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Decision Flexibility vs. Information Accuracy in Energy-intensive Businesses

by

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DECISION FLEXIBILITY VS. INFORMATION ACCURACY IN ENERGY-INTENSIVE BUSINESSES

Research in Progress

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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. Thus, businesses contribute not only to economic but also environmental sustainability minimizing electricity costs. 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 a 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 energy[1] (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 Harjunkoski, 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 Harjunkoski, 2017). This is commonly referred to as energy-aware scheduling – a form of demand response (Albadi and El-Saadany, 2008; Merkert and Harjunkoski, 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 (Harjunkoski et al., 2014; Plitsos et al., 2017). Thus, Information systems (IS) have been enabling the integration of energy and wholesale electricity prices into planning activities.

When designing decision support systems (DSS) for energy-aware scheduling, planning moments, at which production schedules are created, must be determined before the DSS's operative use. We suspect 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 thus 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. In short, decision flexibility will increase with *longer* planning horizons, while information accuracy increases with *shorter* planning horizons. Hence, the length of the planning horizons might have a significant impact on the effectiveness of energy-aware scheduling. The EIB – in advance – locks in the degree of decision flexibility and information accuracy at design time of the DSS. From this, we state the following overarching research question (RQ-O): *How does the length of the planning horizons affect electricity costs in energy-aware scheduling?*

Investigating the trade-off between decision flexibility and information accuracy involves interdisciplinary research at the crossroads of IS and operations research (OR). IS must inform the decision support to optimally size the planning horizon based on proven optimisation methods from OR. 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

[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.

rolling horizons, or considering various electricity market setups. With this Research-in-Progress (RiP) paper, we take a first humble step in the direction of RQ-O and challenge whether the length of the planning horizons impacts electricity costs at all. We state the research question for this RiP paper (RQ-RiP) as follows: *Does the length of the planning horizons affect electricity costs in energy-aware scheduling?*

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* aims to comprehensively characterise a situation (Meredith et al., 1989). Hence, we outlined how EIBs might size their planning horizon for energy-aware scheduling in the introductory sentences.
- The *stage of explanation* embeds this description into a concept (Meredith et al., 1989). In section 3 we review relevant literature to build the hypothesis of the trade-off between decision flexibility and information accuracy from theory.
- The *stage of testing* examines whether the hypothesised concept holds true (Meredith et al., 1989). To do so, an EIB which minimises electricity costs of its production is mimicked in a deterministic simulation (Neumann and Morlock, 2004). We describe the design of this simulation in section 4.1. This also implies the mimicked DSS and the data. We evaluate the hypothesis in section 4.2.

For testing, we consider a simulation to be the best option. Intervening in planning activities of real-world businesses is not possible without impact on their daily business. Moreover, a simulation allows to experimentally vary the length of the planning horizons in different scenarios. In real-world, the scope of varying the length of the planning horizons is very limited and deems inappropriate in timescale. For objectivity and generalization, we conduct scenario analyses and vary the characteristics of the EIB's production and its way to procure electricity. We refrain from modelling the uncertainty in the electricity prices to prevent bias and distortion. Instead we fully rely on historical electricity price data from the German intraday markets, following the expectations theory from Fama and French (1987).
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). Hence, to evaluate the scenarios we take an ex-post perspective on the EIB's total electricity costs – i.e. we compare the realised electricity costs after the EIB's conducted planning activities. In analogy to Häckel et al. (2016), this serves as an established back-testing approach. Regarding RQ-O and RQ-RiP, we attribute and study (opportunity) costs to both the lack of information accuracy and lack of decision flexibility.

This methodology will be applicable to both the initial research cycle regarding RQ-RiP and the following research cycles regarding RQ-O, unless stated otherwise. For RQ-RiP, we only run a relevant proportion of the simulation scenarios, which are specified in section 5.2. A single example will give first evidence that the trade-off exists and legitimate the impact of the length of planning horizons in energy-scheduling. Further scenarios, required to state the general concept, will follow in the (series of) future full paper(s). Likewise, we will present the problem context and the simulation more formally and technically in the (series of) future full paper(s).

3 Hypothesis development

In the following, we define decision flexibility and information accuracy more accurately and refer to existing research to build our hypothesis of the trade-off from theory. 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, 2017a), 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. The effect of the length of planning horizons on information accuracy was e.g. observed by Zhang et al. (2016). Although they forecast future prices instead of referring to the expectations theory (Fama and French, 1987), 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 are bounded. Hence, we assume that the costs attributed to the lack of information accuracy will reach an upper limit.

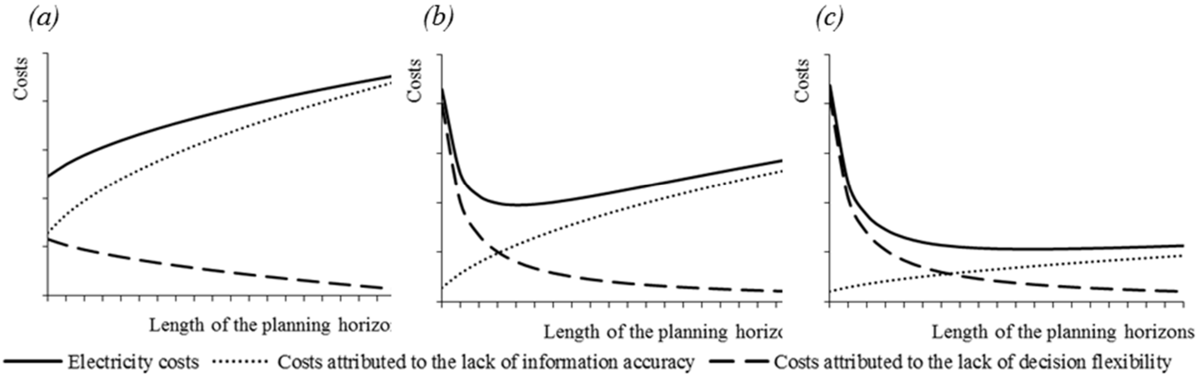

Figure 1. Hypothesised (electricity) cost development in dependence on the length of the planning horizons

In figure 1, the electricity costs result from the sum of the costs attributed to the lack of information accuracy and decision flexibility. Dependent 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 assume 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).

4 Hypothesis testing

4.1 Simulation design

In this paper, we consider EIBs, which schedule their production in sequential planning horizons. The length of each planning horizon corresponds to the timeframe between two planning moments. Scheduling is a periodical task for the EIB and thus the length of the planning horizons remains constant. Planning horizons do not overlap. Furthermore, we assume the EIB is fully exposed to electricity price risk. Rescheduling and adoptions during the planning horizon are not possible.

To mimic an EIB as described, we build a deterministic simulation[2] (Neumann and Morlock, 2004). We programmed the simulation in discrete time steps. In one simulation run the EIB virtually jumps from one planning moment to the next until the end of the simulation timeframe is reached. At every planning moment, a deterministic optimisation problem (Neumann and Morlock, 2004) is solved for the upcoming planning horizon to determine the most cost-effective processing times. This functions as the EIB's DSS. Eventually the simulation sums up the realised electricity costs C_p^r over all planning horizons $p \in P$ to calculate the total electricity costs $TEC = \sum_{p \in P} C_p^r$ for evaluation.

4.1.1 Simulating the Decision Support System

We model the deterministic optimisation problem (Neumann and Morlock, 2004) as binary program (Arkin and Silverberg, 1987; Laalaoui and M'Hallah, 2016; Bartlett et al., 2005). The decision is whether to start a production process t in or not (1.3). Therefore, the optimisation problem is a multidimensional knapsack problem (Fréville, 2004; Kellerer et al., 2004; Bartlett et al., 2005). To isolate the phenomenon of the trade-off, we set a clear focus on electricity costs. We leave the consideration of costs and risks from staff, materials, other forms of energy, capital etc. for further research. Shifting the processing times x_t is the only lever to reduce costs. The objective is to minimise the predicted electricity costs C_p^f (1.0) while considering the demanded target output D (1.1) and the production site's capacity limitations (1.2). We set the production site's capacity such that the EIB can execute no more than one process at a time. The production processes all have a fixed duration d, in the following referred to processing time, and a fixed electricity consumption profile. As a result, costs c_t^f of the production process starting in t is predictable by price and consumption profile. Production processes cannot exceed the start t = 1 and the end t = T of a planning horizon. Since the optimisation program uses predicted costs of production processes, the realised electricity costs C_p^r might differ (1.4).

$$\text{minimize} \quad C_p^f = \sum_{t=1}^{T-d+1} x_t \cdot c_t^f \tag{1.0}$$

$$\text{subject to} \quad \sum_{t=1}^{T} x_t = D \tag{1.1}$$

$$\sum_{k=t}^{t+d-1} x_k \leq 1 \qquad \forall\, t = 1, \dots, T - d + 1 \tag{1.2}$$

$$x_t \in \{0,1\} \qquad \forall\, t = 1, \dots, T - d + 1 \tag{1.3}$$

$$\text{with} \quad C_p^r = \sum_{t=1}^{T-d+1} x_t \cdot c_t^r \tag{1.4}$$

4.1.2 Simulating price uncertainty

As for the electricity prices used to calculate the process costs for 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. Each

[2] The simulation code is available on https://github.com/AndreaSaumweber/Decision-Flexibility-vs.-Information-Accuracy

delivery period is clearly determined by its starting time and its duration. 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 due to continuous trading. We interpret emerging price curves as change in the EIB's level of information.

For price data, we utilise historic electricity prices from the European Power Exchange (EPEX Spot) of the year 2016. The data comprises the German continuous intraday market for quarter hours (CIQ) and the intraday auction for quarter hours (IAQ). In this RiP paper we omitted cross-border trades. The EPEX specifies the data we applied in our simulation online (Epex Spot 2017b). Low, high, weighted average, and last prices are available for review at the EPEX website (Epex spot 2018).

We adapt the time grid of the simulation to the price data. Therefore, each time period encompasses 15 minutes. The intraday auction serves as the initial price of a price curve for a delivery period. This price changes whenever a trade occurred at the continuous intraday market for the same delivery period. The resulting price curve states the observable price at every moment. In the optimization model, these prices are used as a predictor for future spot prices. To provide the simulation model with a consistent time grid, we only capture the electricity prices at potential planning moments, which occur every 15 minutes.

4.1.3 Simulation scenarios

Firstly, we vary the *lengths of the planning horizons* for the specified simulation timeframe, similar to Xie et al. (2004). For comparability between different scenarios regarding the lengths of the planning horizons, we assume the same target output 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. Every length of planning horizons is considered possible. There are no constraints like production deadlines etc.

Secondly, we vary the EIB's *way to procure electricity and its level of information*. This means we change the input data to calculate predicted process costs c_t^f and we change the data to calculate the realised process costs c_t^r. Overall, we consider three scenarios:

- *Future procurement*: At 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. Technically forward prices are used to calculate predicted process costs c_t^f and spot prices to calculate the realised process costs c_t^r. The difference between those corresponds to price uncertainty.
- *Immediate procurement*: The EIB buys immediately and locks in 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 premium[3]. Technically forward prices are used to calculate predicted process costs c_t^f and to calculate the realised process costs c_t^r.
- *Benchmark*: The EIB knows the future spot prices at planning moment and builds the energy-aware schedule on them. The EIB has perfect information and thus neither faces risk premia nor price uncertainty. Technically spot prices are used to calculate predicted process costs c_t^f and to calculate the realised process costs c_t^r.

Thirdly, we vary the EIB's vary the *characteristics of the EIB's production*, since we assume that the version of the trade-off might depend on the characteristics of the EIB's production. These scenarios only applies to RQ-O. In the (series of) future full paper(s) we change the EIB's utilisation – i.e. raising or lowering the target output per planning horizon – and characteristics of production processes – i.e. altering electricity consumption profiles and processing times. In this RiP paper, we fix these parameters: the production processes have a processing time of 45 minutes and represent a prototypical electricity consumption profile with the vector (1.15 MWh, 1.96 MWh, 1.72 MWh). The mimicked EIB's

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[3] 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.

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. 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 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. Table 1 summarises the simulation parameters.

	Unit	**Values**
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. Simulation parameters

4.2 Results and discussion of hypotheses

Referring back to RQ-RiP, we evaluate the impact of the length of the planning horizons on electricity costs. For first indications regarding RQ-O, we put attention to the attribution of costs with regard to decision flexibility and information accuracy.

Decision flexibility: Figure 3a displays the median of the total 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. In figure 3a, 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.

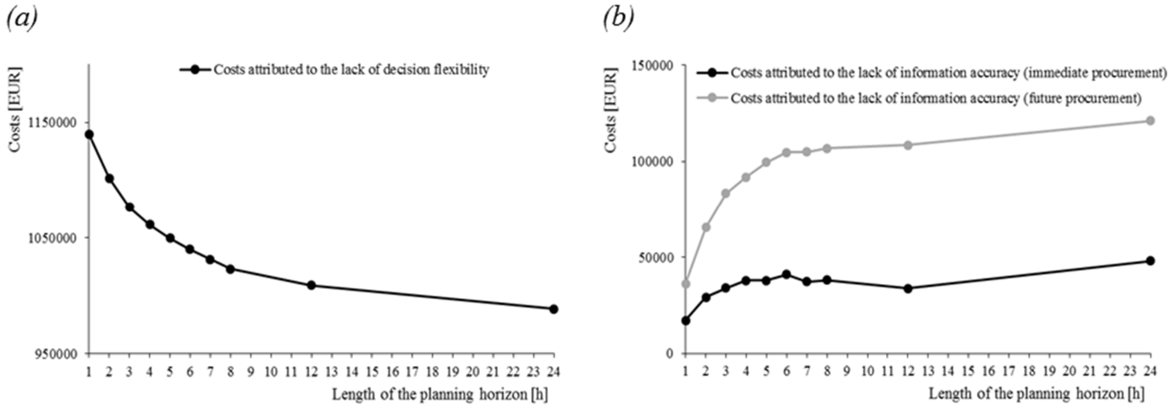

Figure 2. Costs attributed to the lack of decision flexibility (a) and costs attributed to the lack of information accuracy for different length of planning horizons (b)

Information accuracy: Figure 3b displays the median of the differences between the total electricity costs for the immediate/future procurement and for the benchmark (grey/black curve). We interpret this difference as the costs attributed to information accuracy since in the benchmark the EIB has perfect information. The grey curve inclines monotonously with longer planning horizons. The maximum rests at 24 hours as hypothesised. 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 is in the positive range. Hence, immediate procurement is costlier than future procurement without uncertainty. We interpret the black curve as risk premia. Risk premia rise for longer planning horizons. This conforms to more uncertainty for larger timeframes, which 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.

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 total 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.

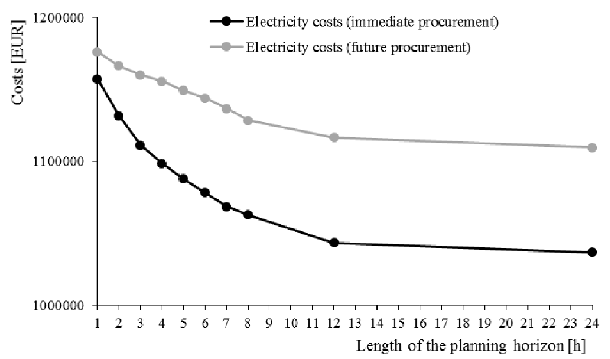

Figure 3. Electricity costs for different lengths of planning horizons

5 Conclusion, limitations, and outlook

In this paper we find clear evidence that the length of the planning horizon affects the economic potential of energy-aware scheduling. That is because the length of the planning horizons functions as a lever to improve either decision flexibility or information accuracy. 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.

From a longer-term perspective, it will be relevant for research to examine at least the following fifth aspects in more detail in future: firstly, it is important to study longer timeframes and thus other forms of electricity procurement (day-ahead markets, forwards etc.). Secondly, 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. Thirdly, as EIBs make use of diverse planning policies 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. Fourthly, the impact of other design parameters besides the planning horizon, e.g., the planning frequency or the planning policy similar to Sridharan and Berry (1990) or Xie et al. (2004) demands further research. Fifthly and finally, we suppose that the suggested trade-off exists in planning activities in other domains with non-storable goods, as well. Generally, when uncertainty in planning increases over time it might conflict with decision flexibility. Similar settings might exist e.g. when an asset manager buys large amounts of one asset and therefore has to execute the order in multiple tranches.

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