Investment decisions in the industrial firm's generation expansion problem

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Abstract

This paper presents an extension of a probabilistic modeling approach to the generation expansion problem including renewable energy sources, where a probabilistic constraint on the supply-demand constraint is imposed. In this setting, the energy manager decides upon installed capacities and does not consider the worst case scenarios which are not in the scope of the probabilistic bound. We extend this model, by penalizing the worst case scenarios in which a power shortfall occurs. These additional payments, which come as the expected costs of a short power supply can be interpreted using techniques of risk management via the conditional value-at-risk and effect the energy manager's investment decision who evaluates riskiness of power supply. This corresponds to the situation, where the energy manager balances supply and demand in the worst scenarios at the electricity wholesale market. We investigate the energy manager's investment policy in renewable energy technologies in a deterministic price scenario, which corresponds to purchasing balancing energy via a fixed-price contract and a stochastic price scenario, which corresponds to purchasing residual power at the spot market. The application to a use case without a feed-in-tariff quantifies the threshold energy price of a fixed-price contract below which the energy manager is reluctant to invest in renewable energy technologies. Energy managers who purchase power at the spot market, where the spot price and the energy park's power output are independent, increase investment in renewable technologies with increasing spot price uncertainty to hedge against spot price volatility.

Keywords: Generation expansion planning, Investment under uncertainty, Risk management

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1 Introduction

The energy manager of an industrial firm aims at developing an energy policy that covers the firm's energy demand at minimum costs. Structural changes in the electricity market like the ongoing integration of renewable energy sources (RES)[1], the liberalization of the energy market and volatile electricity prices has led to an increased focus on incorporating risk management into strategic energy planning of industrial firms (Liu et al., 2006). In the liberalized energy market, large electricity consumers facing energy planning problems constitute a power procurement policy by negotiating contracts with the retailers (Gómez-Villalva and Ramos, 2004). Besides this, industrial firms also consider the opportunity to invest in RES and thereby act as prosumers by covering the demand, at least to some extent via self-generation facilities. In the trend of decreased prices of renewable energy technologies (given in terms of the costs per installed capacity of a specific technology) (Carlsson et al., 2014), the opportunity to invest in RES becomes increasingly valuable, not only from an ecological but also from an economical point of view. Industrial consumers taking this opportunity consequently face the generation expansion problem (GEP). Among several other questions which have to be answered in the course of the GEP, one of the most fundamental is to determine optimally installed capacities of the different technologies, resulting in the optimal energy portfolio (Koltsaklis and Dagoumas, 2018).

Ubiquitous investment risks of the GEP in the power sector arise because future cash flows depend to a large extent on risky electricity and fuel/carbon price (Tietjen et al., 2016). High penetration of intermittent power technologies however, introduces additional uncertainty in the power output. Approaches which incorporate methodologies of risk management allows the energy manager to make a decision in an uncertain environment. One approach to obtain robust solutions in optimization problems including

[1] The International Energy Agency (IEA) forecasts that worldwide shares of RES will increase to 57% by 2050 (IEA, 2012).

uncertainty, is given by the implementation of probabilistic constraints in stochastic optimization problems. This approach is beneficial when it comes to considering the intermittent and unpredictable character of renewable energy technologies. The use of probabilistic constraints in optimization problems goes back to the work of Charnes and Cooper (1959) and was later used in various fields, ranging from applications in financial regulatory problems up to design problems in engineering. Among various other disciplines, this approach also gains increasing attention in the field of energy economics (Geng and Xie, 2019). In the course of a probabilistic modeling approach to the GEP, a probabilistic guarantee is imposed via an ex-ante chosen level of reliability, with which the stochastic supply-demand constraint associated with the energy park has to hold true. In this formulation, the level of reliability is an exogenous variable in the model, imposed by the energy manager. The probabilistic constraint can be equivalently formulated in terms of the value-at-risk with a certain confidence level β, denoted by VaR_β, which is defined via the quantile of the stochastic power shortfall.[2] Besides the clear interpretation of the VaR_β, it can have some drawbacks, e.g. that only the frequency of scenarios exceeding the probabilistic constraint is considered but not the extent of violation. The indifference of the VaR_β risk measure to extreme tails therefore does not reflect the losses in these worst-case scenarios which are not in the scope of the probabilistic bound and are therefore discarded as non responsive scenarios (Sarykalin et al., 2008).

This is of special importance in the GEP, where the energy manager - in case of a power shortfall - has to purchase residual power at the electricity wholesale market, which may come at a high price. However, in case of a probabilistic modeling approach where the energy manager opts for an "energy-autarchy" design with a probabilistic guarantee, the costs associated with the worst case scenarios are not considered. Imposing high levels of reliability corresponds to a situation, where the energy manager installs high capac-

[2]In this setting, the probabilistic constraint imposes a lower bound on the VaR_β.

ities referring to idle costs, which are used on rare occasions and can be economically infeasible. Thus, it is beneficial for the energy manager to choose the level of reliability by balancing the expected costs of purchasing energy at the wholesale market against idle costs.

In this paper we propose a probabilistic modeling approach to generation expansion planning, where a "here-and-now" decision of RES capacities has to be made. In this framework, the energy park is considered in a scenario without a feed-in-tariff, where no opportunity to feed the self-generated electricity into the grid exists. We extend this framework and explore the energy manager's optimal investment policy in renewable energy technologies, which are associated with a volatile power output, when the possibility to procure power at the electricity wholesale market also exists. Purchasing power at the market therefore might come as opportunity costs of a power shortfall. The power available from the self-generation facilities depends on the stochastic influence of the weather conditions, which introduces risks in the power output. We include the resource option to purchase power at the electricity wholesale market in order to balance these risks. In contrast to an approach imposing a probabilistic constraint on the supply of the energy park, the energy manager explicitly considers the expected costs in those scenarios, where the supply falls short of the demand (which occurs with a probability specified by the level of reliability). Therefore, the energy manager introduces a penalty on the power shortfall, which is additionally incorporated in the total costs of power procurement. Introducing a penalty on the power shortfall corresponds to the resource decision to purchase additional power e.g. at the electricity futures market or the spot market. This penalty can be formulated in terms of the conditional value-at-risk (CVaR_β), which is introduced in Rockafellar et al. (2000) and reflects upon the risks in the extreme tails.

The rest of the paper is organized as follows: Section 2 gives an overview of the relevant literature. The energy manager's investment model is introduced in Section 3. Section 4 presents the use case as well as the results of the optimization. Section 5 concludes the paper.

2 Literature overview

In a more general setting, optimal capacity expansion models for the firm have been addressed early in Manne (1961). This problem can be considered in a real options framework, in which optimal investment timing is determined (Dixit et al., 1994). Dangl (1999) discusses an investment problem, where a firm has to determine optimal investment timing and optimal capacity choice simultaneously under demand uncertainty. A general result which highlights the effect of uncertainty is, that the firm invests later in a larger quantity for higher levels of uncertainty.

From a private investor's perspective, a major concern when investing in RES is given by the fact that renewable energy technologies are capital intensive with high fixed costs. Mean variance portfolio theory has been applied in several studies (Awerbuch, 2000; Awerbuch and Berger, 2003; Awerbuch and Yang, 2007) which shows that adding RES in a portfolio of conventional plants with volatile fuel costs lowers portfolio risk for a given level of costs (Tietjen et al., 2016). This, together with the trend of decreasing prices of investment goods for renewable energy technologies, which are forecasted to continue this trend (Carlsson et al., 2014), makes investing in RES increasingly valuable from an economic point of view. High penetration of intermittent power facilities increases the variability of the energy park's power output. In case of a power shortfall, the energy manager balances supply and demand at the electricity wholesale market which includes the option to consume power at the spot market or via forward contracts. Moreover, as spot prices are volatile, the energy manager can use fixed price forward contracts to hedge against this spot price volatility.

An early application of using forward contracts as risk sharing instruments for spot price risks in the electricity market is conducted in Kaye et al. (1990). Woo et al. (2004b) consider an electricity distribution company and approach the problem of determining the optimal amount of forward electricity to reduce the exposure to inherent risks of spot price volatility. Based on this model, an efficient frontier of tradeoff between expected cost and cost risk measured in terms of cost variance is constructed in (Woo et al., 2004a). In this constrained least cost setting however, the authors do not include the opportunity to invest in self-generation facilities. Bjorgan et al. (1999) discuss hedging using future contracts and also investigate how production scheduling of non-intermittent technologies can be used to reduce overall risk, where stochastic input variables are assumed to be normally distributed. Conejo et al. (2008) consider an existing energy park with thermal power plants and addresses the problem to optimally invest in the electricity futures market, where price uncertainty is described by a set of scenarios.

3 The model

To incorporate the unpredictability of the power output associated with RES, we impose a stochastic modeling approach. The energy manager aims at minimizing power procurement costs where the stochastic hourly supply-demand constraint has to hold true. This includes costs associated with the investment decision in RES and excess payments in case of a power shortfall of the energy park. The investment time is assumed to be exogenously fixed and the energy manager has to make a "here-and-now" decision regarding the installed capacities. From the prosumer's point of view, the self-generation facilities are used primarily for own consumption and therefore we consider a scenario without a feed-in-tariff.[3]

[3]In this case, excess power can neither be sold in the market nor stored in the absence of a storage device and therefor has no economic value. However, in case of a shortfall, there is an outside option of last resort to purchase energy at the spot market.

Increasing installed capacities decreases the risk of a power shortfall but comes along with high investment costs. These investment costs become exceptionally high, whenever a very low level to risk exposure is required. High capacities, which are needed to cover the demand in the few worst case scenarios can therefore be economically inefficient compared to the case, where the energy manager purchases residual power at the market. To account for an economically optimal solution of the investment problem, the energy manager evaluates the investment costs of the energy park and additionally introduces a penalty in case of a power shortfall. The penalty reflects the costs of the resource decision to procure residual power to cover the demand d_t at the balancing market. The energy park can supply the total power $\mathbf{x}'\mathbf{P}_t$, where $\mathbf{x}$ denotes the vector of installed capacity of the power sources and $\mathbf{P}_t$ denotes the random vector of output power available per capacity installed at time t. To evaluate the excess payment which occurs in case of a power shortfall $f_t(\mathbf{x}) = \max\{d_t - \mathbf{x}'\mathbf{P}_t, 0\}$, the energy manager introduces the loss function, which penalizes the power shortfall over the planning period c

$$l_t(\mathbf{x}) = c\xi_t f_t(\mathbf{x}), \tag{1}$$

where ξ_t is the unit price of the power shortfall at time t.[4] In terms of the supply and demand this can be equivalently written as

$$l_t(\mathbf{x}) = \begin{cases} c\xi_t(d_t - \mathbf{x}'\mathbf{P}_t), & \mathbf{x}'\mathbf{P}_t \leqslant d_t \\ 0 & \mathbf{x}'\mathbf{P}_t > d_t. \end{cases} \tag{2}$$

The loss l_t itself is a random variable. Its distribution is induced by the joint distribution of energy supply and demand. In a scenario without a feed-in-tariff, high capacities do not constitute a gain, as excess energy can neither be stored nor sold. Whenever the

[4] In order to be able to compare the long-term investment decision with short-term excess payments, these additional expenses are scaled up to typical investment periods of 25 years via the constant c.

demand d_t is higher than the total power available of the energy park, the loss is positive and therefore requires excess payments to satisfy supply demand equality.

The mathematical formulation of the energy manager's GEP is given by minimizing the expected total costs $C(\mathbf{x})$ of the energy park, which are given by the capital expenditures and the expected excess payments in case of a power shortfall. Denoting the price per installed capacity of the renewable energy technologies by p_i and introducing the constant c which scales the hourly measured values up to the planning horizon[5] the total costs are given by

$$C(\mathbf{x}) = \mathbf{p}'\mathbf{x} + E[c\xi_t f_t(\mathbf{x})]. \tag{3}$$

By the law of total probability, the expected excess payments can be split into two parts

$$\begin{aligned} C(\mathbf{x}) = \mathbf{p}'\mathbf{x} &+ E[c\xi_t f_t(\mathbf{x}) | f_t(\mathbf{x}) > 0] \cdot \Pr\{f_t(\mathbf{x}) > 0\} \\ &+ E[c\xi_t f_t(\mathbf{x}) | f_t(\mathbf{x}) \leqslant 0] \cdot \Pr\{f_t(\mathbf{x}) \leqslant 0\} \end{aligned} \tag{4}$$

Let us denote the energy park's level of reliability by $\beta = \Pr\{f_t(\mathbf{x}) \leqslant 0\}$. According to this definition, we find due to $\xi_t \geqslant 0$ that for the value at risk $\mathrm{VaR}_\beta(\xi_t f_t(\mathbf{x})) = \mathrm{VaR}_\beta(f_t(\mathbf{x})) = 0$ holds true. By definition of the power shortfall, the expected costs in case of the energy park supplying enough power are zero and hence the costs are given by

$$\begin{aligned} C(\mathbf{x}) &= \mathbf{p}'\mathbf{x} + c(1-\beta)E[\xi_t f_t(\mathbf{x}) | f_t(\mathbf{x}) > 0] \\ &= \mathbf{p}'\mathbf{x} + c(1-\beta)\mathrm{CVaR}_\beta(\xi_t f_t(\mathbf{x})). \end{aligned} \tag{5}$$

This approach uses techniques of risk management, since calculating expected additional costs of purchasing external power coincides with measuring losses via the conditional

[5] i.e. in the use case where we consider a daytime model with $8h$ per day and a life span of the energy park of $25y$ the constant is given by $c = 8 \cdot 365 \cdot 25$

value-at-risk (or expected shortfall) with confidence parameter β which is defined by the energy park's level of reliability and depends on the installed capacities, i.e. $\beta = \beta(\mathbf{x})$. In case the energy manager consumes additional power at the spot market, and the spot market price and power shortfall are assumed to be independent, the total costs are given by

$$C(\mathbf{x}) = \mathbf{p}'\mathbf{x} + c(1-\beta)E[\xi_t]\mathrm{CVaR}_\beta(f_t(\mathbf{x})). \tag{6}$$

In reality, however, we expect a positive correlation of ξ_t and f_t, i.e. whenever there is short supply, spot prices tend to be high. If pre-contracted, the fixed price ξ_t is constant.

The CVaR_β introduced in Rockafellar et al. (2000) reflects upon the risks on the extreme tails by computing *[...] the conditional expectation of losses above that amount of the VaR_β (Rockafellar et al., 2000).* Tekiner-Mogulkoc et al. (2015) show, that the energy manager's attitude towards risk plays a fundamental role in the investment decision. Therefore, we consider an energy manager who measures the riskiness of electricity supply using the concept of the conditional value-at-risk. Moreover, the confidence parameter β reflects upon the conservatism introduced by the energy manager. For values of β closer to 1, the energy manager considers more unlikely events. In the limit $\beta \to 1$, the situation corresponds to a robust optimization problem, where the "worst-case" scenarios are considered (Anderson et al., 2019). In the energy manager's GEP the confidence level β corresponds to the energy park's level of reliability in a "stand-alone" application. For values $\beta \to 1$ the energy manager opts for an energy-autarchy scenario in which the capacities of the technologies are designed in a cost-minimal way such that the energy park alone can supply the demand. The mathematical formulation of the energy manager's investment problem is given by

$$\begin{aligned}&\min_{\mathbf{x}}\ \mathbf{p}'\mathbf{x} + (1-\beta)\mathrm{CVaR}_\beta(l_t(\mathbf{x}))\\ &\mathbf{x} \in \Omega,\end{aligned} \tag{7}$$

where the CVaR_β is computed according to the underlying loss function $l_t(\mathbf{x})$. The set $\Omega = \{\mathbf{x} \in \mathbb{R}^n : x_i \geqslant 0,\ i = 1, \ldots, n\}$ restricts the installed capacities to positive values and n denotes the number of different technologies involved in the generation expansion problem. In the course of the investment decision, the energy manager has to shape the risk distribution via adapting the amount of installed capacity in order to find the minimum of the total costs.

Rockafellar et al. (2000) show, that minimization problems including the CVaR_β can be reformulated in terms of the function $F_\beta(\mathbf{x}, \alpha)$, which itself can be approximated via a sample of the random variables with sample size N

$$F_\beta(\mathbf{x}, \alpha) \approx \alpha + \frac{1}{1-\beta}\frac{1}{N}\sum_{i=1}^{N}\left[l_t^{(i)}(\mathbf{x}) - \alpha\right]^+, \tag{8}$$

where α denotes the VaR_β and the superscript in the brackets denotes an empirical sample. The second term in this equation measures the additional payments above that of the VaR_β and is referred to as the excess reserve. In terms of a sample representation of the optimization problem based on empirical observations, the energy manager has to solve

$$
\begin{aligned}
&\min_{\substack{\mathbf{x},\\ z_1,\ldots,z_N}} \ \mathbf{p}'\mathbf{x} + \frac{c}{N}\sum_{i=1}^{N} z_i \\
&z_i \geqslant \xi_t^{(i)}(d_t - \mathbf{x}'\mathbf{P}_t^{(i)}) \\
&z_i \geqslant 0, \quad \forall i = 1, \ldots, N, \\
&\mathbf{x} \in \Omega.
\end{aligned} \tag{9}
$$

Therefore, the energy managers investment decision can be formulated as a linear program.

4 Computational Simulations

4.1 The use case

We demonstrate the applicability of the model in the use case of a RES energy park without a feed-in-tariff consisting of wind (i=1) and solar technology (i=2), respectively. The energy manager decides upon the optimal mix of technologies and also includes expected costs of purchasing residual power at the market. Uncertainty in the power available from both technologies is modeled by translating empirical data on solar irradiance and on wind speed via the physical energy model into supply of power. We sample from real world output data of the solar irradiance and the wind speed in Schwechat, Austria.[6] A sample is generated via blockbootstrapping with a block size of three days to incorporate short-term weather trends and contains hourly values of wind and solar output power for one year to incorporate long-term weather characteristics. The demand that has to be supplied by the energy park is assumed to be deterministic and constant $d_t = 1MW$. The costs of investment are given in terms of the prices of the investment

[6]source: www.soda-pro.com (solar irradiance), www.mesonet.agron.iastate.edu (wind speed), location: Schwechat, Austria, hourly data available from 2012 to 2018 in the daytime 10:00-17:00.

goods per installed kW, where we consider two price scenarios based on Carlsson et al. (2014): (i) the high price scenario of 2013, given by $p_1 = 1400€/kW$ for wind technology and $p_2 = 1000€/kW$ for solar technology and (ii) the low price scenario of 2050, where the price for wind technology is $p_1 = 800€/kW$ and the price for solar technology is $p_2 = 640€/kW$.

Moreover, we investigate the energy manager's investment decision in two alternative scenarios of the outside option to purchase residual power at the market. First we consider the case, where the energy manager includes a fixed price contract with price ξ_t per purchased unit of power and inspect how the optimal investment strategy changes with increasing price ξ_t. Furthermore, we compare this scenario with the stochastic price scenario, where ξ_t is assumed to be random, which corresponds to the case of purchasing power at the spot market.

4.2 Computational experiments

We perform 100 runs of the optimization problem, where in each run a sample of hourly values of the associated power output is generated for one year.

Investment with fixed price contract

The fixed-price scenario $\xi_t = \xi$ corresponds to a deterministic penalty in the stochastic loss function (2). The only source of uncertainty in this investment scenario is introduced by RES availability risk. Due to the constant demand, the loss function is deterministic when the energy manager decides not to invest in RES but to procure total power at the market, which corresponds to the case $\beta = 0$, i.e. $C(\mathbf{x}) = c\xi d_t$. In this case, total costs increases linearly with the energy price and the option to consume total power to cover the demand at the market introduces an upper bound of total costs, i.e. investing in RES comes as opportunity costs. We observe, that the energy manager

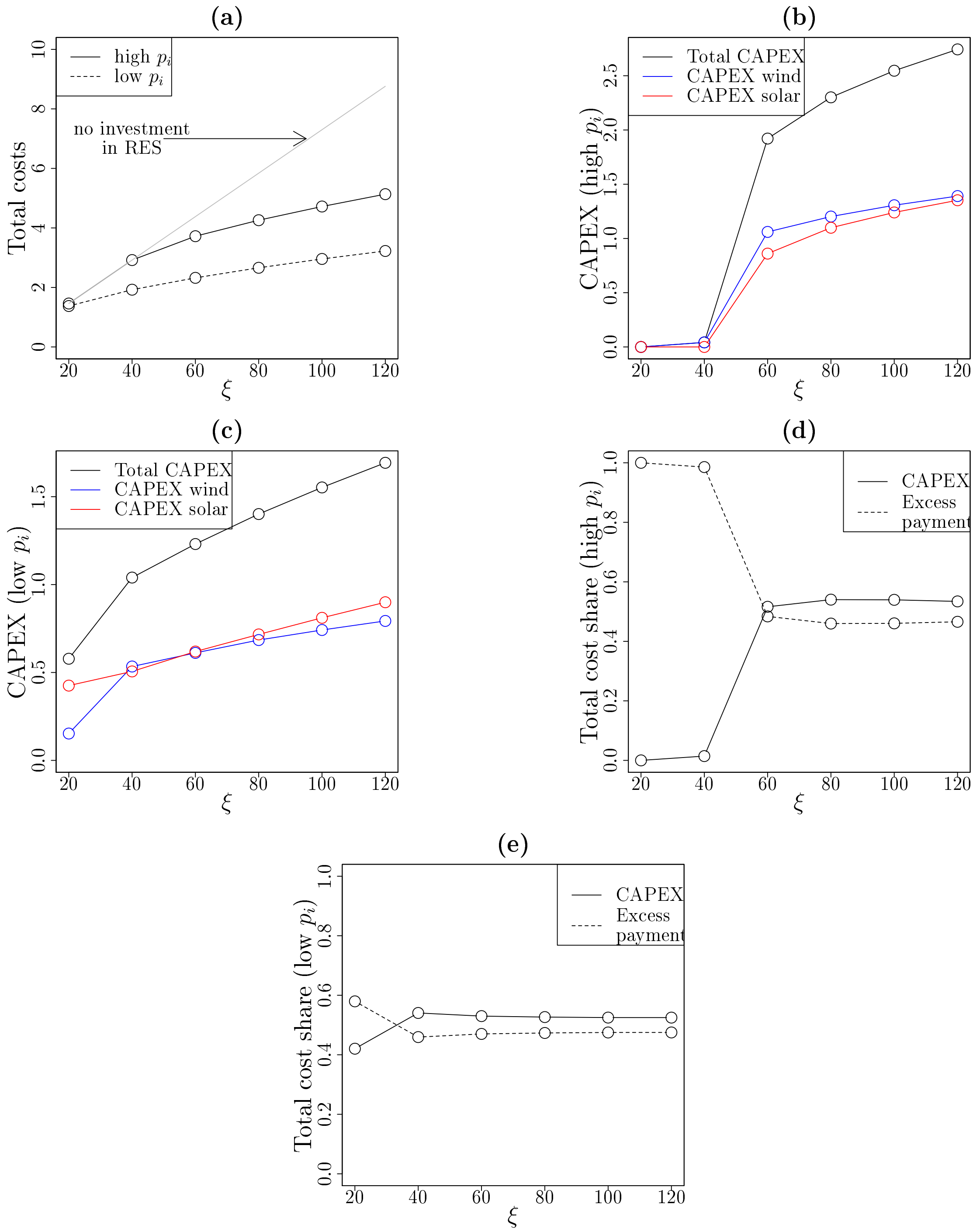

Figure 1: Fig.(a) shows the total costs of the energy park for the two price scenarios of the renewable technology investment goods (solid line: reference case 2013, dashed line: price scenario of 2050). The values are given in units of 10^6€. Fig.(b) shows the CAPEX in the high price scenario and Fig.(c) shows the CAPEX in the low price scenario. Fig.(d) shows the shares of total cost in high price scenario and Fig.(e) shows the shares of total costs in the low price scenario. All values are the mean values of the 100 optimization runs.

does not invest in capital intensive renewable self-generation facilities until the contract price ξ exceeds a threshold price $\xi^*(\mathbf{p})$, see Fig.1(a), where the total costs are plotted. This threshold price illustrates an investment barrier, which reflects upon the energy manager's willingness to invest in RES and is lower, the lower the associated prices of the investment goods. This effect can also be verified in Fig.1(b), where the CAPEX of the energy park are illustrated in the high price scenario of the investment goods. In the regime of low energy prices $\xi < \xi^*(\mathbf{p})$, the energy manager is reluctant to invest in renewable energy technologies and purchases total power to cover the demand at the market. Whenever the energy price exceeds the threshold $\xi > \xi^*(\mathbf{p})$, the energy manager increases investment in renewable energy technologies. The CAPEX in the low price scenario is given in Fig.1(c). In both price scenarios, the energy manager opts for an diversified technology portfolio. A similar effect can be obtained when investigating the shares of total costs of both options, i.e. investment in the energy park and consuming energy via fixed-price contracts given in Fig.1(d) in the high investment price scenario and Fig.1(e) in the low investment price scenario. Whenever the energy price exceeds the threshold price $\xi > \xi^*(\mathbf{p})$ the energy manager tends to balance out investment in RES technologies and consuming power at the market for a wide range of contract prices considered. Lower prices of the investment goods creates an incentive for the energy manager to invest in RES. The increased willingness to invest in RES can be observed in a shift of the amount of installed capacities of both technologies in Fig.2(a) and (b), i.e. energy managers invest in higher renewable technology capacities. Optimally installed capacities define the energy park's level of reliability β, i.e. the probability that the energy park alone supplies the demand in a "stand-alone" scenario. We evaluate the level of reliability ex-post by estimating the energy park's capability to supply the demand based on resampled scenarios, with an a-posteriori sample size of

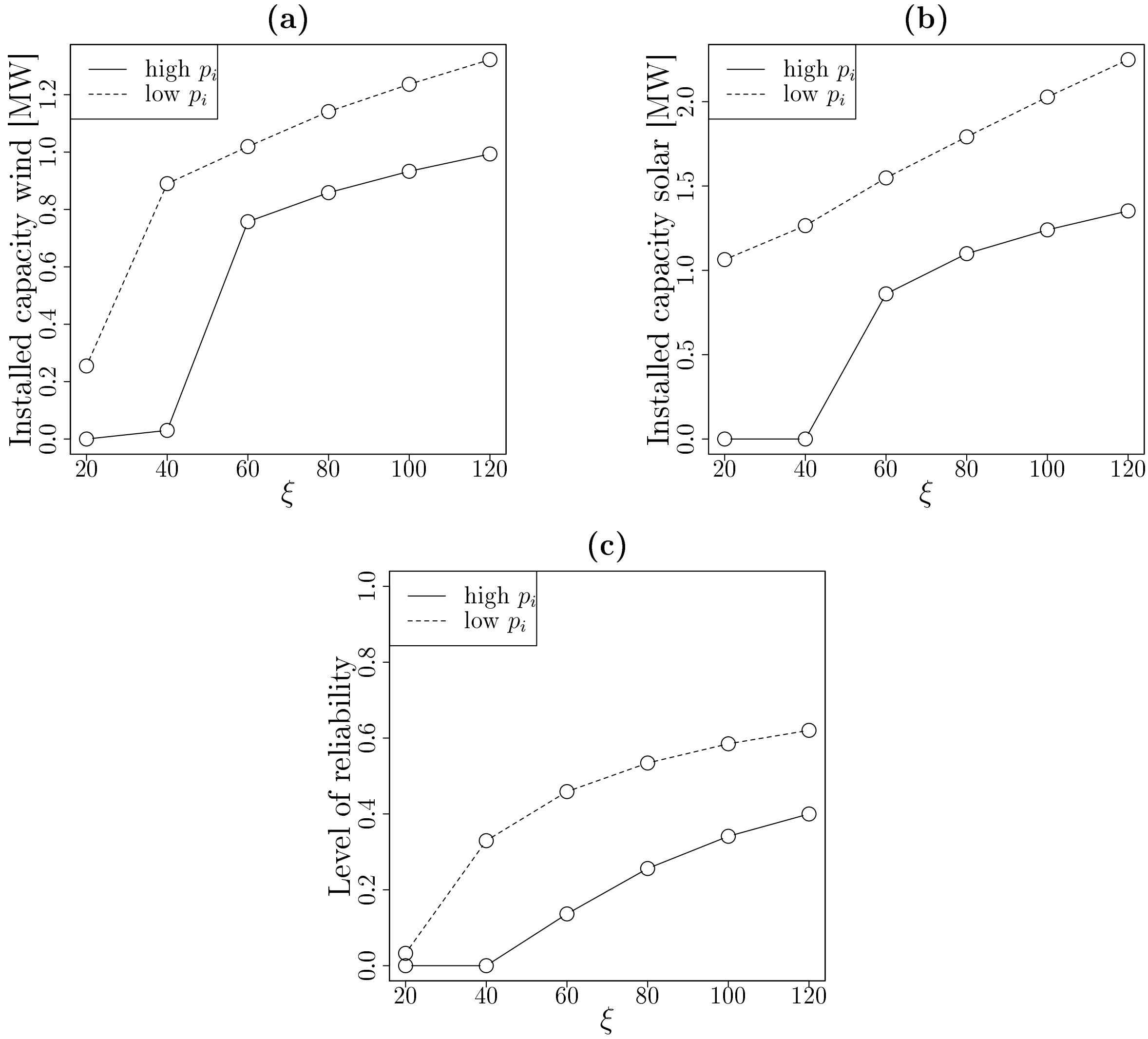

Figure 2: Fig.(a) shows the installed capacities of wind technology and (b) shows the installed capacities of solar technology. Fig.(c) shows the associated ex-post reliability level. All values are the mean values of the 100 optimization runs.

N'. The empirical level of reliability is then given by

$$\hat{\beta}(\mathbf{x}) = \frac{1}{N'} \sum_{i=1}^{N'} \mathbf{1}_{\{\mathbf{x}'\mathbf{P}_t^{(i)} \geqslant d_t\}} \tag{10}$$

and is close (with accuracy ϵ) to the true value with confidence greater than $1 - \beta'$, provided that for the a-posteriori sample size

$$N' \geqslant \frac{\log 2/\beta'}{2\epsilon^2} \tag{11}$$

holds true (Calafiore and Campi, 2005). The ex-post level of reliability in both investment price scenarios is given in Fig.2(c). With increasing prices above the threshold price $\xi > \xi^*(\mathbf{p})$, the energy manager increases optimally installed capacities which implies an increasing level of reliability.

The effect of price uncertainty

Next, we consider the case where the energy manager faces the decision to invest in RES or to purchase power at the spot market. In this setting, the price ξ_t in the loss function (2) is assumed to be stochastic. Therefore, the energy manager considers two potential sources of uncertainty in the investment decision which enables the occurrence of potentially high losses. First, investment in RES introduces RES availability risk and second spot price is also uncertain. The energy manager's problem is therefore to simultaneously balance these risks and to find the optimal investment policy. To investigate the energy manager's investment decision, spot market price is simulated via a truncated normal distribution[7] with mean μ and volatility σ.[8] The plot of the energy manager's optimal investment decision as a function of spot price volatility is given in

[7] We do not consider the possibility of negative prices and left-truncate the distribution at zero.

[8] In this framework, the volatility measures the uncertainty associated with the energy price at the spot market and is assumed to be uncorrelated with the power output of the energy park's self production facilities.

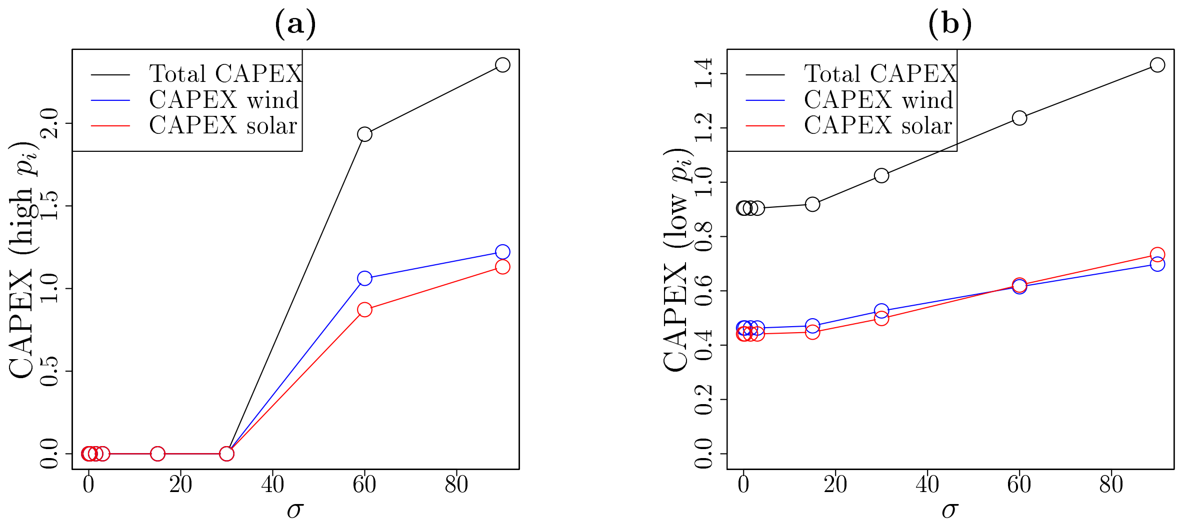

Figure 3: The investment costs as a function of spot price volatility in the low investment price case for $\mu = 30€/MWh$. The simulations are carried out for values $\sigma/\mu = \{0, 0.01, 0.05, 0.1, 0.5, 1, 2, 3\}$. The black line denotes the overall costs, the red line corresponds to the partial investment costs in solar technology and the blue line corresponds to the partial investment costs in wind technology. All values are the mean values of the 100 optimization runs.

Fig.3(a) and (b) for both price scenarios considered.

The deterministic price scenario, corresponding to the case $\sigma = 0$ has been discussed in the previous section. With increasing spot price volatility $\sigma > 0$ the energy manager increases optimally installed RES capacities to hedge against the spot price risk at the wholesale market, even if the expected energy price is below the investment threshold $\mu < \xi^*(\mathbf{p})$ established in the case of a fixed-price contract. Due to the occurrence of multiple sources of uncertainty, the energy manager is sensitive to an increase in the spot price volatility and increases investment in RES.

5 Conclusion

In this paper, we consider the generation expansion problem from an industrial consumer's point of view, who has to make an investment decision in RES. We extend the probabilistic modeling approach to the GEP, where a probabilistic constraint on the stochastic supply-demand imbalance of the energy park alone is imposed, by penalizing the power shortfall in the worst case scenarios which are not in the scope of the probabilistic constraint. These additional payments which come as the expected costs of a short power supply can be interpreted using techniques of risk management via the CVaR_β and has an effect on the energy managers "here-and-now" decision of the installed capacities of the power generation facilities. Increasing investment in RES reduces expenses of power procurement at the market and increases the energy park's level of reliability which is considered as the probability that the energy park in a "stand-alone-application" can supply the demand. However, costs that emerge from a high level of reliability can be economically infeasible and come as idle costs referring to unused capacities. Therefore, it is beneficial to consider the energy park's level of reliability as an endogenous variable which is determined by energy manager's optimal, i.e. cost minimizing choice of optimally installed capacities. Penalizing the power shortfall from the energy park corresponds to the situation, where the energy manager a-priori includes the possibility to procure power at the electricity wholesale market. Within the scope of the model, the energy manager can procure residual power to cover the demand via (i) fixed-price contracts or (ii) at the spot market with a volatile spot market price. The application of the model to a use case without a feed-in-tariff shows, that in the case of a fixed price contract, the energy manager does not invest in RES whenever the energy price associated with the contract is below the threshold price, which itself depends on the prices of the RES investment goods and is decreasing with decreasing prices of the investment goods. In the case of the energy manager procuring power from the spot market, the volatility associated with the spot price is additionally introduced in the investment decision. Simulating spot market prices shows, that due to the occurrence of multiple sources of uncertainty, the energy manager is sensitive to an increase in the uncertainty from spot price and increases investment in RES to hedge against spot price volatility.

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