RISK MITIGATION CAPABILITY OF FLEXIBILITY PERFORMANCE CONTRACTS FOR DEMAND RESPONSE IN ELECTRICITY SYSTEMS

Research paper

Abstract

The transition of the energy system increases the urgency to cope with the intermittency of renewable energy sources to keep the electricity network balanced. Demand Response (DR) measures are a promising approach to align the electricity consumption, especially of industrial consumers, with current electricity supply. While adequate information systems (IS) are already in place to dynamically adapt electricity consumption patterns, industrial consumers are still reluctant to implement DR measures due to uncertainty of their financial performance. Nevertheless, studies on risk transfer instruments related to DR investments are still scarce. To contribute to the closure of this research gap, we examine the risk transfer capability of Flexibility Performance Contracts (FPC). We derive cash flow structures for representative FPC designs, calculate risk premiums and enable the comparison of corresponding risk profiles. Presented FPCs are evaluated based on a real-world industrial use case. Thereby, the financial performance is modelled stochastically, taking electricity price fluctuation, industrial process characteristics and IS-backed decisions into account. Our results reveal that FPCs represent well-suited risk transfer instruments for DR measures. Thus, FPCs have the potential to accelerate the application of DR measures and therefore to complement existing capabilities of IS in the context of electricity networks.

Keywords: Financial Risk Mitigation, Demand Side Management, Demand Response, Energy Management System Aggregators

1 Introduction

The transition of the energy system towards the integration of intermittent renewable energy sources increases the volatility and uncertainty about fluctuations of electricity supply (Ludig, Haller, Schmid and Bauer, 2011). Due to physical constraints, it is crucial to balance supply and demand at any point in time. Therefore, a growing necessity for flexibility in electricity systems arises as a prerequisite to ensure electricity system stability (Boscán and Poudineh, 2016).

A widely-recognized approach to achieve this flexibility are Demand Side Management (DSM) measures, which strive to change electricity demand to follow fluctuations in power generation by influencing timing and magnitude of consumer demand (Palensky and Dietrich, 2011). Demand Response (DR) can be defined as a subclass of DSM and describes short-term changes in consumer's electricity consumption patterns induced by time-varying electricity prices or financial incentives (Albadi and El-Saadany, 2008). Literature states several beneficial effects of DR measures. Shifting load from peak to off-peak periods reduces the need for electricity generation and network capacity (Strbac, 2008). A reduced network capacity can lead to a more efficient utilization of the transmission network (Strbac, 2008). Similarly, DR measures can be used to dissolve network constraints on a distribution level and to reduce network investments (Strbac, 2008). Thus, DR measures can contribute to improve the efficiency of electricity systems and to lower electricity costs for industrial consumers due to their high energy intensity (Paulus and Borggrefe, 2011).

In order to facilitate and to profitably use DR measures, industrial processes must be embedded in interconnected information systems (IS). This IS infrastructure is required for the implementation of intelligent devices and autonomous controllers, which enable bidirectional information and communication streams (Callaway and Hiskens, 2011). Most industrial loads are equipped with fundamental communication technologies (Lund, Lindgren, Mikkola and Salpakari, 2015). Hence, the technical requirements for DR implementation are already fulfilled in many cases. Although DR benefits are widely acknowledged from a practical perspective, industrial consumers are still reluctant to participate in DR measures. Key barriers are market risks that lead to uncertainties concerning financial benefits, potential risks for production processes and changes in the dynamic regulation of the electricity system (Alcázar-Ortega, Calpe, Theisen and Carbonell-Carretero, 2015).

Within electricity systems, flexibility aggregators support industrial consumers in utilizing their flexibility potential and overcoming these barriers. Besides technical installation and system maintenance, flexibility aggregators provide expertise in assessing and exploiting financial benefits as well as in fulfilling necessary requirements, e.g. the prequalification process for participation in DR measures (Ikäheimo, Evens and Kärkkäinen, 2010). As most existing markets for flexibility require certain minimum trading volumes, flexibility aggregators help providers of small flexibility capacities, by combining individual flexibilities (pooling) and reducing transaction costs for all industrial consumers (Ottesen, Tomasgard and Fleten, 2018). Additionally, prices on these markets are usually exposed to a certain volatility and uncertainty. Therefore, revenues from the provision of flexibility are uncertain and represent an economic risk for flexibility providers. Further risks for flexibility providers may arise from operational, technological, contextual as well as measurement and verification challenges (Mills, Kromer, Weiss and Mathew, 2006). The decision-makers of industrial consumers are usually risk-averse (Gambardella and Pahle, 2018). For this reason, investments in expanding the potential for DR provision might be omitted, although being profitable in the long term. Flexibility aggregators may mitigate these risks for an industrial consumer acting as flexibility provider by assuring guaranteed revenues for DR provision. The flexibility aggregator receives a share of the DR measure revenues in return for providing services and taking financial risks. Literature usually calls the amount of reduced risks with such guarantees by the term risk mitigation capability (Töppel and Tränkler, 2019).

The benefit allocation between the flexibility provider (e.g. an energy intensive industrial consumer) and the flexibility aggregator - and therefore the risk mitigation capability - is defined individually in a Flexibility Performance Contract (FPC). Therein, the flexibility provider transfers the right of using its flexibility to the FPC issuer (e.g. a flexibility aggregator) and receives financial performance in return.

Generally, the financial compensation for the FPC consists of a fixed and a variable incentive sharing payment (Behrangrad, 2015).

FPC issuers are able to manage market risk exposure, through a diversified portfolio of flexibilities related to electricity consumption and generation, based on market knowledge, regulatory expertise and their superior access to market information (Harbo and Biegel, 2013). Currently FPCs are mainly implicitly offered by flexibility aggregators in combination with further DR-related services such as the provision of the required operational expertise and technological infrastructure. It is conceivable that entities like insurance companies could issue risk transfer instruments similar to FPCs, deploying their risk management expertise on a portfolio level and complementing their product portfolio. Although the business model and contracted services of flexibility aggregators have already been addressed in current research contributions (e.g. Ikäheimo et al., 2010; Behrangrad, 2015; Ottesen et al., 2018), examinations on the risk transfer capability of FPCs regarding the financial performance of DR measures are still scarce.

While technological aspects of DR-related IS are already relatively well understood, further effort to quantify the economic dimension of DR is still required (Feuerriegel, Bodenbenner and Neumann, 2013). Ongoing advances in IS-enabled data processing and analysis allow a more efficient use of DR measures and build the foundation for a reasonable and efficient offering of FPCs. Thus, the aim of this paper is to answer the following research question*: How do Flexibility Performance Contracts contribute to risk mitigation of Demand Response measures for industrial consumers?* Therefore, we derive FPC designs and provide a profound methodology for industrial consumers to evaluate the profitability and risk profile of contracted DR measures, using a quantitative approach for the comparison of different FPC designs regarding their risk mitigation capability.

We outline the theoretical background of this paper in Section 2. In Section 3, we derive specific cash flow structures of FPC designs. Further, we propose an equivalence principle that allows the comparison of different contract designs with respect to their risk profile. In Section 4, we present the case study of an industrial cooling house with a refrigeration system to evaluate our model. We use real-world data and process constraints as key information for a stochastic forecasting model, whose outcomes are processed in a linear optimization model providing decision support to determine the most beneficial electricity consumption strategy. In Section 5, we present the empirical results of the case study and derive the present value distribution for the application of a Time-of-Use (ToU) electricity tariff as a specific DR measure. We apply proposed FPCs as risk transfer instruments and evaluate their individual risk mitigation capability. Final conclusions are drawn in Section 6.

2 Theoretical Background

Energy informatics is a research discipline that focusses on the analysis, design and implementation of IS to enhance the efficiency of energy systems (Richard T. Watson, Boudreau and Chen, 2010). Advanced IS and communication technologies play a central role to support the optimization of electricity networks (Chen, Boudreau and Watson, 2008; Corbett, 2011). The implementation of DR measures requires advanced metering infrastructures, intelligent devices and specialized processors (Siano, 2014). DR-related IS provide the transmission medium for signals and information, support decisions on when to shift loads, and initiate and control the load shifting process (Fridgen, Häfner, König and Sachs, 2016). Key capabilities of IS in this area are bidirectional communication streams, smart metering and load control between electric utilities and consumers (Callaway and Hiskens, 2011). DR measures necessitate integrated IS that facilitate an automated exchange of information between electricity consumers and suppliers (Richard T. Watson et al., 2010). IS transmit the data required to execute a DR measure, e.g. to apply an optimization algorithm and autonomously trigger adaptions in electricity consumption patterns. Emerging business models build up on this advanced information and communication technologies and IS infrastructure. They strive to establish energy-related services to exploit untapped financial benefits (Richad T. Watson, Lawrence, Boudreau and Johnsen, 2013).

Energy service providers support electricity consumers with the implementation of energy-related investments. Energy services include energy analyses and audits, project design and implementation, maintenance and operation as well as monitoring and evaluation of financial savings resulting from implemented energy services (Bertoldi, Rezessy and Vine, 2006). In literature, energy service companies are related to the implementation of energy efficiency measures and can be defined as a subclass of the more general term of energy service providers (Bertoldi et al., 2006). Energy service companies contribute to financial risk mitigation through energy performance contracts for energy efficiency investments (Bertoldi and Boza-Kiss, 2017). In this context, Mills (2003) proposes an energy savings insurance serving as a risk transfer instrument for an energy efficiency investment in exchange for a premium. Hence, risks of an energy efficiency investment are transferred to the energy service company or insurer (Mills, 2003). For the first time, Töppel and Tränkler (2019) quantitatively model energy efficiency insurances as well as energy performance contracts and compared their risk mitigation capability.

Similar to energy performance contracts, Boscán and Poudineh (2016) suggest such contracts related to investments in flexibility. Entities already providing flexibility-enabling services, which also include adequate contracts, are mostly cited as flexibility aggregators (Carreiro, Jorge and Antunes, 2017). Flexibility aggregators support consumers to exploit prospective financial benefits of DR measures. Thereby, the role of a flexibility aggregator is twofold: First, consumers are provided with the infrastructure and expertise required to use flexibility, such as the implementation of decision support systems to derive the most beneficial electricity consumption strategy. Second, the financial performance of a flexibility investment is insured through a Flexibility Performance Contract (FPC), serving as a risk transfer instrument. These legally binding contracts assure a transparent relationship between both parties, prevent information asymmetry and determine the allocation of benefits resulting from DR measures.

The financial performance of most energy-related investments is affected by various internal and external factors (Mills et al., 2006). This also leads to insecurity regarding decisions for the provision of flexibility and prevents the implementation of DR measures in electricity markets (Alcázar-Ortega et al., 2015). In the following, we define the term financial risk as exposure to a financial underperformance of flexibility investments, due to the influence of internal and external factors. We outline a brief overview of financial risk factors that must be incorporated for a holistic risk assessment of flexibility implementation projects. Therefore, we follow Mills et al. (2006), who analyze the financial risks associated with energy-efficiency projects. The proposed risk categories comprise economic, operational, technological, contextual as well as measurement and verification risks. A detailed explanation for each financial risk category in the context of DR measures can be obtained from Table 1.

From the perspective of an industrial consumer, operational, technological, as well as measurement and verification risks can be summarized as internal risks and rather have technical characteristics. Industrial consumers can usually handle such risks best by themselves, as they have the highest transparency about these internal factors. Contextual and economic risks are external factors, which cannot or only hardly be influenced by industrial consumers. While contextual risks may also be hardly quantifiable, it is usually possible to measure economic risks, especially for external service providers, which are specialized in handling uncertainties on the markets. For this reason, we focus on the economic risks within the scope of this work. Nevertheless, a mitigation of economic risks by FPCs may indirectly affect the other risk categories, by balancing the associated risks with guaranteed revenues.

So far, research contributions to the topic of financial risk transfer instruments for DR measures are very limited. Harbo and Biegel (2013) as well as Behrangrad (2015) state that the allocation of financial benefits determined in a FPC can be constant during the contract lifetime, variable depending on annually realized benefits or any type in between these forms. Nevertheless, contract designs are not elaborated in detail and no specific cash flow structures were proposed. Thus, a thorough definition of remuneration schemes defined within FPCs is still missing (Carreiro et al., 2017).

	Financial Risk Category	Contextualization for DR Measures
External	**Economic**	Economic risk covers uncertainties regarding electricity prices, tariff structures, tariff levels or other financial incentives for the provision of flexibility (Mills et al., 2006). An increased electricity market price volatility, due to the ongoing integration of renewable electricity generation, represents a prevailing economic risk (Mosquera-López and Nursimulu, 2019).
External	**Contextual**	Contextual risk covers the accuracy of information on environmental conditions and the facility (Mills et al., 2006). These include liability and warranty conditions as well as changes in future politics (Weeber, Lehmann, Böhner and Steinhilper, 2017). Due to previous load curtailments, higher peak loads may lead to unintended increased network tariffs charged against the flexibility provider (Alcázar-Ortega et al., 2015).
Internal	**Operational**	Operational risk can be related to a reduced financial performance of flexibility measures due to negative effects on operating processes (Mills et al., 2006). The execution of DR measures may lead to additional process costs, quality losses or operating delays. Flexibility providers must take the economic value of loads into account, which cannot be recuperated somewhere later in time (Paulus and Borggrefe, 2011).
Internal	**Technological**	Technological risk includes the equipment and system performance (Mills et al., 2006). Integrating flexibility to industrial processes tends to increase the overall system complexity and the dependency on detailed and accessible external information (Weeber et al., 2017). Moreover, privacy issues arise from collecting and processing electricity usage information, which contain private information and activities or choices of flexibility providers (Carreiro et al., 2017).
Internal	**Measurement and Verification**	Measurement and verification risk refers to simulation and metering accuracy or measurement bias (Mills et al., 2006). Especially for the metering of bidirectional electricity flows, achieving precise measurement results represents a considerable challenge (Carstens, Xia and Yadavalli, 2018). Thus, high technical requirements on advanced metering infrastructure (e.g. smart metering) are necessary to ensure an accurate documentation of real-time electricity consumption information (Lampropoulos et al., 2018).

Table 1. Definition of risk categories affecting the financial performance of DR measures.

In our work, we consider a FPC as an energy service contract that ensures economic risks related to the implementation and execution of a DR measure. IS and especially autonomous decision support systems are a prerequisite for the efficient execution of DR measures and therefore determine their financial performance. Hence, FPCs also insure the risks associated with executions of such systems. To the best of our knowledge, there is no literature about specific FPC designs or insurance products, which account for the implementation of DR measures. This underlines that current literature does not sufficiently cover risk transfer instruments for DR measures. We argue that further analyses of FPC in the context of DR measures are highly relevant, as the financial risks of DR provision are comparatively high, which can be traced back to the uncertainty and the volatility of electricity markets. This emphasizes the need of risk mitigation itself and the need for adequate designs of FPCs. Therefore, we are the first to derive explicit FPC designs and analyze to which extent FPCs contribute to risk mitigation for industrial consumers and how decisions on FPC designs can be performed.

3 Methodological Approach

The aim of this paper is to evaluate the risk mitigation capability of FPCs. Therefore, we derive current FPC designs, identify corresponding cash flow structures between the flexibility provider and FPC issuer and show how risk premiums can be calculated. Next, we introduce an equivalence principle to enable comparability of considered FPCs. Finally, we apply an established risk measure to determine the most beneficial risk transfer contract from the viewpoint of a risk averse decision maker.

3.1 Introducing Flexibility Performance Contract Designs

We consider a standard setting with a FPC issuer and a flexibility provider and omit transaction costs occurring between the FPC issuer and the flexibility provider for reasons of clarity. Financing costs are not considered in this analysis, as they do not affect the functionality of FPCs. We use the term electricity bill savings referring to the financial benefit arising from the implementation and execution of a DR measure. We distinguish between two major FPC design characteristics:

Flexibility Performance Insurance Contract (FPIC)

A risk event occurs for the flexibility provider if the annually realized electricity bill savings fall below a predefined level. In this case, the FPC issuer is obligated to pay any shortfalls below this level to the flexibility provider. In return for this obligation, the FPC issuer receives a constant annual premium payment. The FPC issuer does not participate in savings exceeding the predefined level of electricity bill savings. From the viewpoint of a FPC issuer, the annual cash flow of the FPIC is defined as follows:

$$CF_t^{FPIC} = \pi^{FPIC} - (K^{FPIC} - S_t)_+, \tag{1}$$

where S_t are the realized electricity bill savings in period t. K^{FPIC} denotes the guaranteed level of annual electricity bill savings in the FPIC. The premium payment π^{FPIC} from the flexibility provider to the FPC issuer is constant during the contract lifetime.

Flexibility Savings Guarantee (FSG)

The FPC issuer guarantees a certain level of annual electricity bill savings to the flexibility provider. Annual shortfalls below this level are reimbursed during the contract lifetime. Electricity bill savings exceeding this level are shared at a predefined rate. The opportunity to participate in savings replaces the fixed premium payment of the FPIC. From the perspective of the FPC issuer, the FSG exhibits the following annual cash flow structure:

$$CF_t^{FSG} = \alpha(S_t - K^{FSG})_+ - (K^{FSG} - S_t)_+, \tag{2}$$

where K^{FSG} is the guaranteed level of annual electricity bill savings in the FSG and $\alpha \in \mathbb{R}_+$ is the share of annual electricity bill savings exceeding the level of K^{FSG}, retained by the FPC issuer. Thus, the FPC issuer obtain a stochastic payment $\alpha(S_t - K^{FSG})_+$, which depends on the annually realized electricity bill savings.

We assume that FPCs are priced under perfect information. This means moral hazard and adverse selection are neglected for our analysis (Akerlof, 1970). Thus, realized electricity bill savings S_t are perfectly observable for all involved parties. Furthermore, FPC issuers are considered to hold a diversified portfolio of assets and to pursue a risk neutral pricing strategy (Rothschild and Stiglitz, 1976). Hence, pricing is based on the expected present value of losses resulting from a specified risk event. In accordance with the assumptions of perfect information and risk-neutral pricing, the fair premium payment π^{FPIC} for the FPIC can be derived as follows:

$$\pi^{FPIC} = \frac{(1+r)^T r}{(1+r)^T - 1} \sum_{t=1}^{T} E\left[\frac{(K^{FPIC} - S_t)_+}{(1+r)^t}\right]. \tag{3}$$

3.2 Equivalence Principle

Following Töppel and Tränkler (2019), we introduce an equivalence principle to ensure comparability of different risk transfer contracts. We apply this equivalence principle to the defined FPCs. Thereby, we take the viewpoint of a FPC issuer, who receives a certain annual premium payment for a given risk transfer policy. A risk transfer contract C_i claims customer premium payments $\Pi_i = \{\pi_{i,1}, \dots, \pi_{i,T}\}$ during the contract lifetime T, where $\pi_{i,t}$ is the premium payment of contract i at time t. A premium payment $\pi_{i,t}$ can be deterministic or stochastic, depending on the individual contract design. Risk transfer contracts are regarded as equivalent, if they exhibit the same present value of expected premium payments during the contract lifetime T. It follows that two equivalent risk transfer contracts C_1 and C_2 with the same maturity T and constant actuarial interest rate r need to fulfil the equilibrium condition:

$$\sum_{t=1}^{T} E\left[\frac{\pi_{1,t}}{(1+r)^t}\right] = \sum_{t=1}^{T} E\left[\frac{\pi_{2,t}}{(1+r)^t}\right]. \tag{4}$$

We apply this general equilibrium condition to the specific risk transfer contracts FPIC and FSG. The premium payment π^{FPIC} is constant over the entire contract lifetime T. In contrast, $\pi_t^{FSG} = \alpha(S_t - K^{FSG})_+$ denotes the stochastic premium payment for the FSG, depending on the annual electricity bill savings S_t. Thus, Formula 4 leads to the following equilibrium condition to ensure the equivalence of FPIC and FSG:

$$\sum_{t=1}^{T} E\left[\frac{\pi^{FPIC}}{(1+r)^t}\right] = \sum_{t=1}^{T} E\left[\frac{\alpha(S_t - K^{FSG})_+}{(1+r)^t}\right]. \tag{5}$$

For a given K^{FPIC}, we can determine π^{FPIC} in accordance with Formula 3. As Formula 5 includes the variables α and K^{FSG}, there is no unique solution for the equilibrium condition. Therefore, we assume $K^{FPIC} = K^{FSG}$ for the guaranteed level of annual electricity bill savings of both contracts. Finally, the equivalence condition can be fulfilled with a unique solution for α:

$$\alpha = \frac{\sum_{t=1}^{T} E\left[\frac{\pi^{FPIC}}{(1+r)^t}\right]}{\sum_{t=1}^{T} E\left[\frac{(S_t - K^{FSG})_+}{(1+r)^t}\right]}. \tag{6}$$

3.3 Risk Mitigation Capability

We apply the Value-at-Risk (VaR) to identify the FPC, which minimizes the financial performance risk of the implementation and execution of DR measures for a risk averse flexibility provider. The VaR is a widely used risk management tool in the financial and non-financial sector and offers a simple quantification and interpretation of risk (Sadeghi and Shavvalpour, 2006). Hendricks (1996) defines the VaR as a decline of the portfolio value, which might occur over a predefined period with a given probability. Most important variables affecting the VaR are the considered time period and the probability of not exceeding a certain shortfall, which is determined by a confidence interval $(1-\gamma)$ expressed in percentiles (Hendricks, 1996). The confidence level is denoted by $\gamma \in]0,1[$ and determines the probability of a shortfall below the VaR (Artzner, Delbaen, Eber and Heath, 1999). We define the VaR as:

$$VaR_\gamma(X) = F_X^{-1}(\gamma), \tag{7}$$

where X is a random success variable and F_X^{-1} denotes the inverse of the cumulative distribution function of X. Hence, $VaR_\gamma(X)$ represents a certain value for the random variable X, which will be undercut only by a given probability γ. The design of a risk transfer contract C_i determines the annual cash flows CF_t^i, which depends on the stochastic annual electricity bill savings S_t for a specific flexibility measure. Hence, discounted annual cash flows CF_t^i result in a present value denoted by Σ_i , that follows a certain probability distribution. In this case, practitioners prefer a high VaR of the random variable Σ_i and, thus, define the risk minimal random variable Σ_* as:

$$\Sigma_* = \max_{\Sigma_0, \Sigma_1, \dots, \Sigma_n} VaR_\gamma(\Sigma_i), \tag{8}$$

where Σ_0 denotes the present value distribution of electricity bill savings without FPC and each Σ_i corresponds to a specific risk transfer contract C_i with $i \in \{1, \dots, n\}$. Formula 8 can be applied to determine the FPC that exhibits the most favorable risk profile from the viewpoint of a risk averse decision maker.

4 Case Study Overview

The following model evaluation demonstrates the applicability of the methodological approach presented in Section 3. We model the financial risk of a DR measure, calculate fair risk premiums and compare the risk profiles of FPIC and FSG. First, we present and use empirical data in a comprehensive statistical process to forecast electricity prices. Second, forecasts are processed in a linear programming model under conditions of a real industrial process, providing decision support to determine the most beneficial electricity consumption strategy. Third, we derive the present value distribution based on annual electricity bill savings for one specific DR measure. Finally, we apply FPIC and FSG contract designs to the DR measure to allow a risk mitigation comparison.

4.1 Project Profile and Data

We examine the economic benefit of a DR measure based on an industrial refrigeration system that is common in the food or retail industry. The cooling pump of a refrigeration system does not need to be in ongoing operation. Therefore, such systems allow a temporal shift in power consumption as long as the refrigeration temperature stays within defined boundaries. The application of a Time-of-Use (ToU) electricity tariff is a well-suited DR measure in this context. A ToU tariff is characterized by a constant electricity price within set time intervals but varying electricity prices among different time intervals (Albadi and El-Saadany, 2008). Peak hours are penalized with a higher price, incentivizing consumers to adapt their consumption pattern and to minimize electricity costs (Palensky and Dietrich, 2011).

The refrigeration system characteristics as well as the fluctuating ToU electricity prices determine the extent to which an adjusted electricity consumption strategy can lead to electricity bill savings. Table 2 summarizes the plant-specific characteristics of the considered refrigeration system. Further, we consider market data from the EPEX SPOT German Intraday Auction to infer historical ToU price levels (EPEX SPOT, 2018). The data comprises the time interval from January 2015 to March 2018. For our analysis, we had hourly mean values of these electricity prices available (in €/MWh). In Section 4.2, we describe the fitting of a stochastic process to this data to pre-estimate future electricity prices.

Refrigeration System Characteristics of Case Study					
Constant	Load ($\boldsymbol{P_{el.}}$)	Maximum Temperature ($\boldsymbol{\vartheta_{max.}}$)	Minimum Temperature ($\boldsymbol{\vartheta_{min.}}$)	Positive Temp. Gradient ($\boldsymbol{g_{pos.}}$)	Negative Temp. Gradient ($\boldsymbol{g_{neg.}}$)
Value	150 kW	5.00 °C	2.00 °C	1.05 °C/h	-1.45 °C/h

Table 2. Summary of refrigeration system characteristics.

4.2 Modelling Uncertainties of Realized Electricity Bill Savings

ToU tariffs rely on electricity market prices and reflect the market situation within an electricity system (Strbac, 2008). Therefore, ToU prices are stochastic as they are exposed to extensive uncertain fluctuations of electricity market prices (Mosquera-López and Nursimulu, 2019). These price fluctuations can be regarded as the decisive factor of uncertainty for electricity bill savings resulting from the use of DR measures in this context. Temporally high prices represent a risk for the flexibility provider, as they lead to high electricity costs compared to a constant electricity tariff.

Since the electricity price data shows autocorrelation, we build on an autoregressive moving average (ARMA) approach developed by Box, Jenkins, Reinsel and Ljung (2015). Additionally, we observe strong daily variations. Thus, we extend the ARMA model for parameters, which take account of a regular pattern that repeats over a certain time lag. We adopt a seasonal autoregressive moving average (SARMA) approach. Moreover, the electricity prices exhibit a time-varying variance. Since the SARMA error terms do not follow a normal distribution with constant variance, we apply a generalized autoregressive conditional heteroscedastic (GARCH) process to model a conditional variance (Bollerslev, 1986). This results in a hybrid SARMA-GARCH process to describe hourly electricity prices. Similar models, which incorporate such time series characteristics are frequently used to model and forecast electricity prices (Garcia, Contreras, van Akkeren and Garcia, 2005; Liu and Shi, 2013; Kumar, Singh, Singh and Mohanty, 2018)Next, we elaborate the optimal schedule for the use of the DR measure, which refers to the electricity consumption strategy of the refrigeration system. We assume the decision-maker, i.e. the flexibility provider, has perfect information about future electricity prices and there are no surcharges on wholesale-prices. Hence, forecasted electricity prices equal actual ToU electricity prices. To determine the optimal electricity consumption schedule, generally an optimization problem is formulated and solved by optimization techniques and algorithms (e.g. Conejo, Morales and Baringo, 2010; Siano, 2014; Deng, Yang, Chow and Chen, 2015). We process forecasted electricity prices in a linear programming model to determine the optimal consumption strategy. The resulting linear program can be written as:

$$\text{Minimize } C(a_t) = \sum_{t=1}^{T} a_t \ p_t \ P_{el.} \ d, \tag{9}$$

subject to:

$$a_t \ d \ g_{neg.} + (1 - a_t) \ d \ g_{pos.} \ \leq \ \vartheta_{max.} - \vartheta_{t-1} \qquad \forall t \in T, \tag{10}$$

$$-a_t \ d \ g_{neg.} - (1 - a_t) \ d \ g_{pos.} \leq \ \vartheta_{t-1} - \vartheta_{min.} \qquad \forall t \in T, \tag{11}$$

$$0 \leq a_t \leq 1 \qquad \forall t \in T, \tag{12}$$

where $P_{el.}, \vartheta_{max.}, \vartheta_{min.}, g_{pos.}, g_{neg.}$ are the refrigeration system characteristics summarized in Table 2. The duration d of each optimization period is one hour and p_t represents the hourly electricity price. The linear program is solved each time for the following day (Day-Ahead). The decision variable a_t denotes the cooling pump utilization of the refrigeration system for each hour. The temperature ϑ_τ at a specific time $t = \tau$ can be calculated in the following way:

$$\vartheta_\tau = \vartheta_0 + \ \sum_{t=1}^{\tau} [a_t \ g_{neg.} + (t - a_t) \ g_{pos.}], \tag{13}$$

where $\vartheta_0 = 3.5$ °C is a permissible starting temperature. The objective of the linear program is to minimize daily electricity costs. Temperature constraints and gradients of the refrigeration system are considered in Formulas 16 and 17. The hourly utilization of the cooling pump is specified in Formula 18.

4.3 Fitting Results

We used the statistical platform R CRAN to estimate the SARMA-GARCH parameters. The packages ‘forecast’ and ‘fGarch’ were applied to estimate the model parameters. Both methods follow a maximum-likelihood approach for estimation. We identified the order of our model with the SARMA $(p, q) \times (P, Q)_S$ and GARCH (k, l) components based on the Akaike Information Criterion (AIC). To ensure model simplicity, we set the parameters $p, q, P, Q, k, l \leq 1$. With an AIC value of about $165{,}000$ the SARMA $(1{,}1) \times (1{,}1)_{24}$ model was found to be the most suitable. Table 3 depicts the estimated model parameters.

Model Component	**SARMA**					**GARCH**		
Parameter	$\boldsymbol{\mu}$	$\boldsymbol{\varphi_1}$	$\boldsymbol{\theta_1}$	$\boldsymbol{\Phi_1}$	$\boldsymbol{\Theta_1}$	$\boldsymbol{\omega}$	$\boldsymbol{\alpha_1}$	$\boldsymbol{\beta_1}$
Mean	31.8731	0.9310	-0.2021	0.9962	-0.9308	0.3470	0.1216	0.8671

Table 3. Parameter means of the fitted SARMA-GARCH electricity price process. The p-Value is smaller than 0.001 for all parameters.

5 Empirical Results

To derive the present value of a ToU tariff application to the refrigeration system, electricity price estimations were processed in the linear programming model, leading to the most beneficial electricity consumption strategy. We defined electricity bill savings as the difference of annual electricity costs incurred through a constant electricity tariff and electricity costs incurred through the adapted consumption through a ToU tariff. Next, the present value of the annual electricity bill savings was simulated $N = 10{,}000$ times for a contract lifetime of $T = 5$ years. Thereby, the constant price for electricity was assumed to be identical for all performed simulations. Moreover, we did not consider operating and maintenance costs. A constant actuarial interest rate of $r = 5\ \%$ was assumed. Figure 1 represents the resulting present value distribution of electricity bill savings.

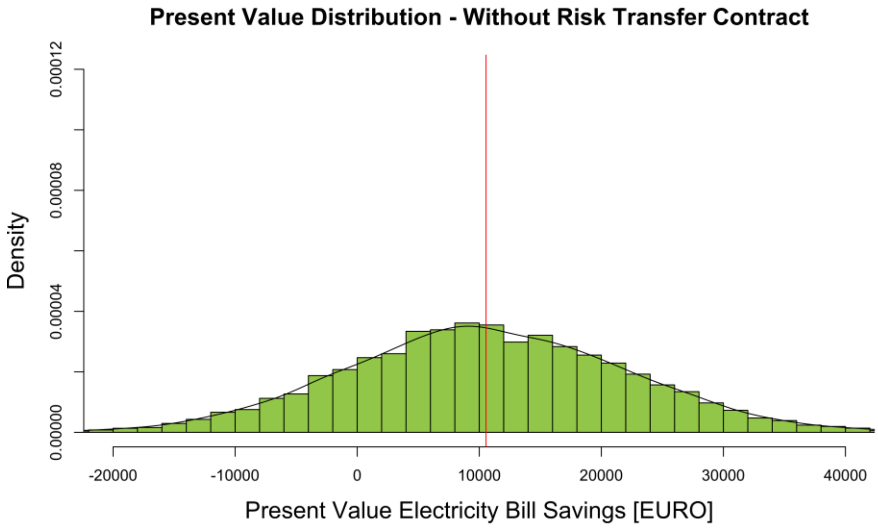

Figure 1. Simulated present value electricity bill savings distribution for an exemplary DR application.

The nearly symmetric distribution has a positive mean value of $10{,}554$ € and a standard deviation of $11{,}619$ €. On a confidence interval with a level of significance $\alpha = 0.001$, the present value takes extreme values from $-27{,}282$ € to $48{,}734$ €. Such extreme values occur if simulated electricity prices of the ToU tariff deviate significantly from the predefined constant electricity price. We suppose that the constant electricity price can be hedged with forward contracts and other derivatives and is therefore not subject to any variation over the considered time interval. Although the positive mean and the right tail of the distribution suggest high prospective benefits from the DR measure, the $VaR_{0.01}$ of $-16{,}310$ € indicates high financial risks. Electricity price peaks can result in high ToU tariffs and even lead to negative electricity bill savings.

To derive the present value distribution for the FPIC, we first set $K^{FPIC} = 1{,}200$ €. Second, we derive the corresponding fair premium $\pi^{FPIC} = 1{,}192$ € for the FPIC by applying Formula 3. With these initial parameters, we obtain the present value distribution of the electricity bill savings as depicted in Figure 2. Since we only assume a fair risk premium, we observe the same mean as obtained without the consideration of a FPC. A standard deviation of $7{,}752$ € indicates less dispersion of the present value. Extreme values range from 36 € to $43{,}575$ € and the $VaR_{0.01}$ can be increased, similarly to the minimum value, to 36 €. This clearly implies a risk transfer towards the issuer of the FPIC.

Next, we use the proposed equivalence principle to determine the share of electricity bill savings retained by the FSG issuer for S_t exceeding K^{FSG}. Given $K^{FSG} = K^{FPIC}$, Formula 6 returns a value of $\alpha = 49\ \%$ for the share of annual electricity bill savings retained by the FPC issuer. The corresponding simulation findings are illustrated in Figure 3. A low standard deviation of $3{,}950$ € leads to a close value range from $5{,}195$ € to $27{,}379$ €. The $VaR_{0.01}$ of the FSG is $5{,}195$ € and indicates a higher risk mitigation capability compared to the FPIC. It should be noted that an increasing α leads to the convergence of the present value distribution towards a constant payment to the flexibility provider until $\alpha = 1$. Thus, the determination of K and α respectively define the risk transfer capability of the FSG. The model evaluation reveals that both contracts, the FPIC and the FSG, contribute to risk mitigation of ToU measures. The FSG is favorable with respect to a smaller standard deviation. In contrast, the FPIC allows to obtain high electricity bill savings at the right tail of the distribution. Therefore, higher risks must be incorporated compared to the FSG.

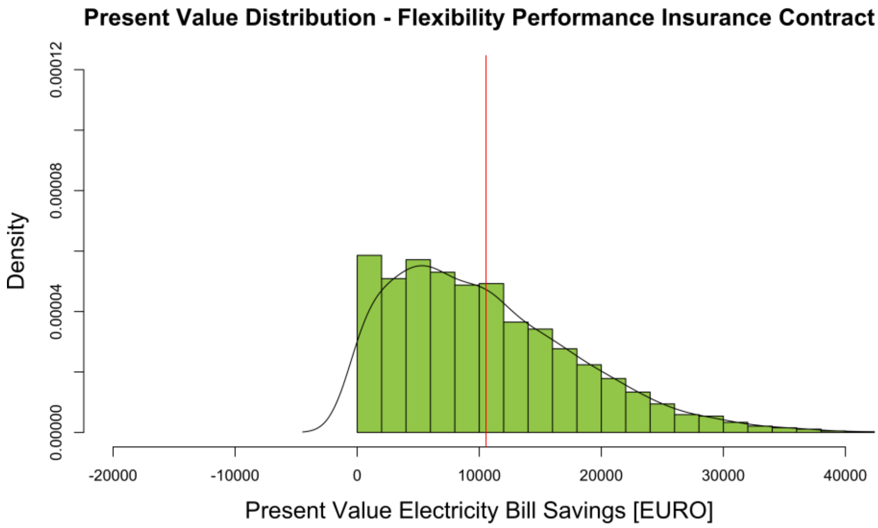

Figure 2. Simulated present value electricity bill savings distribution with FPIC ($K^{FPIC} = 1{,}200$€, $\pi^{FPIC} = 1{,}192$ €).

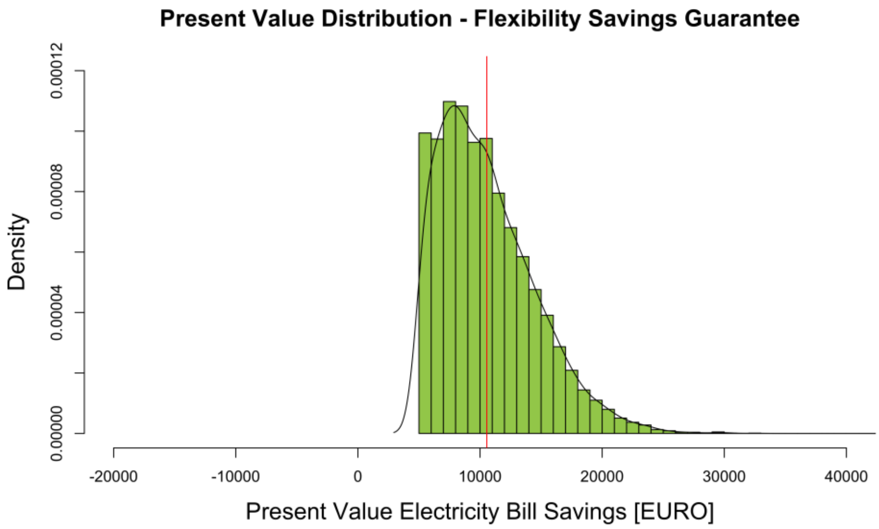

Figure 3. Simulated present value electricity bill savings distribution with FSG ($K^{FSG} = K^{FPIC}$, $\alpha = 49$ %).

Figure 4 presents additional findings that underline the results of the risk mitigation comparison from above for different levels of guaranteed electricity bill savings K. The $VaR_{0.01}$ is shown for the three present value distributions depending on the level of K. The $VaR_{0.01}$ without a risk transfer contract is constant as it is independent of K. In the interval from 0 € to 2,440 € for K, the FSG consistently leads to the highest $VaR_{0.01}$. By applying Formula 6 again, we obtain a $\alpha > 1$ for K exceeding the value of 2,440 €. In this case, annual electricity bill savings exceeding K would lead to additional payments from the flexibility provider to the FSG issuer. Hence, the prior risk mitigation effect of the FSG is inverted as reflected in the vast decline of the $VaR_{0.01}$. Whereas the FSG can even lead to a leverage effect, the FPIC shows a monotonously increasing $VaR_{0.01}$ depending on the predetermined level of K.

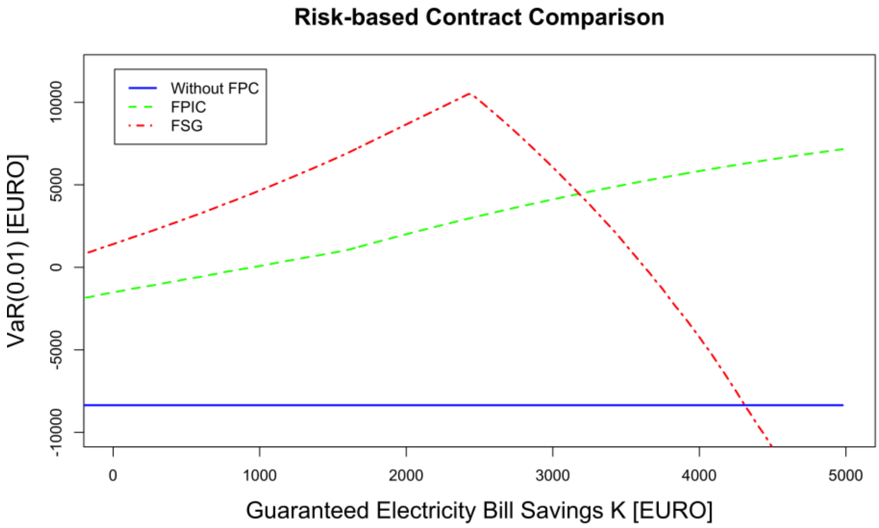

Figure 4. Comparison of risk mitigation capability based on the VaR.

To summarize, the results of our simulation show that the FSG is clearly beneficial with respect to the applied risk measure and is even superior to the FPIC. Only for very high guaranteed electricity bill savings the preference will be reversed in favor of the FPIC. In general, both FPCs offer risk transfer opportunities. Nevertheless, the risk mitigation capability of FPCs is very sensitive to the determination of individual contract parameters. This underlines the importance of an adequate FPC design and appropriately fitted contract parameters for both, flexibility providers and FPC issuers. Hereby, IS can offer an important contribution for an efficient fitting of parameters and therefore significantly reduce the financial risk of flexibility providers. FPCs can contribute to a broad implementation of DR measures and more generally to the adoption of DSM. Therefore, FPCs augment the economically viable and socially useful application of IS.

6 Conclusion

The integration of renewable energy sources in the electricity system increases the importance of a broad implementation of flexibility in electricity demand. IS facilitate the use of flexibility measures and can thereby contribute to a more efficient and sustainable electricity system. This paper assessed the capability of FPCs to mitigate financial risks for flexibility providers. Therefore, we evaluated how FPCs contribute to a transfer of performance risks related to the implementation and execution of DR measures from flexibility providers towards diversified FPC issuers.

We extended existing literature by the concepts of two risk transfer contracts insuring financial risks, illustrated how to calculate a risk premium and derived an equivalence principle to compare different contract designs from a risk transfer perspective. A simulation-based model evaluation was presented for an industrial refrigeration system, which provides flexibility through the application of a ToU tariff. Forecasted electricity prices were processed within a linear programming model to derive the optimal electricity consumption strategy of the refrigeration system. Finally, we performed a simulation for the present value of annual electricity bill savings. Our results reveal that the implementation of a ToU tariff entails high risks as electricity market price developments lead to temporarily or permanently increasing electricity prices for the ToU tariff. In some cases, electricity bill savings do not materialize at all for the flexibility provider. Hence, the ToU tariff can be even unfavorable compared to a conventional constant electricity tariff. Although existing IS already provide the technological foundation that enables the efficient execution of DR measures, these findings underline the necessity for risk transfer instruments to foster a broad implementation of DR measures. Nevertheless, the results have shown to be very sensitive, which emphasizes the importance of determining contract parameters with appropriate risk mitigation.

In line with our methodological approach, we confirmed the functionality of FPCs as risk transfer instruments for flexibility investments. The model evaluation showed that FPCs positively contribute to risk mitigation of investments in the provision of flexibility. While the FSG offers higher risk transfer capabilities for ordinary guaranteed saving levels, the FPIC retains opportunities for high financial benefits. Therefore, considered FPCs are well-suited risk transfer instruments for flexibility providers. They enhance the attractiveness of DR measures and increase incentives to invest in the provision of flexibility for risk averse flexibility providers.

Present business models related to energy services, and particularly FPCs, rely on an advanced information availability and processing. Hence, it is the task of IS to foster the development of forecasting methods and algorithms to ensure the economic profitability of DR measures. Solely an advanced IS infrastructure can process information from different sources with the necessary degree of efficiency and accuracy. For FPC issuers, it is decisive to manage and hedge market risks in a sufficiently large portfolio to keep counterparty risks small. Issuers can hedge FPCs with forward contracts and other derivatives on electricity markets or via over-the-counter trading. Besides flexibility aggregators, the expertise of other entities (e.g. insurance companies) could lead to a forward momentum for the development and propagation of risk transfer contracts in the context of flexibility.

Besides those implications, our work has some limitations: (1) only two different contract designs were derived to demonstrate the impact of the cash flow design on risk transfer capabilities. Therefore, future research may extend the two proposed FPCs for further contract designs. Since there are no limitations for the design characteristics of such bilateral contracts, various manifestations are considerable. Nevertheless, FPIC and FSG are well-suited to illustrate coherencies between contract design and risk transfer capability and provide a solid basis for further analyses. (2) Some reasonable assumptions were stated to allow a simplified comparison of the FPIC and FSG. Pricing under perfect information (Akerlof, 1970) and risk neutral preferences for the FPC issuer (Rothschild and Stiglitz, 1976) were assumed. (3) The empirical case study relies on the application of a ToU tariff that represents only one specific application of a DR measure. Next to our presented case study, future work should examine FPC applications for further DR measures and additional electricity markets. Although a shift of electricity trading volumes towards energy-only-markets can be observed, other market places still offer possibilities to utilize flexibility, e.g. balancing power markets. (4) The fluctuating electricity price is the only risk factor that was regarded for our modelling approach. In addition to this economic risk, other risk categories related to the implementation of DR measures that we outlined in Section 2 could be included in future analyses. Future work should also incorporate additional risk factors of DR measures in combination with FPCs for a holistic evaluation of economic profitability. Special attention should be paid to IS that facilitate decision support systems, which determine and execute optimal electricity consumption strategies and algorithms for industrial processes. Advanced information-driven forecasting models should incorporate long-term effects to improve forecast accuracy. Optimization algorithms should adaptively respond to changes of the market environment and internal process constraints.

Our results have the potential to accelerate the implementation of DR measures through the application of FPCs. This work contributes to the transition of our energy system towards the integration of renewable energy sources and, thus, to achieve the overarching objective of a more sustainable energy system.

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