Decision Support for Structured Energy Procurement

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Abstract: Infrastructure operators in Germany such as airports or factories are confronted with rising energy costs throughout the last years and consequently have to reconsider their energy supply and management. This competitive pressure raises the question of an optimal procurement strategy, which takes into account the individual organizational framework and conditions. In the context of the SmartEnergyHub research project this problem was addressed at the example of the Stuttgart Airport by the implementation of a decision support system to manage and evaluate long-term procurement plans. Uncertainties related to future price developments and load fluctuations have been taken into account with the help of a Monte Carlo simulation. Ex-post analysis show, that the cost of hedging has been between 10 - 15 % of stock procurement costs in the investigated scenarios due to falling energy stock prices. This raises the question, how much certainty in budget may cost. The developed software module creates transparency of the cost structure of historic procurements and facilitates the comparison of different future procurement plans with regard to expected costs and risks. The focus of the presented work lies on infrastructure operators, who follow a structured energy procurement strategy based on a long-term contract with a single energy supplier.

1 INTRODUCTION

Within the last years continuously falling energy stock prices could be observed in Germany, whereas companies have to cope with increasing energy costs due to taxes and levies (German Association of Energy and Water e.V. BDEW, 2016). This leads to a competitive pressure to optimize energy procurement and consumption. On the other hand energy providers have to restructure their grids in face of the switch to renewable energies, necessitating new pricing and participation models (Valipour et al., 2016). Energy companies can thus use price incentives to make their customers adapt their energy consumption to supply (Mitra et al., 2016).

Within the research project SmartEnergyHub[1] a holistic approach is pursued to support infrastructures such as airports, harbors, industrial or chemical parks, factories and public facilities to successfully procure energy in this changing market. In (Florian Maier and Zech, 2016) an architectural concept for a software platform is presented, showing which software components are required to identify and realize energy optimization potentials. Whereas the *internal optimization* module within this solution generates short-term operating schedules taking into account current data like daily production plans or current weather forecasts, the *market optimization* module has its focus on supporting infrastructure operators to find procurement plans which fit to their risk attitude with a long-term perspective.

The German energy market offers a broad variety of options for market participation for both producers and consumers of energy. So the first step in defining an energy procurement strategy is the choice of an appropriate procurement model. In general three different procurement models can be distinguished, which differ from one another with respect to costs, risks and personnel expenditures. Especially small and medium enterprises often conclude full supply contracts

[1]www.smart-energy-hub.de

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with a one-time specified fixed price which minimizes staff costs (1). As an alternative to these contracts different kinds of structured energy supply contracts are offered, which allow buying energy at the future market in advance and trading at the spot market to adjust the previously bought energy to the actual demand (2). Thus the company is given the ability to cope with price and volume risks. For large industrial enterprises there is also the option to realize their own portfolio management which offers the most degrees of freedom but also requires a constant market observation (3).

One example of such a large enterprise is the Stuttgart Airport, which is a partner in the SmartEnergyHub project. Based on this pilot user, this work describes the complex decision-making problem related to energy procurement in large infrastructures. Based on this, a simulation based decision support system is developed to support the infrastructure operator to answer the following question: Which quantity of energy should be bought at which time via which product?

This work is structured as follows. Section 2 gives an overview of models and approaches, which offer solutions to the problem of finding optimal procurement strategies either for SMEs, large companies or energy suppliers. Section 3 takes a closer look at individual aspects of the procurement problem introducing a systematic methodology to describe the solution space. Following this methodology it is explained how this solution space is shaped in the example of the Stuttgart Airport. In Section 4, the prototype implementation of a decision support system based on a Monte Carlo simulation is described. Section 5 describes how this software component, which is one part of the SmartEnergyHub architecture, is used to find appropriate procurement plans. Finally, Section 6 gives a conclusion and an outlook on future work.

2 RELATED WORK

In this section, we examine the areas of energy procurement decisions both from the perspective of consumers, energy suppliers and distributors.

(Kumbartzky and Werners, 2016) focus on optimal energy procurement strategies from the perspective of SMEs based on a two-stage optimization model. Stochastic influences concerning prices and energy demand are taken into account by the introduction of a finite number of scenarios. For all scenarios optimal procurement strategies are found and compared by a minimax relative regret approach. Contract costs are split up to allow modeling take-or-pay clauses as well as additional charges for excess capacities consumed. In a case study the cost saving potential of structured procurement strategies are shown.

Monte Carlo simulations are a numerical simulation technique and a wide spread approach for example for the derivation of an optimal portfolio as described in (Cvitanić et al., 2003) and (Boyle et al., 2008). Variants of Monte Carlo simulations like the least squares Monte Carlo is used to determine energy option value in (Nadarajah et al., 2017).

In (Prokopczuk et al., 2007) a Monte Carlo simulation based model is developed to quantify risks related to wholesale electricity contracts from the perspective of an electricity supplier, who is able to diversify unsystematic risk through a large portfolio of many customers. Within the model the *Risk-adjusted-Return-on-Capital* is used as a risk measure. Price risks are modeled using the SMaPS (Spot Market Price Simulation) developed in (Burger et al., 2004). Uncertainties related to the energy demand are derived by correlating spot market prices to individual load curves thus simulating individual load paths. It is argued that a supplier will offer contracts at a price reflecting risk premiums for the hourly spot market price risk, a risk premium for the volume risk and a risk premium related to the price-volume correlation.

In (Woo et al., 2004) procurement strategies for local distribution companies are developed. Such a company has three possibilities to satisfy customers' electricity demand namely through self-generation, spot market transactions and forward-contracting. A heuristic procedure is presented to minimize expected procurement costs for a given risk tolerance level resulting in the determination of the energy amount which will be bought in advance in future-contracts.

Price structures in German energy market are the subject of (Pietz, 2009) where the presence of risk premiums in German electricity market with a focus on month futures is investigated. It is concluded that there is evidence for positive risk premia, which decreases with increasing time-to-delivery. Similarly, (Daskalakis et al., 2015) investigate electricity risk premia in the European market and find a correlation with the volatility of the spot market and carbon dioxide futures, concluding that carbon price fluctuations are a factor in discounts for electricity consumers.

(Hong and Lee, 2013) focus on an energy consumer who can choose among different suppliers to meet the energy demand. A Monte Carlo simulation is used to quantify each supplier's risk and to allocate orders among multiple suppliers. (Bessembinder and Lemmon, 2002) focus on optimal forward positions for energy producing and retailing firms using an equilibrium approach. The existence and nature of risk premium in forward market is also subject of their investigations.

In (Conejo et al., 2010) the procurement decision problem is modeled as a multi-stage stochastic problem for large consumers. The target function consists of two components, namely the expected procurement cost and the weighted risk measure Conditional Value at Risk (CVaR). This typically represents the trade-off between scenarios with low expected costs and higher risks and scenarios with higher expected costs for reduced risks.

Commercial software solutions address different aspects of the procurement decision problem commonly supporting purchasing processes in portfolio management teams. kWantera's product Faraday[2] for example supports buyers and sellers of energy to place bids and offers on energy markets. Enernocs procurement platform[3] tracks market movements alerting traders and operators in case transactions need to be adjusted. In the context of power plant resource planning similar optimization problems have to be solved. Procom's software Bofit[4] supports power plant operators in planning and optimizing their energy production as well as trading. A stochastic dynamic programming approach is applied in Time-steps' TS Energy[5] to optimize the operation of pumped-storage power plants.

Overall, the related work shows the complexity of finding optimal procurement plans under uncertainty related to price and load fluctuations. However, a tool for infrastructure operators is missing, which helps to reduce this complexity by integrating external information sources and platforms without the need to establish an own portfolio management team. Therefore, to solve the energy procurement problem of large infrastructure operators like Stuttgart Airport, a solution must provide infrastructure operators with the possibility to find procurement plans appropriate for their risk attitude, which we will develop in the following sections.

3 METHODOLOGY

The following steps have been developed in cooperation with the project partners and pilot users to define a systematic methodology with the goal of finding procurement plans, which are consistent with the risk attitude of the company:

[2] www.kwantera.com

[3] www.enernoc.com

[4] www.procom.de

[5] www.time-steps.com

- **Degrees of freedom:** The first step consists of the identification of controllable parameters within the procurement strategy. From a long-term perspective the appropriate choice of a energy supplier and a supply contract can be regarded as one of the main degrees of freedom. If there is already a structured supply contract, this contract allows the choice of one or several of the following parameters:
  - Hedging quote: Defines the ratio of energy procured at the future market to the total energy demand. The more energy is procured on the future market (which results in higher hedging quotes) in advance, the lower the price risk is.
  - Product: On the energy exchange power future market currently year, quarter, month, week, weekend and day products are traded, each as base and peak products. Year products can be traded 6 years in advance whereas day products can only be traded 1 day in advance. It has to be determined which of those products should be bought.
  - Volume: Some contracts include the constraint of minimum quantities which can be bought. Apart from that, it has to be decided, if a certain amount of energy should be bought in fixed or variable tranches.
  - Purchasing time: It has to be decided in which period of time energy is bought on the future market and at which point in time during this period.
- **External and stochastic influences:** Apart from controllable parameters within the procurement process there are the following external stochastic influences:
  - Energy prices: Energy prices on the future market as well as the spot market are not known in advance and have to be modeled as stochastic influences in the decision.
  - Energy consumption: The actual energy consumption is usually also not known in advance because it depends on production plans and weather conditions. However, to a certain degree the energy consumption can be influenced, e.g. by load shedding or self-generation. This short term optimization is part of the internal optimization module and is not further covered here. For the following considerations it is assumed that the energy consumption is also stochastic.
- **Notion of risk:** It can be assumed that the security of supply is ensured independently from the supply contract and the choices which are made by

the company within the frame of the contract. Depending on the contract some decisions may lead to higher costs or even penalties nevertheless. The main risk can be derived from stochastic influences such as unexpected increases in energy prices or deviations in the actual energy consumption. Most of the companies not only try to minimize expected procurement costs but try to minimize procurement costs for a given risk level or try to find an optimal combination of risks and costs.

- **Finding appropriate procurement plans:** After modeling the controllable parameters, the external and stochastic influences as well as choosing an appropriate risk measurement, different procurement plans can be compared according to their risk and expected costs. This can be done retrospective to gain insight into past procurement plans and decisions as well as for future procurement periods.

The following section describes how the previously defined steps have been practically applied to support the creation of the procurement process at Stuttgart Airport.

The first step was to analyze the current situation in several workshops to identify the framework conditions as well as the degrees of freedom. Until the end of 2013 the Stuttgart Airport procured energy based on a full supply contract. Since 2014 a structured energy procurement was introduced using an energy service provider. This opens up new possibilities to procure parts of the required energy in advance on the future market in the form of year, quarter or month products. With the purchase of those products for base (0-24 hours) and peak time slots (8-20 hours) it becomes necessary to replicate the actual load curve by purchases and sales on the spot market. To mitigate the risk of purchases at high prices, those purchases can be split up into several even tranches. Due to internal operational requirements the procurement starts 1 to 2 years before delivery. Within those framework specifications decisions can be made to determine, when to buy which amount of energy in the form of which product. So far a significant part of the total required energy has been procured at the future market in advance.

Uncertainties exist mainly with regard to the price development at the spot and future market as well as with regard to the load profile during delivery. Having said that the module market functions is one part of the SmartEnergyHub platform, existing modules could be used to take into account these stochastic influences. In this way spot price forecasts provided by the external company ICIS [6] can be used by appropriate import interfaces. ICIS is a market information provider and offers e.g. forecasts for the German spot market. The spot price forecasts are regularly updated allowing working with latest market information in the market function module. Within this context the question arises, whether the existence of positive risk premiums can be assumed in the German energy market, which has been examined from different perspectives (Pietz, 2009).

With the support of the SmartEnergyHub forecast module load predictions based on historic load profiles have been generated. Workshops with the Stuttgart Airport allowed the distinction of different forecast scenarios. It should be noted that estimates by the infrastructure operator concerning changes compared to previous years are an essential prerequisite for accurate predictions. Changes occur for instance with the installation of additional photovoltaic plants or the construction of new buildings.

Assuming that there are positive risk premia observable on the future market and transaction costs both on the future and on the spot market are equal, an exclusive minimization of total expected procurement costs results in a hedging quote of 0, which means that the total energy demand is covered through transactions on the spot market. In practice an exclusive minimization of total expected procurement costs is rarely observed. Instead, a risk-aware procurement strategy is usually pursued, which leads to hedging quotes larger than 0. This is why the comparison of procurement costs should be run in consideration of expected costs and the related risk. Following (Prokopczuk et al., 2007) CFaR has been chosen as a central risk measurement and is defined as $Q_\sigma - \mathbb{E}$ where Q_σ is the 95 % quantile of the procurement cost distribution and $\mathbb{E}$ represents the expected procurement cost.

For the generation of procurement plans an approach has been developed, which allows the splitting of the total required energy amount, derived from the load forecast, into individual products (see also Section 4). Based on the spot price forecast a Monte Carlo simulation is run to determine the expected procurement cost $\mathbb{E}$ as well as the risk measure CFaR. The aim of the developed software module is to visualize the effects of different parametrization and allow a comparison of several alternatives with respect to costs and risks. For ex-post analysis of historic procurement plans transactions were scaled to simulate various hedging quotes.

[6] www.icis.com

4 IMPLEMENTATION

The procurement process entails four steps:

1. In the *planning phase* a procurement plan gets generated based on load and price forecasts. It consists of the planned future transactions in the procurement period.
2. In the second step, the *procurement phase*, these transactions are conducted with aid of the energy provider.
3. In the *delivery phase* the power then gets delivered and potential over and under coverages are counterbalanced through spot transactions.
4. In the *accounting phase* the effected transactions are billed based on the previously signed contract.

Hereafter we primarily focus on the first phase of the procurement process despite the goal for the module market functions to support the entirety of the procurement phases. The module market functions interact with other system components and provides the infrastructure manager respectively its procurement agent with a graphical interface for analysing and executing procurement plans. To import data into the database in a coherent format, external services such as spot price forecasts, current EEX market data and procurement platforms of energy providers are integrated through the Non-Sensor import module of SmartEnergyHub (Florian Maier and Zech, 2016). Additionally long-term power forecasts, that are internally generated, are also provided through the database. For a systematic access of these resources the proxy pattern was used. A PriceService proxy for accessing historic, current and predicted prices exists, that caches time series on demand. An analogues LoadCurveService proxy was created to encapsulate the access to historic and predicted load curves. Historic transactions are retrievable through a TransactionService proxy for ex post analysis. Newly generated procurement plans for prospective delivery periods can be saved and managed using the module. For the actual execution of transactions an individual communication process with the energy provider is required, for example by transmitting an order through mail or using a graphical user interface supplied by the energy provider.

4.1 Domain Model

A central domain object is the *time series*, which is used for representing price forecasts and load curves amongst others. The procurement plan is another essential object, which is defined by its set of transactions. Each transaction is associated with exactly one

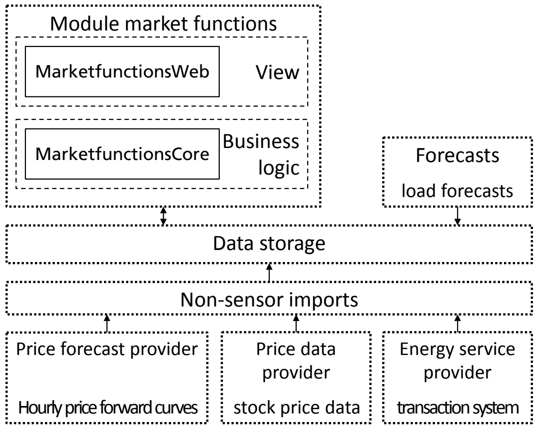

Figure 1: Overview of main components.

procurement plan and encapsulates the following properties: product type, power, delivery start and end, timestamp of the transaction, cost as well as unit information. The sum of all transactions costs constitutes the overall procurement cost of a procurement plan. A procurement plan always refers to one delivery year and enables the coverage of a companies energy requirements in this period.

4.2 Transaction Generation Procedure

In the following an approach for generating a valid procurement plan is shown. This encompasses the determination of the amount of energy to be bought on the future market for each product type. Then, for each product type times of purchase are determined, which is a preliminary step for defining tranches. A previously generated power forecast in hourly resolution for the delivery year is required. Procurement shall be separated into base and peak products to model the characteristic nightly load decrease.

1. In the first step the hedging quote is defined. Based on a hourly load prediction the energy amount to be procured on the future market can be determined by taking the sum over the hourly energy consumption, which is then multiplied with the hedging quote.
2. Afterwards the type of product with the shortest delivery period is identified. This could be a quarter, month or week product for example. Under the assumption of a requested separation into base and peak products, the sum of the hourly energy consumption for Peak (8-20 hours) and Offpeak (20 - 8 hours) time slots is calculated for the identified product with the shortest delivery period. In the case of month products the following outcome could be achieved:

Table 1: Initial time slices.

time span	work (in MWh)	power (in MW)	hours of use
January peak	1104	4	276
January offpeak	936	2	468
February peak	1008	4,2	240
February offpeak	820,8	1,9	432

3. Based on the hours of use the power values can be determined for each product. To transform the peak-offpeak-split into base(0-24 hours) and peak-products, the power of the offset hours is used for the base product. The resulting power of the peak product can then be calculated as the difference between the base product power and the previous peak hours:

Table 2: Base and peak products.

product	work (in MWh)	power (in MW)	hours of use
January base	1488	2	744
January peak	552	2	276
February base	1276,8	1,9	672
February peak	552	2,3	240

4. The duration of the trading period for EEX standard products depends on the duration of the delivery period. If it is requested, that future transactions should begin 1 - 2 years before delivery, month products with a maximum trading period of 9 months before delivery are out of scope. Nevertheless it is possible to partially substitute several products with a short delivery period with a product with a longer delivery period, resulting in potentially different costs. As an example one can think of 3 month base products with a power of 3 MW (April), 2 MW (Mai) and 4 MW (June), which can be replaced by a quarter base product with 2 MW and 2 month products with 1 MW (April) and 2 MW (June). This substitution does not change the amount of energy delivered, whereas the purchase of the quarter product would be possible 33 months in advance. This is why in the following products with a short delivery period are always replaced by products with longer delivery periods thus increasing the flexibility to choose the purchase time.
5. After splitting the expected energy amount for one year into different kind of products with the goal of an optimal approximation of the predicted load curve, the next step consists of finding transaction timestamps and purchase amounts. There are different alternatives for this task such as splitting the amount of energy, which should be bought in equal tranches, which are bought periodically during the procurement stage. Another possibility is to determine the amount to purchase in a more flexible way based on market observations, which results in higher time efforts.

4.3 Graphical User Interface

The graphical user interface supports the infrastructure operator in managing procurement plans, conducting retrospective analysis of finished procurement plans and allowing the comparison of future procurement plans with respect to expected costs and risks.

The screenshot 2 displays how a user can configure the creation of a procurement plan by selecting the procurement period for year as well as quarter products and defining the number of tranches. On the side there is a slider which allows setting the hedging quote. Based on the user input a procurement plan is generated in the backend based on the previously described procedure.

The procurement plan is then displayed to the user as a table (see Figure 3) and can be used as a schedule for energy purchases.

5 EVALUATION

The developed decision support system was applied in a use case to analyze historic procurement decisions as well as to create future procurement plans at the Stuttgart Airport.

In retrospective procurement simulations for the exemplary delivery year 2014 it is noticeable that the hedging quote had a major impact on total procurement costs as can be seen in Figure 4, which shows hedging quotes ranging from 0 - 100 percent on the x-axis, correlated with the resulting normalized total procurement costs on the y-axis. A procurement strategy with a hedging quote of 100 percent would have caused procurement costs which lie about 15 percent higher compared to a hedging strategy with a zero hedging quote. So an increase of 10 percent in the hedging quote and thus higher price certainty resulted in about 1.5 percent higher procurement costs. This strong increase of costs with increasing hedging quotes is mainly due to falling energy spot prices within the relevant period. The picture is similar for the following year 2015 where the costs of hedging in a 100 percent hedging scenario were 12 percent higher compared to a zero hedging quote strategy.

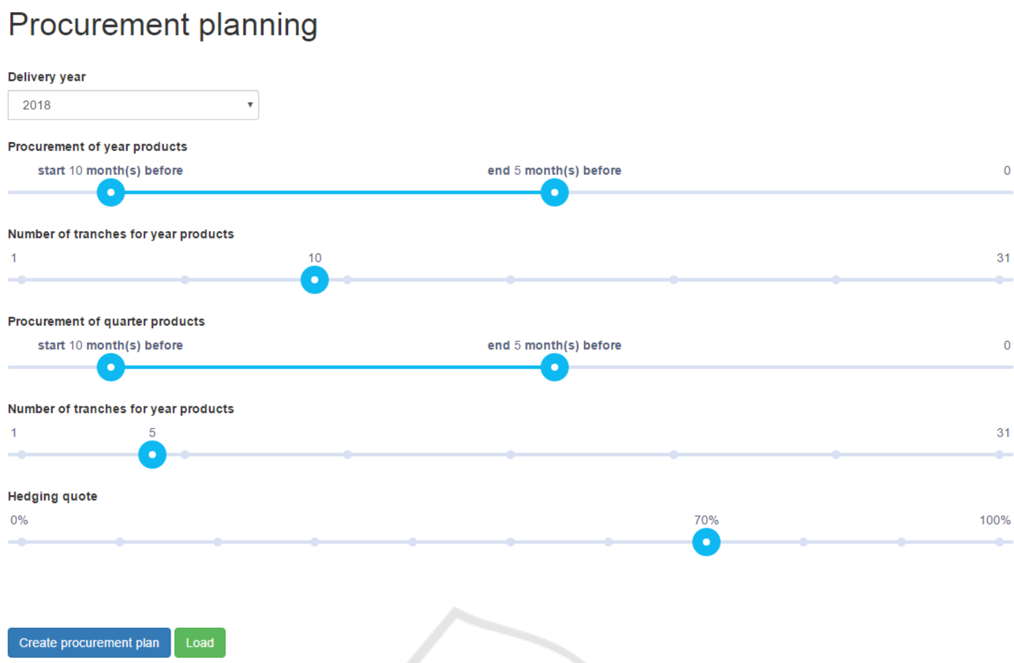

Figure 2: Configuration of procurement plan generator.

Timestamp ▲	Exchange	Power in MW	Quantity in MWh	Delivery start	Delivery end	product type 1 (all)	product type 2 (all)
07.03.17	EEX_DEU	0,899	7.875,240	01.01.18	01.01.19	BASE	J
07.03.17	EEX_DEU	0,075	58,500	01.01.18	01.04.18	PEAK	Q
07.03.17	EEX_DEU	0,133	416,556	01.01.18	01.01.19	PEAK	J
06.06.17	EEX_DEU	0,004	3,120	01.04.18	01.07.18	PEAK	Q
06.06.17	EEX_DEU	0,027	58,968	01.04.18	01.07.18	BASE	Q
05.09.17	EEX_DEU	0,087	192,096	01.07.18	01.10.18	BASE	Q
05.12.17	EEX_DEU	0,012	26,508	01.10.18	01.01.19	BASE	Q
05.12.17	EEX_DEU	0,090	71,280	01.10.18	01.01.19	PEAK	Q
Total			**8702.268**				

Figure 3: Procurement plan.

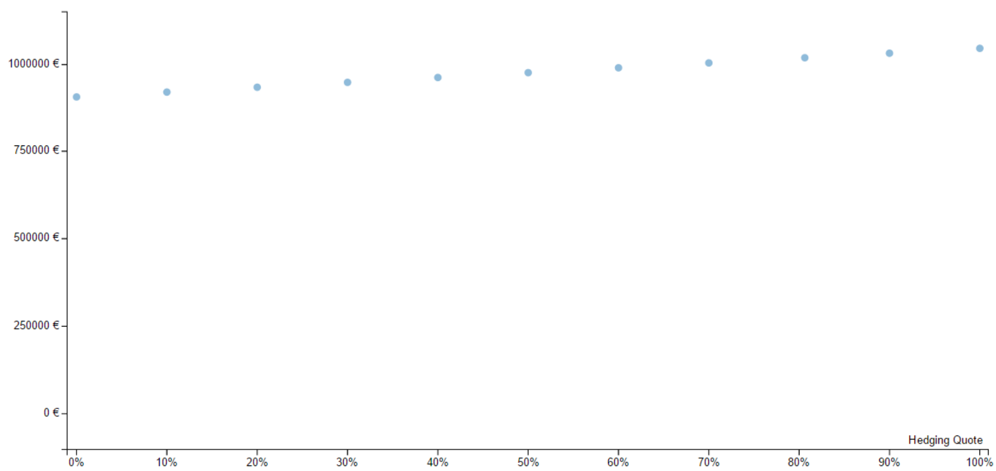

Figure 4: Ex-post correlation between hedging quote and procurement costs 2014.

To study the effects of various influence factors on the resulting procurement costs and risks, different kind of simulation scenarios have been defined. In the first scenario the load curve was assumed as given, whereas spot prices were assumed to be fluctuating. The second scenario starts from the opposite assumption with given spot prices and fluctuating load curves. In the third scenario fluctuating spot prices as well as fluctuating load curves were used to give a realistic picture of the correlations.

Figure 5 shows the cost distribution for different hedging quotes based on a Monte Carlo simulation. It is assumed that spot prices are on average lower than future prices, which results in higher expected costs for higher hedging quotes. At the same time one can observe that the scattering is smallest for a hedging quote of 100 percent, reflecting the lowest price risk. Even with a hedging quote of 100 percent, the total average procurement costs are not fully deterministic as random variations in the energy demand make spot market transactions inevitable.

To provide the infrastructure operator with the possibility to investigate the effects on costs and risks of a specific parametrization, an interactive simulation element has been integrated into the user interface (see Figure 6), allowing the user to start a Monte Carlo simulation and see an updated frequency chart after each iteration step 6. After a simulation run the user is provided with the aggregated results of the simulation, essentially the expected total procurement cost as well as the CFaR based on a confidence level of 95 percent quantifying the risk of the procurement plan. The outcome depends heavily on the assumptions made for the accuracy of the load prediction by the prediction module and the integrated spot price forecasts provided by ICIS. Under the assumption that those estimates are unbiased on an hourly basis the simulation over the 8760 hours within one year result in frequency charts with low variances resulting in low CFaRs for a hedging quote of 70 percent.

This heuristic approach offers an easy-to-use possibility to compare a manageable amount of alternatives with regard to risk and expected costs. The tool could be extended by the explicit solution of the decision problem determining optimal values for all degrees of freedom.

After successful evaluation with historic and simulation data with a focus on the years 2014 and 2015, the decision support system is in productive use at Stuttgart Airport to determine the energy procurement plan in 2018.

6 CONCLUSIONS AND OUTLOOK

In this work we developed a simulation based decision support system for energy procurement of large infrastructure providers.

We evaluated this system based on historical data of Stuttgart airport as well as simulation data, finding that the ex-post cost of hedging lay with 15 percent of the total procurement costs for 2014 and 12 percent for 2015 due to falling spot prices. On the other hand this system supports infrastructure operators to investigate the effects of the parameter choice in the creation process of future procurement costs. Higher hedging quotes reduce the price risk resulting in higher expected procurement costs.

Based on this specific use case it was assumed, that the infrastructure operator makes procurement decisions within the frame of a long term energy contract with a single energy supplier. The selection process of this energy supplier within a public tender or a reverse auction process is not part of the investigation. By taking into account multiple contracts with different energy suppliers at the same time the approach could be extended.

The system is currently in productive use at Stuttgart Airport for 2018. This work is a part of the market optimization module in the SmartEnergyHub platform, which aims to optimize energy production, consumption and procurement for large infrastructure providers.

In future work we plan to compare the estimated procurement costs and related risks based on our simulations with the realized costs. This implies the comparison with other algorithms like dynamic stochastic optimization as well as the use of other risk measures. Besides, it should be possible to realize purchase decisions with the energy provider automatically within the same module.

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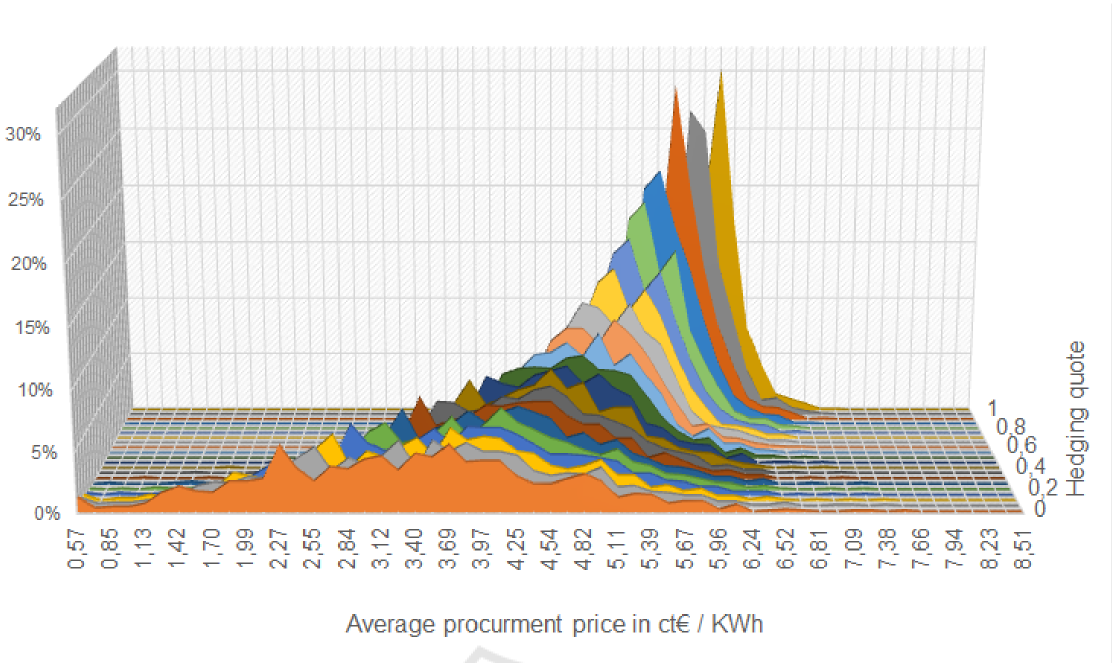

Figure 5: Procurement costs and influence factors.

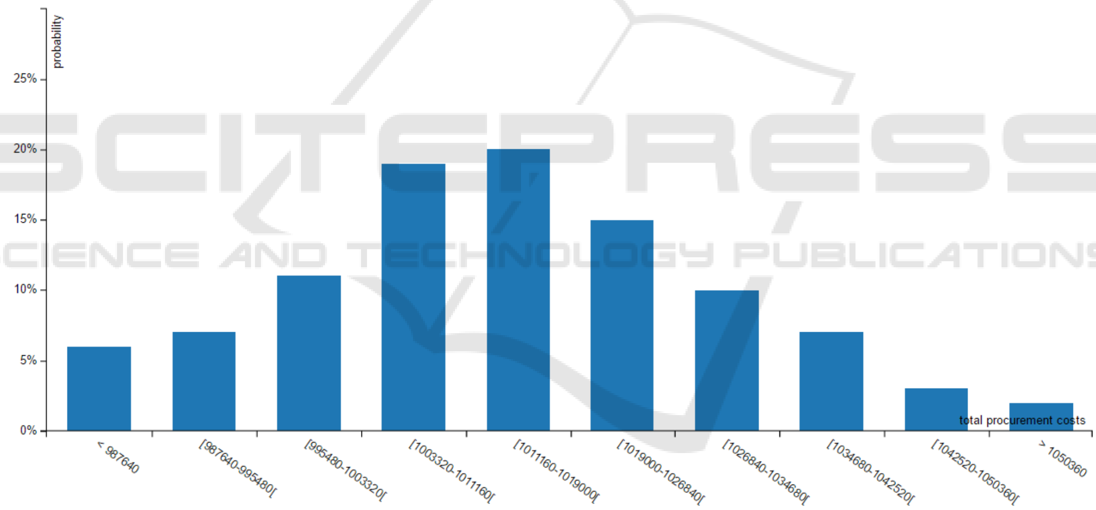

Figure 6: Frequency chart.

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