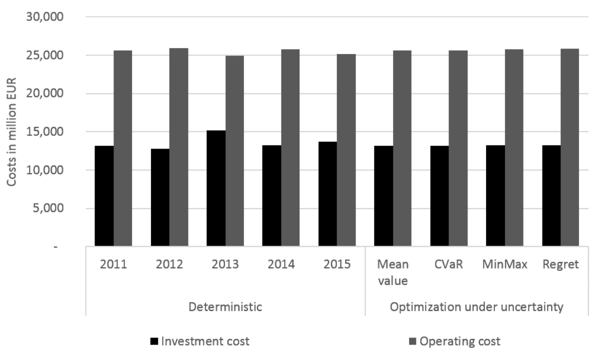

Fig. 2. Investment and average operational costs for considered approaches (excluding costs for unserved load)

D. Discussion

The results highlight the relevance of a stronger consideration of uncertainties inherent to electricity systems with increasing shares of non-dispatchable renewable energy sources. Deterministic approaches are not able to account for these uncertainties with the resulting risk of a non-robust capacity mix and consqeuently high operational costs in unexpected situations due to insufficient generation capacities. Through an explicit consideration of system uncertainties, optimized capacity mixes are less sensitive to unexpected uncertainty realizations and can provide a robust capacity mix at only slightly higher system costs. Even in the rather risk-averse setting with CVaR and finally in the two robust optimization settings, an extensive increase of system costs cannot be observed, but rather a minor increase due to slight adjustments of the technological mix and the total capacity. Remarkably, the different approaches of robust optimization, minmax and regret, differ significantly due to a varying economic rationale: whereas the minmax approach focuses solely on the worst-case, the regret approach aims to minimize the cost difference between the optimal decision under certainty and the decision under uncertainty, thus minimizing the additional costs of a robust capacity mix. Consequently, the selection or application of a specific type of robust optimization requires special attention and probably some economic foundation within the application context.

Finally, it is important to note that the current application of the different uncertainty methods is stylized with respect to the German electricity system and consequently has important limitations. First, the application focuses solely on Germany without any feedback to neighboring or other European countries. Thus, the option to employ generation flexibilities from these countries is neglected which could potentially intensify the differences between the different approaches. Secondly, the current model setup is static without different investment periods and abstracting from the option to "continuously" adjust the generation mix. Moreover, our analysis focuses on particular short-term uncertainties. A consideration of additional uncertainties, both long- and short-term, e.g. long-term evolution of load levels and cross-sectoral evolution or technological costs, would provide a more realistic representation of the future challenges in the electricity and energy system.

V. Conclusion

In this paper, we analyze the impact of different modeling approaches to deal with uncertainties inherent to electricity systems with growing shares of renewable generation. Besides the widely applied deterministic setting, stochastic as well as robust approaches are developed and implemented in the open-source generation expansion model DIETER using linearized formulations. The different model variants are applied to the German electricity system for the year 2035 to evaluate their impacts on the capacity mix, robustness and total costs. The analysis shows that deterministic approaches are insufficient to provide a robust capacity mix. Robustness can be achieved by applying stochastic or robust optimization approaches at the expense of slightly higher system costs. However, the technological mix differs in particular among the two robust approaches as the underlying definition of the worst case is different.

Given the focus of the presented application and the inherent limitations, future research should focus on extending the uncertainty approaches in generation planning to address long- as well as short-term uncertainties. Moreover, an extension of the model framework to a dynamic setting with uncertainties could be of value to evaluate the path-dependencies in generation planning.

Acknowledgment

The authors gratefully acknowledge the support by the German Ministry for Economic Affairs and Energy (BMWi) in the project 'Long-term Capacity Planning for Electricity Generation in Germany under Consideration of Uncertainties and Cross-sectoral Interdependencies'(LKD-EU, 03ET4028B).

References

[1] Ben-Tal, Aharon, Laurent El Ghaoui, and Arkadi Nemirovski (2009). "Robust optimization". Princeton University Press.
[2] Bloom, J. A. (1982). "Long-Range Generation Planning Using Decomposition and Probabilistic Simulation." IEEE Transactions on Power Apparatus and Systems PAS-101 (4): 797-802. doi:10.1109/TPAS.1982.317144.
[3] BMUB (2015). Projektionsbericht 2015 gem. Verordnung 525/2013/EU. Federal Ministry for the Environment, Nature Conservation, Building and Nuclear Safety (BMUB). www.bmub.bund.de/N51715/.
[4] Carrión, Miguel, Andy B. Philpott, Antonio J. Conejo, and José M. Arroyo (2007). "A stochastic programming approach to electric energy procurement for large consumers." IEEE Transactions on Power Systems 22(2): 744-754.
[5] Chen, Bokan, Jianhui Wang, Lizhi Wang, Yanyi He, and Zhaoyu Wang (2014). "Robust optimization for transmission expansion planning: Minimax cost vs. minimax regret." IEEE Transactions on Power Systems 29(6): 3069-3077.
[6] Dehghan, Shahab, Nima Amjady, and Ahad Kazemi (2014). "Two-stage robust generation expansion planning: a mixed integer linear programming model." IEEE Transactions on Power Systems 29(2): 584-597.

[7] Gonzales Aparicio, Iratxe, Andreas Zucker, Francesco Careri, Fabio Monforti, Thomas Huld, and Jake Badger (2016). EMHIRES dataset. Part I: Wind power generation European Meteorological derived HIgh resolution RES generation time series for present and future scenarios; EUR 28171 EN; doi:10.2790/831549.

[8] Li, Shuya, David W. Coit, and Frank Felder (2016). "Stochastic optimization for electric power generation expansion planning with discrete climate change scenarios." Electric Power Systems Research 140: 401-412.

[9] Lucas, Nigel, and Dimitrios Papaconstantinou (1982). "Electricity Planning under Uncertainty Risks, Margins and the Uncertain Planner." Energy Policy 10(2): 143-52. doi:10.1016/0301-4215(82)90026-X.

[10] Malcolm, Scott A., and Stavros A. Zenios (1994). "Robust Optimization for Power Systems Capacity Expansion under Uncertainty." The Journal of the Operational Research Society 45(9): 1040-49. doi:10.2307/2584145.

[11] Möst, Dominik, and Dogan Keles (2010). "A Survey of Stochastic Modelling Approaches for Liberalised Electricity Markets." European Journal of Operational Research 207(2): 543-56. doi:10.1016/j.ejor.2009.11.007.

[12] Mulvey, John M., Robert J. Vanderbei, and Stavros A. Zenios (1995). "Robust Optimization of Large-Scale Systems." Operations Research 43(2): 264-81. doi:10.1287/opre.43.2.264.

[13] Munoz, Francisco D., Adriaan Hendrik van der Weijde, Benjamin F. Hobbs, and Jean-Paul Watson (2016). "Does risk aversion affect transmission and generation planning? A Western North America case study." EPRG Working Paper 1621.

[14] Murphy, F.H., S. Sen, and A.L. Soyster (1982). "Electric Utility Capacity Expansion Planning with Uncertain Load Forecasts." AIIE Transactions 14 (1): 52-59. doi:10.1080/05695558208975038.

[15] Nagl, Stephan, Michaela Fürsch, and Dietmar Lindenberger (2013). "The Costs of Electricity Systems with a High Share of Fluctuating Renewables: A Stochastic Investment and Dispatch Optimization Model for Europe." The Energy Journal 34(4).

[16] Open Power System Data (2016). Data Package Conventional power plants, version 2016-10-27. http://open-power-system-data.org/.

[17] Takriti, Samer and Shabbir Ahmed (2003). "On Robust Optimization of Two-Stage Systems." Mathematical Programming 99 (1): 109-26. doi:10.1007/s10107-003-0373-y.

[18] Wallace, Stein W. and Stein-Erik Fleten (2003). "Stochastic Programming Models in Energy." In Stochastic Programming, 10:637-77. Handbooks in Operations Research and Management Science.

[19] Zerrahn, Alexander and Wolf-Peter Schill (2015). A Greenfield Model to Evaluate Long-Run Power Storage Requirements for High Shares of Renewables. DIW Discussion Papers 1457. http://www.diw.de/documents/publikationen/73/diw_01.c.498475.de/dp1457.pdf

[20] Zou, Jikai, Shabbir Ahmed, and Andy Sun (2016). "Partially Adaptive Stochastic Optimization for Electric Power Generation Expansion Planning." http://www.optimization-online.org/DB_FILE/2015/01/4721.pdf.