



Research Center
Finance & Information Management



Project Group
Business & Information
Systems Engineering

Decision Flexibility vs. Information Accuracy in Energy-intensive Businesses

by

Gilbert Fridgen, Andrea Saumweber, Johannes Seyfried, Lars Wederhake

presented at: 26th European Conference on Information Systems (ECIS),
Portsmouth, UK, June 2018

WI-738

University of Augsburg, D-86135 Augsburg
Visitors: Universitätsstr. 12, 86159 Augsburg
Phone: +49 821 598-4801 (Fax: -4899)

University of Bayreuth, D-95440 Bayreuth
Visitors: Wittelsbacherring 10, 95444 Bayreuth
Phone: +49 921 55-4710 (Fax: -844710)



DECISION FLEXIBILITY VS. INFORMATION ACCURACY IN ENERGY-INTENSIVE BUSINESSES

Research in Progress

Fridgen, Gilbert, University of Bayreuth, Bayreuth, Germany, gilbert.fridgen@fim-rc.de

Saumweber, Andrea, University of Augsburg, Augsburg, Germany, andrea.saumweber@fim-rc.de

Seyfried, Johannes, University of Augsburg, Augsburg, Germany, johannes.seyfried@fim-rc.de

Wederhake, Lars, University of Augsburg, Augsburg, Germany, lars.wederhake@fim-rc.de

Abstract

Demand-side management and demand response are integral building blocks for environmental sustainability. Exchange-based power pricing serves as an economic mechanism to set incentives to shift demand to periods where prices are low. Low power prices also serve as an indicator for green(er) power, since high feed-ins from variable renewable sources push the electricity price downward. For businesses, minimizing electricity costs thus not only contributes to economic but also environmental sustainability. Hence, especially energy-intensive businesses can become greener and more competitive by integrating volatile electricity prices into their production planning activities. In this paper, we demonstrate that the length of the planning horizons is key to achieve more sustainable outcomes due to the trade-off between decision flexibility and information accuracy. Decision flexibility – i.e. the capability to shift processes – increases with longer planning horizons. Information accuracy – i.e. price accuracy – increases with shorter planning horizons. Information Systems (IS) can help to balance this trade-off. We follow a data-driven approach and derive both actual and predicted electricity spot prices from historic electricity intraday market data in Germany. We find that decision flexibility and information accuracy affect the planning horizon as conceived. First results indicate that more sustainable outcomes are achieved with longer planning horizons.

Keywords: Decision support systems, demand response, energy-aware scheduling, sustainability.

1 Introduction

Energy-intensive businesses (EIBs) can be described by their large energy consumption (Song and Oh, 2015), as prevalent in industries like aluminum, basic chemicals, pulp and paper, or steel (U.S. Energy Information Administration, 2016). Globally, EIBs consume more than a quarter of the total delivered energy¹ (U.S. Energy Information Administration, 2016). The energy costs can reach up to 40% of their total productions costs on average (European Commission, 2016) making it a very relevant economic lever. As for electricity, an EIB consumes at least 150 GWh annually, corresponding to 50,000+ households (Eurostat, 2017; Agora Energiewende, 2014). Wholesale electricity prices exhibit very high volatility (Zhang and Grossmann, 2016) which is higher than most other commodities' volatility (Aggarwal et al., 2009). Since an EIB can manage large proportions of its electricity consumption, it can exploit this volatility over time (Merkert and Harjunoski, 2017). If an EIB's capacities are not running at full-load and production processes are sufficiently decoupled from other production stages (Merkert et al., 2015), the EIB can align its production with exchange-based electricity prices (Merkert and Harjunoski, 2017). This is commonly referred to as energy-aware scheduling – a form of demand response (Albadi and El-Saadany, 2008; Merkert and Harjunoski, 2017). When variable renewable sources generate electricity, the additional supply pushes the wholesale price downward (Hirth, 2013). Low exchange prices thus indicate a green(er) power mix (Hirth, 2013). Most important with regard to sustainability is thus that aligning electricity consumption with wholesale prices does not only contribute to economic but also environmental sustainability. This link gives especially EIBs an edge to foster energy transitions while improving their competitiveness (Finn and Fitzpatrick, 2014).

Smart grid technologies establish the required infrastructure for data collection and exchange (Zhang and Grossmann, 2016; Yalcintas et al., 2015), improvements in modelling and algorithms lay the basis for energy-aware scheduling (Merkert et al., 2015). Moreover, automated decision and optimisation support with regard to the sustainable use of energy has become pivotal (Harjunoski et al., 2014; Plitsos et al., 2017). Information systems (IS) thus have been enabling the integration of energy and wholesale electricity prices into planning activities. Despite these advances in favour of energy-aware scheduling, there are unresolved challenges, which necessarily have to be addressed (Zhang and Grossmann, 2016). In that vein, we suggest that there is a trade-off regarding the timeframe, which is considered for scheduling, i.e. – the length of the planning horizon: the longer the planning horizon the more price periods are taken into account. More price periods are more likely to incorporate larger price differences and price valleys - i.e. periods of low prices. We refer to this as decision flexibility. The more decision flexibility the higher are the cost saving potentials (Feuerriegel et al., 2012). However, at planning moment, future spot prices are uncertain and the level of uncertainty in the electricity price increases the longer it is planned ahead (Zhang et al., 2016; Aggarwal et al., 2009; Ierapetritou et al., 2002). We take an IS view of this and regard it as a lack of information (Watson et al., 2010). Poor price assumptions lead, in turn, more probably to suboptimal scheduling (Ierapetritou et al., 2002). Thus, better information accuracy can lower the total electricity costs. Decision flexibility will increase with *longer* planning horizons, while information accuracy increases with *shorter* planning horizons. The length of the planning horizons might have a significant impact on the effectiveness of energy-aware scheduling. Therefore, determining the length of the planning horizon should be part of IS for energy-aware scheduling. Addressing this involves interdisciplinary research at the crossroads of IS and operations research (OR) in order to study the trade-off between decision flexibility and information accuracy. IS must inform the decision support to optimally size the planning horizon based on proven optimisation methods from OR. From this, we state the following overarching research question (RQ-O):

How does the length of the planning horizons affect the electricity costs in energy-aware scheduling?

We strive to address the various facets of RQ-O in a (series of) future full paper(s) – such as the quantification of the potential environmental improvements, the separate analysis of EIB's planning by sequential versus rolling horizons, or considering various electricity market setups. With this Research-

¹ Delivered energy corresponds to the heat content of energy consumed by the end-user. It incorporates electricity without conversion losses and fuels used for combined heat and power facilities.

in-Progress (RiP) paper, we take a first humble step in the direction of RQ-O. We refine the research question for this RiP paper (RQ-RiP), which is based on the hypothesis that there is a trade-off between decision flexibility and information accuracy having an impact on electricity costs, as follows:

Does the length of the planning horizons affect the electricity costs in energy-aware scheduling?

This and potential future articles in this stream shall contribute to the body of knowledge informing the design parameters of energy-aware-scheduling. With regard to the trade-off between decision flexibility and information accuracy, the planning frequency or the planning policy similar to Sridharan and Berry (1990) or Xie et al. (2004) might have a relevant impact as well.

2 Methodology

We follow the research cycle proposed by Meredith et al. (1989). The cycle comprises the three consecutive and iterating stages of description, explanation, and testing. To the best of our knowledge, there is no prior research examining the aforementioned trade-off, which we wish to demonstrate with RQ-O and RQ-RiP. Hence, we launch an initial research cycle with this RiP paper, to which we will tie in our (series of) future full paper(s). The stage of description of the research cycle aims to comprehensively characterise a situation (Meredith et al., 1989). Hence, we outline how EIBs might size their planning horizon for energy-aware scheduling. The stage of explanation embeds this description into a concept (Meredith et al., 1989). We hypothesise, supported by prior research, that the length of planning horizon exhibits a trade-off between decision flexibility and information accuracy. The stage of testing examines whether the hypothesised concept holds true (Meredith et al., 1989). We intend to make research on the trade-off both, objective and transparent. However, intervening in planning activities of a real-world business is not possible without impact on its daily business. Furthermore, the scope of varying the length of the planning horizons is very limited and research deems inappropriate in timescale. Therefore, we mimic an EIB which minimises electricity costs of its production in a deterministic simulation (Neumann and Morlock, 2004). The simulation allows to experimentally vary the length of the planning horizons in different scenarios. For objectivity, we conduct a scenario analysis and vary the characteristics of the EIB's production and its way to procure electricity. Within the simulation, we use a deterministic optimisation model (Neumann and Morlock, 2004) to optimise the production schedule with regard to electricity prices. The EIB cannot know the future exchange prices but can only assume them – i.e. we mimic the EIB from an ex-ante perspective. For price assumptions, we utilise historical electricity price data from the German intraday markets, following the expectations theory from Fama and French (1987). For evaluation of the scenarios, we take an ex-post perspective. While the EIB utilises price assumption for scheduling, the final electricity costs are evaluated with realised prices. In analogy to Häckel et al. (2016), this serves as an established back-testing approach. In this paper, we present the description, the explanation and the simulation used for testing in section 3. They are applicable to both research questions RQ-O and RQ-RiP, if not stated otherwise. However, we will present the problem context formally in the (series of) future full paper(s) to come because of a RiP's brevity.

For RQ-RiP, we focus on running a relevant proportion of the simulation scenarios, only. A single example will give first evidence that the trade-off exists and legitimate the impact of the length of planning horizons in energy-aware scheduling. Further scenarios, required to state the general concept, will follow in the (series of) future full paper(s). Hence, we only vary between the lengths of the planning horizons and the way of procuring electricity. All other parameters are fixed. We present these and evaluate the instantiation by the back-testing approach in section 4. In section 5, we eventually draw a conclusion with regard to RQ-RiP. We show limitations and give an outlook on our future research activities referring to RQ-O.

3 Problem context

Because EIBs are business organisations, decisions regarding planning activities are at least greatly influenced, if not entirely determined, by economic rationale (Simon, 1979). EIBs strive to improve (optimise) economic metrics e.g. economic-value added (Chen and Dodd, 1997). With regard to production

planning, cost management and corresponding metrics are most prevalent (Beamon, 1998). In this paper, we try to isolate the phenomenon represented by the trade-off. Hence, we set a clear focus on electricity costs leaving the consideration of costs and risks from staff, materials, other forms of energy, capital etc. for further research. We furthermore assume that the EIB is fully exposed to electricity price risk, as rescheduling and adoptions during the planning horizon are not possible.

Relying on automated decision support for energy-aware scheduling, the EIB must – in advance – fix planning moments, at which it creates production schedules. In this paper, we consider EIBs, which schedule their production in sequential planning horizons. This means that at every planning moment, the EIB schedules the production processes for the upcoming planning horizon. The length of each planning horizon corresponds to the timeframe between two planning moments. The lengths of the planning horizons remain constant as scheduling is a periodical task for the EIB.

We postulate that the length of the planning horizons determines the level of decision flexibility and information accuracy, which will affect the business’ electricity costs. For decision flexibility, we follow the view of Merkhofer (1977): “[...] the more alternatives available for a decision – the greater the decision flexibility.” Applied to the trade-off in this paper, longer planning horizons comprise more alternatives to operate production processes and thereby more decision flexibility. Such an effect was e.g. observed by Fridgen et al. (2016). They find that the savings from shifting the charging time of an electric vehicle increase for longer time windows. This ties in with Feuerriegel and Neumann (2014) and Feuerriegel et al. (2012). They find that savings from shifting and cutting loads increase with longer timeframes. They argue that with more time periods larger price differences are considered, what supplements the savings. We schematically illustrate trade-off in three hypothesised versions in figure 1. All graphs display that with longer planning horizons costs attributed to the lack of decision flexibility decrease. As electricity prices are bounded (Epex Spot, 2017), we assume that the costs attributed to the lack of decision flexibility will reach a lower limit. For information accuracy, we refer to the accuracy of price assumptions. Information accuracy decreases with longer planning horizons as the future becomes increasingly uncertain. Such an effect was e.g. observed by Zhang et al. (2016). Although they forecast future prices instead of utilising market prices for predictions, we rest assured their findings are applicable to our context. Likewise, we transfer the findings from Aggarwal et al. (2009). They note that longer forecast horizons decrease the accuracy of forecasting models. Furthermore, Sridharan and Berry (1990) investigate design parameters to determine a businesses’ production program under demand uncertainty. They find that longer planning horizons lead to worse decision-making. The graphs in figure 1 display this behavior, as the costs attributed the lack of information accuracy increase with longer planning horizons. As electricity prices are bounded (Epex Spot, 2017), the costs attributed to the lack of information accuracy will reach an upper limit.

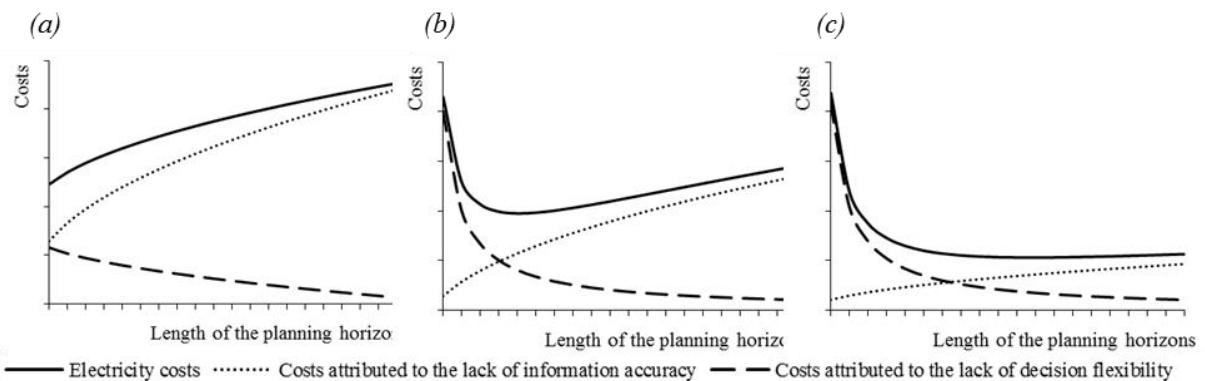


Figure 1. Hypothesised (electricity) cost development in dependence on the length of the planning horizons

In figure 1, the electricity costs result from the sum of the costs attributed to the lack of information accuracy and decision flexibility. Dependend on the level of impact of information accuracy or decision flexibility, we conceive three different versions of the trade-off. If information accuracy has higher

impact than decision flexibility we suppose rising electricity costs with longer horizons (cf. figure 1a). This means that the EIB shall plan with the minimum possible length of the planning horizons. If decision flexibility has higher impact than information accuracy we suppose declining electricity costs with longer horizons (cf. figure 1c). This means that the EIB shall plan with the maximum possible length of planning horizons. If the level of impact for decision flexibility and information accuracy is or becomes similar, we suppose that electricity costs are minimal for a certain planning horizon (cf. figure 1b).

To demonstrate this effect, we apply a deterministic simulation (Neumann and Morlock, 2004). We mimic an EIB, which schedules production processes with respect to electricity prices in sequential planning horizons. We run the simulation in different scenarios and vary the lengths of the planning horizons for the specified simulation timeframe, similar to Xie et al. (2004). Figure 2 displays the simulation with two different lengths of planning horizons. At each planning moment, the business decides for the upcoming planning horizon when to operate production processes. The objective is to minimise electricity costs while considering the demanded target output and the production site's capacity limitations. The production processes all have a fixed duration, in the following referred to processing time, and a fixed electricity consumption profile. Thereby, shifting the processing times is the only lever to reduce electricity costs. We apply a deterministic optimisation model (Neumann and Morlock, 2004) to determine the most cost-effective processing times. For the target output, we assume the same utilisation relative to every length of planning horizons. This means that a planning horizon twice the length of another one also has twice the target output. This makes different lengths of the planning horizons comparable. We set the production site's capacity such that the EIB can execute no more than one process at a time. We consider production processes, which cannot exceed the start and the end of a planning horizon. Every length of planning horizons is considered possible. There are no constraints like production deadlines etc. We suppose that the version of the trade-off might depend on the characteristics of the EIB's production. Hence, for generalisation, we conduct a scenario analysis and vary the input parameters of the simulation. For characteristics of the production processes, we, in this RiP paper apply only one archetypal electricity consumption profile. Also, in this first step, we refrain from changing characteristics of the production site such as the utilisation – i.e. raising or lowering the target output per planning horizon.

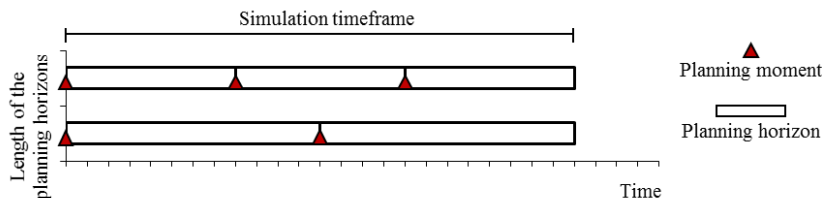


Figure 2. Simulation runs with different length of planning horizons

As for the electricity prices used in the optimisation model, we rely on the expectations theory from Fama and French (1987). According to this theory, the expected future spot price equals the price of a forward or futures contract plus a risk premium. Therefore, prices of forward or future contracts are a predictor of future spot prices. Huisman and Kilic (2012) and Haugom and Ullrich (2012) e.g. show the predictive power of forward and future contracts in the electricity markets of the Netherlands, NordPool or Pennsylvania-New Jersey-Maryland (PJM). We transfer these findings to the German intraday markets. We view all trades before gate closure as (very) short-term forward or future contracts for the referenced time period, in the following referred to delivery periods. The price at gate closure functions as the spot price. In the continuous intraday markets, the forward prices for a delivery period change over time what we interpret as change in the EIB's level of information.

As for the simulation, at each planning moment, the EIB observes the current prices and uses them to build the energy-aware schedule. As the spot price might be different from the forward price, the EIB faces the risk of suboptimal scheduling. However, the EIB can also buy immediately and fix the current price instead of postponing the procurement to the future. It has the possibility to avoid price risks.

However, the risk prevention might come in exchange for a risk premium². We test whether the trade-off exists for both cases.

The simulation eventually computes the realised electricity costs for each scenario over the whole simulation timeframe. We want to stress that when procuring electricity immediately the electricity prices at planning moment and the realised prices are the same. When procuring electricity in the future, the realised prices do not correspond to the prices at the planning moment. This is the price uncertainty the EIB faces. For benchmarking purposes, we compare both ways of procurement against an ex-post case with perfect information. The EIB knows the future spot prices at planning moment and builds the energy-aware schedule on them. The EIB thus neither faces risk premia nor price uncertainty. Hence, information accuracy does not influence the results in this scenario, only decision flexibility.

4 Problem instantiation

4.1 Exemplary data set

As stated in section 2, we only run a relevant proportion of the simulation scenarios in this RiP paper. We legitimate that the length of the planning horizons affect the electricity costs but to not intend to examine the trade-off in-depth, yet. Examples shall give first evidence with regard to the trade-off in specific and our RQ-RiP in general. Hence, in this RiP paper, we fix some parameters, as displayed in table 1: the production processes have a processing time of 45 minutes and represent a prototypical electricity consumption profile. The mimicked EIB's planning horizons are utilised by 75 %. This is the percentage of time, at which the EIB executes processes within every planning horizon. Consequently, in 25% of the time, the EIB executes no processes.

	Unit	Exemplary Data
Processing time	[min]	45
Electricity consumption profile	[MWh]	1.15, 1.96, 1.72
Utilisation	[%]	75
Length of planning horizons	[h]	1, 2, 3, 4, 5, 6, 7, 8, 12, 24
Simulation timeframe	[yr]	1
Time grid of the simulation	[min]	15
Number of simulation runs	[1]	32

Table 1. Exemplary data set of the simulation

As for price data, we utilise historic electricity prices from the European Power Exchange (EPEX Spot) of the year 2016. Precisely, the data comprises the German continuous intraday market for quarter hours and the intraday auction. These products cover delivery periods of quarter hours. We adopt the time grid of our simulation model to these. Each time period in the simulation thus encompasses 15 minutes. From the price data, we derive a price curve for each delivery period. The intraday auction of this delivery period provides an initial price. This price changes whenever a trade occurred at the continuous intraday market for the same delivery period. We only capture the electricity prices at potential planning moments, which occur every 15 minutes. This provides the simulation model with a consistent time grid. The resulting price curve states the observable price at the electricity market for the particular delivery period. In the simulation, these prices are used as a predictor for future spot prices and as price for the immediate procurement. Eventually, the intraday and the specified production data allow testing all planning horizons with the lengths of all full hours between one and eight. Moreover, it is possible to

² We want to stress that research about whether risk premia exist in electricity markets is inconsistent (Benth et al., 2013). However, the results in this paper (cf. section 4.2) indicate that there is a risk premium in the intraday market. We leave an in-depth-analysis on this topic to future research.

test 12 hours and 24 hours. The intraday data allows 32 possible simulation starts (every 15 minutes between 4:00 pm and 11:45 pm). We run the simulation for all these starts to prevent biased results due to the daily intraday price pattern.

4.2 Results and discussion of the problem instantiation

Referring back to our research question in this RiP paper, we study whether the length of the planning horizons affects electricity costs. As we view the trade-off as a cause of this impact, we now put attention to the attribution of costs with regard to decision flexibility and information accuracy. In order to do so, we first discuss costs attributed to decision flexibility, second costs attributed to information accuracy, and finally the electricity costs.

Decision flexibility: Figure 3a displays the medians of the electricity costs of the 32 simulation runs of the benchmark. We interpret the benchmark as costs attributed to the lack of decision flexibility since information accuracy does not increase the total electricity costs in those scenarios. Figure 3 illustrates that the length of the planning horizons does affect decision flexibility or the electricity costs. In the problem instantiation, the costs attributed to decision flexibility decline monotonously with longer planning horizons as hypothesised. The cost curve is convex, which indicates that the costs attributed to the lack of decision flexibility might reach the perceived lower limit.

Information accuracy: Figure 3b displays the medians of the differences between the electricity costs for the immediate/future procurement and for the benchmark. We interpret this difference as the costs attributed to information accuracy since in the benchmark the EIB has perfect information. The grey curve depicts the difference between the costs attributed to information accuracy (future procurement) and the benchmark. It inclines monotonously with longer planning horizons. The maximum rests at 24 hours. This is because greater uncertainty increases the likelihood of suboptimal scheduling. However, the curve is not concave between six and eight as well as eight and 24 hours. Thus, we cannot yet validate that information accuracy will reach an upper limit. The black curve depicts the difference between the costs attributed to information accuracy (immediate procurement) and the benchmark. When the prices at the planning moments are fixed, the schedules are more costly than in the benchmark. We interpret this as a risk premium. The risk premia rise for longer planning horizons. This conforms to more uncertainty for larger timeframes and more uncertainty again should lead - ceteris paribus - to higher risk premia. However, the incline is not monotonous. This might be an indication that electricity sellers do not only price risk premia in terms of time.

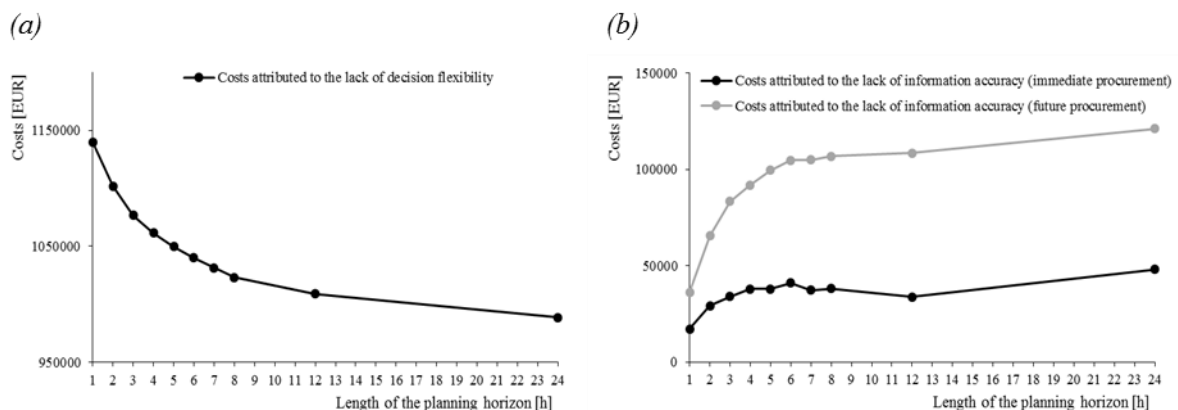


Figure 3. Costs attributed to the lack of decision flexibility (a) and costs attributed to the lack of information accuracy for different length of planning horizons (b)

Electricity costs: Figure 4 displays the medians of the electricity costs from the 32 simulation runs for both types of procurement. In view of RQ-RiP, the planning horizon affects the electricity costs for either type of procurement. The curves both monotonously decline and reach their minimum at the length of the planning horizons with 24 hours – i.e. the maximum is a boundary value. Within the 24

hours, this corresponds to the stylised version of the trade-off, in which the impact of decision flexibility outweighs the impact of information accuracy (cf. figure 1c). However, the curves for costs attributed to information accuracy are not concave. Therefore, we cannot state if the curves would rise again for longer planning horizons. This prevents assigning the problem instantiation to a stylised version of the trade-off depicted in figure 1.

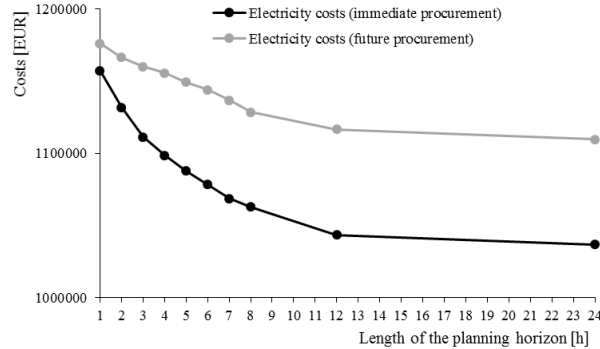


Figure 4. Electricity costs for different lengths of planning horizons

5 Conclusion, limitations, and outlook

In this paper, we identify two factors, which an EIB should consider when striving to realise the economic potential of energy-aware scheduling: decision flexibility and information accuracy. The length of the planning horizons functions as a lever to improve either decision flexibility or information accuracy. We hypothesise that these two factors are conflicting. Shorter planning horizons result in greater information accuracy and *fewer* related costs. Shorter planning horizons, however, result in less decision flexibility and *higher* related costs. We test this proposition by building a deterministic simulation, which mimics energy-aware scheduling for different lengths of planning horizons. We run the simulation on real-world data from the German intraday markets. We find clear evidence for our hypothesis that the planning horizon affects the electricity costs. In particular, we attribute costs to both the lack of information accuracy and lack of decision flexibility for all studied lengths of the planning horizons. We validated that the costs due to the lack of information accuracy increase on average with longer planning horizons. However, costs attributed to the lack of decision flexibility, in turn, decrease with longer planning horizons. Our results give some evidence that there is a trade-off between decision flexibility and information accuracy.

In view of RQ-O, we are going to analyse how the trade-off behaves when changing electricity consumption profiles and the utilisation of the production site. By doing so, we aim at generalising insights with regard to how the length of planning horizons affects the electricity costs. From a longer-term perspective, it will be relevant for research to examine at least the following three aspects in more detail in future: first, it is important to study longer timeframes and thus other forms of electricity procurement (day-ahead markets, forwards etc.). Second, as EIBs make use of diverse planning procedures such as planning in a rolling horizon environment like Sridharan and Berry (1990) or Xie et al. (2004). Research should test, if our hypothesis remains observable in such settings as well. Third and finally, shifting consumption to times of lower prices positively influences the environmental performance of an EIB. As researchers in the domain of Green IS, we feel obliged to extend our research by explaining how planning horizons affect the EIB's (indirect) greenhouse gas emissions. With its methods from OR and decision sciences as well the more design-oriented research from decision support systems, the IS discipline is well positioned to contribute to the sustainability of EIBs which are crucial to energy transitions worldwide.

References

- Aggarwal, S. K., L. M. Saini and A. Kumar (2009). "Short term price forecasting in deregulated electricity markets: A review of statistical models and key issues." *International Journal of Energy Sector Management* 3 (4), 333–358.
- Agora Energiewende (2014). *Comparing electricity prices for industry: An elusive task – illustrated by the German Case*. Agora Energiewende.
- Albadi, M. H. and E. F. El-Saadany (2008). "A summary of demand response in electricity markets." *Electric Power Systems Research* 78 (11), 1989–1996.
- Beamon, B. M. (1998). "Supply chain design and analysis: Models and methods." *International Journal of Production Economics* 55 (3), 281–294.
- Benth, F. E., R. Biegler-König and R. Kiesel (2013). "An empirical study of the information premium on electricity markets." *Energy Economics* 36, 55–77.
- Chen, S. and J. L. Dodd (1997). "Economic value added (EVA): An empirical examination of a new corporate performance measure." *Journal of Managerial Issues* 9 (3), 381–333.
- Epex Spot (2017). *Trading on EPEX Spot 2017*. URL: http://static.epexspot.com/document/36894/2017-01_EPEX%20SPOT_Trading%20Brochure_E.pdf (visited on 11/26/2017).
- European Commission (2016). *Report from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions: Energy prices and costs in Europe*.
- Eurostat (2017). *Compilers guide on European statistics on natural gas and electricity prices: 2016 edition*. European Union.
- Fama, E. F. and K. R. French (1987). "Commodity futures prices: Some evidence on forecast power, premiums, and the theory of storage." *The Journal of Business* 60 (1), 55–73.
- Feuerriegel, S. and D. Neumann (2014). "Measuring the financial impact of demand response for electricity retailers." *Energy Policy* 65, 359–368.
- Feuerriegel, S., J. Strücker and D. Neumann (2012). "Reducing price uncertainty through demand side management." In: *ICIS 2012 Proceedings*. Orlando, Florida, USA.
- Finn, P. and C. Fitzpatrick (2014). "Demand side management of industrial electricity consumption: Promoting the use of renewable energy through real-time pricing." *Applied Energy* 113, 11–21.
- Fridgen, G., L. Häfner, C. König and T. Sachs (2016). "Providing utility to utilities: The value of Information Systems enabled flexibility in electricity consumption." *Journal of the Association for Information Systems* 17 (8), 537–563.
- Häckel, B., A. Lindermeir, F. Moser and S. Pfosser (2016). "Evaluating Different IT Innovation Investment Strategies from an Ex Ante and Ex Post Evaluation Perspective." *International Journal of Innovation and Technology Management* 13 (04), 1650015.
- Harjunkoski, I., C. T. Maravelias, P. Bongers, P. M. Castro, S. Engell, I. E. Grossmann, J. Hooker, C. Méndez, G. Sand and J. Wassick (2014). "Scope for industrial applications of production scheduling models and solution methods." *Computers & Chemical Engineering* 62, 161–193.
- Haugom, E. and C. J. Ullrich (2012). "Market efficiency and risk premia in short-term forward prices." *Energy Economics* 34 (6), 1931–1941.
- Hirth, L. (2013). "The market value of variable renewables: The effect of solar wind power variability on their relative price." *Energy Economics* 38, 218–236.
- Huisman, R. and M. Kilic (2012). "Electricity futures prices: Indirect storability, expectations, and risk premiums." *Energy Economics* 34 (4), 892–898.
- Ierapetritou, M. G., D. Wu, J. Vin, P. Sweeney and M. Chigirinskiy (2002). "Cost minimization in an energy-intensive plant using mathematical programming approaches." *Industrial & Engineering Chemistry Research* 41 (21), 5262–5277.
- Meredith, J. R., A. Raturi, K. Amoako-Gyampah and B. Kaplan (1989). "Alternative research paradigms in operations." *Journal of Operations Management* 8 (4), 297–326.
- Merkert, L. and I. Harjunkoski (2017). "Integrating energy optimization and production scheduling in energy-intensive industries." In: *Advances in energy systems engineering*. Ed. by G. M. Kopanos, P. Liu and M. C. Georgiadis. Cham, Switzerland: Springer International Publishing, p. 601–620.

- Merkert, L., I. Harjunkoski, A. Isaksson, S. Säynevirta, A. Saarela and G. Sand (2015). "Scheduling and energy – industrial challenges and opportunities." *Computers & Chemical Engineering* 72, 183–198.
- Merkhofer, M. W. (1977). "The value of information given decision flexibility." *Management Science* 23 (7), 716–727.
- Neumann, K. and M. Morlock (2004). *Operations Research*. 2nd Edition. Munich, Germany: Hanser.
- Plitsos, S., P. P. Repoussis, I. Mourtos and C. D. Tarantilis (2017). "Energy-aware decision support for production scheduling." *Decision Support Systems* 93, 88–97.
- Simon, H. A. (1979). "Rational decision making in business organizations." *The American economic review* 69 (4), 493–513.
- Song, C. and W. Oh (2015). "Determinants of innovation in energy intensive industry and implications for energy policy." *Energy Policy* 81, 122–130.
- Sridharan, V. and W. L. Berry (1990). "Freezing the master production schedule under demand uncertainty." *Decision Sciences* 21 (1), 97–120.
- U.S. Energy Information Administration (2016). *International Energy Outlook 2016*.
- Watson, R. T., M.-C. Boudreau and A. J. Chen (2010). "Information Systems and Environmentally Sustainable Development: Energy Informatics and New Directions for the IS Community." *MIS Quarterly*, 34 (1), 23–38.
- Xie, J., T. Lee and X. Zhao (2004). "Impact of forecasting error on the performance of capacitated multi-item production systems." *Computers & Industrial Engineering* 46 (2), 205–219.
- Yalcintas, M., W. T. Hagen and A. Kaya (2015). "Time-based electricity pricing for large-volume customers: A comparison of two buildings under tariff alternatives." *Utilities Policy* 37, 58–68.
- Zhang, Q., J. L. Cremer, I. E. Grossmann, A. Sundaramoorthy and J. M. Pinto (2016). "Risk-based integrated production scheduling and electricity procurement for continuous power-intensive processes." *Computers & Chemical Engineering* 83 (4), 90–105.
- Zhang, Q. and I. E. Grossmann (2016). "Planning and scheduling for industrial demand side management: Advances and challenges." In: *Alternative energy sources and technologies: Process design and operation*. Ed. by M. Martin. Cham, Switzerland: Springer International Publishing, p. 383–414.