Flexibility for Future Electricity Systems - Analyzing Challenges related to Coordination, Complementarity and Predictability

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Table of Contents

1 INTRODUCTION

1.1 MOTIVATION AND RESEARCH QUESTIONS

The current electricity system faces new challenges due to significantly increased infeeds from renewable energy sources (RES). Renewable electricity generation is politically and socially desired and supported in order to make electricity supply more sustainable. Yet, its intermittent character impacts electricity load flows and changes the electricity grid situation.
Traditionally, electricity was generated by large power plants which were usually centrally located or built close to load centers. In contrast, typical new generators such as wind parks and photovoltaic (PV) systems are characterized by the following aspects:

- Generation systems are among others small and micro-plants (PV systems have partly a capacity of less than 10 kWp, wind parks start in the single-digit MW range).
- They are not necessarily located centrally: Due to specific environmental conditions, efficient locations can be outside the traditional system. For example, offshore wind parks benefit from favorable wind situations. (Yet, these parks are typically large-scaled and connected to the transmission grid level, which is not in the scope of this thesis.) As support schemes for PV systems are attractive for small investors such as farmers or home owners, generation systems are distributed amongst urban and rural areas. Particularly the location within the electrical grid is of interest here, as the connection of electric generators to the low voltage level does not correspond to the traditional structure of the grid.
- Their electricity generation is not driven by demand: The conversion of primary energy into electrical energy by these systems depends very much on environmental conditions (such as sunshine or wind speed), and therefore their output is less controllable.

To summarize, electricity is produced nowadays partly by small-scale, distributed and supply-dependent systems and is fed into the grid at the low voltage level. This causes new load situations for the electricity grid, which was built to transmit electricity from higher voltage levels to lower ones. Even with generation occurring geographically close to demand locations, supply is not driven by demand. Additionally, generation as well as demand are small-scaled and a lack of aggregation on low voltage levels leads to a lack of compensation effects between various users. Consequently, the typical flow direction of electricity from higher to lower voltage levels is reversed frequently, which can lead to local congestion situations. The distribution grid faces already today voltage problems as well as overloads at critical locations (cf. dena 2012).
As a consequence, making the demand side more flexible and incentify additional storage operators to enter the electricity markets, would help to balance supply and demand in a more efficient way.

From a technical point of view, thermal devices, electric vehicles and smart household devices (as dishwashers or washing machines which are connected to smart household controllers) can be used to shift electricity demand. Due to inherent storage capacities (like thermal capacities of heat-pump heated buildings) or flexibilities of "background" electricity consumption (e.g. in charging processes or cleaning programs) private households theoretically have a high potential to shift load without loss of comfort (cf. e.g. Klobasa 2007).
Yet, the existing situation is that small-scale consumers are used to use electrical devices on demand. And even in case consumers are willing to use electricity flexibly and financial incentives for load shifting are given, there are still numerous restrictions for small-scale consumers and storage operators: Private consumers will not abandon certain comforts (e.g. instant desires as enjoying freshly brewed coffee or entertainment activities as watching TV) and require technical support to transmit usage decisions to algorithm-based devices. And even storage systems are not unlimitedly flexible. Capacity and filling level affect possible charges and discharges and moreover, charging strategies are influenced by storage specific properties, e.g. aging processes in case of batteries.
Concerning the technical equipment, it can be stated that solutions for acting flexibly and receiving relevant information are more and more available. The field of information technologies has developed significantly over the recent years. Data processing has been accelerated, digital storage capacities have increased, computing power has been improved. Furthermore, automated processes are enabled and it is possible to link far distant users in short times. Regarding the electricity grid, lower voltage levels are starting to be observed and controllable, gateways for means of measuring and sending signals become attractive and bidirectional communication becomes possible. For residential demand side management,timer switches for washing machines and dishwashers together with home-energy-management systems or home-automatization systems and smart meters become available (cf. Bundesministerium für Wirtschaft und Energie 2014).
Yet, the focus of this thesis is not on the challenge of suitable technical equipment, but on the question of how to provide adequate incentives in order to induce a grid usage, which is appropriate in view of requirements of the grid and the market. To be more precise, incentives are required, which

(1) are able to affect consumers' and storage operators' behavior and

(2) lead to an improved system situation.

The latter implies not only the task to balance supply and demand, but also to ensure grid stability by resolving potential congestions, maintaining frequency stability and ensure sufficient reactive power compensation. Moreover, it is to take into account that incentivizing schemes always have certain distribution effects, bringing along advantages and disadvantages for various groups of grid users.
First practical experiences to coordinate renewable generators and flexible consumers or storage suppliers were gained in field tests under the heading "E-

Energy - Smart Energy made in Germany" already (cf. Bundesministerium für Wirtschaft und Energie 2014). Yet, automatization of grid and electrical devices were still in early stages then. More advanced smart equipment will enable a better coordination so that certain questions are the more relevant, e.g. in regard of secure and non-discriminating electricity supply.
In short, the main research questions for this thesis can be formulated as follows:

- Given the technical preconditions for communication and device control, what are further restrictions and how do they limit the benefits of flexibility? Or, to turn it the other way around: What flexibility can be provided realistically by consumers and storage operators?
- Which market instruments help to incentivize and coordinate flexibilities of consumers and storage operators in an appropriate way and what consequences do they have? Namely, grid-related issues as the security of supply, the matter of privacy and distributional effects are considered as critical issues.

1.2 KEY ASPECTS FOR ANALYSIS AND MODELLING

In order to gain a better understanding of the potential to shift electric consumption, special focus is set in the following on the behavior of individual grid users with specific restrictions and possible operation modes for power usage. Assuming a well-advanced technical state for grids and households, the question still remains who can contribute to a secure electricity system even given a high share of volatile infeed. In case of flexible demand, the original objectives of electricity consumption derived from daily needs, comfort seeking and leisure activities should not be impeded by adjustments according to system needs. Also in case of storage systems with a system oriented operation, certain restrictions have to be taken into account, as charging cycle processes depend on technical conditions (mainly capacity and power-to-energy ratio) and may also affect the system's life time.
As specific examples, heat pumps and battery storage systems are analyzed in this thesis. Heat pumps are electrical devices with promising storage potential and decentralized locations. Among a number of technically mature storage systems, the technology 'battery' has the main advantage to be not site-dependent and to be able to store electricity in Megawatt-hour range. Economically beneficial ways of operation are subsequently discussed in the context of certain market situations for both flexibility options.
The applied methodology is mainly an optimization based analysis of operation modes. For the investigated systems, the context of certain market designs is modeled. Thereby exemplary simple restrictions related to certain flexible electrical devices are considered. Further on, available information and existing uncertainties for small-scale users are taken into account, namely uncertain information on prices and environmental conditions as the ambient temperature. Therefore specific heuristics are included in the investigated operation strategies.

The question of setting appropriate incentives to increase flexible demand and storage is a complex one, as it is even hard to decide on the optimal allocation of demand considering the needs of market participants and grid operators at the same time. As a matter of principle, the European zonal electricity market design separates between the market and the grid operation. As a consequence, the general wholesale market does not reflect local balance situations nor critical situations of the physical grid. But e.g. due to occurring infeed at low voltage levels, the congestion problems occur locally in the distribution grid. Particularly voltage violations, which occur more and more often, have to be solved locally. Therefore it is increasingly questionable, whether a general wholesale market, disregarding congestion, provides efficient results. Local markets, defined by current load situations, can reflect scarcity more efficiently.
Therefore a novel market concept is introduced and investigated in this thesis. It is fundamental here that suitable scarcity signals are provided according to current load situations, e.g. resulting from high RES infeed with extreme weather situations. From an economic point of view, a local grid area becomes a separated - and therefore a local - market when congestion limits exchanges with other grid areas (cf. Trepper et al. 2013). As illustrated in Fig. 1, the grid is then separated into a general one and a local one. With advanced automatization, communication and new products, such a market can provide price signals according to current grid requirements.
The aim of this thesis therefore is to investigate an effective pricing mechanism, which computes situation-based signals and interlinks grid users efficiently. Further on, the provision of incentives for all grid users and allocations of benefits in various ways are analyzed.
Due to the fact that willingness and possibility to shift demand as well as amounts of renewable infeed are at least hard to predict (if not generally uncertain), contracts in the very short term are required. Therefore the investigations of suitable pricing mechanisms take into account critical issues as real-time pricing and avalanche effects in this thesis. Particularly real-time pricing mechanisms and expectable response behaviors haven't been subject of the mentioned E-Energy projects as suitable automatization equipment was not available and volatile infeed still limited.

For the simulation of operation decisions and interacting grid users, an agent-based modeling framework is used mainly. By modeling individual agents, individual operation decisions resulting from local market situations and the various grid users can be represented adequately. E.g., within a VDI guideline, an agent is defined as follows: "An agent is an encapsulated (hardware/software) entity with specified objectives. An agent endeavors to reach these objectives through its autonomous behavior, in interacting with its environment and with other agents." (VDI-Richtlinie 2653, Blatt 1, p. 4). Similarly, grid users each have a certain objective, an individual scope of actions and specific limitations. Moreover, the environment - given by technical and environmental conditions as well as by other system participants - affects various system grid users. A certain agent, i.e. an implemented class, can be modeled for each type of grid user,

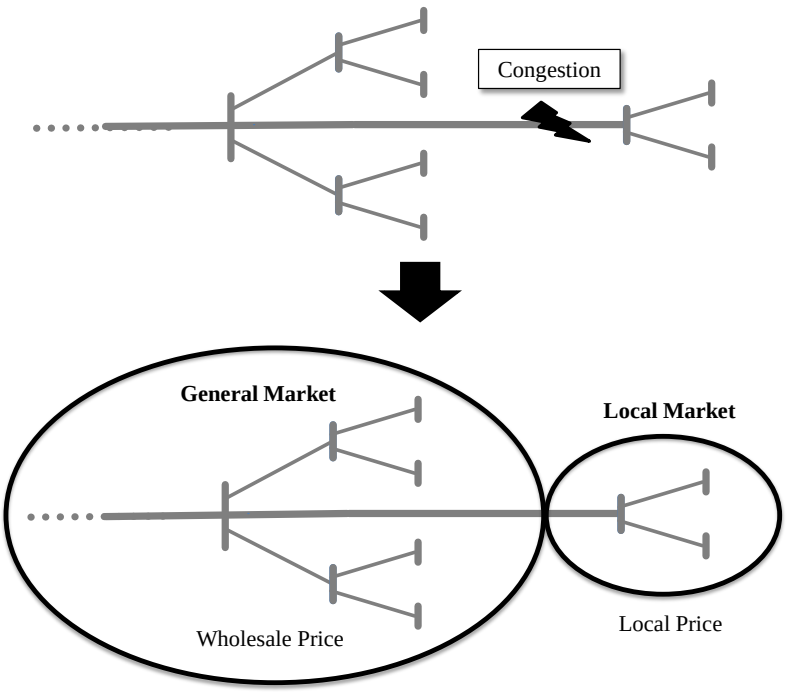

Figure 1: Market Separation due to Congestion

so that specific conditions of e.g. PV systems, heat pumps, electric vehicles, etc. can be represented. Additionally, individual entities of each type or agent, with e.g. specific geographic location, certain technical data and individual dimensions, can be simulated easily. One further advantage of an agent-based structure is that the mentioned variations for types and entities can be modeled easily and clearly (which is advantageous not only for a team-based work). (Cf. Bellifemine et al. 2007)

1.3 STRUCTURE OF THE THESIS

1.3.1 Flexibility of Consumers and Storage Operators

Battery systems as well as heat pumps in (residential) buildings are chosen to analyze selectively instances which provide flexibility by storage resp. by load shifting. The conventional storage system "battery" can be operated as a large-scale, immobile application, so that electricity consumption as well as generation can be adjusted e.g. towards market signals. Electrically driven heat pumps are loads with a flexible consumption ability, as the heated building as well as a possibly added storage tank can store supplied heat.

Investigations focus on factually possible flexibility and given obstacles. Thus, the operators' perspective is investigated in the context of given market prices. Namely, obstacles are:

- Specific flexibility limitations as certain restrictions have to be fulfilled (batteries have certain technical conditions, heat-pump operation has to fulfill comfort conditions initially).
- Due to uncertainties (concerning e.g. prices or weather conditions) heuristic decisions have to substitute perfectly optimal decisions.

Both issues are addressed in the following two papers:

Battery Storage Systems in the Australian Electricity Market - Optimal Operation for various Battery Technologies

by Jessica Raasch, Daniel Ziegler and Christoph Weber

The aim of this paper is the investigation of different storage applications in real-market conditions considering operation restrictions and price uncertainties. Various types of large-scale batteries are investigated. Thereby the market context is the Australian National Electricity Market (NEM) (due to a cooperation with the Queensland University of Technology in Brisbane, Australia, the specific case of the electricity grid in the North-East of Australia has been investigated (cf. Boulaire et al. 2015)). The investigated systems include sodium-sulphur, lead-acid, vanadium redox-flow and lithium-ion batteries. In order to decide on a profitable investment, a detailed battery model and an operation optimization are implemented in GAMS. Special limitations for operation decisions are given here by aging processes. Further on, a heuristic operation mode requires a forecasting mechanism so that the consequence of uncertain prices can be estimated.
As a result it can be stated that the lithium-ion battery is a promising technology. Yet, uncertainties (concerning prices) lead to significant profit reductions here: With a simple forecasting heuristic, operation margins reduce to 7% of the value obtained in simulations with perfect forecast.

Flexible Use of Residential Heat Pumps - Possibilities and Limits of Market Participation

by Jessica Raasch

As an example for relevant flexible demand in private households, the case of a heat pump in a single-family house is investigated. A detailed heating system model with heat pump, thermal storage tank and building is implemented as a MATLAB optimization. Operation simulations are applied within an agent-based model, considering weather agents and market agents in order to represent a realistic context. In order to investigate reasonable market behaviors of small-

scale flexible grid users, spot markets are assumed to allow households' direct participation. Of special interest is the bidding behavior of a residential heat-pump operator, as comfort conditions and limited storage capacities have to be taken into account as well as uncertainties (mainly on weather conditions). Day-ahead as well as intraday procurement are examined in terms of feasibility and profitability.
In fact, it turns out that the matter of uncertain weather conditions is crucial and that purchasing as promptly as possible is advisable.

1.3.2 Market Instruments for Flexibility Coordination and their Consequences

The aforementioned papers have shown that flexibility (including the demand side) is available in general, even if it is subject to certain restrictions. Yet, it is highly important to set adequate incentives to activate these flexibilities. To be more precise, incentives should guarantee

- that flexibility will be provided actually - which implies e.g. the acquisition of applications (as storage systems, smart meters, controllable devices,...) - and
- that given flexibility is coordinated to the benefit of the overall system.

To address these aspects, a local pricing mechanism is applied in the following papers. As a background it can be stated here that a market splitting into local market places with local prices is economically efficient, when the existing grid fails to transmit electricity sufficiently (cf. Trepper et al. 2013). Of certain interest here is that price differences are determined at the distribution grid level. Similar approaches at the transmission grid level are well understood (cf. Schweppe 1988, Hogan 1992, Neuhoff 2013) and implemented with the Local Marginal Prices (LMP), e.g. in North America and New Zealand (cf. Schweppe 1988, Hogan 1992, Neuhoff 2013). Experiences and investigations for the lower grid levels are limited (e.g. Sotkiewicz 2006) but increasingly important in the context of increasing amounts of distributed volatile infeed.
Yet, adequate local prices, reflecting the grid situation of a certain area when congestion occurs, have to be determined carefully. Particularly the problem of avalanche effects and privacy issues have to be taken into account.
Further on, critical issues for a local pricing mechanism are its functionality and the resulting distributional effects. These are addressed in the following two papers.

Decentralized Local Pricing - Improving Network Usage in a Smart-Grid Environment under Limited Information

by Jessica Raasch and Christoph Weber

A decentralized pricing algorithm, which computes local prices with respect

to the local grid situation, is introduced here. Through an iterative process, local prices are determined based on grid users' responses and physical grid limitations. Thereby private data are not required, except of current quantity bids. This algorithm is implemented as a market agent within an agent-based model. Here further agents reflect a sample network, infeed from solar systems and consumption from private households. It is based on a multi-agent system modeled by J. Kays and A. Seack (cf. Kays et al. 2013, Kays 2014). Various operation modes for grid users are investigated, depending e.g. on the underlying market. Namely the current German market design as well as a local market concept are analyzed. Thereby, changing flexibility opportunities for PV generators and private households are discussed.
This model shows the theoretical feasibility of local prices as grid users are incentivized to help alleviating critical grid situations. Further on, it becomes obvious that additional flexibility leads to less extreme local prices.

Photovoltaics and Heat Pumps - Limitations of Local Pricing Mechanisms

by Björn Felten, Jessica Raasch and Christoph Weber

A real application of theoretical pricing mechanisms has to take into account the existing framework and distributional impacts. Local prices have better chances to be accepted, when incentives are given for several grid users. Thus, an innovative pricing system has to yield benefits. Yet, the allocation of potential benefits to system participants (grid operator, generators, consumers) is not that clear and therefore investigated in this paper.
The local pricing mechanism introduced in the previous paper is analyzed in the context of the existing market framework. The German market premium is applied as framework for a local pricing system corresponding to a certain grid area. To be more precise, a premium is assumed to be paid to various market participants: to conventional and flexible consumers and also to operators of small-scale electricity producers.
Represented grid users are solar-system operators, heat-pump operators and inflexible households. System benefits as well as costs and earnings for the market participants according to various allocation regimes are modeled. Incentives for flexible operation change, so that distributional implications for several market participants can be analyzed.
It turns out that a possible implementation of local prices should be considered carefully: At least for the considered test case, costs for the system operation are not reduced significantly and redistributive effects are huge. E.g., incentives, which are suitable to give rise also to investment decisions for flexibility provision, would imply huge costs for other grid users- which would rise further acceptance questions. The results obtained are however also a consequences of the low complementarity of the considered flexible participants (heat pumps and PV systems).

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2 BATTERY STORAGE SYSTEMS IN THE AUSTRALIAN ELECTRICITY MARKET - OPTIMAL OPERATION FOR VARIOUS BATTERY TECHNOLOGIES

Battery Storage Systems in the Australian Electricity Market - Optimal Operation for various Battery Technologies

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Abstract

Due to increasing amounts of electricity generation from renewable energy sources storage systems are of increasing interest. As large-scale battery storage systems are independent from geographical conditions these storage units are advantageous. But simultaneously these complex chemical systems are still expensive and have specific requirements.

In order to analyze the profitability of the operation of battery storage systems in an electricity market an optimization model is developed and applied to Sodium-Sulphur batteries, Lead-acid batteries, Vanadium Redox-flow batteries and Lithium-Ion batteries. Various operation modes are considered, notably impacts of the chosen depth of discharge are regarded. For a better understanding of technology-specific optimal performances we first optimize under perfect foresight. Afterwards the operation strategy of each battery technology is investigated in the context of uncertain prices. As a test case we consider a battery operation within the Australian electricity market which faces high demand peaks and therefore extreme prices frequently.

Assuming perfect foresight our results show that only with Lithium-Ion batteries a positive profit may be obtained under the typical electricity market conditions in Australia. This is mainly due to their power-to-energy ratio. Yet, when price uncertainty is considered none of the analyzed battery technologies is beneficial and the feature of high power-to-energy ratio turns out to be rather disadvantageous.

Keywords: Large-scale Batteries, Storage System Investment, Battery Service Time, Depth of Discharge, NEM.

1 Introduction

Against the background of increasing fluctuating generation from renewable energy sources, the balancing of electricity supply and demand at any time be-

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comes more and more difficult. Especially in times of peak demand the provision of flexibility can be beneficial - from an investor's perspective but also in a social welfare view. Therefore storage systems gain increasing interest. As large-scale battery storage systems (BSS), contrarily to pumped-hydro or compressed air storage, do not depend on any geographical characteristics, those are particularly attractive. Additionally battery systems are already today an active field of research, e.g. due to their application for electric vehicles.

Yet, BSS are complex systems especially as they are based on multiple chemical processes. To operate such systems the specific battery operation restrictions have to be taken into account adequately. Additionally the various chemical processes within the cell are strongly interrelated (cf. e.g. [1], [2], [3]). Of particular interest is the limited number of cycles for charging and discharging, which is strongly related to the depth of discharge (DoD) that is carried out. Further on the decrease of the available storage capacity during the service time is one of the major specifics that has to be considered. Thereby it has to be regarded that key parameters vary significantly between different battery technologies.

In general, several possible systems for large-scale storage exist. The most important ones, which have been analyzed theoretically and tested in practice already are the following: Sodium-Sulphur batteries (NaS), Lead-acid batteries (PbA), Vanadium Redox-flow batteries (VRB) and Lithium-Ion batteries (Li-Ion). Since these systems consist of various chemical substances the different battery technologies have specific features concerning the key parameters cycle life, calendar life, capacity, power rating and efficiency (cf. e.g. [4], [5], [6]).

However, key features for various battery technologies are that the number of cycles is limited and that waiving deep discharges is advantageous in terms of service time (cf. e.g. [7]). Therefore as a market application a BSS faces one main trade-off: In order to operate the storage system as long as possible and thus reduce annualized fix costs, cycles should occur rarely and be rather shallow. Yet, price spreads are monetarised best with frequent cycling. Therefore the most beneficial cycling performance is a matter of both the specific battery system and the price profile in a market.

The literature has investigated the impact of battery utilization on the duration of service time from various perspectives and within diverse applications. [8] presents a study on the battery life time for e.g. PbA and Li-Ion batteries applied to electric vehicles, focusing especially on charging and discharging activities as well as external conditions as the temperature.

Optimal BSS operations with regard to service time are provided in the context of diverse battery applications, e.g. supplying isolated systems with battery systems (cf. [9]) or operating a BSS in addition to wind turbines, solar panels or electric vehicles within hybrid systems (cf. [7], [10], [11], [12]). The additional operation of supercapacitors for BSS is proposed as those systems can be used to avoid seldom extreme charges or discharges carried out by the BSS (cf. [13], [14], [15]). Yet, the specific goals are different here compared to standalone batteries in a market application. The battery has to adapt its output as much as possible to other single devices with specific operation characteristics

instead of being oriented towards market prices.
A specific focus on operations of BSS as stand-alone systems in various contexts is laid e.g. in [16], [17] and [18]. Here the chemical characteristics and the resulting requirements of batteries as PbA and Li-Ion are taken into account aiming e.g. at load leveling without any consideration of the systems profitability itself. In contrast the prospects of storage systems within a market-based application are evaluated in [19]. As storage systems in general are considered there, the BSS analysis does not go into detail.
In [20] the profitability of large-scale BSS is investigated with specific focus on the impact of cycle depth, including a comparison of the same technologies considered in our paper. However, a technology-specific operation within a simulated market situation is not presented there. In [21] a battery operation oriented towards price signals is introduced, while the matter of lifetime limitation is neglected. Both, a view to prices and to the battery's state of charge and state of health, are considered in [22], but a certain market application to examine profitability in a more practical context is not investigated. [23] includes a price prediction in a battery operation model. But as the observed battery is used within an electric vehicle the operation is oriented primarily towards a mobility guarantee.
In this paper we present an optimization model to operate various BSS in a market in the most profitable way. Thereby our model approach allows a comparison between battery technologies applicable for large-scale storage, namely NaS, PbA, VRB and Li-Ion. Thereby the main battery-specific characteristics are implemented, particularly the impact of various DoD utilizations is considered through a number of model runs. An application of the regarded BSS in the Australian National Electricity Market (NEM) shows profitability prospects.
The paper is organized as follows: In Chapter 2 the battery model and the optimization of its operation are introduced, reflecting the technology-specific battery parameters and their interdependencies. The results of a simulated execution in the NEM under perfect foresight on prices are presented in chapter 3. In chapter 4 a more realistic model with price forecasting and strategy variations are investigated. Chapter 5 concludes.

2 Battery Storage Systems

BSS gain profit in a market application from price spreads. As the capability to charge or discharge in time steps of extreme prices is desirable, a schedule for charging and discharging has to be determined in advance. Profitability of an operation according to such a schedule can be evaluated by a comparison of investment costs, annualized over the effective service time, and the operation margins, resulting from buying and selling electricity.
However, the capability to charge and discharge and the resulting service time depend strongly on the technology-specific parameters and especially on the operation itself. Therefore particularly the internal relationships and processes have to be reflected.

2.1 The Battery Model

Investment costs per MWh, the capability to charge resp. discharge during time steps of low resp. peak prices and the service time are battery parameters affecting costs and earnings.
With regard to the operation costs we neglect any maintenance costs or additional requirements (as e.g. heat supply), so that the operation margin is determined by charging and discharging amounts, remunerated and paid at market prices. Assumed investment costs range from 374,500 AU$ to 963,000 AU$ per MWh capacity installed, as listed in Table 1. The Li-Ion battery is the most expensive one, while the NaS and the PbA batteries are at the lower end. When annualized investment costs are computed, an interest rate of 5% is assumed throughout.

One of the most important technical key parameters of BSS is the power rating. As the various battery technologies are based on different chemistries and constructions, the maximum available power range differs as well. In order to compare all technologies, we assume battery systems of the same size (1 MWh capacity). The power rating is derived from current or formerly existing systems (cf. [4], [6]). All assumed technical parameters are listed in Table 1 above. Compared to the other battery technologies the Li-Ion battery is the most expensive technology but has also the highest power rating. As the power rating exceeds the battery capacity, complete charging or discharging within one time step is possible even in case of half-hour schedules. For all other technologies the proportion between power rating and capacity, which roughly corresponds to the C-rate, is lower than 1. Thereby NaS and PbA are characterized by the lowest values with 0.17 MW and 0.25 MW.
In addition, the amount of energy, which can be sold in the market, is affected by the round-trip efficiency η. For all considered technologies the efficiency lies

Table 1: Battery Parameters[1]

	Investment Cost [AU$ / MWh]	**Capacity [MWh]**	**Power [MW]**	**Efficiency**	**Cycle Life (100% DoD)**	**Calendar Life [Years]**
NaS	374,500	1	0.17	0.83	2,500	15
PbA	428,000	1	0.25	0.77	800	10
VRB	615,250	1	0.67	0.78	10,000	15
Li-Ion	963,000	1	4.0	0.87	7,000	15

[1] according to [4], [5], [6] and own estimation

between 70% and 90%. The average values per battery technology are given in Table 1.
As mentioned before, we assume 1 MWh capacity for each technology. In fact the capacity of battery systems is not that constant as it may seem. First of all, batteries suffer from self-discharge, so that the full capacity is not available over a longer period. Thereby self-discharge occurs especially with long standstills and particularly when the state of charge is high. However, we neglect this kind of reversible capacity loss here, as we expect an active charging behavior in case of a certain market application.
Further on, a significant feature of these chemical systems is that capacity fades over time with increasing age of the battery. Additionally this decrease depends on the operating schedule. Chemical reasons for capacity fade are manifold: e.g. crystallization or sulfation of active masses, grid corrosion and loss of water. And those are partly mutually dependent. These reactions are caused particularly by deep discharge or over-charge. To be more precise, even the period of time a certain state of charge persists, or which combination of cycles - concerning their DoD - is carried out, may impact the available capacity. As these processes depend strongly on chemical reactions, which are affected additionally by external conditions such as the temperature, they can not be predicted properly (cf. [1], [3], [24]). Therefore the effect of cycle combinations or durations of certain states are not included in our optimization model. Regarding the fact that this impact is greater with longer durations of certain charge stages, it is expected anyway that a frequent charging activity will limit the aforementioned harming effects.
Yet, the main aspects of capacity fade can be modeled via two key parameters of batteries: the calendar time and the cycle life. As the defined 'end of life' of a battery is commonly understood to be the state, where only 80% of the regular capacity is left, the indicated service time already reflects the matter of capacity fade.[2] As capacity fades with the passing of time as well as with utilization, the effective lifetime for each technology is given in terms of years as well as in cycles (the calendar life CL and the cycle life NoC, see Table 1).
We assume that an optimal exploitation of a battery system is given only in case of operation during the whole calendar time. I.e. the maximum number of cycles determines the number of allowed cycles per year over the calendar life.[3]
Yet, the parameter cycle life itself is not at all a single constant. In fact the DoD is the main factor that affects capacity fade, so that the measure cycle life is related strongly to the DoD. According to the decreasing number of cycles with increasing DoD, an optimal operation strategy including the decision of a maximum discharge level, has to be chosen. This is taken into account in our model through a sensitivity analysis. The computation of optimal charging and discharging amounts per time step is carried out for each technology and each

[2]The utilization of the remaining capacity even when the stated 'end of life' is reached is neglected here, since the succeeding capacity degradation takes place acceleratedly, especially for battery operations with deep cycle charging (cf. [24]).

[3]The validity of that rule was checked in further investigations for each battery technology which is analyzed here.

level of maximum DoD.
Table 2 shows the number of cycles per battery technology depending on the DoD. The most durable battery concerning the number of cycles is the VRB technology. Only for extremely shallow cycling the Li-Ion battery is advantageous. The shortest cycle life is observed for the PbA battery.

To consider a certain level of DoD (100%, 75%, 50%, 25%, and 10%), the normalized capacity parameter is reduced correspondingly to the limiting percentage of allowed capacity usage in our model. This implies that even rarely used deep charges are not permitted in our model (except for the case of 100% DoD). And further on it is not reflected that the execution of lower cycles occasionally leads to less reduction of the remaining cycles. In spite of this, the restriction of allowed DoD throughout all charging and discharging cycles, seems to be an appropriate guideline to choose an optimal strategy for a market application of battery systems: Various analyses have shown that storage systems, which orient their charging cycles towards prices, carry out charging and discharging cycles typically with their full available capacity. Either a price is beneficial for charging, or it is beneficial for discharging - otherwise no operation occurs. Charging partly is usually not advantageous. Therefore the constant limitation of allowed DoD does not imply an inappropriate simplification of the model.
As some capacity losses are even reversible, specific charging cycles, which are responding to the current physical state of the battery, can be executed (cf. [18], [25]). However for a market application a foresighting and planning view is required as the possibility to charge in times of low prices and discharge in times of peak prices has to be arranged. Therefore a consideration of the battery's current needs and possible recovering cycles is not possible.

Table 2: Number of Cycles for different DoD[4]

DoD	**100%**	**75%**	**50%**	**25%**	**10%**
NaS	2,500	4,500	7,000	10,000	40,000
PbA	800	1,200	2,400	5,000	10,000
VRB	10,000	35,000	60,000	85,000	100,000
Li-Ion	7,000	10,000	20,000	60,000	400,000

2.2 Optimal Operation Model

The optimization model, which is implemented in GAMS as a mixed integer program (MIP), aims to find the most profitable way to operate the battery in the market. To be more precise, it is to decide on charging and discharging activities for each time step, i.e. for each price. As large-scale battery storage systems typically are applied in a double-digit megawatt range, which is small

[4] cf. [20] and [4]

compared to the overall size of typical markets, we do not simulate any effect on prices. Initially we assume perfect foresight on prices.
Additionally, various allowed DoDs with the corresponding available numbers of cycles are analyzed within a sensitivity analysis in order to find the most beneficial way to operate the BSS.
The decision variables for charging and discharging amounts ($c(t) \geq 0$ and $d(t) \geq 0$) are considered for each time step $t \in \{1, ..., T\}$ of a year aiming at a maximization of the operation margin:

$$\max_{d(t),c(t)} \sum_{t=1}^{T} p(t) \cdot (d(t) - c(t)), \tag{1}$$

where $p(t)$ indicate prices, given by historical data.
Restrictions are given by the battery's charging states and technical limitations corresponding to the specific battery technologies. The SoC $s(t) \geq 0$ is affected by charging and discharging, where also the technology-specific efficiency η is taken into account. As starting SoC we assume a battery discharged to the minimum SoC (see (2)). As certain DoDs should be regarded, s_{min} is given by 1 minus the specific DoD. Further on this minimum level has to be respected during all time steps (see (3)). The maximum SoC of 1 corresponds to a battery charged at full capacity, as it is represented in (4). The temporal interdependency, given by the sequence of states of charge (SoC), is represented in (5).

$$s(0) = s_{min} \tag{2}$$
$$s(t) \geq s_{min} \text{ for } t \in \{1, ..., T\} \tag{3}$$
$$s(t) \leq 1 \text{ for } t \in \{1, ..., T\} \tag{4}$$
$$s(t+1) = s(t) + \eta \cdot c(t+1) - d(t+1) \text{ for } t \in \{0, ..., T-1\} \tag{5}$$

The technology-specific power limitations P_{max} restrict the charging and discharging per time step Δt (see (6) and (7)). Thereby the binary variable $D(t) \in 0, 1$ ensures that discharging and charging do not occur at the same time. This additional variable is necessary if negative prices occur. Otherwise the optimal strategy during longer periods with negative prices may be to discharge and charge simultaneously in order to waste energy and earn money for doing so.

$$d(t) \leq P_{max} \cdot \Delta t \cdot (1 - D(t)) \text{ for } t \in \{1, ..., T\} \tag{6}$$
$$c(t) \leq P_{max} \cdot \Delta t \cdot D(t) \text{ for } t \in \{1, ..., T\} \tag{7}$$

To guarantee the battery operation over its full calendar life, the full charged or discharged energy must be lower than or equal to the allowed cycled energy per one year of the calendar life CL:

$$\sum_{t=1}^{T} d(t) \leq \frac{NoC \cdot DoD}{CL} \tag{8}$$

The investment cost are annualized assuming an interest rate of 5%.

2.3 Operation with Forecast

Scheduling a storage operation implies filling the system before beneficial prices for discharging occur. In other words, an estimation of prices is required in advance and is taken into account along the previously described optimization model.
I.e. in (1) prices $p(t)$ are substituted by price predictions $\tilde{p}(t)$, while the operation margin is derived based on computed charging and discharging quantities and realized prices $p(t)$.
Given that observed prices exhibit typical daily patterns that are undermined by week-end effects we assume a simple forecast model, where prices are forecasted using prices of the previous week (called PS for prediction scheme).

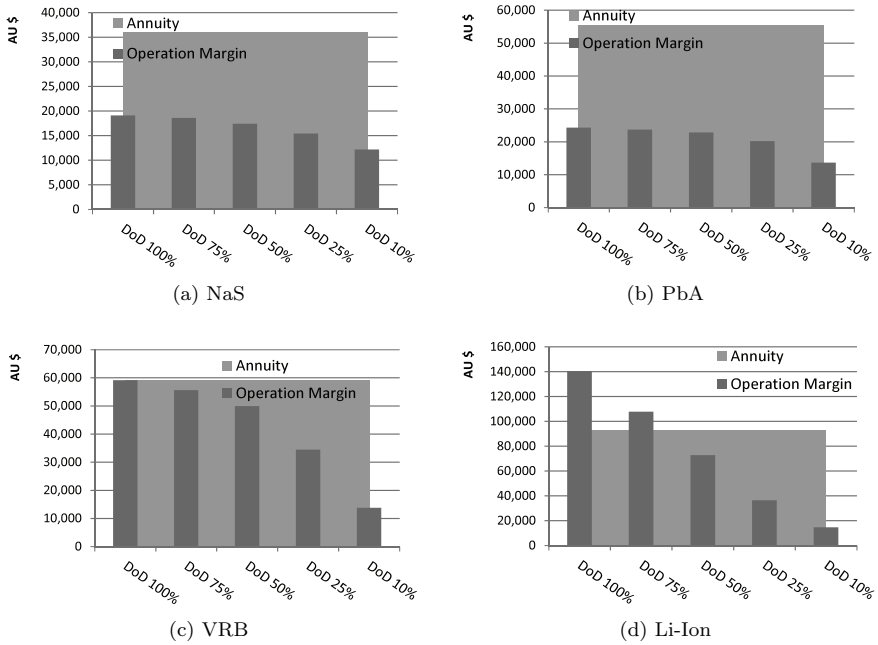
$$\tilde{p}(t) = p(t - \frac{168}{\Delta t}) \tag{9}$$

(For values out of range data corresponding to the previous year are used here.)

3 Simulation with Perfect Foresight

We simulate one year of storage operation exemplarily by using historical prices of the Australian National Energy Market (NEM), from 2013 in Queensland (cf. [26]). As aforementioned the NEM faces frequently extreme prices - negative ones as well as peaks of more than 1000 AU$/MWh - and therefore promises to be beneficial for storage applications. Due to half-hourly negotiated prices in the NEM, the chosen resolution is a half-hourly one ($\Delta t = \frac{1}{2}$). Consequently $T = 17520$ time steps are simulated.
In order to analyse various operation modes we assume DoDs of $1, 0.75, 0.5, 0.25$ and 0.1. Therefore s_{min} is chosen to be $0, 0.25, 0.5, 0.75$ and 0.9 respectively.
Fig. 1 displays the results for the maximum operation margin of NaS, PbA, VRB and Li-Ion battery systems for various levels of allowed DoD under perfect foresight (see grey bars). In addition the light grey background indicates the level of annualized investment costs.
Overall, the market-based operation of a BSS is only beneficial in two cases: in the case of the Li-Ion battery the profit is maximal for a battery utilization of 100% DoD, and in case of a slightly reduced capacity exploitation (75% DoD) the difference between operation margin and annualized investment costs is still positive.

For all other technologies and assumed levels of discharge, the overall profit is negative. Only in case that a full DoD is assumed for the VRB, the yearly difference between investment costs and earnings at the market is about 100 AU$ and therefore the operation is close to profitability.
Further more the revenues are throughout higher with deeper permitted levels of discharge. Even more, the allowed number of cycles per year, which is limited through the allowed amount of cycled energy per year (see (8)) is not fully used for all cases with shallow cycling: For 10% DoD the restriction is irrelevant for



(a) NaS (b) PbA

(c) VRB (d) Li-Ion

Figure 1: Operation Margins of different BSS

each technology, and up to 50% DoD this holds for each technology except the PbA battery. In contrast, in case of the VRB battery the limiting number of cycles is never exploited, i.e. the calendar life is the more limiting restriction. Thus, our model results show that even a more active cycling performance can not make a better use of price spreads, when the capacity use is limited significantly.

Another interesting result is that the two most costly BSS are also the most profitable ones - the Li-Ion and the VRB. As power rating and cycle life are high in both cases (see Table 1), the importance of a high cycling potential is emphasized here.

In the context of the regarded market with high price peaks especially the extremely high power rating of the Li-Ion battery is beneficial.

For a more detailed analysis of the technology-specific operation we look at a selected period of sequential price peaks, exemplarily twelve hours in February (see Fig. 2). The corresponding discharge activities are depicted for the case of 100% DoD. The order is chosen according to the available power rating: NaS and PbA are rather slow battery technologies, VRB and particularly Li-Ion are batteries with high power capabilities. As displayed in Fig. 2, all BSS realize a benefit from extreme price peaks (e.g. at 7 p.m.), but benefits are limited by the power rating. Due to the fact that the stored energy can not be retrieved fully

for battery technologies with an hourly power rate lower than two, discharging occurs in these cases also at surrounding still high prices (see Fig. 2a, 2b, 2c). Yet, Fig. 2d indicates that the operation of the Li-Ion battery allows to take better advantage of peak prices. Discharging occurs here at 7 p.m. with an amount equal to the full available capacity.

Overall, an operation oriented towards the few extremely high prices is carried out as much as possible. This implies that discharging occurs more frequently, the lower the power rating is. It is to state here, that the frequency of cycles can be affected also by the number of cycles according to the cycle life. In order to operate the battery during the full calendar life some cycles have to be waived in some cases.

To sum up, it becomes evident that the power rating is the most decisive factor in case of this market application. High investment cost can be compensated when high power ratings are given, life duration is not very limiting and high price peaks are present.

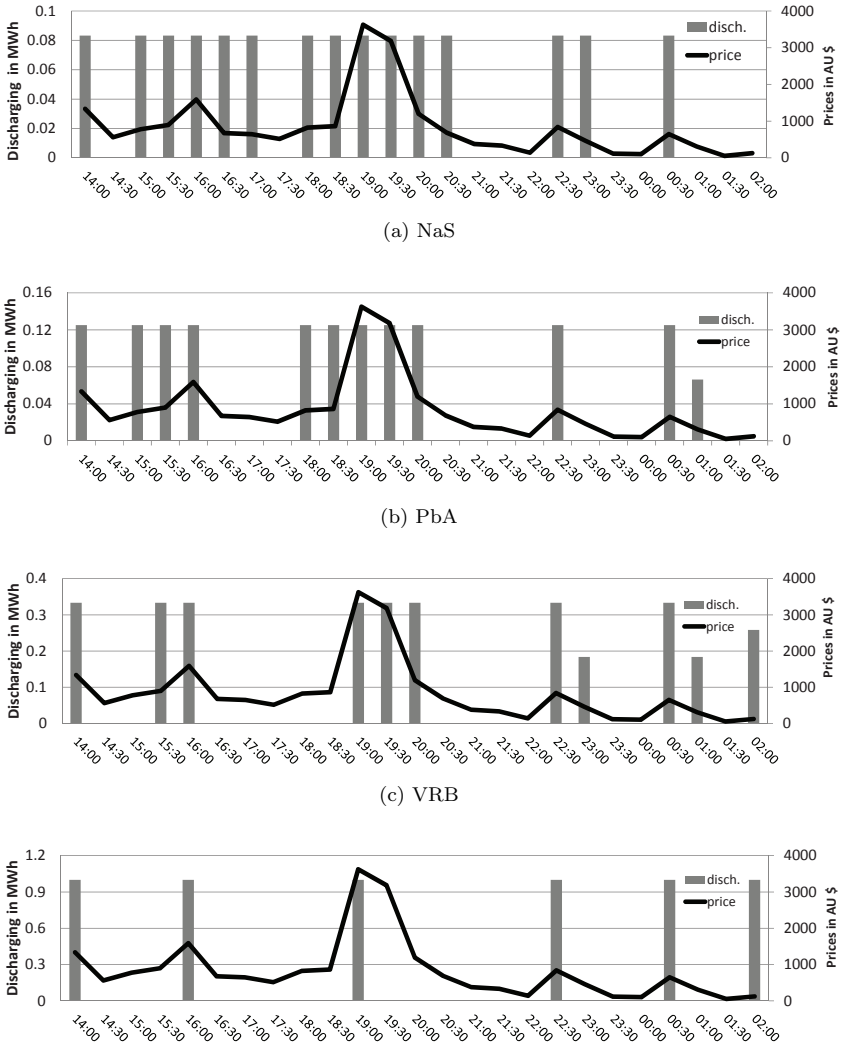
4 Simulation with Price Prediction

4.1 Price Prediction

So far perfect foresight on prices was assumed. Therewith the result that profitability holds only for the technology, which has the highest power rating, is crucial. The ability to make use of seldom but extreme high price peaks becomes less useful when these peaks are uncertain. In order to investigate the profitable operation of BSS in the NEM more realistically, we present further results, taking into account a price prediction scheme as described in 2.3.

As the best solution has been so far to make use of the full DoD for all modeled technologies - even under consideration of the corresponding reduction of the cycle life - we investigate the cases of 100% DoD here. Fig. 3 shows the revised operation margins compared to the technology-specific annualized investment costs of NaS, PbA, VRB and Li-Ion, under an assumed DoD of 100%. As expected, the yearly operation margin is significantly lower for all battery technologies and is below the specific annualized investment costs in each case. Notably the operation margin of the Li-Ion battery under perfect foresight is reduced to 7% of the formerly gained value. Thus, the Li-Ion battery turns out to be not profitable under a more realistic setting for the charge and discharge planning. In this case, the operation margin even faces the strongest reduction among all technologies. Operating in a market with extreme price peaks implies that losses are even more harming. Obviously the impact is stronger for storage systems with high power rating, as the bidden quantities are higher. To put it differently: storage systems with high potential for market operation face also the greatest risk.

As a consequence the presented strategy concerning price prediction and battery operation has to be reconsidered.



(a) NaS

(b) PbA

(c) VRB

(d) Li-Ion

Figure 2: Exemplary price-peaks (February) and corresponding discharge behavior, from 2 p.m. to 2 a.m.

4.2 Prediction Model Modification

In order to address the problem of large losses due to charging with unexpected high prices or discharging with unexpected low prices, we investigate a simple

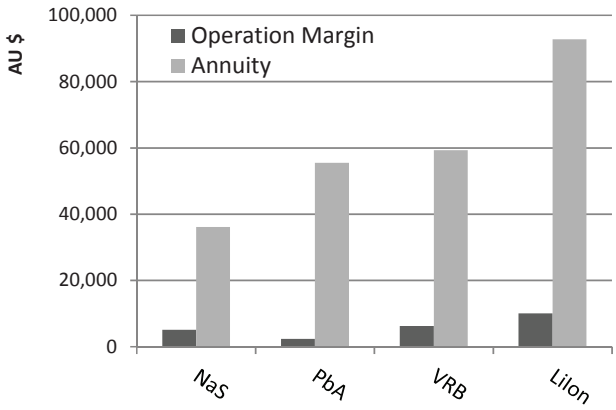


Figure 3: Operation Margin and Annualized Investment Costs with Price Prediction (100% DoD)

alternative prediction scheme. Therewith we intend to reflect the given specific data features, as the observed market is characterized by promising, but hard to predict, high price peaks.
Concerning the prediction scheme, it might be advantageous to give less weight to extreme peak prices. Anyway a correct prediction of extreme price peaks is difficult as these events occur usually not with obvious patterns. In contrast, the common level of prices (high or low) can be estimated properly. Therefore a revised, more robust price prediction scheme is obtained by censoring extreme prices and including only restricted prices (called RPS for restricted prediction scheme). As a consequence charge and discharge behavior is less oriented towards extreme price peaks, which are uncertain.
Thus, the RPS is based on equation (9), but resulting price estimates are restricted to a range of 44 to 98AU$. These values correspond to the 5% and 95%-quantiles of the historical NEM price data for 2013.
We analyze the gained operation margin for the case of 100% DoD for the optimization based on the restricted price prediction scheme (RPS) in contrast to the unrestricted scheme (PS). Fig. 4 displays the results. The profitability is negative for all modeled technologies and price prediction schemes.

It is shown in particular that the modified prediction model improves the results for the LiIon and the PbA technology, while margins are lowered for the NaS battery and the VRB battery.
For the Li-Ion technology as the most promising one, a prediction schema with neglected extreme price peaks is beneficial compared to the first introduced scheme. This is due to the fact that the occurrence of low or even negative prices, when a high price was expected, leads to a significant deterioration of the operation margin for the high pulse Li-Ion battery. Neglecting high price peaks is advantageous here as erroneous estimation is less harming.

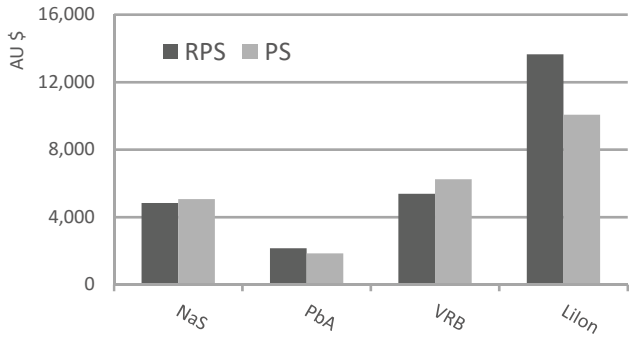


Figure 4: Operation Margin with modified price prediction scheme

In case of the NaS battery it can be stated that the low power rating implies a low impact of extreme price peaks. Therefore improperly estimated price spreads are less harming than for other technologies. Consequently the avoidance of of these extreme predictions can not improve the output. For the VRB battery with its high cycle life, the modified prediction model has as a consequence that less cycles are incentivized, which lowers the operation margin.
Overall no unique scheme emerges that allows to get the highest operation margin for a BSS in a market with high but uncertain price peaks. Price prediction as well as the technology-specific parameters have an impact on the attainable benefit. Here additional investigations on improved price prediction schemes and robust operation strategies are certainly useful, although beyond the scope of this paper.

5 Conclusion

This paper presents an optimization model to operate BSS in an energy market. From a private investor's perspective the best way to operate a BSS as a stand-alone application is investigated, in order to evaluate the profitability for various technologies of suitable large-scale battery systems.
A battery is a chemical system where the operation has impact on the system's state, particularly on the duration of service time. Therefore an abstract model reflecting the complex internal processes as much as required is presented. Investigating the profitability of market operation for several battery technologies, an optimization of the operation in an exemplary market is carried out for each technology and various levels of maximum DoDs.
With the assumption of perfect foresight on prices a rather theoretical analysis of BSS in a market is investigated firstly. Therefrom an improved understanding of the specifics of battery operation, the key parameters and the most limiting parameters for each battery technology is derived. The optimization with forecast prices instead of realized prices reveals then a more realistic view on the

battery operation and profitability in the market.
As a test case the Australian energy market NEM is investigated since this is a market with high price peaks and therefore with potentially good prospects for profitable storage operation. It turns out that theoretically the Li-Ion battery is the one which is most suitable for a market with high price peaks. With its high power rating this technology is the only one with profitability on a yearly basis under the assumption of perfect foresight. The VRB technology slightly misses a beneficial result here. The importance of high power-to-energy ratio is underlined for this setting by the fact that a permission for deepest discharge is advantageous across all battery technologies, although this reduces the number of available cycles.
Without the assumption of perfect foresight on prices, the high power ratings turn out to be disadvantageous. A forecasted schedule based on predicted prices implies the risk of charging and discharging activities at inappropriate prices. It is shown that the expected degradation of the operation margin is immense, particularly for the Li-Ion battery. Here it becomes obvious that an effective orientation towards expected price peaks is risky. A simple variation of the prediction scheme confirms this fact: Neglecting extreme price predictions improves the outcome for this case of an extremely high peaking market for the Li-Ion battery. Yet, profitability is still not given by far. In sum, the choice of an optimal operation strategy is not that clear. The outcome depends very much on the technology-specific features and also the specific price profile that is faced in a certain market.
Regular rules deduced from analyses under simplifying assumptions like perfect foresight are not directely transferable to real market conditions. Under real conditions BSS turn out to be still too expensive and moreover they are also complex in their behavior so that a general statement for all BSS cannot be derived.

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3 FLEXIBLE USE OF RESIDENTIAL HEAT PUMPS - POSSIBILITIES AND LIMITS OF MARKET PARTICIPATION

Flexible Use of Residential Heat Pumps - Possibilities and Limits of Market Participation

Jessica Raasch *

Abstract

The increased amount of electricity supply from intermittent renewable energy sources leads more and more to high price volatility in electricity spot markets. An increasing share of generation is less dispatchable than in the past, and therefore higher amounts of flexible demand, which can be adjusted towards supply, are required. Even residential consumers are potential market participants, if the smart equipment of buildings and the electricity grid are readily available.

This paper investigates the possibility for heat-pump operators to participate in spot markets. Especially problems and possible benefits are investigated when uncertainties in ambient temperatures or prices are considered. Therefore an optimization model, including an air-to-water heat pump, a storage tank and the heated building is implemented in MATLAB. In order to investigate the heat-pumps operation according to optimized heat-supply schedules along different scenarios, an agent-based model is used. Namely operations with day-ahead and intraday market participation are investigated, using historical EPEX spot electricity prices for 2014.

Results show that uncertainty is a critical issue when private consumers participate in electricity markets. Even with a certain amount of system flexibility, there are tight operational constraints for the heating device, which are hard to fulfill. Short-term decisions including responses to current information are required. The system behavior is acceptable with very short-term decision making, namely a hourly reoptimization with intraday-market participation. Further on, benefits can be yielded, when a combination of procurement before (day-ahead) and adjustments in the very short term (intraday) are applied.

Keywords: Heat-Pump Operation, Flexible Consumption, Residential Market Participation, Spot Market Bidding.

1 Introduction

The current electricity system is undergoing significant changes, especially due to increasing amounts of infeed from renewable energy sources. This generation

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depends significantly on environmental conditions and is therefore volatile and not dispatchable. This results in a physical system, which is more complex to operate. Further consequences are reflected in changed market features: E.g. the level of EPEX spot market prices in the bidding zone Germany/Austria has dropped during recent years, while end-consumer prices went up due to increasing additional charges (especially the EEG levy for RES generation has grown, cf. [1]). Consequently the task to balance demand and supply becomes more and more complex. But also a high potential for a profitable spot market participation of flexible bidders is given. Higher amounts of flexible market participants could facilitate the coordination of demand and supply. Particularly end consumers - in case of lower market entry barriers and given suitable incentives - could contribute to balancing the system by participating in the competitive market.

Yet, defining the term "flexibility" in electricity systems is a not obvious. Various system participants have a certain degree of flexibility, e.g. to shift load, to control infeed or to adjust technical conditions for electricity transmission. However, primary objectives of electricity consumers and generators are independent from physical grid requirements and there are typically various restrictions for behavior adjustments for grid users. According to [2], limitations arise particularly from (1) a limited range of possible actions, (2) the necessity for fast reactions and (3) the uncertainty of favorable conditions.

For residential grid users a supply of flexibility becomes more and more feasible. The development of smart equipment of grids, households and private electric devices makes bidirectional communication as well as response to received signals viable.[1] Therefore small-scale consumers and producers are increasingly enabled to enter e.g. the wholesale electricity market. These improved conditions may enable a large amount of individual demand units to react to e.g. weather-dependent supply situations. Instead of taking the demand curve as inflexible, here a balance can be achieved by a higher degree of adaptability in a more liquid market.

The problems and obstacles related to adequate incentives as well as the potential of flexibility supply from residential consumers are discussed in the literature, e.g. by [5] and [6] . Especially the operation of thermal energy storages is promising, e.g. according to [6].

The relevance of integrating residential users into the market and the design of incentives is analyzed by several authors: E.g. [7] introduce a pricing mechanism aiming at the integration of residential generators into balancing markets, while [8] and [9] discuss contracts or market mechanisms for small-scale consumers in order to react to present supply situations. Yet, consumers are not specified further and thus individual restrictions are neglected. [10] in contrast focus on the specific load behavior of electric vehicles. A day-ahead price mechanism here aims at a total demand profile without extreme peaks.

The behavior of small-scale consumers in existing markets is analyzed e.g.

[1] Various field tests, including smart equipment and integrated residential users, have been carried out during recent years, cf. e.g. [3] and [4].

by [11] and [12]. The authors state, with regard to the Dutch resp. the Iberian day-ahead market that electricity costs can be reduced, in case an aggregator provides adequate incentives and thus smartly coordinates individual consumption. In [13] similar results are obtained for the specific case of heat-pump consumption with view to the day-ahead market in UK. Again an aggregator, aiming at a smart coordination of participants, has to collect individual information and has to coordinate individual users to act for a common goal.
At a technical level, heat pumps can be interpreted as thermal capacity providers and have therefore great potential to supply residential consumption flexibility. Such a heating system is operated by electric power and can be activated partly independently from heating needs. The building itself has a certain heat capacity, and an additional thermal storage tank can help to decouple electricity consumption and heat supply further. E.g. [14] state that heat pumps are suitable and beneficial components for an energy system characterized by high amounts of intermittent renewables, when combined with cogeneration and wind power. On the other hand, there are specific restrictions, which reduce flexibility of these systems. Heat pumps are originally designed to supply a building with heat and a certain level of comfort for the inhabitants has to be kept necessarily. Particularly in the case of residential heat-pump operators, storage capacities of the building and the thermal storage tank are limited. Therefore the necessity of an acceptable temperature has to be considered as a constraint when flexibility is to be provided or the operation is scheduled according to competitive prices. Further on, several uncertainties affect the decision on optimal heat-pump operation, since a schedule has to be planned in advance. The system consisting of a heat pump, possibly a thermal storage tank and a building is complex, especially since the operation states of all components and all time steps are interdependent. An optimal operation schedule has to consider these interdependencies. The optimal operation is strongly impacted by the ambient temperature: heat losses are a function of the difference of indoor and ambient temperature, but also the efficiency of heat pumps depends on the available source temperature, which is equivalent to the ambient temperature in case of air-to-water heat pumps. Scheduling the heat operation in advance implies the need of a temperature forecast and leads to a certain amount of uncertainty. In addition, consumption costs can be uncertain, depending on the underlying market or pricing system. (cf. e.g. [13])
Specific requirements for heat-pump operation and the resulting available flexibility are analyzed in various context situations in the literature. E.g. [15] and [16] investigate residential generators and heat pumps, aiming at an optimal private consumption. In [17] and [18] pricing and market models are introduced to induce a smart flexibility utilization. Thereby goals are a grid-oriented operation respectively the reduction of peak load.
Another issue to keep in mind is the uncertainty of relevant parameters, such as prices and ambient temperatures. As the level of required heat supply and occurring heat losses have to be estimated as precise as possible, an optimal operation can be scheduled adequately only in the short term. Against this backdrop, spot markets as day-ahead and intraday markets might be suitable

markets for heat-pump participation.
E.g. a beneficial integration of heat pumps is stated in [19] for the Austrian spot market in 2011. In [20] a control mechanism for heat pumps and air conditioning is introduced in order to analyze benefits of participation in the ERCOT market in Texas. Here a variation of the set point, representing the interior comfort temperature, is allowed to gain flexibility. The authors conclude that the market participation of heat pumps has welfare-increasing effects by reduction of the system's electricity costs and by cutting off load peaks while the level of comfort is only slightly decreased. [21] computes a positive outcome for multi-family heat pumps when the operation is driven by the price signals observed at the Swiss intraday and balancing markets. The intraday market is the underlying market for heat pump integration also in the Danish case in [22]. Yet, instead of direct participation of individual heat-pump operators, the authors assume that an aggregator has to match the flexibility of several residential heat-pump operators.
German spot markets promise to offer a similar potential for flexible consumption for the following reasons. Day-ahead prices are characterized by a relatively low level but high volatility, since renewable energy sources supply a significant amount of electricity (cf. [1]). And [23] state an increased liquidity of the intraday market during recent years, so that acting nowadays in these markets is less risky and more and more attractive.
This paper presents a detailed analysis of heat-pump operators, who participate in German competitive electricity markets, namely the day-ahead and the intraday market. The focus is set on specific heat-pump restrictions, while existing market-entry conditions as well as additional trading costs are neglected. Thus, the comfort conditions, which need to be fulfilled, are regarded firstly and flexibility is achieved by an optimally dispatched thermal storage tank. In case internal interdependent system restrictions have to be considered, the choice of purchase time steps is not a simple one. Therefore a detailed heating system consisting of an air-to-water heat pump, a thermal storage tank and the heated building is considered. The operation of the observed heating system is optimized against given historical spot market prices. The optimization is formulated as a linear problem in MATLAB. Further on, a simulation of optimal schedules, reoptimization and resulting system states is carried out within an agent-based model. Thus, a realistic operation taking into account uncertain ambient temperatures is modeled. The possibilities and the potential benefits are compared for the participation in the day-ahead and the intraday market, and additionally for a combined procurement in both markets. It turns out that uncertainties are significant obstacles for private consumers and therefore a very short-term decision making is advisable.
The remaining paper is organized as follows: Chapter 2 introduces the system of heat pump and building as well as the corresponding optimization problem. The simulation environment, which is an agent-based model and includes the mentioned optimization, is presented together with implemented foresight assumptions and several scheduling strategies. In Chapter 3 the test-case data are drawn (determining the heating system and the simulation time span) and

concrete market participation variants are described. These include a pure day-ahead-market participation, an intraday-market participation and a bidding strategy combining both markets. Results are presented in Chapter 4, where the fulfillment of system and comfort restrictions as well as economical benefits are evaluated in detail. Chapter 5 concludes.

2 Methodology - Heat-Pump Operation

The considered heating system consists of an air-to-water heat pump, a thermal storage tank and the heated building (see Fig. 1). The building is heated by

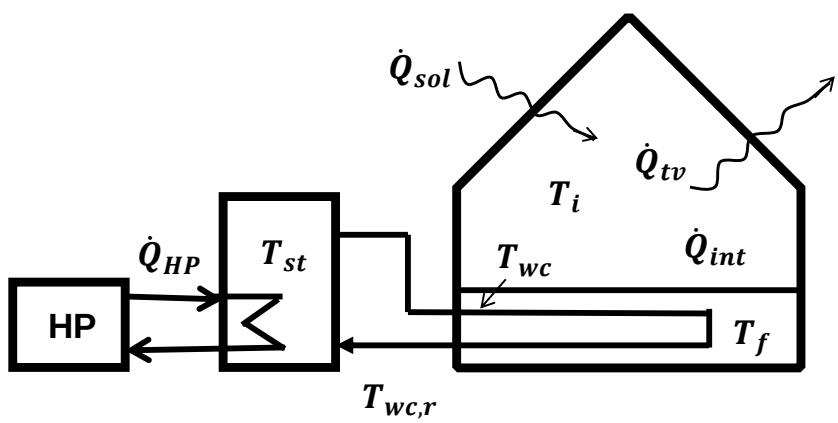


Figure 1: Heating System

means of underfloor heating, which is fed from the storage tank. In case the heat output of the heat pump is too low, a heating rod may supply additional heat in the thermal storage tank. The opportunity for night setback is neglected here, and warm water is not heated by the heat pump.
Air-to-water heat pumps are characterized by the utilization of ambient air. Thus the available heating power $\dot{Q}_{HP}^{max}$ as well as the required electric power P_{el}^{max} vary with the current ambient temperature T_{amb}. Additionally the supply temperature T_S, entering into the thermal storage buffer, affects the electricity demand. Characteristic curves to model these relationships can be approximated by quadratic equations (cf. [24], p.2):

$$\dot{Q}_{HP}^{max} = a_1 + a_2 T_{amb} + a_3 T_S + a_4 T_{amb} T_S + a_5 T_{amb}^2 + a_6 T_S^2 \tag{1}$$

$$P_{el}^{max} = b_1 + b_2 T_{amb} + b_3 T_S + b_4 T_{amb} T_S + b_5 T_{amb}^2 + b_6 T_S^2 \tag{2}$$

In order to control the indoor temperature T_i, which is affected implicitly by the heat supply (from heat pump and eventually heating rod) $\dot{Q} = \dot{Q}_{HP}(+\dot{Q}_{HR})$,

the thermal behavior of the whole system has to be modeled. Namely the temperatures of the storage tank T_{st}, the circulating water of the underfloor heating T_{wc}, the floor temperature T_f and the returning water within the pipe system $T_{wc,r}$ are of interest: Thereby the thermal storage temperature T_{st} is mainly affected by the adjoining temperatures of the tank's surrounding (T_{sur}, assumed to have a fix value of $15°C$, e.g. in a relatively cool basement room) and the return flow temperature $T_{wc,r}$.[2] The temperature of the water circuit T_{wc} depends on its delta to the floor temperature and to the thermal storage temperature. Beside the exchange with the water circuit temperature, the floor temperature is affected by the indoor temperature, while the latter one is reduced by losses due to the ambient temperature T_{amb}, but can be increased also by heat gains through solar radiation and internal gains ($\dot{Q}_{sol}$ and $\dot{Q}_{int}$). Finally the return temperature $T_{wc,r}$ is driven by the heat exchange with the floor and heat inflow from the storage tank. The amount of exchange is respectively affected by the size of surfaces and the thermal characteristics of adjacent materials, which can be seen in detail in the following formulas (based on [25]):

$$\rho_w c_w V_{st} \dot{T}_{st} = \dot{Q} - S_{st} C_{hl} \left(T_{st} - T_{sur}\right) - \dot{m}_{wc} c_w \left(T_{st}^{av} - T_{wc,r}\right) \tag{3}$$

$$c_w m_{wc} \dot{T}_{wc} = U_{p,f} A_{pipe} \left(T_f - T_{wc}\right) + \dot{m}_{wc} c_w \left(T_{st}^{av} - T_{wc,r}\right) \tag{4}$$

$$\rho_{ce} c_{ce} V_f \dot{T}_f = -U_{p,f} A_{pipe} \left(T_f - T_{wc}\right) - U_{bui} A_{bui} \left(T_f - T_i\right) \tag{5}$$

$$C_{bui} \dot{T}_i = U_{bui} A_{bui} \left(T_f - T_i\right) - H_{tv} \left(T_i - T_{amb}\right) + \dot{Q}_{sol} + \dot{Q}_{int} \tag{6}$$

$$m_{wc} c_w \dot{T}_{wc,r} = -\dot{m}_{wc} c_w \left(T_{st}^{av} - T_{wc,r}\right) - U_{p,f} A_{pipe} \left(T_f - T_{wc}\right) \tag{7}$$

Thereby the mass flow $\dot{m}_{wc}$ has to be determined, while material-dependent factors such as specific heat capacities c_w, c_{ce} and densities ρ_w, ρ_{ce} for water and cement are given (see Table 1). In addition, building-specific parameters affect the interrelationship of the temperatures: C_{bui} is the building's heat capacity (including indoor air), A_{bui} is the heated area, V_f is the volume of the (cement) floor, A_{pipe} stands for the surface of the pipe system, m_{wc} for the mass of the water circuit, $U_{p,f}$ is the heat exchange coefficient between pipe and floor, U_{bui} the heat transition coefficient (aggregation of all building components which separate the inside from the outside) and H_{tv} represents the coefficient of transmission and ventilation losses. V_{st} and S_{st} are the volume and surface of the thermal storage tank and C_{hl} its heat loss coefficient.

2.1 Optimization - Scheduling the Heat-Pump Operation

An optimal heat-pump operation aims at buying electricity when prices are low, while a certain level of comfort is maintained. The latter one is measured with the delta of indoor temperature and a comfort temperature T_{comf} of $20°C$. A dead band of two degrees, symmetrically distributed around the set point is defined as an acceptable indoor temperature.

[2] The average storage temperature T_{st}^{av} is used as simplification, here. The temperature varies with the layer within the tank, which is not mapped in detail here. The average temperature is assumed to be the average of allowed minimum and maximum storage temperature.

Table 1: Physical Properties

ρ_w	density water	1000 $\frac{kg}{m^3}$
c_w	specific heat capacity water	1.164 $\frac{Wh}{kgK}$
ρ_{ce}	density cement	2000 $\frac{kg}{m^3}$
c_{ce}	specific heat capacity cement	0.28 $\frac{Wh}{kgK}$

As initial information the time horizon for optimization, the current state of system temperatures as well as prices and (forecasted) ambient temperatures for the specified time horizon are required. To ensure that values with acceptable prediction accuracy enter into the optimization, the time horizon is chosen to be at most 24 hours. But depending on available price information, even a shorter planning period can be chosen.
Based on the received ambient temperature information, the required mass flow for each hour is determined initially. Here the corresponding losses, reduced by available gains, and the heat transport parameters are considered. $\dot{m}_{wc,t}$ for hour t is given by

$$\dot{m}_{wc,t} = \frac{H_{tv}(T_{comf} - T_{amb,t}) - \dot{Q}_{sol,t} - \dot{Q}_{int,t}}{c_w\,(T_{st}^{av} - T_{wc,r,0})}, \tag{8}$$

where $T_{amb,t}$ is the (forecasted) ambient temperature in hour t, $T_{wc,r,0}$ the last available information on the return temperature of the circulating water. In case of values exceeding a previously defined minimum or maximum value, $\dot{m}_{wc,t}$ is set to the corresponding value.
With given mass flow the above defined relationship of system temperatures is linear in heat supply and system temperatures. Thus, the optimization problem can be formulated as a linear problem, which is implemented in MATLAB. Variables of the problem are then temperature values $(T_{st}, T_{wc}, T_f, T_i, T_{wc,r})$ and heat supply values $(\dot{Q})$ for each time step. It is to decide on $\dot{Q}$ for each hour, depending on corresponding prices. The equations (3) - (7) describe in discretized form equality restrictions on the temperature changes between time steps. Additionally, inequality restrictions have to be included in order to maintain comfort and storage conditions. The maximum available heat capacity $\dot{Q}_{HP}^{max}$ and the corresponding electric load P_{HP}^{max} are determined for each hour in advance according to equations (1) and (2). (Information on the ambient temperature is assumed to have an hourly resolution, while the thermal behavior can be simulated with a finer resolution in order to avoid instable system dynamics due to inadequate discretization.). The heating rod has a constant level of efficiency. Yet, in this model the heating rod is dispatched only in case the heating capacity of the heat pump is insufficient to meet the required heat level over the total time horizon considered.[3] Internal gains can be determined for each hour

[3]This makes a difference only in case of negative prices as the efficiency of the heat pump is throughout significantly better. From a pure economic point of view, wasting energy at

in advance, too. Being a result of individual inhabitant behavior (heat gains from humans and active devices), internal gains are difficult to predict precisely. Therefore a constant average value is assumed, which is based on the heated building area ($\dot{Q}_{int} = 5\frac{W}{m^2} \cdot A_{bui}$, cf. [26], p. 84). Gains due to solar radiation are given as exogenous input (see Chapter 2.2).
In detail, the linear optimization problem is defined as follows: The objective function includes the costs for the heat supply summed over all time steps, implying a specific electric load:

$$\sum_{l=1}^{N \cdot H} p_t \cdot \frac{P_{HP,t}^{max}}{\dot{Q}_{HP,t}^{max}} \cdot \dot{Q}_{HP,l} \cdot \Delta t, \tag{9}$$

where H is the optimization horizon and N the number of finer time steps of length Δt per hour. (This finer time resolution is used for the thermal behavior simulation.) The hour t of the current simulation step l is then given by $t = \lceil l \cdot \Delta t \rceil$. p_t is the exogenous price information and $\dot{Q}_{HP,l}$ is the heat pump's heat supply, chosen for time step l. In case of required additional heat supplied by the heating rod, the objective function is supplemented by the following term:

$$\sum_{l=1}^{N \cdot H} p_t \cdot \frac{1}{\eta_{HR}} \cdot \dot{Q}_{HR,l} \cdot \Delta t, \tag{10}$$

where η_{HR} is the efficiency of the heating rod and $\dot{Q}_{HR,l}$ is the chosen additional heat supply of time step l.
The thermal dynamics of the building and heating system form equality restrictions. The thermal system's behavior equations (see (3) - (7)) are thereby included in a discretized version for every time step modeled:

$$\begin{aligned}
&\rho_w c_w V_{st} \frac{(T_{st,l} - T_{st,l-1})}{\Delta t} = \\
&\dot{Q}_{HP,l} + \dot{Q}_{HR,l} - S_{st} C_{hl} \left(T_{st,l-1} - T_{sur}\right) - \dot{m}_{wc,t} c_w \left(T_{st}^{av} - T_{wc,r,l-1}\right) \\
&c_w m_{wc} \frac{(T_{wc,l} - T_{wc,l-1})}{\Delta t} = \\
&U_{p,f} A_{pipe} \left(T_{f,l-1} - T_{wc,l-1}\right) + \dot{m}_{wc,t} c_w \left(T_{st}^{av} - T_{wc,r,l-1}\right) \\
&\rho_{ce} c_{ce} V_f \frac{(T_{f,l} - T_{f,l-1})}{\Delta t} = \\
&- U_{p,f} A_{pipe} \left(T_{f,l-1} - T_{wc,l-1}\right) - U_{bui} A_{bui} \left(T_{f,l-1} - T_{i,l-1}\right) \\
&C_{bui} \frac{(T_{i,l} - T_{i,l-1})}{\Delta t} = \\
&U_{bui} A_{bui} \left(T_{f,l-1} - T_{i,l-1}\right) - H_{tv} \left(T_{i,l-1} - T_{amb,t}\right) + \dot{Q}_{sol,t} + \dot{Q}_{int,t} \\
&m_{wc} c_w \frac{(T_{wc,r,l} - T_{wc,r,l-1})}{\Delta t} = \\
&- \dot{m}_{wc,t} c_w \left(T_{st}^{av} - T_{wc,r,l-1}\right) - U_{p,f} A_{pipe} \left(T_{f,l-1} - T_{wc,l-1}\right),
\end{aligned}$$

negative prices is optimal. Yet if the observed prices are distorted by some regulatory settings (e.g. mandatory take-off of renewable electricity), limiting the use of electricity may still be beneficial in a longer term system view.

for $l = 1, ..., N \cdot H$. Further on,

$$\dot{Q}_{HP,l}, \dot{Q}_{HR,l}, T_{st,l}, T_{wc,l}, T_{f,l}, T_{l,l}, T_{wc,r,l}$$

for $l > 0$, are variables corresponding to time step l.[4]
Due to technical restrictions and in order to maintain the comfort conditions, the following inequality restrictions have to be fulfilled as well: The heat-pump output can be chosen in each time step only within the range of zero and the heat capacity:

$$0 \leq \dot{Q}_{HP,l} \leq \dot{Q}^{max}_{HP,t}, \text{ for } l = 1, ..., N \cdot H, \tag{11}$$

where $t = \lceil l \cdot \Delta t \rceil$.
In case of possible supply from the heating rod, the minimum and maximum heat capacity have to be reflected as well:

$$0 \leq \dot{Q}_{HR,l} \leq \dot{Q}^{max}_{HR}, \text{ for } l = 1, ..., N \cdot H. \tag{12}$$

Additionally, the thermal storage tank is facing several limits: A declining storage temperature beneath a specific minimum temperature T^{min}_{st} would imply effectively that heat supply to the building would fail and is therefore avoided. An upper limit for the storage temperature is modeled by T^{max}_{st}. This restriction reflects the fact that at some point more heat supply does not imply an increasing storage temperature. This is due to the fact that the heat pump can deliver heat effectively to the storage tank only in case of positive gap between supply temperature of heat pump and storage temperature. Thus, additional inequality restrictions are given as follows:

$$T^{min}_{st} \leq T_{st,l} \leq T^{max}_{st}, \text{ for } l = 1, ..., N \cdot H. \tag{13}$$

Finally, the comfort conditions are formulated as follows:

$$T_{comf} - \Delta_{TBand} \leq T_{i,l} \leq T_{comf} + \Delta_{TBand}, \text{ for } l = 1, ..., N \cdot H, \tag{14}$$

where $T_{comf} = 20$ and $\Delta_{TBand} = 1$.
A function f that computes an (optimal) heat-supply schedule is the result. Input data are the optimization time horizon H, price data, ambient temperature data and solar-gain data for that time horizon as well as the current states of system temperatures:

$$f\left(H, \vec{p}, \vec{T_{amb}}, \vec{\dot{Q}}_{sol}, T_{st,0}, T_{wc,0}, T_{f,0}, T_{i,0}, T_{wc,r,0}\right) = \left(\dot{Q}_{HP,1}, ..., \dot{Q}_{HP,H}\right), \tag{15}$$

where $\vec{p} = (p_1, ..., p_H)$, $\vec{T_{amb}} = (T_{amb,1}, ..., T_{amb,H})$ and $\vec{\dot{Q}}_{sol} = \left(\dot{Q}_{sol,1}, ..., \dot{Q}_{sol,H}\right)$ are vectors containing hourly data, respectively for prices, ambient temperatures and solar gains. In case heat demand can only be served by additional heat from the heating rod, the output is defined by

$$\left(\dot{Q}_{HP,1}, ..., \dot{Q}_{HP,H}, \dot{Q}_{HR,1}, ..., \dot{Q}_{HR,H}\right).$$

[4]The equations belonging to $l = 1$ differ slightly from the latter ones, as the initial temperatures $T_{st,0}, T_{wc,0}, T_{f,0}, T_{i,0}$ and $T_{wc,r,0}$ enter as parameters instead of being variables.

2.2 Simulation

As a simulation framework an agent-based model is chosen. A JADE-based multi-agent simulation is used including a heat-pump agent, which represents the combination of heat pump and heated building. Within this agent, the invoking of the optimization algorithm f (see (15)) and the following operation (based on the same thermal-behavior equations) are executed. This framework enables the execution of various simulations: the impacts of possible forecast errors, i.e. differences between predicted and realized ambient temperatures, can be represented. But also cases with perfect forecast can be simulated. Additionally, the agent can apply the optimization model in two ways: either a heat supply schedule is computed in advance (e.g. once per day) or a rolling planning repeats the optimization (e.g. hourly).
Additionally the framework includes agents, which provide required information: A market agent sends vectors of price data and a weather agent provides current weather data (ambient temperature and solar radiation). Data are provided hourly. The structure of known prices (or price forecasts) depends on the chosen market context. Therefore, assumptions on price information are explained in Chapter 3.1 resp. 3.2. The weather agent is based on an implementation by J. Kays and A. Seack (cf. [27], [28]), who develop an agent-based model for distribution grid planning purposes.
Based on provided solar radiation data, the heat-pump agent then determines building specific solar gains: The computation here is similar to the effective solar radiation reaching photovoltaic panels in [28], (p. 79). The computation is executed for all facades of the building and corresponding window areas $A_{w1}, A_{w2}, A_{w3}, A_{w4}$ and is corrected by average reductions due to e.g. glazing and incidental shadowing ($F_F, F_S, F_C, F_W, g_{senk}$ according to [29], p. 213).
With extremely warm indoor temperatures, it is assumed that inhabitants shade the windows, so that additional warmth from solar radiation is avoided. Consequently, solar gains are set to zero in hours with initial indoor temperatures which approach the upper limit by 0.1 K.[5]

2.2.1 Foresight Modes

Simulation with Perfect Foresight For simulations with assumed perfect foresight, prices as well as ambient temperatures and solar radiation are assumed to be known in advance. Required weather data are stored as parameters of the heat-pump agent.

Simulation under Uncertainty Usually relevant input data, such as weather data, are not known in advance. Thus, simulations which show effects of uncertainties on heat pump operation can be applied. In order to simulate weather forecasts and their deviations a simple myopic forecasting scheme with updating is used, since actual forecasts are not easily available for sites with his-

[5]The possibility to cool the building is not regarded, as the focus is set on flexible heat supply, which is given particularly in winter months.

torical weather records. The heat-pump agent stores the weather agent's data with assignment to the corresponding hour of day as historical data, noted $T^{hist}_{amb,1}, ..., T^{hist}_{amb,24}$. When receiving current information on the temperature T_{amb,t_0}, the delta Δ_{t_0} to the last known temperature for this hour (which is from the previous day) is computed as follows:

$$\Delta_{t_0} = T_{amb,t_0} - T^{hist}_{amb,t_0},$$

where t_0 is the current hour of the day. The ambient temperatures $T^{fc}_{amb,t}$ for the subsequent 24 hours are then assumed to be shaped as the historical data, but shifted by the estimated level change:

$$T^{fc}_{amb,t} = T^{hist}_{amb,t} + \Delta_{t_0}, \text{ for } t = 1, ..., 24.$$

For solar radiation a myopic forecast is applied, using the historic data directly as forecasts. Thus, the occurrence of the same solar data as during the bygone 23 hours for the following 23 hours is assumed.

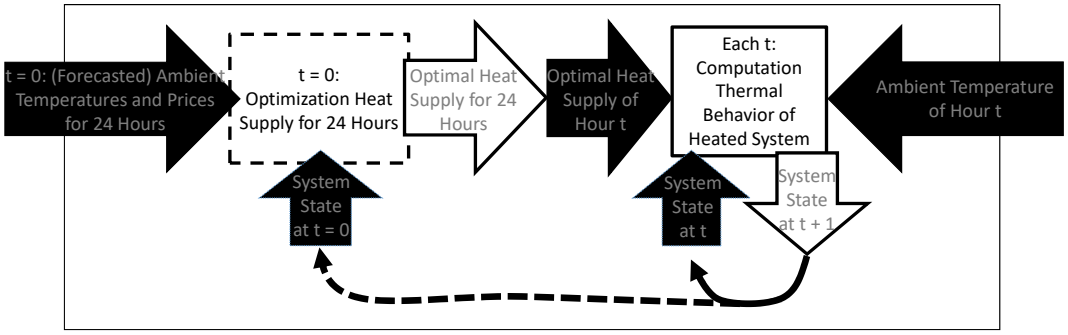
2.2.2 Scheduling Strategies

In order to reflect possible uncertainties on weather data, two simulation modes are implemented concerning the sequence of optimization and operation. An ex ante determined operation for 24 hours as well as an hourly rolling planning for variable time horizons can be chosen.[6]

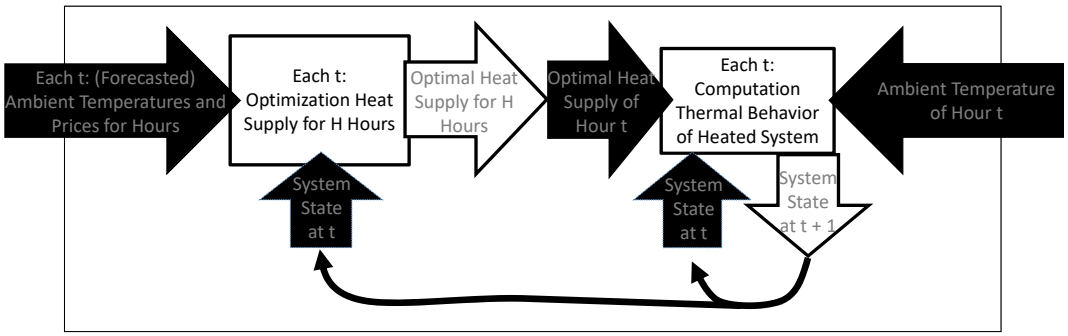
Scheduling in Advance Every day at midnight, the optimization algorithm is invoked and the operation is scheduled for the following 24 hours. The operation is carried then out according to the previously scheduled plan. (See Fig. 2a, where dashed lines indicate daily process steps, while continuous lines show hourly steps.)
In the presence of uncertainties, a predetermined schedule may turn out to be not optimal or even infeasible in actual operation - e.g. because the actual heat supply has to be higher than anticipated to keep indoor temperatures within the comfort range. In order to cope with such problems or prevent them, the following heuristic modifications to both the optimization and the simulation models are proposed - partly as precautions in order to avoid violations on operation limits, and partly as instantaneously required adjustments.
For the *optimization* the following modifications are implemented:

(1) The given restrictions in the optimization model may be changed in order to gain a more robust operation in case of uncertainty. Notably imposing tighter storage temperature limits in the optimization, allows to use additional leeway in storage operation to fulfill all original restrictions during operation, even when heat requirements occur unexpectedly.

[6]These scheduling methods correspond naturally to existing market structures - namely the auction based day-ahead market and the continuous trading of the intraday market.



(a) Scheduling in Advance and Operation



(b) Hourly Rolling Planning and Operation

Figure 2: Schemes of Scheduling Strategies

(2) Another possibility to gain some flexibility in operation, is to modify the mass flow in the heating system compared to the optimal mass flow as given in (8). In order to cope with situations with too much or too little heat in the system, the mass flow may thus be lowered or increased by a factor of 2 for up to four time steps.

(3) As a fall-back option also a heuristic is implemented. When an optimal solution can not be achieved in acceptable computation time, then the estimated heat supply of the full time horizon is distributed equally to each hour.

During the *simulation* of the heat-supply operation the following modifications are permitted (e.g. deviations between scheduled plan and effective heat-pump operation):

(a) In case the realized ambient temperature is lower than the forecasted one,

the available maximal heat capacity $\dot{Q}_{HP}^{max}$ is lower, too. As a consequence, the planned heat supply for a specific hour can not be delivered fully. The heat supply is set to the minimum of the currently available heat capacity and scheduled heat supply of that hour. (The amount of demanded electricity is assumed to be constant. This seems to be legitimate, as the maximum electric power consumption is only weakly dependent on ambient temperatures.)

(b) When temperature forecasts are badly wrong, then the earlier scheduled heating plan may fail to fulfill the restrictions concerning storage and comfort conditions.

   (i) When the indoor temperature is too high/low in a specific time step, then the previously defined mass flow (see (8)) is lowered/ increased by a factor of 2 (but not below a minimum $\dot{m}_{wc}^{min}$ or above a maximum $\dot{m}_{wc}^{max}$ size for the mass flow). This correction is chosen when the indoor temperature approaches the indoor temperature limits by less than 0.1 K.

   (ii) When the storage temperature is close to violations (i.e. the temperature approaches the limits by 0.5 K), then instantaneous adjustments of heat supply from the market are assumed to be possible. Namely, additional electricity purchase or the resale of previously bought electricity is carried out by setting the heat supply to $\dot{Q}_{HP}^{max}$ or 0.

   (iii) As adjustments of mass flow lead to a quicker or slower heat supply from the thermal storage tank, an additional measure, which combines the two aforementioned adjustments, is implemented: if the storage temperature is relatively low/high (i.e. the limits are approached by 4 K) and simultaneously the indoor temperature is close to be too low/high at the beginning of an hour (i.e. the limit is approached by 0.2 K), then a mass flow adjustment and a following storage temperature violation are likely. Therefore heat supply is assumed to be necessary resp. superfluous and thus set to $\dot{m}_{wc}^{max}$ resp. 0.

Hourly Rolling Planning In case of the rolling planning, the optimization is carried out in each hour for a certain time horizon (see Fig. 2b). On an hourly basis, the following steps take place: prices and price forecasts are received from the market agent for a certain time horizon, temperature forecasts maybe computed and the optimization function f is applied for the given time horizon. Due to typical lags between the reception of information and effective operation, the optimization schedule is determined for the operation, starting with the following hour. The actual heat supply in each hour is then done according to the latest schedule available. Thus, only the very first scheduled hour of each optimization is carried out, taking place in the next hour.
In comparison to the strategy 'Scheduling in Advance' as described before, there

are less adjustment possibilities required as the used information are newer. Yet, the following adjustments may be called: optimization adjustments as described in (1), (2) and (3) are possible as well as operation deviations due to less available heat or instantaneously required mass flow variations (see (a) and (b)(i) above).

3 Test Case

An application for the described agent-based simulation with optimized heat-pump operation is carried out for a sample heat pump, which heats a single-family house (according to a model given in [30], p. 38ff). The building has one floor and a partly heated basement, the roof space is unheated. In total the heated area is 110 m^2 and the corresponding air volume 272.9 m^3. Further detailed data are given in Table 2.

The heating system considered consists of a heat pump with thermal nominal capacity of 9 kW and electrical nominal capacity of 1.86 kW (Panasonic WH-SDC09F3E8, the system is dimensioned with regard to the nominal ambient temperature in Essen (Germany) and additional supply from a heating rod, cf. [31]). Parameters the for temperature depending thermal and electrical capacity, as defined in (1) and (2), are listed in Table 3. In order to yield high flexibility, a constantly high level of $42°C$ is chosen for the supply temperature. The volume of the thermal storage tank and the supply temperature have significant impact on the opportunity to operate the heat pump independently from building heat demand. This is due to the fact that the storage tank can take more heat, when its volume increases (and thus its thermal inertia) and when the upper bound of storage temperature (related to the supply temperature) is higher. Preceding investigations have shown that the thermal storage-tank volume V_{st} beyond 3.52 m^3 and the supply temperature T_S above $42°C$ does not yield additional benefits.[7] Thus, the data for supply temperature and tank volume are fixed at the mentioned levels. The storage tank then has a surface S_{St} of 36.88 m^2 (a combination of eight equal units of the system PAW-TE0E3STD is considered).

Regarding the market context, two simulations are carried out. In order to apply information with adequate accuracy, only short-term trading is taken into account, namely participation in a day-ahead and an intraday market are simulated.

In order to obtain stable simulation results for the thermodynamic system, the time resolution for the optimization of the heat-pump operation is chosen to be a two-minute pace in the MATLAB code, i.e. $\Delta t = \frac{1}{30}$. The optimization performance is more robust, when heat supply is chosen for each two-minute-time-step, too. Yet, as market transactions are assumed to be hourly contracts, heat supply as well as corresponding electric load are finally defined as average

[7] The investigations to determine supply temperature and storage-tank size are carried out in the context of an average daily profile of ambient temperatures around $0°C$ and constant prices. As a market participation in general is to be investigated, the focus is set on flexibility here, and therefore a high storage volume is chosen without consideration of the investment costs.

Table 2: Parameters Thermal System

C_{bui}	building heat capacity	7982 $\frac{Wh}{K}$
A_{bui}	heated area	110.5 m^2
A_{w1}	area windows to the north	4.49 m^2
A_{w2}	area windows to the east	3.87 m^2
A_{w3}	area windows to the south	5.82 m^2
A_{w4}	area windows to the west	0 m^2
V_f	volume floor	6.63 m^3
A_{pipe}	surface pipe system	27.87 m^2
m_{wc}	mass water circuit	123.85 kg
$\dot{m}_{wc}^{min}$	minimum mass flow	50 $\frac{kg}{h}$
$\dot{m}_{wc}^{max}$	maximum mass flow	1200 $\frac{kg}{h}$
$U_{p,f}$	heat exchange coefficient (pipe to floor)	78.42 $\frac{W}{m^2K}$
U_{bui}	heat transition coefficient (building components in-/outdoor)	13.33 $\frac{W}{m^2K}$
H_{tv}	coefficient transmission/ventilation losses	282.23 $\frac{W}{K}$
V_{st}	volume storage tank	3.52 m^3
S_{st}	surface storage tank	36.88 m^2
C_{hl}	heat loss coefficient storage tank	0.48 $\frac{W}{m^2K}$
T_{st}^{min}	minimal storage tank temperature	28°C
T_{st}^{max}	maximal storage tank temperature	39°C
η_{HR}	level of efficiency heating rod	0.98
$\dot{Q}_{HR}^{max}$	thermal capacity heating rod	3 kW

values for each hour.
For all scenarios the simulation is performed for the first quarter of 2014. Here market operations can be observed for both a 'real' winter month and a relatively warm March, implying also a relatively high level of temperature volatility.

3.1 Day-Ahead Market

For the day-ahead market simulation it is assumed that prices for the following day are known at midnight and procurement can be settled for the whole day then. As simulation mode the 'Scheduling in Advance', described in Chapter 2.2.2, is applied. That is, at midnight a presumably optimal heat-supply operation for the following day is scheduled and followed as closely as possible. Price information is provided previously as a vector of day-ahead prices from

Table 3: Parameters Heat Pump

$\dot{Q}_{HP}$		P_{el}	
a_1	10.12 kW	b_1	0.811 kW
a_2	-0.003 $\frac{kW}{°C}$	b_2	-0.058 $\frac{kW}{°C}$
a_3	-0.015 $\frac{kW}{°C}$	b_3	0.055 $\frac{kW}{°C}$
a_4	0.001 $\frac{kW}{°C^2}$	b_4	0
a_5	-0.002 $\frac{kW}{°C^2}$	b_5	0
a_6	0	b_6	0

the market agent. Data is given by historical day-ahead EPEX spot prices for 2014. Thus, day-ahead trading of heat-pump operators is analyzed without consideration of uncertainty in prices nor market-entry barriers for small-scale consumers nor transaction fees. The aim is to analyze the theoretical potential for the participation of heat-pump operators in real spot markets.
In case improperly estimated heat capacity or thermal behavior lead to the need of instantaneous adjustments of the heat-supply operation (modeled as described in (b)(ii) and (iii)), an additional intraday-market contract is assumed to be concluded. In case of uncertainty (i.e. uncertain weather data), the restrictions of the optimization are chosen tighter than properly required (see $\tilde{T}_{Sp}^{min}$, $\tilde{T}_{Sp}^{max}$, $\tilde{T}_{i}^{min}$ and $\tilde{T}_{i}^{max}$ in Table 4).

Table 4: Adjustment Parameters

	Day-Ahead	Intraday
$\tilde{T}_{Sp}^{min}$	32 $°C$	29 $°C$
$\tilde{T}_{Sp}^{max}$	35 $°C$	38 $°C$
$\tilde{T}_{i}^{min}$	19.5 $°C$	19 $°C (= T_i^{min})$
$\tilde{T}_{i}^{max}$	20.5 $°C$	21 $°C (= T_i^{max})$

3.2 Intraday Market

In order to simulate the participation of a heat-pump operator in an intraday market, the simulation mode 'Hourly Rolling Planning' (see Chapter 2.2.2) is chosen. Price data from the intraday market is provided each hour. Again a vector of prices is given, but the number of prices varies and therefore also the time horizon for heat-supply optimization. A decreasing number of prices is available throughout the day, as only contracts for all following hours within the same day are traded in the EPEX Spot intraday market. Yet, at 3 p.m. the market for the following day opens. Therefore again prices for the next 24

hours can be taken into account for an optimal schedule. Except a price for the current hour is lacking in each case. This is due to the fact that contract conclusion and execution may be at minimum 30 minutes apart. As mentioned above (see Chapter 2.2.2) the optimization is done for a period starting the following hour, while heat-supply operation of the current hour is executed according to the previously determined schedule.
Historical price data are again used as input: for each scheduling hour, the weighted average price of contracts traded in that period in the EPEX Spot intraday market are used as price expectations for the hours of the planning horizon. The price for the next hour is assumed to be the actual price of delivery, which can be chosen for a contract or not. In contrast, no actual trading is considered for the following hours. The size of the price vector (and correspondingly the planning horizon H) depends on the current time as the optimization is carried out for at most 24 hours but also at most until gate closure.
In addition, the same simplifications concerning market participation of residential consumers are made as for the day-ahead market simulation. Particularly, market liquidity is assumed to be sufficient, so that contract partners for trades are always available.
In case of uncertainty the storage temperature range is again chosen tighter than properly required (see $\tilde{T}_{Sp}^{min}$ and $\tilde{T}_{Sp}^{max}$ in Table 4).

3.3 Combined Bidding Strategy

Another application attempts to make use of the benefits of both described strategies: the planning in advance, which fulfills the schedule (in theory) without corrections (but is rather critical under uncertainty) on the one hand, and the rolling planning, which reschedules optimal solutions using newest information on the other hand. Here first a day-ahead procurement for the following day is carried out according to the schedule determined in advance. Subsequently, changing electricity quantities are bought or sold in the intraday market after reoptimization. The heat-pump operation, including possible adjustments, is carried out similarly to the intraday application. In terms of implementation the only difference to the intraday simulation is an additional optimization each day, which has no effect on the applied heat-supply operation.
This strategy is expected to be advantageous due to the following reasons: First, a greater choice between two prices should lead to lower procurement costs (even if future prices are uncertain and may not be locked in the setting described here). A procurement in advance allows to avoid purchasing of currently required electricity. Even more, it is possible to sell electricity in some cases, when prices are high.
The costs of procurement are computed after the simulation including both the day-ahead procurement and the effective heat-pump operation supplied from the intraday market.

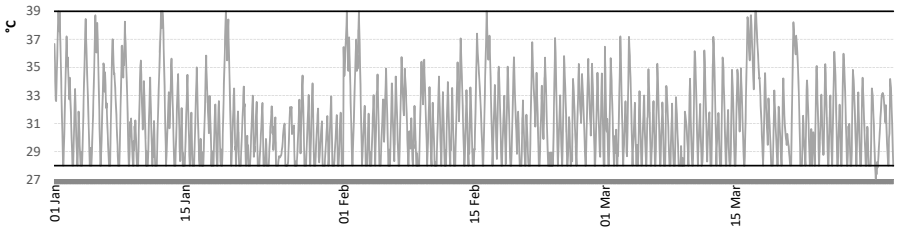
4 Results

From the outset it can be stated that comparisons of procurement costs obtained for various market applications are not biased by systematic differences in price levels, as the EPEX spot day-ahead and intraday market have nearly the same mean price for the investigated time period (3.350 ct/kWh for the day-ahead, 3.349 ct/kWh for the intraday market). Concerning the volatility of prices, the intraday market is slightly advantageous for participants with purchasing and reselling intentions as there are on average greater price spreads (the standard deviation is 14.7 ct/kWh for the day-ahead compared to 17.59 ct/kWh for the intraday market).
The simulated time range is from January to March. Thereby January and February represent a rather typical heating period, while in March heat supply is required as well, but there are also some hours of relatively high temperatures. With $-5.15°C$ as lowest and $23.85°C$ as highest ambient temperature the temperature range is quiet large. The highest temperatures difference within one day occurs on 30 March with $25°C$. Remarkably, on this day the maximum of $23.85°C$ is reached, which exceeds the accepted indoor temperature of $21°C$.

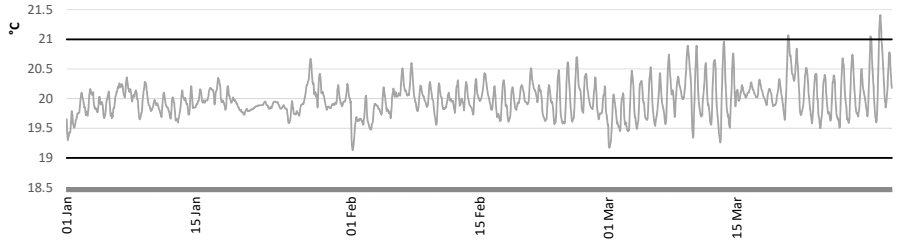
4.1 Simulation with Perfect Foresight

Obviously, the simulations with perfect foresight are rather theoretical ones, but serve as pre-analysis to check the operation functionality and to compare the scheduling strategies disregarding the impact of uncertainty. Especially basic differences between the described scheduling strategies may be identified and the impact of weather conditions on operation patterns can be observed therewith.

Day-Ahead Market For the day-ahead-market application Fig. 3 shows the obtained values for the constrained temperatures, i.e. storage and indoor temperature. Only a few small violations of the imposed temperature limits are observed in March. The reasons for these violations are discussed below. As a mean procurement price 2.791 ct/kWh is realized (compared to an average price of 3.350 ct/kWh on this market).
In an additional computation 2.709 ct/kWh is determined as a lower limit for the procurement price in the same market and weather context. This price holds under the assumption of maximum within-day flexibility, i.e. when total daily heat demand is allocated as far as possible - given the heat capacity of the heat pump - to the lowest market prices of the day. Hence the realized price in the context of perfect foresight is only 3% higher than the price with full flexibility, indicating that the system-depending restrictions for storage and indoor temperature are rather low obstacles from an economic point of view.
The observed constraint violations occur only in in hours with high ambient temperatures and large temperature spreads. On 30 March no optimal solution can be found and instantaneous corrections with short-term heat supply occur twice. Nevertheless, violations of the lower storage temperature limit can



(a) Storage Temperature Behavior and Limits



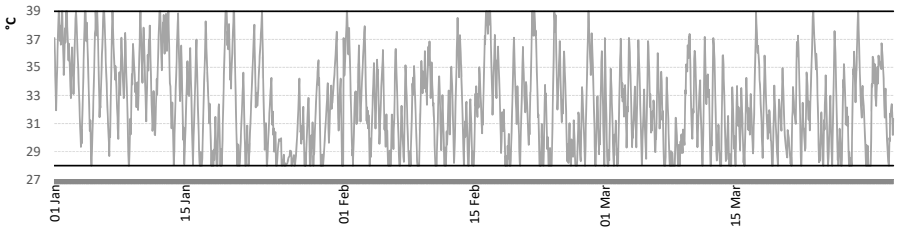
(b) Indoor Temperature Behavior and Limits

Figure 3: Temperature Performance Day-Ahead-Market Application under Perfect Forecast

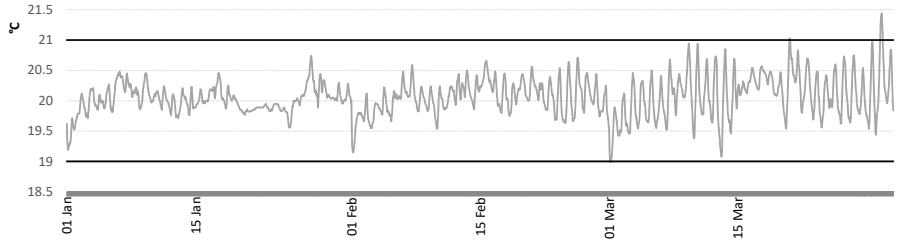
not be avoided in the cold morning hours. And later on, ambient temperatures of more than $23°C$ imply a violation of the upper indoor temperature limit. Further slight violations of the same temperature limit (12 times) are due to relatively high outdoor temperatures (above $20°C$) combined with missing cooling possibilities and the systems inertia.

Intraday Market In case of the intraday-market application, the system and comfort constraints are fulfilled nearly throughout the whole simulation period (see Fig. 4). Violations occur only on 30 March for the indoor temperature (too high), when it comes to the mentioned high ambient temperatures. Again, the performance is more difficult for the spring month March: On three days heuristic schedules have to be called. In the end, these substituting schedules operate the system in a way that no deviations between scheduled and effective operation are needed. Thus, no adjusting mechanisms are required to fulfill all restrictions in case of the intraday-market operation. The frequently updated information and the avoidance of subsequent faults due to repeated reoptimization lead to a more robust strategy in the context of critical weather conditions.

The price paid per kWh is about 2.690 ct/kWh in average, where the market's mean price is 3.349 ct/kWh. The theoretical procurement price with maximal flexibility, which is computed similarly to the day-ahead case above, is 2.550 ct/kWh. I.e., the realized price with perfect foresight implies with a deterioration of 5% again only a limited loss due to technical and comfort restrictions.



(a) Storage Temperature Behavior and Limits



(b) Indoor Temperature Behavior and Limits

Figure 4: Temperature Performance Intraday-Market Application under Perfect Forecast

Noteworthy, the consumed electricity is higher for the case of the reoptimizing intraday application. While the optimization in advance (within the day-ahead market) ends up with 2772 kWh for the three simulation months, the reoptimizing mode implies a consumption of 2805 kWh.[8]

4.2 Simulation under Uncertainty

Day-Ahead Market A more realistic simulation for the day-ahead-market application is done with uncertain ambient temperatures. Naturally the performance of the heat-pump operation turns out to be significantly worse. Especially the maintenance of technical and comfort restrictions is critical: From January to February the upper indoor temperature limit is violated slightly in 9 cases. The temperature ranges are $28.05°C$ to $37.83°C$ for the storage tank and $19.03°C$ to $21.02°C$ for the indoor temperature. As before, the performance for March is more critical: Mainly due to high indoor temperatures the number of violations increases to 51 for the period January to March (where 43 violations belong to the upper indoor temperature limit) and the ranges for storage and indoor temperatures are extended to $26.65°C$ to $37.85°C$ resp. $18.83°C$ to $21.8°C$. Even with mass flow variations and instantaneous heat supply ad-

[8]The reason for deviating electricity amounts may be the higher price volatility of intraday prices: Then prices have a relatively deeper impact than ambient temperatures and therefore the achieved COP on average is declined.

justments these violations can not be avoided. Significant violations of indoor temperatures are due to inaccurate estimates of ambient temperatures (there are hours with deviations of up to $17K$) so that they can not be absorbed by mass flow adjustments. Violations of the storage temperature limits occur during longer periods of under- resp. overestimated ambient temperatures and subsequent mass flow variations, with the consequence of too slow or too quick storage discharging.
Intraday adjustments of the precomputed schedule take place in 141 of 2160 hours. Thus, the procurement price now is increased significantly to 3.298 ct/kWh. In comparison to the theoretical price with full flexibility this is a deterioration of 22% (see also Table 5). Still, the realized price is below the market mean. But additionally it is to note that the consumption in total is increased in comparison to the operation with perfect foresight assumption. Due to adjustments of mass flow, instantaneous heat supply and subsequent deviations between optimal schedule and operation, now 2864 kWh are consumed, where before 2772 kWh were required.

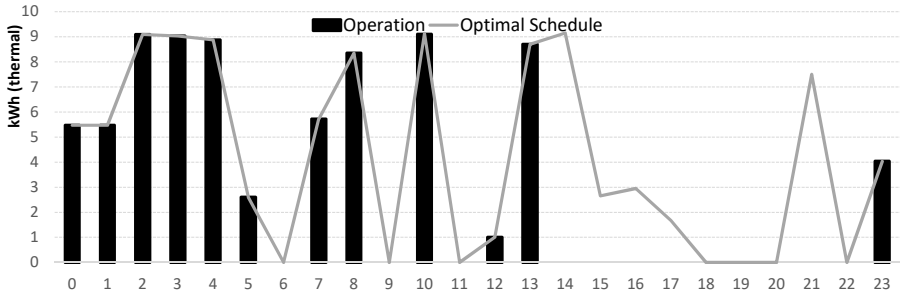
An example of schedule adjustments due to improperly estimated ambient

Table 5: Comparison of Prices

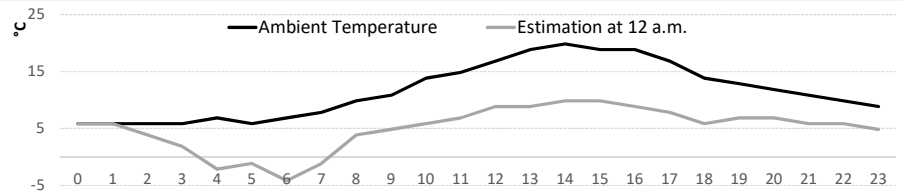
	Day-Ahead $[ct/kWh]$	**Intraday** $[ct/kWh]$	**Combined Bidding** $[ct/kWh]$
Market Mean	3.350	3.349	
Theoretical Price	2.709	2.550	
Perfect Foresight	2.791	2.690	2.608
Under Uncertainty	3.298	2.762	2.684

temperatures is illustrated for 9 March (see Fig. 5a and 5b). Estimations at midnight, which are too low throughout the day, lead to an optimal schedule at midnight, which has to be adjusted from 2 p.m. onwards by heat-supply interruptions.
In sum, one can not stick to the optimal schedule, and the average procurement price deteriorates here significantly compared to the perfect foresight simulation. Planning one day in advance turns out to be a long period for residential heating with myopic weather forecasts as inaccurate estimates lead to violations of given restrictions and rather bad economic results. Even the numerous adjustment mechanisms can not guarantee a satisfactory performance within the predefined constraints. Thus, planning in advance is theoretically a good solution, but not practicable in the end - at least in the absence of accurate weather forecasts.

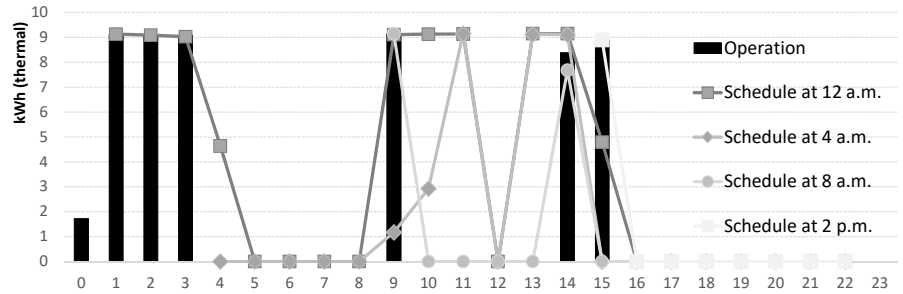
Intraday Market Waiving the assumption of perfect foresight has less consequences for the case of the intraday-market application. Naturally, the reoptimizing strategy can respond to inaccurate estimates better. The performance for the restricted storage and indoor temperatures is acceptable in this case



(a) Day-Ahead: Optimal Schedule at 12 a.m. for 12 a.m. to 11 p.m. and Operation



(b) Ambient Temperatures and Estimations at 12 a.m.



(c) Intraday: Optimal Schedules form hour t onwards (scheduled in hour t-1) and Operation

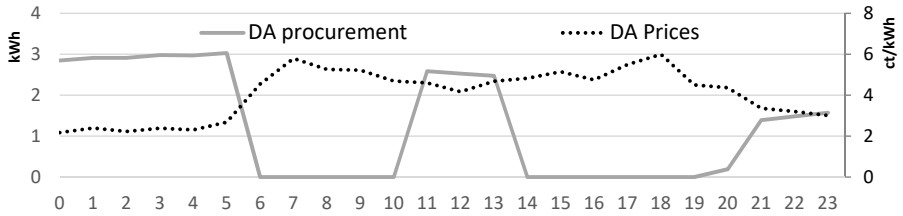
Figure 5: Optimal schedules for 12 a.m. to 11 p.m. on 9 March and Adjustments

(ranging from 28.05°C to 39.0°C resp. 19.06°C to 21.64°C for the full period from January to March). High indoor temperatures are occurring only in three days of March (18th, 20th, 30th), where ambient temperatures are high or relatively high and badly estimated over a period of a few hours. Some adjustments of the mass flow are called and avoid further violations. As an illustration of the intraday performance in comparison to the one of the day-ahead operation, schedules and effective operation are displayed in Fig. 5c also for 9 March. The optimal schedule at 12 a.m. is based on the same weather information as the corresponding day-ahead plan, and is valid for the hours from 1 a.m. onwards. It coincides with the operation (black bars) for the first three time steps, so that the following hourly optimal schedules are omitted in the illustration. Effectively deviating schedules are computed at 4 a.m., 1 p.m. and 2

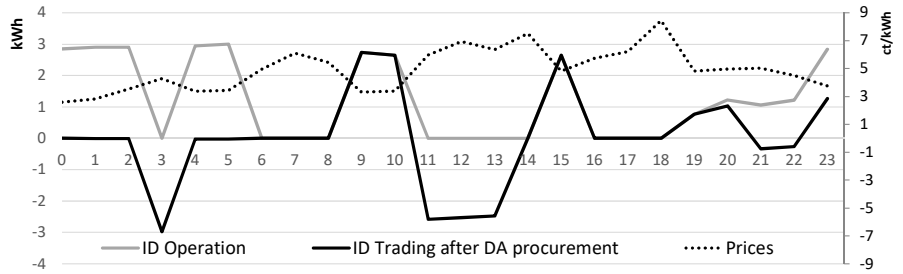
p.m. as displayed (belonging to the periods beginning at 5 a.m., 2 p.m. resp. 3 p.m.). Updated information on ambient temperatures lead to reductions of supplies scheduled earlier and to rescheduled supply time steps, each the result of new optimal decisions. Previously estimated low ambient temperatures can be corrected and an excess of heat supply avoided, while later on, an earlier heat supply takes into account that following hours (e.g. early morning hours of the next day) are expected to require more heat.
In the end, a procurement price of 2.762 ct/kWh is realized, which is 8% above the theoretical price with full flexibility. Abandoning the perfect-foresight assumption, leads therefore to a further deterioration by only 3 percentage points. (For a comparison of prices see also Table 5.)
Total consumption increases again in comparison to the simulation under perfect foresight (2827 kWh instead of 2805 kWh). Yet, consumption as well as procurement price and performance degradate significantly less with uncertain information than in the case of the day-ahead-market application.

Combined Bidding The combined bidding makes use of the theoretically beneficial day-ahead procurement, which becomes practicable with the additional hourly intraday-market participation.
As a result a final procurement price - implying costs and earnings of the day-ahead and the intraday trading - of 2.684 ct/kWh is realized (where the pure intraday participation reached 2.762 ct/kWh).[9] Thus, even the realized price with assumed perfect foresight is outperformed (see Table 5).
Yet, the dual purchasing (and possible reselling) improves the balance on a daily basis not in every case: In 49 out of 90 cases, the final price per kWh is reduced when combined bidding is applied, while the other cases lead to a higher daily price per kWh. As an example with a benefit, the day-ahead (DA) and intraday (ID) tradings on 10 February are illustrated (see Fig. 6a and 6b). In this case, at midnight scheduled and effectively demanded electricity are in total nearly the same, and at the end of the day the combined bidding leads to 37.63 ct cheaper heat supply then the pure intraday procurement. Fig. 6a shows the day-ahead procurement and corresponding day-ahead prices. Fig. 6b displays beside intraday prices of 10 February (dotted line) the effective intraday operation (coinciding with the intraday procurement in case of pure intraday-market application, see grey line) as well as the intraday trading after day-ahead procurement in case of combined bidding (black line). It can be observed that a coincidence of a low day-ahead price and an intraday price peak corresponds to intraday reselling in case of combined bidding (see 3 a.m., 11 a.m., 12 p.m., 1 p.m.), while the pure intraday application simply avoids procurement.
In fact, the main difference between intraday trading and combined bidding is that opportunities to resale electricity are given and thereby procurement is on average cheaper than reselling. Table 6 provides an overview over all com-

[9] Total consumption or the system's temperature behavior do not change in comparison to pure intraday participation as the effective operation is the same as the one for intraday operation without preceding day-ahead procurement.



(a) DA Procurement



(b) ID Operation And ID Procurement

Figure 6: Combined Bidding

binations of day-ahead (DA) and intraday (ID) prices in a simplified manner. Assuming that a strict price limit is given for the day-ahead trading as well as one for the intraday trading (so that procurement takes place if and only if prices are lower than the mentioned price limit), the table shows operation decisions and their consequences. It turns out that only the cases with 'DA Price $\leq$ DA Price Limit' imply changes in comparison to the pure intraday trading. But given this assumption, the first case ('ID Price $\leq$ ID Price Limit') has as result on average neither benefits nor losses. The second case ('DA Price $\leq$ DA Price Limit', 'ID Price $>$ ID Price Limit') implies a benefit for one single time step in the most cases.[10] In sum, benefits are more likely than losses and therefore the combined bidding is generally advantageous compared to pure intraday trading.

[10]Conclusions are valid only if compared procurement amounts are equal and price limits are strict (which is not exactly the case when results are observed in detail). Yet, highlighted tendencies seem to be legitimate. Further more, the conclusion of the likeliness of benefits in the latter described case can be sharpened with tighter assumptions: Assuming additionally that DA and ID price limits are the same, then a profit from procuring and reselling is a fact, and not only more likely, for this time step.

Table 6: Combination of Day-Ahead and Intraday Price Levels

	DA Price $\leq$ DA Price Limit	**DA Price $>$ DA Price Limit**
ID Price $\leq$	decision to buy DA decision to buy ID $\rightarrow$ effectively no ID procurement	decision against buying DA decision to buy ID
ID Price Limit	$\triangleright$ beneficial if DA price $<$ ID price $\triangleright$ 0 benefit on average	$\rightarrow$ no difference to pure ID trading
ID Price $>$	decision to buy DA decision against buying ID $\rightarrow$ reselling DA procurement	decision against buying DA decision against buying ID
ID Price Limit	$\triangleright$ beneficial in most cases (as DA price is low, ID price high)	$\rightarrow$ no difference to pure ID trading

5 Conclusion

This paper analyzes electricity-market participation of residential heat-pump operators as heat appliances (in aggregation) have a high flexibility potential. At the same time, a single operator, who is a private consumer, has strict restrictions and typically less sophisticated prediction tools.

Therefore a system consisting of heat pump, storage tank and building, operating in the context of a market situation is implemented as a MATLAB optimization model. In order to implement a realistic application for this optimization, which allows to modify number, types and parameters of observed participants easily, an agent-based model is used.

In order to investigate the critical issue of uncertain information, various market situations are simulated. Besides the comparison of theoretical perfect foresight situations and realistic error-prone forecasts, the participation in two real markets with different time span between contract and delivery time are modeled. Namely, participations in the short term EPEX Spot markets (day-ahead and intraday) are investigated for January to March 2014. Further on, a combined bidding strategy, which includes both markets, is investigated and resulting average procurement prices are compared.

Results show that a simple participation of residential consumers in day-ahead markets is problematic in terms of practicability. Single small-scale consumers have strict restrictions and limited prediction tools. Thus, uncertainties lead to unsatisfactory results in a market with a daily planning horizon. The day-ahead-market application shows that the operation performance is insufficient in terms of respecting constraints in storage and indoor temperatures as well as in the resulting supply plan. Shorter term decisions with continuously updated information are a feasible alternative, as shown with an intraday-market application under uncertainty.

From an economical point of view, the mean intraday procurement price can be improved with a combined bidding strategy: A day-ahead procurement in advance of an intraday trading according to hourly reoptimized schedules lowers the procurement price from 2.762 ct/kWh to 2.684 ct/kWh. In the end, the combined bidding reaches a better price than the intraday-market participation with assumed perfect forecast. Thus, the critical issue of uncertainties is fully compensated. In contrast, a day-ahead operation under realistic conditions results not only in significantly worsened procurement prices but also fails to respect operational limits in critical situations. Consequently, our results indicate that a market participation for residential consumers is conceivable only when including the very short term markets.

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4 DECENTRALIZED LOCAL PRICING - IMPROVING NETWORK USAGE IN A SMART-GRID ENVIRONMENT UNDER LIMITED INFORMATION

Decentralized Local Pricing - Improving Network Usage in a Smart-Grid Environment under Limited Information

Jessica Raasch and Christoph Weber*

Abstract

With a smart grid environment, flexible load devices and provided local price incentives a more efficient grid usage may be achieved in the future. Bidirectional communication, smart devices and shiftable loads as electric vehicles and heat pumps have the potential to be coordinated with local supply when suitable incentives are provided. This can bring relief especially for distribution grid areas where infeeds from fluctuating renewable energy sources increase.
This paper presents a decentralized local pricing mechanism, aiming at local prices that reflect the current load situation. That is in case of congestion a local price, deviating from the wholesale market price, is determined. With an iterative search algorithm suitable prices can be computed without gathering full-fledged bidding data. Simultaneously self-reinforcing effects are avoided. Further on this concept can be implemented rather easily precisely where and when required so that only areas with grid congestion are affected.

Keywords: Smart Grid, Real-Time Pricing, Network Pricing, Agent-Based Modeling, Price-Elastic Behavior.

1 Introduction

In recent years, distribution grids in Germany and other countries are facing significant new challenges. The high amount of decentralized and volatile power production, primarily from wind turbines and solar systems, leads to an increasingly complex task to operate the grid and to guarantee system stability.
Today many small-scale renewable energy source (RES) devices have no regulation equipment and typically the current local weather conditions instead of

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demand are drivers for supply. Further more, the grid infrastructure was designed originally to transport electricity from central large-scale power stations down to lower voltage levels. With local supply, the direction of load flow is inverted more frequently and causes congestion in terms of thermal capacity and voltage restrictions.

Furthermore, the energy consumption behavior is likely to change in the future. Load profiles will change with a broader presence of electric vehicles and electrical heating systems. Critical load situations may arise especially when these devices are used simultaneously. Yet these operations can be executed more flexibly: charging and heating processes can be performed decoupled from utilization due to the storage capacity of batteries and the thermal capacity of buildings. Hence, demand response (DR) from private consumers will gain importance in the near future.

In some places, these changes lead already to constrained networks (see e.g. [1]), but within smart-grid environments an efficient usage of existing networks can be enabled. Grid usage of numerous private consumers, prosumers and small-scale generators could be adjusted in case of congestion, when modified prices indicate the current congestion situation via smart meters. Bidirectional data exchange together with smart components as energy management systems and automated devices would allow a prompt response from network users to specifically modified prices.

The concept of nodal pricing provides a pricing scheme indicating scarcities in the network (cf. e.g. [2], [3], [4] and [5]). Thereby price differences occur when electricity flow has to be reduced due to restricting grid elements. This concept is implemented in electricity markets in the USA and in New Zealand, but so far only at the transmission network level.

In order to implement nodal prices or other forms of local prices in the distribution grid, the availability of local information is more crucial. Local information encompasses notably detailed data on consumption and generation behavior of private households. Gathering such large numbers of data will be facilitated in the future by expansions of intelligent communication infrastructure. Therefore, setting up a market mechanism at the level of small-scale low voltage grids may be challenging. Thereby also the acceptance of individual prices is required from small-scale grid users. Applications of the nodal pricing concept to the distribution grid are investigated already in e.g. [6], [7], [8] and [9]. Yet, the specific problem of available data and the need for an explicit bidding mechanism are not discussed there.

Local markets as a consequence of congestion within the distribution network are subject of [10]. This theoretical discussion emphasizes that a separation into local markets is efficient only when congestion occurs.

In order to design efficient local markets the demand side has to react more flexible than in conventional electricity markets. Opportunity and consequences of flexible demand - e.g. incentivized by prices - are investigated e.g. in [11], [12], [13]. But suitable price mechanisms to incentivize demand adjustments efficiently are not discussed there. In contrast, e.g. [14] and [15] investigate the issue of generating usage-based prices to coordinate grid users' behavior, but

neglect that data affecting the grid are not known by a grid operator in advance.
The problem that the load situation results from the combination of a huge number of grid users but relevant information are not available centrally, is answered variously in the literature: Average grid use is assumed to estimate the load situation e.g. in [16], [17] and [18]. I.e. consequences of individual user behavior are not discussed. In [19], [20], [21], [22], [23] and [24] in contrast the concept of cooperation between grid users is introduced so that data exchange allows an efficient coordination of grid affecting behavior without a system operator's overview. Yet, the precondition of incentives and technical requirements for a fast communication and cooperation are questionable.
Another way to answer the problem of lacking coordinated behavior adjustment in the context of incentivizing prices - it may result in changed but again extreme situations (e.g. congestion caused by supply substituted by congestion caused by consumption) - is chosen in some models and also some German field tests. There the use of selected addresses is made (cf. [25], [26] and [27], [28]). Therewith adjusting responses of participants do not occur at the same time and avalanche effects may be avoided. Yet, the choice of responding users might be unclear, inefficient or discriminating, and it becomes obvious that no proper market price is given in that way.
In contrast a pricing mechanism where suitable prices are determined within an iterative process, requiring a minimum of data exchange, is given in [29] and [30]. But the focus is not set to the distribution grid level and the network capacity is not explicitly reflected in the model. Aiming at loss minimization a physically detailed approach to compute node-specific prices is given in [31]. Here grid restrictions are considered and an iterative negotiation process is used. Yet, this approach is rather theoretical and implies specific assumptions (e.g. a quadratic function for line losses).
In this paper we introduce a decentralized local pricing mechanism, which determines price adjustments in the case of congestion situations in the distribution grid. Efficient grid usage is incentivized with increasing or lowering the general price in a certain local grid area because grid usage is adjusted consequently (e.g. via load shifting or reduction of local feed-in). Thereby the pricing mechanism is based on an iterative negotiation process. Only current quantity bids from grid users are required to determine efficient prices, full demand curves are not needed to transmit. That is, gathering and exchange of numerous and particularly private data are not needed. As a consequence this pricing scheme requires no adjustments in case of changed conditions as e.g. varied grid user's equipments or changed numbers of grid users. Additionally the application of this market-clearing mechanism can be implemented precisely with view to the individual grid situation. Thus, implementing in wide network areas with rare congestion situations can be avoided.
The paper is organized as follows: In Chapter 2 the decentralized pricing mechanism is introduced. As an simulation environment, an agent-based model is described in Chapter 3 with local demand and supply agents as well as a market agent. Exemplary applications are presented in Chapter 4 including different

settings concerning price-elastic grid users. Chapter 5 concludes.

2 Methodology

From an economical point of view, the lack of transport capacities has to imply the separation of a market into two market places. In the current and future distribution grid congestions due to local supply or large amounts of simultaneous consumption can take place at various locations and are typically not permanent. Hence, there is usually not a certain local market. Yet, a mechanism to reflect the imbalance of the global market and a current isolated grid area can be the same for various congestion situations and even for uncritical grid usage. Here we focus on such a pricing mechanism itself, assuming that a congestion leading to isolated grid areas has been detected (see Fig. 1). The market mechanism provides individual price signals, which reflect the current congestion situation for a local grid area in time steps and locations where such a separation of markets arises. In order to reflect local scarcity the market mechanism computes a markup on the wholesale price. Given an excess feed-in the markup will be negative, for congestion caused by consumption it will be positive.

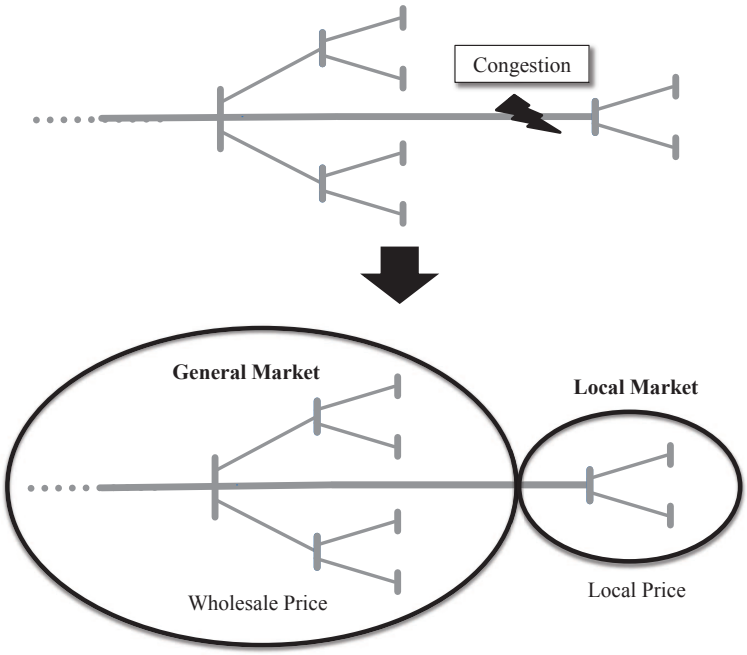


Figure 1: Separated Markets in Case of Congestion

Particularly an algorithm is needed to determine an adequate magnitude of the

markup. Local prices should be efficient but also self-reinforcing effects have to be avoided. E.g. reducing local infeed simultaneously with activation of large amounts of load may result in an inefficient use of the available grid capacity or even overloading in the inverse flow direction, which is obviously not desirable. Therefore the magnitude of price adjustments has to depend on technical network restrictions as well as on the market participants' behaviors. Especially the possibly time-dependent capability and willingness to respond to prices is prima facie a private information not known to a central planning coordinator. Therefore a negotiation process based on bidirectional communication is organized by a market coordinator. This includes iterative adjustments of price and quantity bids (see Fig. 2), so that local prices can be determined without centralized optimization and centrally known response curves. The choice of price adjustments follows the approach of bisection (cf. e.g. [32]). This simple but efficient method requires no further information, as steepness parameters of bidding functions, for an successful convergence. Hence, our approach is effective without making usage of bidding functions and therefore provides a robust mechanism for various conceivable user behaviors. Iterative price bids are computed here with view to (a) resulting quantity bids and corresponding load situations and (b) information achieved with previous price bids. The interval for possible local prices is halved thereby in each time step. In the context of unavailable information repeatedly halving the price interval in question is the quickest way to approximate suitable local prices.

The whole iterative process of the decentralized local pricing mechanism is

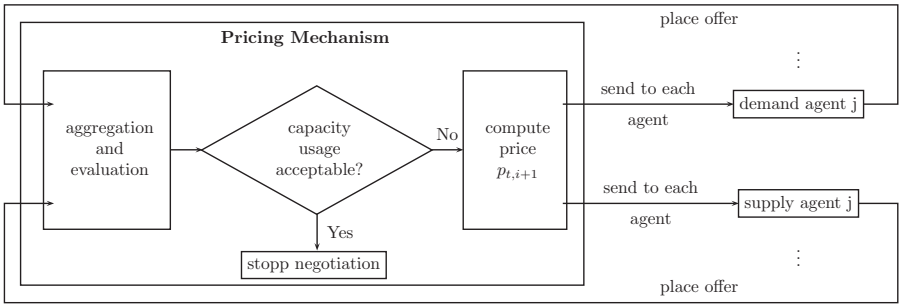


Figure 2: Negotiation Process to determine Decentralized Local Prices

as follows (see also Fig. 3): In each turn of the bidding process the first step consists of evaluating whether the present local price - being the initial wholesale price $p_{t,0}$ or the previously modified price - is suitable or not. That is the balance of the aggregation of individual power $P^{gen}_{t,i,k}$ and load $P^{load}_{t,i,k}$, bidden in response to the current price, has to be compared to the grid capacity c (t, i, k are indices for time, iteration step and the local grid users respectively). Basically two cases of congestion can occur: a congestion due to excess feed-in or one due to excess demand. The first one is indicated by violations of the

following inequation:

$$\sum_k P^{gen}_{t,i,k} - \sum_k P^{load}_{t,i,k} > c. \tag{1}$$

But in order to avoid in this situation also adjustments with a larger extent than necessary, a second inequation has to be fulfilled:

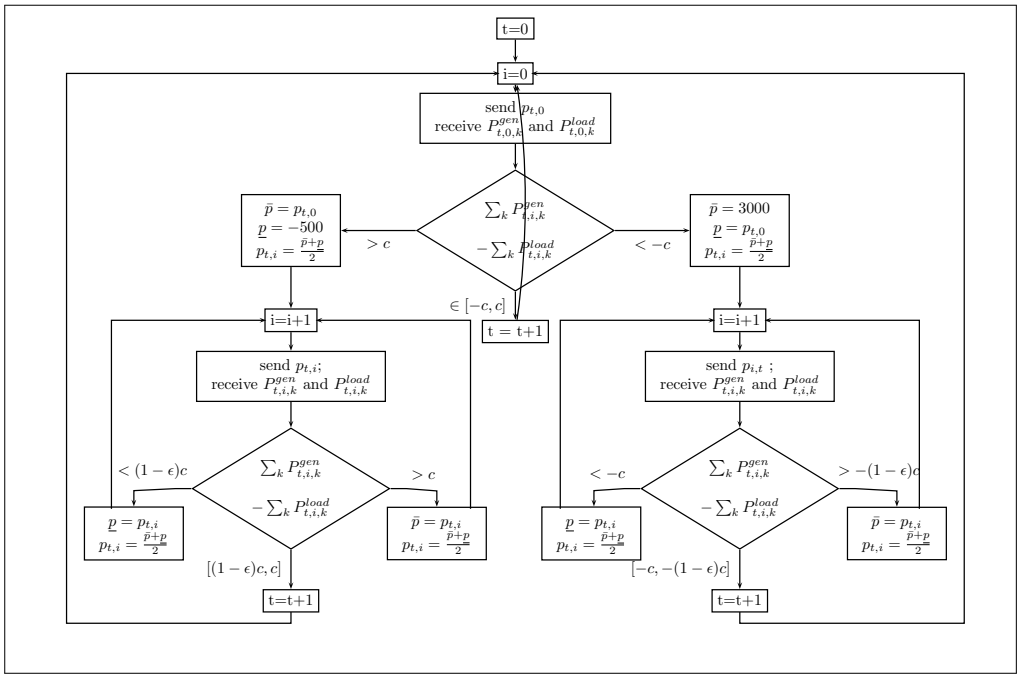


Figure 3: Pricing Algorithm - Process during one Time-Step

$$\sum_k P^{gen}_{t,i,k} - \sum_k P^{load}_{t,i,k} < (1-\epsilon) \cdot c, \tag{2}$$

where ϵ is a small quantity.
The determination of a target range $[(1-\epsilon) \cdot c, c]$ after an initial violation ensures as well that an opposite violation is avoided.
Analogously the second case of congestion due to excessive demand is given, when the following inequation is violated:[1]

$$\sum_k P^{gen}_{t,i,k} - \sum_k P^{load}_{t,i,k} < -c. \tag{3}$$

[1]Current grids have been designed and built to serve household demand, therefore congestion due to excessive demand is unlikely as of today. Yet the possibility should be considered, particularly as heat pumps and electric vehicles may lead to increased demand and subsequently congestion in the years to come.

Here the inequalition

$$\sum_k P^{gen}_{t,i,k} - \sum_k P^{load}_{t,i,k} > -(1-\epsilon)\cdot c \tag{4}$$

has to be fulfilled, when inefficient overreactions should be prevented.
According to these possible violations - is there a congestion given or do users change their behavior in succession of a congestion too extremely - the pricing mechanism determines whether a price bid is too high, too low or suitable. The last bid was too high when feed-in reduced by demand exceeds the capacity bound (see (1)), but also when consumption minus generation was reduced too sharply in succession of a congestion caused by demand (see (4)). Likewise the price is too low for the case of capacity overrun due to high demand (see (3)), and again when the capacity is not used by at least $(1-\epsilon)\cdot c$ succeeding an extreme feed-in situation (see (2)).
Initially, generally valid lower and upper price limits ($\underline{p}_0$ and $\bar{p}_0$) are chosen. During each time step these price limits may vary with the bidding process: After stating the current price bid to be too high or too low, it is stored as the current upper resp. lower price limit ($\bar{p}$ resp. $\underline{p}$) and a new price bid has to be computed. This results according to the bisection method from the average of the highest too low price $\underline{p}$ and the lowest too high price $\bar{p}$:

$$p_{t,i} = \frac{\bar{p}+\underline{p}}{2} \tag{5}$$

or

$$p_{t,i} = \frac{\bar{p}_0+\underline{p}}{2} \tag{6}$$

or

$$p_{t,i} = \frac{\bar{p}+\underline{p}_0}{2}. \tag{7}$$

The whole negotiation process is carried out until the market mechanism detects an appropriate network relief according to the users' bids. To be more precise, the final price is given, when

- the congestion was caused by local supply in that time step and

$$\sum_k P^{gen}_{t,i,k} - \sum_k P^{load}_{t,i,k} \in [(1-\epsilon)\cdot c, c] \tag{8}$$

- or when the current congestion was due to high demand and

$$\sum_k P^{gen}_{t,i,k} - \sum_k P^{load}_{t,i,k} \in [-c, -(1-\epsilon)\cdot c]\,. \tag{9}$$

The convergence of this bidding process is guaranteed as demand and supply functions are assumed to be continuous and monotonous.

3 Modeling Environment

To analyze the efficacy and performance of the presented decentralized local pricing mechanism it is implemented within a multi-agent system representing an electricity market and grid (cf. [33], [34]). Here the grid users as well as the conceptual and technical system are represented by agents, namely these are

- local agents (generators and consumers),
- a market agent,
- a network agent,
- weather agents.

This modeling environment enables a flexible simulation of local grids with a specific grid topology and individual grid participants, which are characterized e.g. by their specific location. Here it is used to model a distribution grid at the low voltage level. Thus, generators are mainly RES plants and consumers are private households. Beside the dependence on technical data of specific RES systems the feed-in behavior of generators is mainly affected by local weather conditions. Therefore each instance of a RES agent belongs to a certain type, for example a solar system agent (PV agent). Further on, each instance of a specific type of agent has individual data, e.g. capacity, location, inclination of solar systems, etc. Weather agents provide information corresponding to the specific location and time for each individual instance of local agents.
A stochastic model determines hourly amounts of consumption for each instance of the household agent, based on typical load profiles.
The network agent is used to represent the grid topology and to compute the load flow after consumption and supply are determined in the market.

3.1 The Market Agent

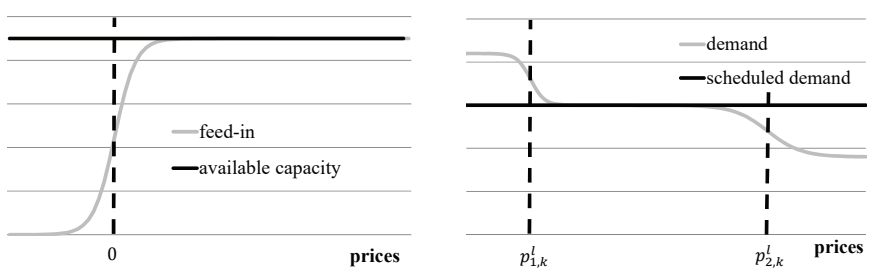
The market agent may be used to describe the prices obtained from the wholesale market or to model a local market clearing (according to the introduced pricing mechanism). In both cases the wholesale price is set exogenously since the exchange price in a market area like Germany is not affected by the balance of demand and supply within a small-scale network area as investigated here.
Without local market clearing the market agent passes the wholesale price on to the local agents.
With local market clearing the iterative negotiation process starts, when a congestion situation is detected as described above. Further on, the market agent states that a new time-step can be simulated when a local price is determined or when the separation of a local market is not required currently.
In order to gain an efficient grid usage incentivized by local prices a price elastic-behavior of the local agents is required here. The specific shaping of demand and supply function has no impact on the pricing mechanism and its convergence in general. The price-elastic behavior for generators and consumers as it is modeled in this sample is described in the following chapter.

3.2 Price-elastic Behavior

Within smart-grid environments and with provided real-time prices a price-elastic behavior may be implemented for small-scaled generators as well as for consumers. That is actual generation and consumption patterns may deviate from the originally scheduled ones depending on the actual prices. For generation systems we can assume a simple choice between feed-in and curtailment, with the marginal generation cost as threshold value. In contrast there is less empirical evidence available on price-elastic demand behavior for private households. Most available studies are using data from field tests with limited size (e.g. [27], [35]). Yet we may expect with smart household equipment both a reduction of consumption and demand increase (as a reaction to low prices).
We model both kinds of price responsive behavior as smoothened step functions applying a sigmoid function: RES systems can generate electricity with zero operation costs so that the step from zero to full available capacity feed-in is given at a price limit of zero. The currently available feed-in potential $P^{gen}_{t,0,k}$ is dependent on weather conditions and technical system data. It is determined in each time-step and corresponds to the feed-in level without price response. We then define a price-quantity relation for each time-step and RES agent through a sigmoid function (see Fig. 4a):

$$P^{gen}_{t,i,k} = P^{gen}_{t,0,k} \cdot \frac{1}{1 + e^{-\beta_{gen} \cdot p_{t,i}}}.$$

Thereby $\beta_{gen} > 0$ is a parameter to model steepness, for β_{gen} tending towards



(a) RES Supply (b) Demand

Figure 4: Price-elastic Response

infinity the price-response is approaching a step function.
For households the scheduled demand $P^{load}_{t,0,k}$ is taken as starting point. It is computed using a stochastic model and taking into account the time and type of day (there is a distinction between weekdays, Saturdays and Sundays) (cf. [33]). Further on it is assumed that demand response is possible in both directions within certain limits l_{red} and l_{exp}. This yields the relationship:

$$P_{t,i,k}^{load} = P_{t,0,k}^{load} \cdot \left(1 + l_{exp}\left(1 - \frac{1}{1+e^{-\beta_1 \cdot (p_{t,i} - p_{1,k}^{l})}}\right) - l_{red} \cdot \frac{1}{1+e^{-\beta_2 \cdot (p_{t,i} - p_{2,k}^{l})}}\right),$$

where $p_{1,k}^{l} < p_{2,k}^{l}$ are price limits corresponding to thresholds for behavioral changes: When prices increase above $p_{2,k}^{l}$, then consumption is decreased. But when prices fall below $p_{1,k}^{l}$, then additional electric loads are activated, $\beta_1, \beta_2 > 0$ are again steepness parameters (see Fig. 4b).[2]

4 Case Study

The proposed methodology is applied to a real low voltage distribution system in Germany. It consists of 38 nodes (including the substation), with 31 households connected to the network and 7 solar systems with an aggregated nominal capacity of about 200 kW. As input data for weather conditions and the wholesale market we use data from 2011. As especially the feed-in from solar installations is of interest we focus on some summerdays.

Overload situations are detected with focus to lines, which are linked to the transformer. Thus, the coupling point between low voltage and medium voltage grid is chosen as the critical location for congestion and price differences. To reflect future developments and possible congestion situations we assume doubled amounts of local supply and consumption. The current carrying capacity with 0.27 A per substation-linked line is not altered in our sample. These simple and theoretic assumptions are a suitable backdrop to analyze the functionality of the introduced pricing mechanism. With constant network capacity but increased solar system capacity, network overload may especially occur during daytime around noon.

Results concerning the users behavior are illustrated in aggregation for the whole observed network, while those concerning network conditions are displayed exemplarily for a node at the end of one line with connected PV system. This is due to the fact that most critical situations arise in distant nodes with connected generators.

We present a reference case, where local congestion does not affect prices, and further on, two cases with local price determination. Here initially only price-elastic behavior of generators is assumed. Afterwards additionally demand behavior is simulated to be flexible.

[2]Note that further components of household retail tariffs such as levies, taxes and grid charges are not modeled here. Yet, a detailed representation of these costs would just mean to adjust the price thresholds accordingly.

4.1 Reference Case - The Present Wholesale Market

The reference case represents a wholesale market as it is common in many European electricity markets.
Here the behavior of local agents is price-inelastic: Private households are not affected by price fluctuations as these are not reflected within typical retail contracts and flexible electrical devices are presently not wide-spread. The corresponding household agents act therefore without adjusting their scheduled consumption pattern.
Distributed generators are only solar systems. Again the behavior of the operators is assumed to be price-inelastic. This behavior is consistent with the one of operators of solar systems who are remunerated by a flat feed-in tariff as it is paid to small-scale solar systems e.g. in Germany even after the legislative amendment of the renewable law (EEG) 2014.
Since the global wholesale price is given exogenously here, the market agent's task is to read out the current price from a database and pass it on to the local agents.

4.2 Price-elastic Supply

In case of simulation of the pricing mechanism local generators are modeled with price-elastic behavior. I.e. the remuneration of RES devices by flat feed-in tariffs are replaced by a remuneration based on local prices here and the PV agents behavior is simulated according to the price-elastic behavior described in Chapter 3.2 with parameter $\beta_{gen} = 0.5$.
The market agent carries out the local market-clearing mechanism. Initial upper and lower price limits and the coefficient ϵ, which defines the acceptable line load in succession of a congestion situation, are chosen as listed in Table 1.
Household agents do not act price-elastic in this case, in order to investigate the situation with local incentives when no automation appliances or smart meter devices are given in typical households.

4.3 Price-elastic Supply and Demand Response

The same scenario is analyzed with a variation concerning the household agents behavior. It is plausible that flexible electric devices and a smart environment enable a price-elastic demand behavior in the future. Thus, beside the PV agents also the household agents adjust their consumption in response to prices as introduced in Chapter 3.2. Relevant parameters are listed in Table 1. Concerning PV agents and the market agent the assumptions laid down in Chapter 4.2 hold.

4.4 Results

The results are illustrated in Fig. 5. Prices, aggregated feed-in, aggregated demand and the voltage state of a distant node with connected PV system are

Table 1: Parameters

Price-elastic Supply	
$\underline{p}_0$	-500 €/MWh
$\bar{p}_0$	3000 €/MWh
ϵ	0.1
β_{gen}	0.5
Demand Response	
β_1	0.5
β_2	0.2
$p^l_{1,k}$	20 €/MWh
$p^l_{2,k}$	90 €/MWh
l_{red}	40%
l_{exp}	40%

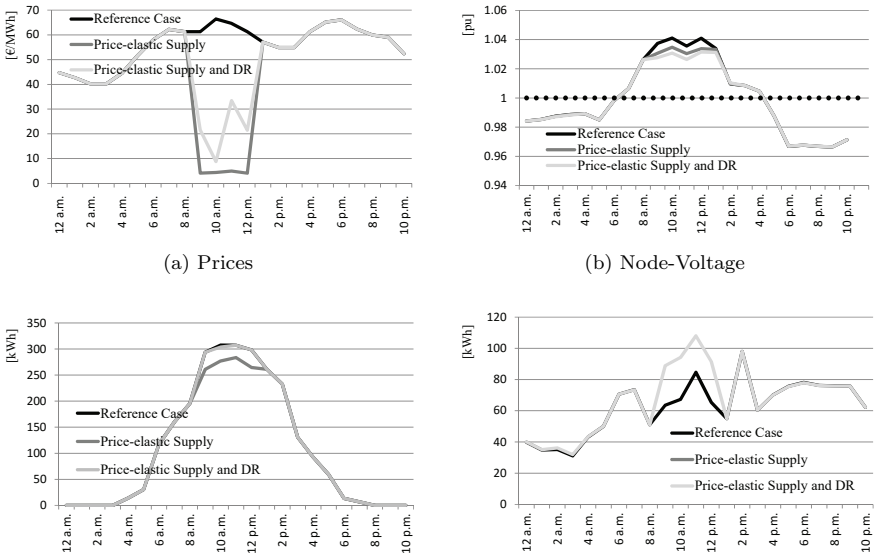
given. Thereby black lines each indicate the reference case, dark grey lines the case of price-elastic supply and the light grey lines the one, where additionally DR is assumed.

In the first case the prices comply with wholesale prices as the possibility of deviating local prices is not considered here (see Fig. 5a). The curve of aggregated feed-in from solar installations (see black line in Fig. 5c, which is nearly equivalent to the light grey one) shows a typical intra-day profile according to the local solar radiation. With increasing local solar feed-in voltage is quiet high with deviations of more than 4% (see Fig. 5b).[3]

In case of price-elastic behaving generators, the market agent identifies a grid overload for each hour during the hours from 10 a.m. to 1 p.m.. Feed-in from solar systems is too high, so local prices have to be reduced in order to make feed-in less profitable. Nevertheless a complete shut-down is not beneficial for grid usage as well, therefore the bidding process of the market agent ends up with prices of about 4 to 5 €/MWh (see dark grey lines in Fig. 5a). In consequence aggregated feed-in from PV agents is reduced as it is illustrated in Fig. 5c in comparison to the current available potential - which corresponds to a feed-in of the reference case. Due to this relief the highest voltage values are reduced and are closer to the normal level with a maximum deviation of 3.5% (see Fig. 5b).

When additionally demand is assumed to be price-elastic, then prices are reduced throughout the period of grid overload from 10 a.m. to 1.p.m. again (see light grey lines in Fig. 5a). In this case, local prices are consequently higher in comparison to the one without DR. E.g. at noon, a reduction to 33.39 €/MWh

[3]E.g. in Germany the allowed deviation of 10% is typically allocated to low and medium voltage level with 6 and 4% (cf. [36]).



(a) Prices

(b) Node-Voltage

(c) Aggregated Local Supply

(d) Aggregated Demand

Figure 5: Results

implies a suitable network relief. Feed-in reduction from solar systems is nearly not incentived. Firsty, demand is increased during these hours. Thus, solar feed-in corresponds roughly to the one in the reference case, while the adjustments of demand can be observed in Fig. 5d. Intensifying electricity consumption in times of high distributed feed-in can relieve the congestion situation as well. Similarly to the case with shut-down of local generators a reduction of voltage deviations is realized here (see Fig. 5b). The deviations of voltage amounts are even more reduced than in the case without DR: The maximum deviation now is 3%.

One main result therefor is that additional flexibility in the system lead to lower fluctuations in local prices: As households are willing to adjust their behavior earlier than local suppliers in this sample, local prices of about 10 €/MWh to 35 €/MWh are the results of the pricing mechanism, while in the case without DR local prices of about 5 €/MWh are required (see light and dark grey lines in Fig. 5a).

In fact the interrelation of local prices on the one hand, and the opportunity to adjust behavior as well as the current load situation on the other hand, becomes clear in this example: At 12 p.m. a minimal reduction of local prices is suitable as demand is anyhow high and therefore the load situation in spite of high local feed-in is less critical. In contrast a significantly lower price is required at 11 a.m., when available upward demand flexibility is not sufficient and so genera-

tion has to be reduced, too. That feed-in from RES agents is adjusted in that single hour can be seen in Fig. 6.

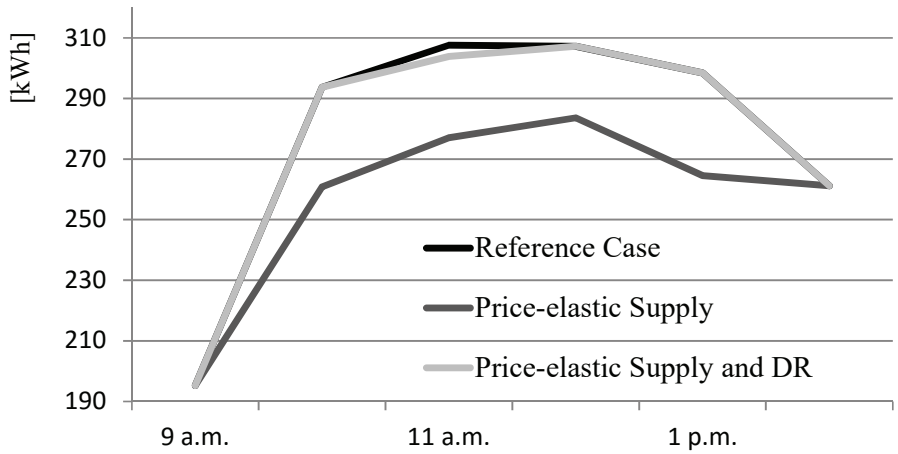


Figure 6: Detail of Aggregated Supply

4.5 Performance of the Decentralized Local Pricing Mechanism

As the decentralized local pricing mechanism is based on a negotiation process, which avoids gathering a multitude of supply curve data, the simulation time is likely to increase in time steps with congestion. But at most ten iterations are required in the first case with local market clearing (see 4.2). Compared to the reference case, where a time step takes about 0.4 - 0.5 seconds, the simulation time of a single time-step with iterative market clearing is at most a factor of 1.8 higher.

For the case where additionally DR is assumed (4.3) the simulation performance is not degraded. The number of required iterations is at most eight and the longest run time is a factor of 1.9 higher compared to the case without local prices.

Taking a closer look at the negotiation process, we exemplarily describe the process in the case without DR in more detail for the hour at noon (see also Fig. 7). The initial wholesale price $p_{t,0}$ of more than 60 €/MWh comes along with too high solar feed-in, so that the market agent adds a negative surcharge and passes the resulting price $p_{t,1}$ of approximately -220 €/MWh to the agents (which results from the average of $p_{t,0}$ and the initial lower price limit of -500 €/MWh). Consequently local feed-in would be completely curtailed then. So further on price bids increase again in order to use the available potential

with more than 90%. Yet, a price of 27 €/MWh (price $p_{t,4}$) is again too high and leads to excess feed-in. The following reduction to nearly 9 €/MWh does not improve the predicted grid situation so that the prices decrease once more. Finally the adjustment from nearly 0 €/MWh to price bid $p_{t,7}$ of approximately 4.5 €/MWH induces both, a congestion relief and still a high amount of feed-in from renewable energy sources.

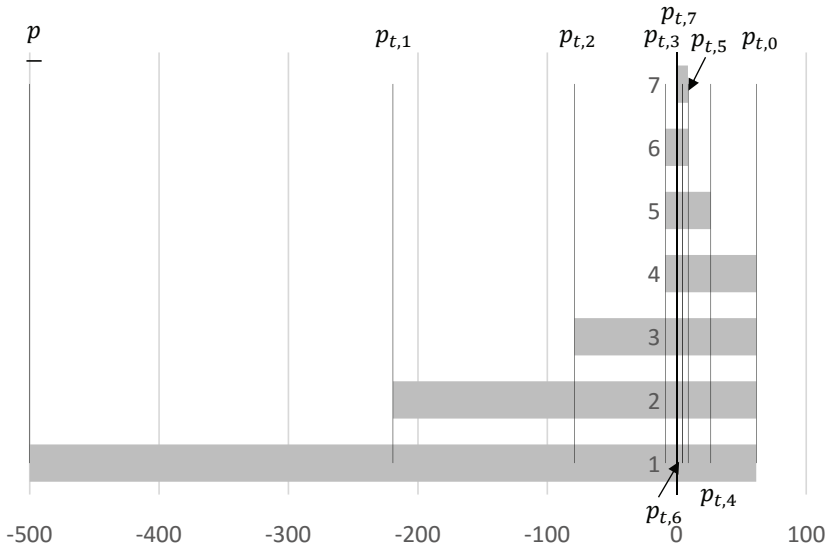


Figure 7: Exemplary Price Bid Process with Final Price $p_{t,7}$

5 Conclusion

The contribution of this paper is the introduction of a decentralized local pricing mechanism to determine suitable real-time prices aiming at an efficient grid usage in the context of smart environments. It is shown how local prices can coordinate local suppliers and potentially also private consumers in the context of the physical grid restrictions. Individual preferences, current personal circumstances and meteorological conditions are considered. Self-reinforcing effects are avoided.

The chosen iterative search algorithm is a computationally simple scheme which ensures a high performance in the context of unknown participants' responses and therefore unknown effectiveness of prices. This kind of iterative search procedure gives the opportunity to determine local prices without gathering and storing specific bidding curves - what would be a large quantity of data and even critical in the sense of privacy. Another advantage of the concept of this

market-clearing mechanism is that there is no adjustment required when the context varies, e.g. when the households' equipment change. Additionally, this mechanism can be implemented precisely when and where it is needed. In areas of sufficient grid capacity a separate local pricing mechanism is not efficient. With the presented concept a costly and permanent market splitting is not required.

Further on, the presented test case has shown that appropriate adjustments of grid usage can help to relieve congestion situations. Concerning the resulting grid situation it does not matter whether an excess of decentralized energy generation is responded with feed-in curtailment or with consumption increases. In contrast, it does make a difference in terms of prices: Integrating DR into the system leads to less price adjustments in comparison to a situation where only distributed suppliers respond to price signals. As diverse types of grid users have distinct price limits for rearrangements it is worthwhile to make use of all available flexibility in the system.

It is to state that the investigated test case is rather a theoretical one. In order to analyze the introduced pricing mechanism beyond its mere functionality, more test cases as well as a more detailed look on available consumer flexibility is required. Another issue to keep in mind for a real implementation is to detect possible winners and losers of such novel market mechanisms.

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5 PHOTOVOLTAICS AND HEAT PUMPS - LIMITATIONS OF LOCAL PRICING MECHANISMS

Photovoltaics and Heat Pumps - Limitations of Local Pricing Mechanisms

Björn Felten, Jessica Raasch and Christoph Weber *

Abstract

With the increasing amount of volatile infeed from renewable energy sources the need for flexibility becomes more and more urgent. This holds especially for the distribution grids where critical load situations caused by high local renewable infeed occur increasingly often. Therefore, demand side management with broad participation of households has been proposed as one cornerstone for a future sustainable energy system. Local prices may contribute substantially to enable a smart behaviour of grid users by providing appropriate incentives. Although the benefits of both demand side management and local prices seem evident in theory practicalities have to be considered when it comes to assessing their effectiveness. Notably individual restrictions for different kinds of grid users have to be regarded in detail. Eventually, the potential contribution of local pricing to a secure and efficient energy system may be called into question.

In this paper, a typical rural low voltage grid is analysed having local electricity generation from PV systems and typical household consumption. In addition, a high penetration of heat pumps is supposed as well as the implementation of a framework of local prices. With households heated by electric heat pumps a potentially flexible consumer type is implemented in detail. Thus, a model of a possible future rural low voltage system is implemented and used to assess the limitations of local pricing mechanisms - firstly, by a sequential deduction of the possibly leveraged potential of the local market mechanism under existing technical constraints and, secondly, by a scenario analysis of the allocation of economic benefits. Results show that even with given local incentives the consumption adjustment towards an efficient grid usage cannot be realized frequently as comfort and system needs have priority. I.e. due to limited complementarity of heat pump consumption and photovoltaic infeed patterns expected operational system cost reduction is low - especially in comparison to required investments in smart systems. Hence, the example disproves any generalized claims about the efficiency of local pricing - yet obviously it does not prove that local pricing is of no worth in general. As second main result, stylized policy choices are analysed. Thus, it is demonstrated how

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the benefits of local pricing mechanisms can be distributed to the market participants and which are the difficulties that policy makers will have to face. Ultimately, for the present case study, it is not possible to set sufficient investment incentives for the installation of flexibility measures for heat pumps without either causing disadvantages to renewables-based electricity generators or without receiving additional regulatory payments from the overarching system.

Thereby, the paper contributes to the existing literature by analysing a novel pricing mechanism and, more importantly, demonstrating the effects of these pricing mechanisms on the system costs and the economic figures of the market participants. As main result, it can be seen that practicalities play an important role and must be taken into account when considering the implementation of local pricing mechanisms. Furthermore, policy makers have to pay attention to the redistributive effects as they might be substantial even though the costs savings of the overall system will not necessarily be meaningful.

Keywords: Integration of Renewables, Distribution Grid, Local Pricing, Agent-Based Simulation, Demand Side Management, Heat Pump.

Abbreviations

amb (index)	ambient
C	capacity constraint
c	grid charges
c_W	specific heat capacity of water
$c_{Z/fh}$	absolute heat capacity of the heating zone / floor heating
$CAPEX_{flex,annualised}$	capital expenditures of additional flexibility measures (annualized)
CF	cash flow
COP	coefficient of performance
D	discount
DSM	demand side management
DSO (also index)	distribution grid operator
$glob$ (index)	global (simplified for the non-local pricing mechanisms)
E	electrical energy
ECC	end consumer charge
eoo (index)	end of operation
HGL (also index)	higher grid level
HH	households
hp (index)	one individual heat pump
HP	heat pump (as index: group of heat pumps within the system)
H_{TV}	design heat load of the building (accounting for transmission and ventilation losses)
LVG	low voltage grid
loc (index)	local
LV	low voltage
max (index)	maximum (possible)
min (index)	minimum
MP	market premium
$OPEX_{flex}$	operational expenditures of additional flexibility measures
p	price (with index comp also used for the compensation rate for being curtailed)
P	electrical power (consumed or supplied)
$\tilde{P}$	curtailed power
PV (also index)	photovoltaics
RE (also index)	renewable energy
rem (index)	remaining, i.e. the part of electricity not generated and consumed locally
RES	renewable energy sources
ρ_w	density of water
SC	system costs
soc (index)	start of congestion
st (index)	storage
SYS (index)	system (all elements within the system boundary as shown in figure 3)
t (index)	time step
τ_{summer}	non-heating period
T	temperature
TF (index)	transformer
tol (index)	tolerable
tot (index)	total
U	markup
V	volume
$VARMA$	vector autoregressive moving average
WSM (index)	wholesale market
z (index)	heating zone

1 Introduction

During the last decade, renewable energy (RE) found its way into the electricity generation portfolio. In 2014, the gross electricity generation from wind and solar energy sources (non-dispatchable renewables-based technologies) in Germany amounted to approx. 91 TWh representing 14.7 % of the total gross electricity generation (BDEW (2015)). The increasing capacities of RE installations in Germany have led to highly fluctuating electricity infeed occurring independently from demand. Such circumstances have entailed the necessity of repeated curtailment of RE generators. Curtailment being caused by the distribution grid has increased substantially in recent years (BNetzA and BKartA (2015)). In 2014, compensations of approx. 42.1 million € were paid and a RE generation of 659.1 GWh was prevented due to remedial measures having its cause in the German distribution grids. The reduction of RE generation with causation of the German transmission grid is still higher (921.4 GWh), but, in terms of compensation (40.6 million €), the distribution grid is already more significant.

One possibility to face this challenge is the grid extension according to the traditional N-1-criterium. In order to avoid curtailment dena (2012) states that up to 42.5 billion € have to be invested into the German distribution grids by 2030, which includes the extension of electricity circuits by up to 192,900 km and installation of additional transformation capacities of 93,290 MVA.

If being the only measure such a principle would lead to a grid designed for extreme situations, which causes, on the economical side, the need for high investments and, on the technical side, a low number of annual full-load hours of grid devices. In combination, this can lead to an inefficient utilization of resources which is not economically-reasonable. This is probably the reason why the consideration of curtailment of up to 3 % of the yearly generation in the grid planning is currently foreseen (CDU, CSU, SPD (2013), E-Bridge, IAEW, Offis (2014) and BMWi (2015)).

As solution for the near future - especially with better technical systems and automated processes - the use of demand side flexibilities has been proposed in order to avoid curtailment. When technical conditions are provided and shifting of energy consumption is possible without loss of comfort, then, demand side management (DSM) may help to release congested grid situations. The potential for peak load shaving through DSM measures is analysed, inter alia, in Veldman et al. (2013), Papadaskalopoulos and Strbac (2013) and Papadaskalopoulos et al. (2013).

Yet, appropriate incentives for shifting load at certain hours are required. Traditionally, retail prices do not provide these incentives. Firstly, because commonly retail prices do not reflect real-time wholesale market prices. Secondly, even if this was the case, wholesale market prices do not reflect local grid constraints / local congestion. The use of local price signals has been proposed as a means to align demand and supply at higher spatial resolution. Locational marginal pricing for distribution grids is similar to concepts for the transmission grid level (Hogan (1992), Schweppe et al. (2000)). This concept and further al-

ternative approaches are discussed in Brandstätt et al. (2011). Trepper et al. (2013b) present a conceptual approach of congestion-oriented grid charges for European-style, non-nodal markets. They explain various benefits of a system that provides local incentives when the grid is congested due to extreme local infeed. Particularly, curtailment of RE generation is said to be avoided and therewith compensation payments for not delivered electricity are prevented. Furthermore, the increased use of electricity generated close-by is the intention of congestion-oriented grid charges. Thus, utilisation and congestion of overlaying grid levels shall be reduced. Yet, electricity losses with transmission are rather low, and therefore differing local incentives are efficient only in case of congested grid capacity. As the national wholesale market price does not always provide sufficient signals to trigger RE generation according to the needs of the distribution grid (cf. Picciariello et al. (2015), Velik and Nicolay (2014)) and as the occurrences of congestion (in terms of local and timely variance) depend on the situation of the distribution grid, the adequacy of the price signal can only be reached in a local market. For the purpose of this paper, congestion-oriented grid charges in combination with the underlying wholesale market price are called local prices. The organisational issues of the bidding process (as described in Trepper et al. (2013a) and Trepper et al. (2013b)) are not taken into focus. However, the results of this paper can be understood as those of an efficient organisation.

Certainly, several regulatory, market and technology barriers which have to be removed to implement dynamic pricing concepts have already been identified (e.g. Shen et al. (2014), BMWi (2014)). Other critical points are the consumers acceptance of such schemes (e.g. Kowalska-Pyzalska et al. (2014), Leonard and Decker (2012), Dütschke and Paetz (2013), Brandstätt et al. (2011)). The present work uses the hypothesis that these barriers can be overcome as long as the socio-economic welfare effect is sufficiently advantageous. Instead, the focus of this work is laid on the evaluation of the actual realization of these theoretical benefits of local pricing mechanisms. On the one hand, financial benefits also need to be apparent to potential market participants in order accept a local pricing regime. In any case, loss of comfort must be avoided, which poses technical restrictions to the involved equipment.

Heat pumps (HPs), for example, have a great flexibility potential within the residential sector (as it is analysed e.g. in Di Giorgio and Pimpinella (2012), Hedegaard and Balyk (2013), Waite and Modi (2014), Papaefthymiou et al. (2012), Prognos AG, Ecofys Germany GmbH (2011), Mueller et al. (2014), ETG (2015)). Firstly, HPs feature a high electrical power consumption compared to the ordinary household loads as environmental thermal energy is made usable through a thermodynamic process which is driven by an electrically-powered compressor. Moreover, a certain amount of flexibility is readily available by the thermal inertia of buildings. That is, heat supply and HP operation is decoupled to a certain extent. Additionally, a storage tank can serve as expanded thermal capacity which allows a more flexible operation of the HP as times of storage tank charging and heat supply to the building may differ. E.g. Schmidt et al. (2010), Verhelst et al. (2012) and Vanhoudt et al. (2014) have demonstrated

that air-water HPs provide flexibility in order to adjust consumption towards external objectives.
However, one has to consider that additional flexibility (e.g. through installation of storage tanks including additional subsidiary equipment for HPs) has its costs and a remuneration has to be provided by the incentivising framework. In turn, on the supply side, claims will be made that RE generators should not have disadvantages in regional markets with local prices over a national wholesale market (cf. Brandstätt et al. (2011)). Therefore, the possible allocation of operational system cost savings to the different market participants is an important aspect.
In summary, before planning an incentivising concept for local adjustment of infeed and consumption - at least - two tasks should be carried out:

a) an assessment of actually achievable advantages of the local pricing regime for the regarded system, and

b) an analysis of the consequences for each market participant and the resulting long-term incentives.

In this paper, an energy system is presented that includes the above mentioned concept of local prices which provide short-term incentives for price responsive HPs. An agent-based simulation shows the interplay of the pricing mechanism, local RE generators and flexible and inflexible consumers within a structurally-congested distribution grid. Modelling each agent by means of individual and detailed sub-models provides the necessary precision for such analysis. The advantageousness of the local pricing mechanism is analysed with the focus on both the system benefits and the impacts for the individual participants. For the latter analysis, scenarios are evaluated which can be seen as extreme positions of regulatory setups illustrating how policy makers can influence the benefits of the participants in local markets. As a test case a low voltage grid (LVG) in a rural environment is chosen which is based on an existing grid sample in Germany. Considered are, among others, photovoltaic (PV) systems and households with HPs. Their penetration has been set according to forecast values (taken from the literature) while the grids technical features remains unchanged from todays status. Thus, the concept of local pricing is analysed in a situation as it may arise in the future distribution grid.
This paper is structured as follows: Section 2 describes how the technical features and supposed market mechanism are modelled. Section 3 continues with the demonstration of the methodology for the assessment of the potential of such market mechanisms. It is followed by the introduction of a test case including policy scenarios which are made subject to assessment (section 4) and by the corresponding results (section 5). Finally, the relevant conclusions are drawn in section 6.

2 Modelling Approach

2.1 General Model

The present study links several sub-models which represent the behaviour and features of the grid and the grid users. They are coordinated by a market clearing entity which is an individual sub-model itself (also referred to as market agent) and which includes a local pricing mechanism. It uses information about the operational status of the grid to calculate local market prices with the aim of incentivising demand shifting in a way that congestion is avoided. Thus, the following sub-section starts with the explanation of the local pricing mechanism.
The resulting local prices impact the flexible consumers operation decisions. These will consume electricity if prices are below consumer and situation specific threshold derived from the respective cost minimisation strategy under consideration of technical constraints. This strategy is discussed further in section 2.3.
All sub-models are implemented in a Java framework which is discussed in section 2.4.
The simulation notably allows to derive the local prices, hours of congestion, avoided hours of congestion due to DSM, changes in generation and consumption, savings and revenue changes of consumers and generators, respectively, avoided curtailment, etc. All results are available in hourly resolution.
The algorithms for obtaining the above results are described in detail in Raasch and Weber (2016) and Felten and Weber (2016) and, therefore, are only illustrated briefly in the present document. Here, the focus is laid on the aggregate results of the interplay of all sub-models.

2.2 Incentivising Framework: Local Pricing Mechanism

Typically, wholesale market prices reflect the supply and demand situation on a national level and at high timely resolution (usually hourly). However, due to regional heterogeneity of the power system (especially on the generation side), the price formation process on a national level frequently results in grid constraints at local level (cf. section 1). If using prices as prior means to improve system balance in affected regions the respective local equilibrium prices must diverge from the national wholesale market price. Thus, a concept of local pricing, which indicates local temporary scarcity of grid capacity when it is apparent, is implemented.
As will be explained below, generators will chose to feed in electricity once they are reimbursed at an appropriate price. Consumers will decide to consume if prices are acceptably low. Based on the initial bids and asks on the local market, which are based on the (national) wholesale market price, the balance of anticipated local infeed and load is evaluated for each hour and is compared to the available grid capacity. If (and only if) the balance exceeds the grid capacities, an additional markup or, respectively, a discount to the wholesale market price is computed. The local clearance price is achieved in real-time by an iterative

process during which local generators and flexible consumers adjust their bids and asks. Hence, the main objective of the process is the most efficient use of grid capacities. The algorithm for determining the local price is shown in figure 1.

Thus, appropriate incentives for reducing curtailment are computed and ap-

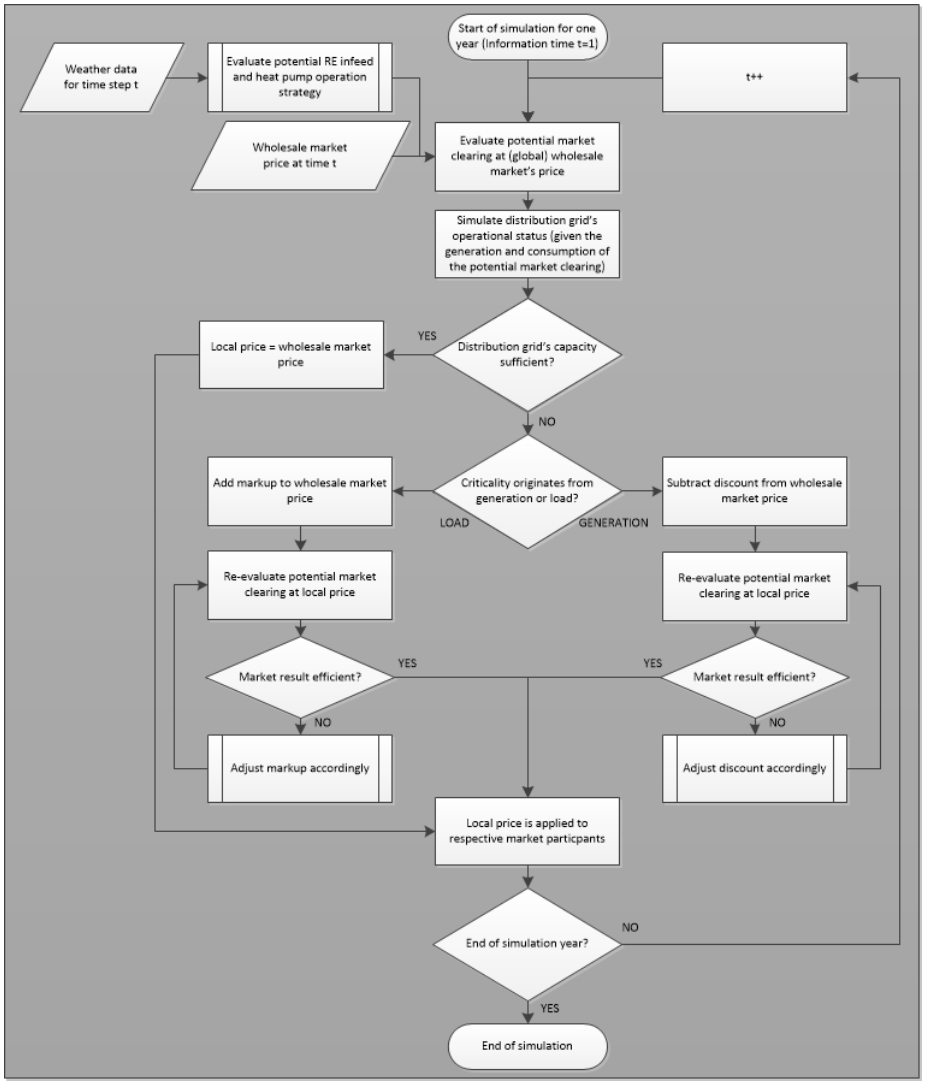


Figure 1: Flow chart of the used local pricing algorithm

plied to the market participants. The corresponding local price $p_{loc,t}$ can be

formulated as follows:

$$p_{loc,t} = \begin{cases} p_{WSM,t} + U_{loc,t} & \text{when residual load induces grid constraint violation} \\ p_{WSM,t} - D_{loc,t} & \text{when residual infeed induces grid constraint violation} \\ p_{WSM,t} & \text{otherwise} \end{cases} \quad (1)$$

Here, $p_{WSM,t}$ represents the wholesale market price at the time t, $U_{loc,t}$ a suitable markup and $D_{loc,t}$ a suitable discount. Thus, signals for additional load or reduced RE infeed are provided and a behaviour which is oriented towards an optimized grid utilization is induced. Further details on the pricing mechanism and its implementation are given in Raasch et al. (2014) and Raasch and Weber (2016).

These local prices provide an incentive to RE generators to turn off whenever the sum of the local price and a possibly paid "market premium" becomes negative. The price responsive behaviour of flexible consumers is discussed in more detail in the following section.

2.3 Flexible Consumption: HP System and Control Methods

As HPs are frequently-referred to as one of the most promising electric devices for DSM of private households, the HP systems are modelled in detail and its operation is simulated in the context of the described local pricing concept. A thermal storage tank belonging to each heating system provides additional flexibility. Among other differences to further models simulating HP operation strategies (cf. Schmidt et al. (2010) and Verhelst et al. (2012)) the most relevant is the integration of a price forecast enabling the HPs to perform a rolling planning of its cost-optimized operation. Thereby, the sub-model can be used in a modelling framework which determines local prices endogenously.

The used heating model has been developed by applying the first law of thermodynamics for each sub-system of the building system (including storage) and dynamics are represented by a set of linear differential equations. The technical constraints such as maximum and minimum storage temperature and the set value of the zone temperature need to be fulfilled by the DSM device. A model-predictive cost optimizing control is implemented which uses two specific vector autoregressive moving average processes of first order (VARMA(1,1)) to forecast local prices and ambient temperature, respectively. By establishing the relation between forecast ambient temperature, anticipated supply temperature and HP efficiency (coefficient of performance (COP)), and combining it with the forecast of the local prices, the forecast price of heat is calculated. This is used to predict the most cost-efficient times of HP operation. Considering the heat demand restriction (which always needs to be fulfilled), this leads to a threshold of the local price below which the HPs operation is forecast to be optimal. The forecasting and decision processes are executed on an hourly basis with a 24 hour look-ahead horizon. The algorithm is explained in more detail in Felten et al. (2014) and Felten and Weber (2016). Figure 2 provides a schematic flow chart.

In figure 2, the hours within the look-ahead horizon that are highlighted are the

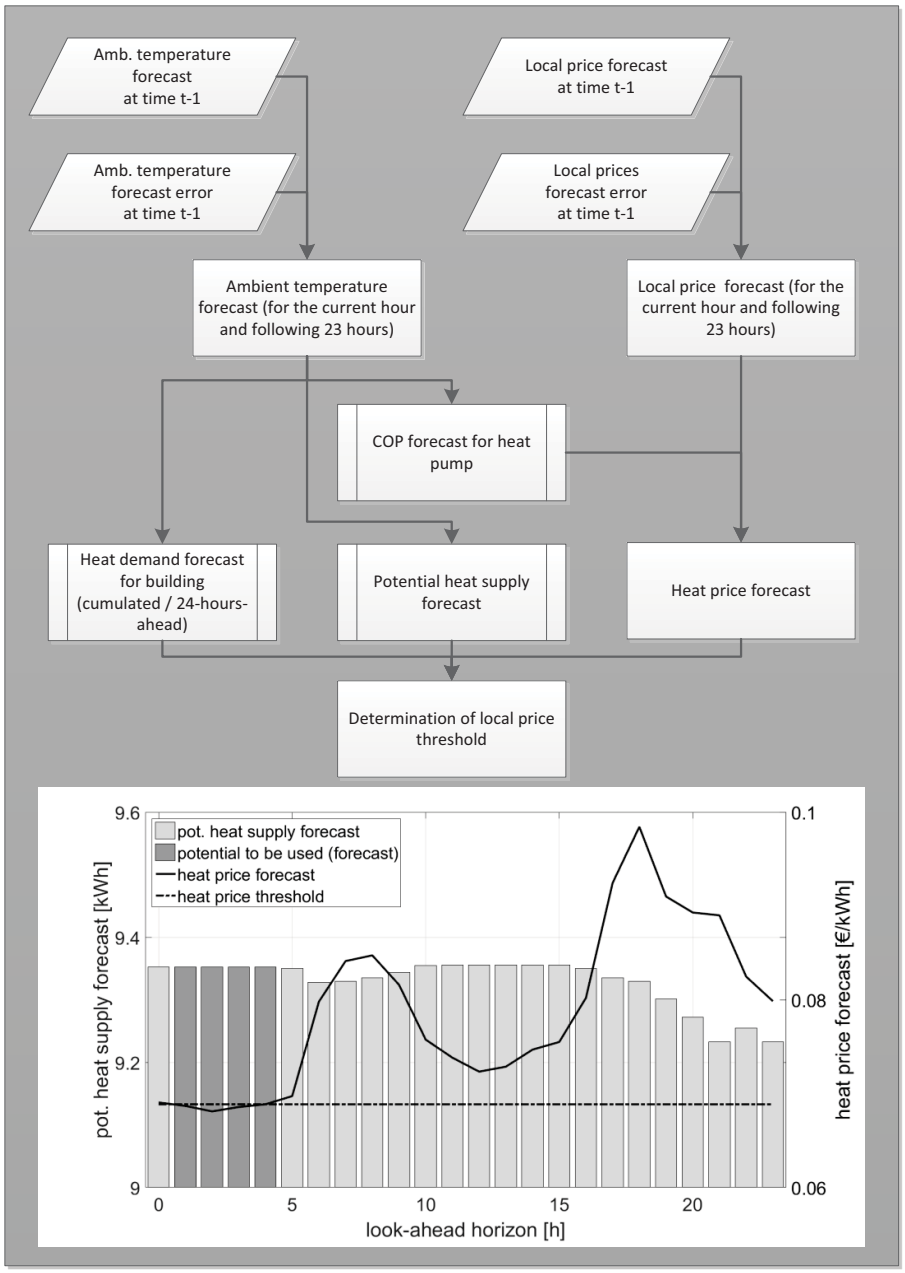


Figure 2: Illustration of the forecasting algorithm and its main results for one exemplary hour

ones during which HP operation is expected to be most cost-efficient given the information available at time t. The optimal strategy identified for the current hour (hour 0) is put into practice whereas the further planned operation steps are subject to revision as new information becomes available. Hence, the only immediate consequence is that, at hour 0, the HP will remain switched off (in the used example).
It is noteworthy that the operation of the floor heating is independent from HP operation as the floor heating is supplied by the thermal storage tank. Thus, by providing local prices an orientation of HP operation towards local supply and efficient grid utilization is generally enabled. But, in each operation mode, basic requirements as comfortable zone temperatures may not be jeopardized.

2.4 Model Framework:Agent-Based Simulation

The heterogeneous behaviour of market participants is simulated within an agent-based model which is implemented in the Java framework Jade. This simulation is based on a multi-agent system presented in Kays et al. (2013). Overload situations of individual lines and grid devices can be identified (or anticipated) and notified to the market agent. Local generators can be modelled as PV systems and wind farms. The consumption is given by typical household loads as well as by more sophisticated HPs. Representing each grid user by an own agent enables a highly detailed simulation, which is important as specific technical characteristics (e.g. orientation of solar panels, capacities of generators, building characteristics, HP capacity and thermal storage size), local environmental conditions (e.g. irradiation including shading, ambient temperature, etc.) and individual preferences (set zone temperatures, household demand profiles) can vary for each agent. This leads to individual decisions of each generator and consumer which provides a more adequate depiction of the market mechanisms.

3 Methodology of Assessment

3.1 Assessment of Electricity Flows

The present study supposes a distribution grid which has two types of loads: The regular household load and the HP load. The methodology of evaluation is capable of capturing further consumer types, but the test case has been limited to these two for the sake of a more concise analysis. The same applies for electricity generators of which only PV installations are used as typical example. Thus, figure 3 illustrates the groups of considered consumers and generators, the system boundary and physical and financial flows between the different participants and the overarching system.

In figure 3, each physical flow (i.e. electricity transmission) is understood to cause a financial flow. Some electricity remains within the system boundary: I.e. electricity flows which originate from local RE generators (index “RE”)

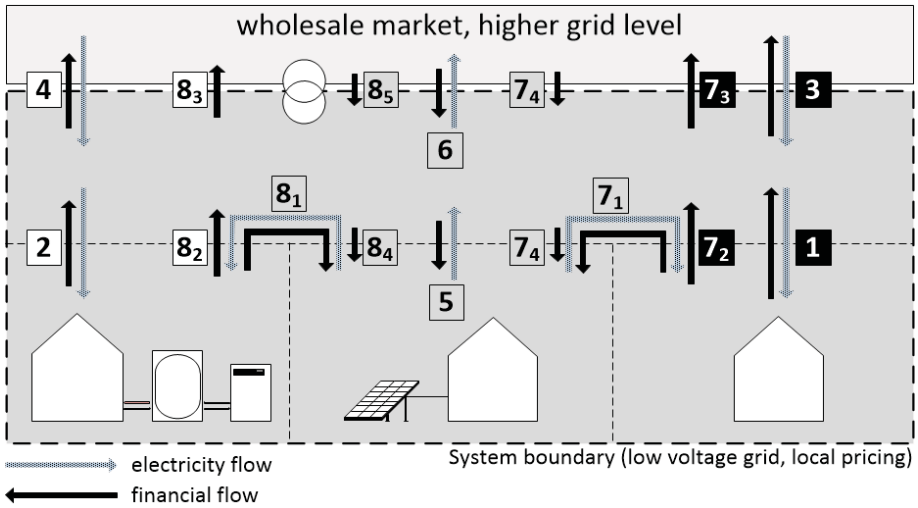


Figure 3: Schematic of the regarded system, its electricity flows and corresponding financial flows

are consumed locally by households (index "HH") and / or heat pumps (index "HP") at the same time t. The denotation of the electricity flows (which are assumed to be constant during each time step) and its reference in figure 3 (in parentheses) are $P_{HH,loc,t}$ (7_1), $P_{HP,loc,t}$ (8_1) and $P_{RE,loc,t}$ ($7_1 + 8_1$). The relation between the three values is given as follows:

$$P_{HH,loc,t} + P_{HP,loc,t} = P_{RE,loc,t} \tag{2}$$

The remaining demand needs to be procured from the higher grid level (HGL) and is symbolized by $P_{HH,rem,t}$ (figure 3: 1) and $P_{HP,rem,t}$ (figure 3: 2), respectively. In order to simplify the grid constraints, in the subsequent sections, only simple power transfer limitations of the following form are discussed.

$$P_{RE,rem,t} \leq C \tag{3}$$

This limit may be imposed by the capacity of a transformer or by the maximum current on a line. Equation 3 refers to the supply side, i.e. surplus of power (symbolized as $P_{RE,rem,t}$ (figure 3: 5)) is exported to the HGL to the extent technically possible. The analogous constraint applies to the demand side.

3.2 Assessment of Technical Potential

As the main objective of local pricing mechanisms is the reduction of curtailment this section describes how curtailment can be quantified and how the potential for stepwise deduction of curtailment can be assessed. Without loss of generality, the methodology of assessment is illustrated for a structurally congested grid in

which only situations of a surplus of RE infeed occurs and the bottleneck is the transformer capacity C_{TF}. Each step is indicated by a new literal which serves as reference in section 5.2.

a) If the local demand plus transformer capacity is smaller than the maximum possible RE generation $P_{RE,max,t}$, this leads to curtailment of RE generators. If using C_{TF} efficiently, the curtailed power $\tilde{P}_{RE,t}$ can be expressed as follows:

$$\tilde{P}_{RE,t} = P_{RE,max,t} - C_{TF} - P_{HH,loc,t} - P_{HP,loc,t} \tag{4}$$

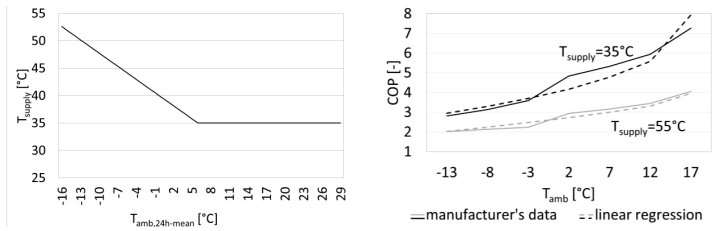
b) In above equation, it must be considered that HPs are typically taken out of operation for the summer period. Thus, there is a technical constraint:

$$P_{HP,loc,t} = 0 \ \forall \ t \in \tau_{summer} \tag{5}$$

c) Usually, HP layout is based on the design heat load of the respective building (DIN EN 12831 (2003)). Thus, the nominal HP capacity is oriented towards the building characteristics (cf. Novelan (2013)) with the goal of achieving an appropriate amount of monovalent operation hours during the year (reduced use of supplementary heating element). A typical HP control uses a characteristic map which aims at achieving the highest COP. This characteristic map is HP specific and its input parameters are the ambient temperature and the supply temperature (cf. Panasonic Deutschland (2014a)). These parameters are often interrelated by a so-called heating curve (Schmidt et al. (2010) and Verhelst et al. (2012)), which - in essence - is a consequence of limited floor heating surface area and the thermal inertia of the building. I.e. in order to provide sufficient heat to the heating zone during days of low ambient temperature T_{amb} the supply temperature T_{supply} needs to be raised. Such a heating curve is shown in figure 4a.

The foregoing technical interdependencies are implemented in the agent-based simulation in more detail and are used for the actual operation mode as well as for the model-predictive control strategy of the HP. For the purpose of the ex-post assessment, a simplified relationship to calculate the maximum possible electricity consumption of the heat pumps $P_{HP,max,t}$ is used (shown in figure 5).

d) Although additional flexibility is made available by thermal storages it is not infinite. If assuming that the HP was controlled in a congestion-optimal way (i.e. the thermal storage at the first hour of grid congestion was at its minimum temperature $T_{st,min}$ and the heating zone temperature of the building was at its minimum allowable temperature $T_{comf} - \Delta T_{tol}$ the HP can only remain turned on until the thermal storage reaches its



(a) Illustration of a typical heating curve (supply temperature as a function of 24-hour-mean ambient temperature)

(b) COP of the simulated HP as a function of the ambient temperature given for two supply temperature settings (on basis of Panasonic Deutschland (2014a))

Figure 4

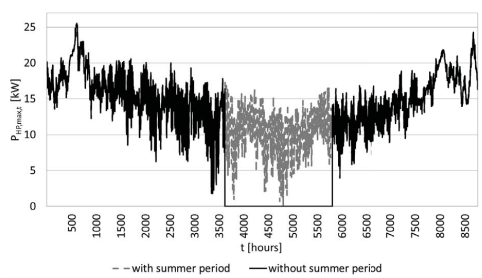


Figure 5: Maximum possible electricity consumption by HPs over the year (considering supply temperature settings according to technical operation criteria)

maximum temperature $T_{st,max}$) following HP operation restriction must be fulfilled.

$$c_w \rho_w V_{st}(T_{st,max} - T_{st,min}) + 2C_z \Delta T_{tol} + C_{fh} \Delta T_{f,max} +$$

$$\sum_{t=t_{soc}}^{t_{eoo}} H_{TV} \frac{(T_{z,t} - T_{amb,t})}{(\Delta T_{design})} \Delta t \geq \sum_{t=t_{soc}}^{t_{eoo}} P_{hp,th,t} COP_t \Delta t \qquad (6)$$

Here, c_w is the specific heat capacity of water, ρ_w its density. V_{st} is the storage volume (filled with water), C_z the absolute heat capacity of the heating zone of the building, ΔT_{tol} the temperature tolerance by which the heating zone temperature may diverge from its comfort temperature, C_{fh} the absolute heat capacity of the floor heating, $\Delta T_{f,max}$ the maximum temperature increase of the floor heating during hours of congestion, H_{TV} the design heat load of the building, $T_{z,t}$ the zone temperature of the building, $T_{amb,t}$ the ambient temperature, ΔT_{design} the design temperature difference, Δt the duration of the time step (here: 1 hour). t_{soc} indicates the time step of the start of congestion. t_{eoo} is the time step

at which the HP operation must / can end. The HP operation must end when the maximum storage temperature is reached. It can end - considering a curtailment minimization logic - when no congestion is apparent anymore (indicated by the time step t_{eoc}).

$$t_{eoo} = \min\left(t(T_{st,max}), t_{eoc}\right) \tag{7}$$

e) A forecasting algorithm will always have some degree of inaccuracy. Furthermore, achieving the optimal starting temperature as described under literal d may not be possible if periods of congestion are interrupted shortly and the buildings heat demand meanwhile is not high enough to lower the minimum storage temperature. Thus, thermal storage temperature will not always be at $T_{St,min}$ at the first hour of congestion. This implies a further reduction of flexibility. The remainder of the actually achieved curtailment reduction and the reduction potential under literal d can be assigned to these effects. This is in line with the scenarios of the forecasting algorithm shown in Felten et al. (2014).

f) Finally, there is some amount of curtailment which HPs with an ordinary control (according to technical criteria) would avoid anyhow as times of operation coincide with a surplus of RE generation. Therefore, the additionally-avoided curtailment is expressed as the balance of the actually-avoided curtailment under the local pricing mechanism (literal e) and the"anyhow" quantity.

3.3 Assessment of Economic Distribution Impacts

Implementing new policies does not only impact the system costs, but also the market participants economic figures. Presumably, the implemented policies may not only lead to winners, but might also make people become losers. The latter group is likely to raise complaints which then cause additional (e.g. judicial) friction to the political process. On the other hand, the economic figures are one motivational factor influencing the homeowners investment decision and, thus, in the long run, have an impact on the share of environmentally-friendly heating technologies in the market (cf. Michelsen and Madlener (2013), Bauermann et al. (2014)). Therefore, it is important to take a closer look at the distributive effects of different design options. The following section gives a general derivation of equations used for the assessment. Stylized choices representing different policy option are explained thereafter.
For the purpose of evaluating the distribution effects, the scheme in figure 3 and, in particular, the financial flows illustrated therein are reconsidered. The electricity consumption results in cash flows (for convenience, also called payments $CF^{out}_{HH/HP}$). For ease of understanding, the variable costs of end consumers are divided into two components: The local price $p_{loc,t}$ and the end consumer charges $ECC_{HH/HP,loc}$ which include, among others, constant grid charges of the local grid and higher levels, levies (e.g. for renewable support) and taxes.

Analogically, the marginal revenue is split into local price and into a local market premium $MP_{RE,loc}$. Thus, the end consumer charges and the market premiums represent regulatory components whereas the local price represents the market-driven component. By changing the regulatory components, the policy maker can influence the distribution of system benefits as will be shown below.

The system does not only contain the local generators and consumers, it also contains the distribution grid which is controlled by the DSO. In addition to the provision of technical services, for the purpose of this analysis, the DSO is seen as agent who has to source the remaining electricity demand from and pass the remaining generation through to the overarching system.[1] The present work supposes that the overarching (or "global") market conditions are exogenous to the local system and, therefore, the balance of the electricity which is not generated and consumed locally is procured or sold respectively at the wholesale market conditions (i.e. the prevailing wholesale market price $p_{WSM,t}$ and the end consumer charges $ECC_{HP/HH,glob}$ and the market premiums MP_{glob} of the overarching system). The DSO position encompasses the residual claims, i.e. the system cost reduction corrected by the benefits and costs assigned to other stakeholders. The question whether and how the DSO may pass on these costs or benefits to the rate payers or tax payers is excluded from the discussion.

In table 1, the equations for the payments of consumers $CF^{out}_{HH/HP}$and from a system perspective CF^{out}_{SYS} and the payments to producers / the system $CF^{in}_{RE/SYS}$ are listed. The system perspective considers all financial flows which cross the system boundary in figure 3. For the electricity used locally, grid charges for the HGL c_{HGL} are included in CF^{out}_{SYS}. Furthermore, the grid charges for the LVG remain within the system. SC_{SYS}, in turn, stands for the system costs which incur to the considered system, i.e. the aggregate of HH, HP, RE and DSO. These are evaluated at the global market conditions as explained above. The columns differentiate between a "local pricing regime" (applicable for the considered system) and a "global pricing regime" which would be the classical regulatory pricing scheme without local price signals and which always builds the base case for comparison. In the global pricing regime, RE generators receive a compensation payment at a rate of $p_{comp,t}$ (per curtailed quantity). Such payment is not necessary in the case of a local pricing regime as - in an efficiently-designed local market - the local prices will adjust in a way that RE generators are not willing to feed in any more electricity as the grid reaches its technical limit.

Table 1: Summary of cash flows, system cost and the DSO position

	Local Pricing Regime	**Global Pricing Regime**
CF^{out}_{HH}	$\sum_{t=1}^{8760} P_{HH,tot,t}\left(p_{loc,t} + ECC_{HH,loc}\right)\Delta t$	$\sum_{t=1}^{8760} P_{HH,tot,t}\left(p_{WSM,t} + ECC_{HH,loc}\right)\Delta t$ (8)
CF^{out}_{HP}	$\sum_{t=1}^{8760} P_{HP,tot,t}\left(p_{loc,t} + ECC_{HP,loc}\right)\Delta t$	$\sum_{t=1}^{8760} P_{HP,tot,t}\left(p_{WSM,t} + ECC_{HP,loc}\right)\Delta t$ (9)

[1] Which holds if the percentage of regions with local prices is small compared to the overarching system.

CF_{RE}^{in}	$\sum_{t=1}^{8760} P_{RE,tot,t}\left(p_{loc,t} + MP_{loc}\right)\Delta t$	$\sum_{t=1}^{8760} P_{RE,tot,t}\left(p_{WSM,t} + MP_{glob}\right)\Delta t +$ $\sum_{t=1}^{8760} \tilde{P}_{RE,t} p_{comp,t} \Delta t$ (10)
CF_{SYS}^{in}	$\sum_{t=1}^{8760} \left(P_{RE,tot,t} MP_{glob} + P_{RE,rem,t} p_{WSM,t}\right)\Delta t$	$\sum_{t=1}^{8760} \left(P_{RE,tot,t} MP_{glob} + P_{RES,rem,t} p_{WSM,t}\right)\Delta t$ (11)
CF_{SYS}^{out}	$\sum_{t=1}^{8760} \left(P_{HH,loc,t}\left(ECC_{HH,glob} - c_{HGL} - c_{LVG}\right) + P_{HH,rem,t}\left(p_{WSM,t} + ECC_{HH,glob} - c_{LVG}\right) + P_{HP,loc,t}\left(ECC_{HP,glob} - c_{HGL} - c_{LVG}\right) + P_{HP,rem,t}\left(p_{WSM,t} - ECC_{HP,glob} - c_{LVG}\right)\right)\Delta t$	$\sum_{t=1}^{8760} \left(P_{HH,loc,t}\left(ECC_{HH,glob} - c_{HGL} - c_{LVG}\right) + P_{HH,rem,t}\left(p_{WSM,t} + ECC_{HH,glob} - c_{LVG}\right) + P_{HP,loc,t}\left(ECC_{HP,glob} - c_{HGL} - c_{LVG}\right) + P_{HP,rem,t}\left(p_{WSM,t} - ECC_{HP,glob} - c_{LVG}\right)\right)\Delta t$ (12)
SC_{SYS}	$CF_{SYS}^{out} - CF_{SYS}^{in}$	$\mathrm{CF}_{SYS}^{out} - CF_{SYS}^{in}$ (13)
SC_{DSO}	$SC_{SYS} - CF_{HH}^{out} - CF_{HP}^{out} + CF_{RE}^{in}$	$\mathrm{SC}_{SYS} - CF_{HH}^{out} - CF_{HP}^{out} + CF_{RE}^{in}$ (14)

Table A.1 in Appendix A provides a further breakdown of above equations. The savings for the consumers can be expressed as the difference of payments in a global and a local pricing regime. Similarly, the change in revenues of RE generators can be assessed. Furthermore, a decrease in system costs (i.e. balance between local and global values) can be interpreted as system benefits. If the change in the DSO position (local minus global values) is negative, it indicates operational cost savings. These can be used either to finance support schemes for RE, flexible consumers, cost coverage for the additional system services of the DSO (related to the implementation and operation of a local market) or remain as socio-economic welfare gains. The different options of distribution of the system cost savings are analysed by means of a scenario analysis presented in section 4.2.

4 Application

4.1 TestCase

A grid sample which contains PV systems and households with and without HPs is used as a test case. The grid topology represents a typical example for a low voltage (LV) level grid in rural regions in Germany. The grid representation is based on real grid data, including grid topology, transformer capacities, line properties and installed grid devices. As it is aimed at evaluating the benefits of local pricing policies as alternative to traditional grid expansion the grid characteristics are not altered from the current status.
In addition, the locations of currently-installed PV systems and their orientations are used. The installed PV capacities are scaled up in order to anticipate future grid load situations. The overall scaling factor is 2.3, which reflects the forecasted increase of the German PV capacity until 2050 (cf. Prognos AG, EWI, GWS (2014)). The nodes to which PV systems are connected are assumed to remain unchanged.

Similarly, an increased percentage of households is equipped with space heating by air-water HPs. The percentage is chosen in accordance to the expected market share of HPs in the heating market for households in 2050 (according to Biogasrat e.V. (2012)). Thermal and other building characteristics are chosen in accordance to the sample one-family house given in DIN EN 12831 (2003). The layout of HPs is preformed according to the technical planning guidelines (Novelan (2013)), the technical data (HPs and thermal storages) is then sourced from the manufacturers documents (Panasonic Deutschland (2014a) and Panasonic Deutschland (2014c)).
In the present model, it is assumed that HPs and PV systems can behave elastic in response to price signals while common household appliances are supposed to be inflexible and being modelled by historic load measurement data of the DSO. Irradiance observations of 2014 at a close-by location to the assessed grid is sourced from DWD (2015a). End consumer charges and market premiums are also based on 2014 data (BMWi (2015), BDEW (2014)).
The real grid contains 5 feeders which, for the purpose of this study, are presumed to be identical. That is to say, it is sufficient to analyse one feeder in detail. Figure 6 illustrates the grid topology of the considered LV grid and its schematic including the numbers of connected market participants.

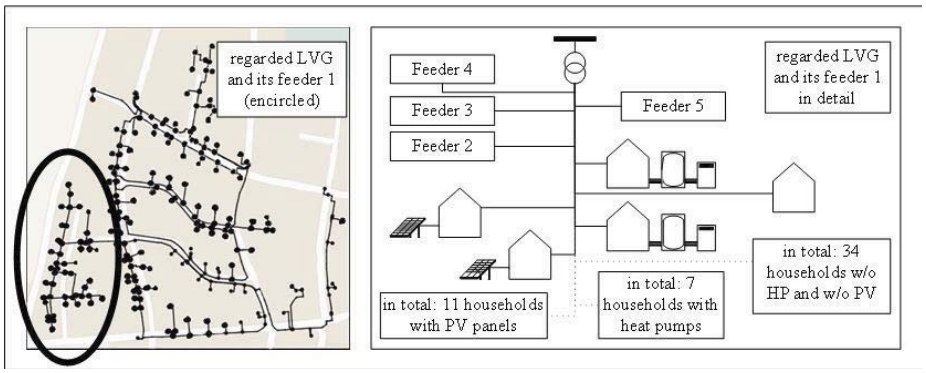


Figure 6: Scheme of grid topology of the considered LV grid (left) and abstracted illustration of the feeders including the market participants in feeder 1 (right)

A short summary of key characteristics is given in table 2. For a more comprehensive list of test case data sources and methods, the reader is referred to table B.1 in Appendix B.

4.2 Scenarios

In order to evaluate the impact of various design choices (cf. section 3.3) stylized scenarios are considered representing the extreme choices satisfying the claims

Table 3: Key characteristics of test case (feeder 1)

Description	Value
Aggregated installed PV peak capacity	220 kW_p (11 units)
Number of HPs	7
Nominal thermal output and corresponding electrical consumption of each HP	9 kW_{th} / 1.86 kW_{el}
Thermal storage volume for each HP	$1,760\ l$
Voltage level of LVG	400 V
Transformer capacity (available to feeder 1)	80 kVA

of different interest groups. The scenario description is given in table 3.

Table 3: Explanation of tested scenarios and describing equations

Scenario description	Main equations
Scenario 0/ No local policy adjustment	
There is no difference between local and global end consumer charges and market premiums. The savings and the change in revenues solely result from the difference between the local and global market price and the compensation for curtailment	$ECC_{HH,loc} = ECC_{HH,glob}$ $ECC_{HP,loc} = ECC_{HP,glob}$ $MP_{loc} = MP_{glob}$
Scenario A/ No non-flexible profiteers	
As HHs do not participate in the local market (not adjusting the demand to the local supply), the end consumer charges of HHs are adjusted in a way that the sums of their payments in a global and a local pricing regime are equal. I.e. there are no savings for HHs.	$ECC_{HH,loc} = ECC_{HH,glob} + \frac{1}{\sum_{t=1}^{8760} P_{HH,tot,t}\Delta t} \sum_{t=1}^{8760} P_{HH,tot,t} \left(p_{WSM,t} - p_{loc,t}\right) \Delta t$ $ECC_{HP,loc} = ECC_{HP,glob}$ $MP_{loc} = MP_{glob}$
Scenario B/ No disadvantage to RE generators	
Germany and other countries provide RE generators with certain privileges such as off-take prioritization and compensation payments in case of curtailment. If such privileges are to be maintained without exception (e.g. to incentivise additional investments), the sums of payments to the RE generators shall be equal in a global and a local pricing regime.	$ECC_{HH,loc} = ECC_{HH,glob} + \frac{1}{\sum_{t=1}^{8760} P_{HH,tot,t}\Delta t} \sum_{t=1}^{8760} P_{HH,tot,t} \left(p_{WSM,t} - p_{loc,t}\right) \Delta t$ $ECC_{HP,loc} = ECC_{HP,glob}$ $MP_{loc} > MP_{glob}$, so that $CF^{in}_{RE\|localpr.regime} = CF^{in}_{RE\|globalpr.regime}$
Scenario C/ Economic feasibility of flexible HPs	

In order to provide long-term incentives for the installation of flexibility measures for HPs (thermal storage and related equipment, smart grid/forecasting equipment, etc.),potential owners of such equipment must anticipate that the installation is economically feasible. The electricity cost savings of the HP, which result from relatively low local prices and local end consumer charges, may contribute to such economic viability. Thus, in scenario C, the local end consumer charges are adjusted in a manner that the annual electricity cost savings provide for the increase of operational expenses $\Delta OPEX_{flex}$ and the increase of the annualised capital expenses $CAPEX_{flex,annualised}$ due to flexibility measures.	$ECC_{HH,loc} - ECC_{HH,glob} = \frac{1}{\sum_{t=1}^{8760} P_{HH,tot,t}\Delta t} \sum_{t=1}^{8760} P_{HH,tot,t} \left(p_{WSM,t} - p_{loc,t}\right) \Delta t$ $ECC_{HP,loc} < ECC_{HP,glob}$, so that $CF^{out}_{HP\|localpr.regime} + CAPEX_{flex,annualised} + \Delta OPEX_{flex} = CF^{out}_{HP\|globalpr.regime}$ $MP_{loc} = MP_{glob}$
Scenario D/ Orientation towards local market participant	
This scenario combined the claims of HP owners and RE generators as stated for scenario C and B, respectively.	$ECC_{HH,loc} - ECC_{HH,glob} = \frac{1}{\sum_{t=1}^{8760} P_{HH,tot,t}\Delta t} \sum_{t=1}^{8760} P_{HH,tot,t} \left(p_{WSM,t} - p_{loc,t}\right) \Delta t$ $ECC_{HP,loc} < ECC_{HP,glob}$, so that $CF^{out}_{HP\|localpr.regime} + CAPEX_{flex,annualised} + \Delta OPEX_{flex,annualised} = CF^{out}_{HP\|globalpr.regime}$ $MP_{loc} > MP_{glob}$, so that $CF^{in}_{RE\|localpr.regime} = CF^{in}_{RE\|globalpr.regime}$

The resulting allocation of system cost savings, the operational cost savings for HPs and HHs and revenue changes for RE generators are given in section 5.3.

5 Results and Discussion

5.1 Price Signals for Grid-Beneficial HP Operation

Figure 7 shows the HP electricity consumption, the local prices and whether the upper storage restriction is binding during one exemplary week. It can be observed that the operating decision of HPs is clearly driven by the local prices as long as the technical constraints allow. Thus, during times of relatively low

local prices (for the case in figure 7 due to congestion) the HP starts to operate and continues until the thermal storage is fully charged or the prices increase again (due to disappearing congestion). If the local prices remain at a very low level for several hours HPs can hardly benefit from the oversupply any longer as the technical limits are reached frequently.

Especially in transition months such as March, heat demand as well as local

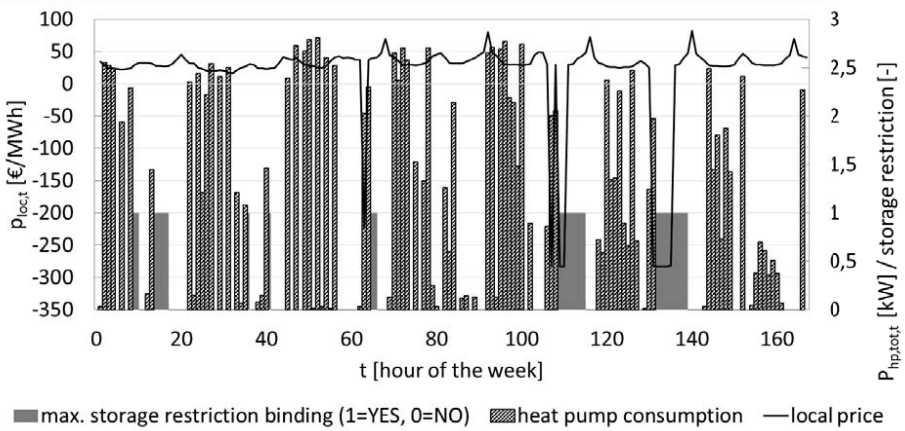


Figure 7: Consumption of one HP (bars), indicator whether upper storage restriction is binding (area, 1= binding, 0 = non-binding) and local prices (line) for one exemplary week of March

infeed occur concurrently so that the local price signals incentivise HPs to operate (cf. the three periods of negative prices in figure 7 and HP consumption at the beginning of these periods). Notably, the second period of negative local prices is interrupted, i.e. the HP operation contributes to the elimination of congestion. Thus, the analysis shows that local prices allow, in general, to incentivise price-oriented HPs to operate in a more grid beneficial way. However, the results also make clear that certain restrictions exist which prevent further reduction of curtailment. E.g. this can be observed in the second and third period of negative prices where a charged storage prevents the further use of the HPs. The effects of this and other restrictions are quantified as follows.

5.2 Potential Analysis - Theoretical and Exploited Potential

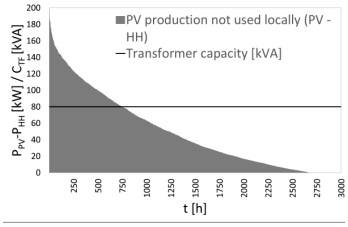
Figures 8a and 8b show the curtailed amounts and, thus, the quantities which the use of DSM aims to integrate into the energy system. Figures 8b to 8e illustrate the impact of various real-world restrictions on the achievable demand side flexibility. Figure 8f includes the “anyhow” quantity. The literals of the figures correspond to the literals of the methodological explanation in section 3.2. The respective quantities are provided in table 4.

For the given test case, it is observed that - without local prices - the curtailed power reaches up to 120 kW (distance on the vertical axis in figure 8a) and curtailed electricity generation during the complete year is around 26 MWh. Thereof, 49.6 % occur during the non-heating period, which decreases the DSM potential by HPs accordingly.
In figure 8c, the steepness of the duration curve of the curtailed power induces that the electrical power which the HPs could possibly consume (under due consideration of their control explained in section 3.2) is frequently insufficient to avoid the entire curtailment. This limitation diminishes the DSM potential further by 34.6 %.
Additional reductions of 4.0 % and 8.2 % are caused by storage capacity restrictions and forecasting impreciseness, respectively.
Finally, the net avoided curtailment (figure 8f) by applying local prices under the given setup is only 882 kWh (actual minus "anyhow" avoided curtailment).

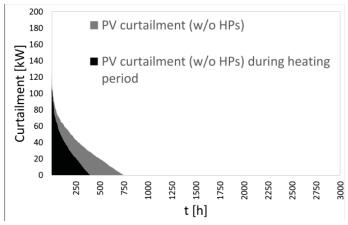
Table 4: Summary of quantitative results of the potential assessment

Position	**Quantity**	**Share of curtailment without**	**Share of maximum possible PV generation**
Maximum possible PV generation	199,979 kWh	n.a.	100.0%
PV production not used locally (PV HH)	146,537 kWh	n.a.	73.3%
PV curtailment (w/o HPs) (a)	26,198 kWh	100.0%	13.1%
PV curtailment (w/o HPs) during heating period (b)	13,195 kWh	50.4%	6.6%
Potential decrease of curtailment by maximum possible HP load (c)	4,151 kWh	15.8%	2.1%
Potential decrease of curtailment considering storage restrictions and assuming perfect foresight (d)	3,084 kWh	11.8%	1.5%
Actual decrease of curtailment by DSM with HP (e)	**933 kWh**	**3.6%**	**0.5%**
"Anyhow" decrease of curtailment by HPs (f)	51 kWh	0.2%	0.0%
Actual decrease without "anyhow" quantity	**882 kWh**	**3.4%**	**0.5%**

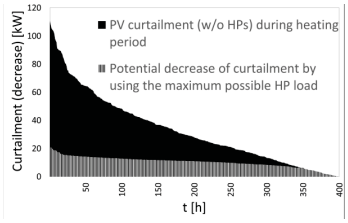
The discrepancy between curtailed PV generation without DSM by HPs and the achieved reduction of curtailment by that means is significant. In the test case, only 3.6 % of the curtailment can be avoided. Thus, it is appropriate to discuss the sensitivity of the results which is done subsequently following the sequence of the literals of table 4 and section 3.2.
It is obvious that the test case represents a quite extreme example with high curtailment. Therefore, the percentage figures should not be over-interpreted. However, in terms of absolute curtailment reduction, the case is rather opti-



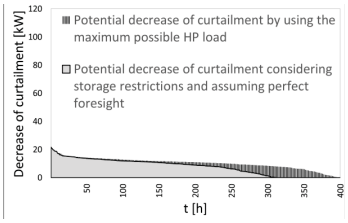
(a) Duration curve of residual PV infeed and capacity constraint of the transformer



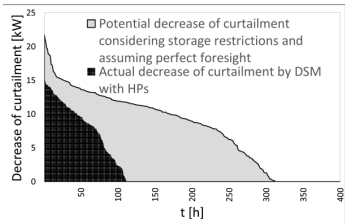
(b) Duration curve of PV curtailment during all hours of the year and during heating period only



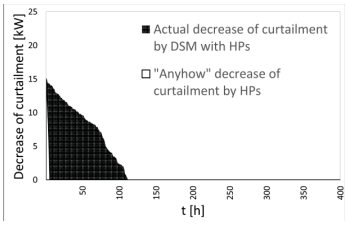
(c) Duration curve of curtailment without HPs and its potential decrease if using maximum possible HP loads



(d) Duration curve of potential decrease of curtailment using maximum possible HP load considering storage restriction or not



(e) Duration curve of decrease of curtailment under perfect and imperfect foresight



(f) Duration curve of decrease of curtailment by operating HPs in a price responsive manner and according to technical criteria

Figure 8

mistic on the contribution of flexibility from HPs for the same reason.
Creating additional use of the HPs during the summer months may be thinkable. Air conditioning may raise the capacity factor of HPs. Yet, due to its currently limited installation numbers in Germany and other central European countries, increasing the use of air conditioning would have adverse effects with respect to the original climate goals. Warm water supply by HPs is another option which is more compatible with the climate goals. However, its share in end consumption of heating appliances is much lower than the one of space heating (in Germany: 17 % vs. 76 %, cf. AGEB (2014)) and technicalities related to

supply temperature levels (cf. section 3.2) further decrease its leverage.
Increasing the penetration of HPs could help avoiding further curtailment. However, the marginal utility of each HP will decrease. Section 5.3 will provide the reasoning why the installation of further HPs will not be beneficial from a system cost perspective. The same argument applies for the installation of additional storage capacity.
An evident upside potential is the improvement of the forecasting adequacy (local prices, heat demand and ambient temperature). Great part of these potentials could certainly be leveraged so that the avoidance of around 2000 kWh of curtailment seems realistic for the given test case. Further upside potential exists for other combinations of RE types (such as wind power) and/or other DSM devices/facilities (like household appliances, industrial plants, etc.). Their complementarity is likely to bear greater potential as the correlation of daily infeed and daily demand may be higher. However, such analyses would require a whole new scenario setup. I.e. the regarded grid would be different as wind power plants are typically connected to higher voltage levels to which, in turn, other consumer types are connected. Thus, this assessment is left to further research.
Finally, it should be noted that the potential analysis shown above does not consider the transaction costs in local pricing regimes. These would decrease the potential for operational system cost savings even further.

5.3 Allocation Scenarios - Distribution of Benefits

5.3.1 Base Case - Scenario 0

In Figure 9, the absolute and relative economic impacts on the considered market participants are illustrated. The numbers show that implementing local prices without adjusting regulatory pricing components especially affects the revenues of RE generators. These are diminished by approx. 45.3 % of which 12.5 % (7,848 €) are due to missing compensation of curtailment and the remaining decrease of 32.8 % (20,561 €) results from the RE generation at times of congestion (or prevented congestion[2]) at accordingly low (mostly negative) prices. The fact that RE generators continue to feed in electricity to the grid is a consequence of their economic rationale: Even though the local prices are negative the market premiums will still make the contribution margin for RE generator be 0 or slightly positive. At such contribution margins, it is reasonable for RE generators to feed in electricity to the distribution grid. However, these contribution margins are significantly lower than the lowest contribution margin that RE generators could have achieved under a global pricing regime.[3]

[2]Prevented congestion refers to times where the local pricing mechanism eliminates congestion.

[3]In 2014, the minimum wholesale market price was -6.5 ct/kWh. Considering the average remuneration of PV infeed at 31.6 ct/kWh (BMWi (2015)), the average wholesale market price of 3.2 ct/kWh and, thus, an average market premium of 28.4 ct/kWh leaves a contribution margin of 21.9 ct/kWh during the most-unfavorable hour of 2014 under a global pricing regime.

The HP owners electricity cost savings are quite low only representing approx. 4.0 % of the electricity costs under a global pricing regime. Such low improvement is reasonable as the average price decrease (local vs. global) is only 2.47 ct/kWh. Compared to the reference end consumer price this constitutes only 8.5 %. Analysing the reasons for HPs using less than half of the average price decrease is straightforward considering the results of section 5.2.
The HHs are able to take an above-average advantage from local prices as the correlation between the HH loads and RE infeed is higher. The change of the DSO position is quite positive (savings of 24,380 €). However, this is a consequence of the distribution effects (i.e. the revenue decrease of RE generators) rather than of cost savings in the overall system which only contribute 2.4 % to such improvement.

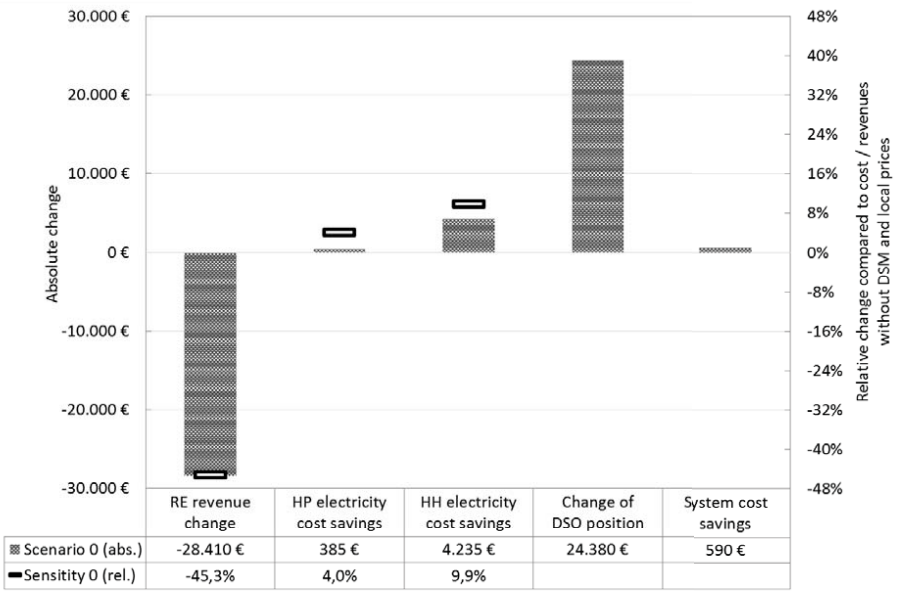
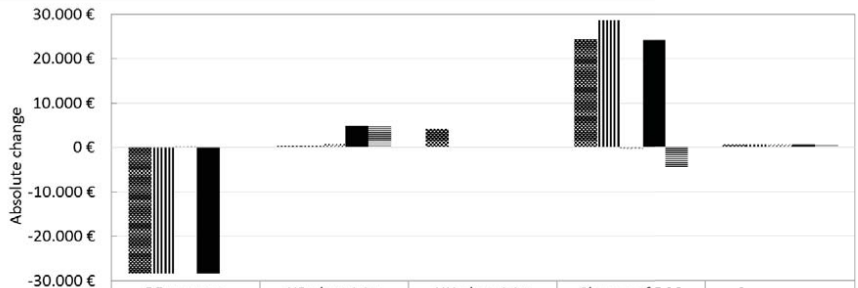


Figure 9: Distribution effects between market participants for scenario 0

5.3.2 Scenarios A - D

Figure 10 shows how alternative policy mechanism designs which change the regulatory components of the local prices may alter the economic impacts on the market participants. For scenario A, the main observation is that the net benefits for the DSO increase (while the benefits for the HHs are 0 - which has been the scenarios stipulation). The end consumer charges have no effect on the remaining market participants as the HH behaviour does not change due to its inflexibility.

Scenario B provides some more interesting results: The revenue change of RE generators is 0 (as postulated), but the electricity cost savings for HPs



	RE revenue change	HP electricity cost savings	HH electricity cost savings	Change of DSO position	System cost savings
Scenario 0 (abs.)	-28.410 €	385 €	4.235 €	24.380 €	590 €
Scenario A (abs.)	-28.410 €	385 €	- €	28.615 €	590 €
Scenario B (abs.)	195 €	746 €	- €	-342 €	600 €
Scenario C (abs.)	-28.410 €	4.869 €	- €	24.130 €	590 €
Scenario D (abs.)	195 €	4.869 €	- €	-4.465 €	600 €
Sensitity 0 (rel.)	-45,3%	4,0%	9,9%		
Scenario A (rel.)	-45,3%	4,0%	0,0%		
Scenario B (rel.)	0,3%	7,8%	0,0%		
Scenario C (rel.)	-45,3%	50,7%	0,0%		
Scenario D (rel.)	0,3%	50,7%	0,0%		

Figure 10: Distribution effects between market participants for scenarios 0 and A to D

increase. It can be observed that the electricity cost savings of HPs increase by about 94 %. This is the consequence of the higher local market premium which the RE generators receive: In order to compensate the revenue losses that the RE generators incur due to lower local prices and abolished compensation for curtailment the market premium has been increased from approx. 28 ct/kWh to more than 70 ct/kWh for scenarios B and D. Considering the economic rationale of RE generators (explained in section 5.3.1) the pricing mechanism induces much lower local prices at times of congestion. Hence, the average price decrease (local vs. global) is 5.77 ct/kWh meaning 19.8 % of the end consumer price. Still the leverage for HPs is bound to the technical limitations explained in section 3.2 and the HP electricity cost savings remain far from what would make the additional flexibility investments economically feasible. This would require a reduction of the $ECC_{HP,loc}$ by 12.3 ct/kWh enabling HP operational cost savings of approx. 4,869 € (scenarios C and D).

For all scenarios, the system cost savings remain almost unchanged from scenario 0. This is the implication of the technical restrictions analysed in sections 3.2 and 5.2. The slight improvement in system costs in scenario B and D results from the more pronounced price signals for the cost-optimizing control of the HPs.

Finally, scenario D reveals that the net effect on the DSO position is negative. I.e. if RE generators are not to suffer from disadvantages (compared to the situation in a global pricing regime) and the incentives for features enabling

HPs to operate flexibly are to be sufficient the operational costs of the DSO (i.e. of the rate payers and/or tax payers) will increase.
An alternative policy choice might then be to avoid extra costs to the DSO. Then, at least one market participant would need to make up for the gap of 4,465 €. Applying the costs-by-cause principle RE generators would suffer a decrease of approx. 7.1 % of the former revenues. This would enable the integration of more RE into the energy system (avoidance of 882 kWh of curtailment) and imply the advantage of enabling HPs to operate more resource-efficiently (reduction of electrical consumption by 488 kWh due to the increased flexibility). Translating this to reduced CO_2 emissions that is almost 1 ton of CO_2 reduction per year.

6 Conclusions

The results in section 5.1 indicate that local pricing mechanisms can provide short-term incentives for orienting HPs towards grid-beneficial operation. However, the analysis in section 5.2 reveals that the complementarity of HPs and PV is limited and the potentials claimed in several publications may be called into question. The technical measures to achieve a positive effect in terms of operational system cost reduction are very limited for the given scenario. Outside the scenario, e.g. different combinations of generator and consumer types may offer higher potential. Hence, the analyses disprove any generalized claims about the efficiency of local pricing - yet obviously it does not prove that local pricing is of no worth in general.
Section 5.3 demonstrates that it is not feasible - in the given setup - to incentivise investments into flexible HP installation without accepting additional societal cost or reducing the revenues of RE generators. It is shown that - despite limited merits in terms of system costs - the redistributive effects of local pricing mechanisms are very significant. Given the huge redistributive effects, any proposal for the use of local prices will encounter massive opposition unless accompanied by a proposal for readjustment of charges and levies.
Concluding, any change towards local pricing policies will require careful cost-benefit analyses and policy makers have to pay attention to the redistributive effects as they will impact the long-term incentives for investment.

Appendix A - Further Breakdown of Equations for Assessment

Table A.1: Further breakdown of equations for assessment

Described Figure	Descriptive Term
SC_{SYS}	$E_{HH,tot}\left(ECC_{HH,glob} - c_{LVG}\right) - E_{HH,loc}c_{HGL} + \sum_{t=1}^{8760} P_{HH,rem,t}p_{WSM,t}\Delta t +$ $E_{HP,tot}\left(ECC_{HP,glob} - c_{LVG}\right) - E_{HP,loc}c_{HGL} + \sum_{t=1}^{8760} P_{HP,rem,t}p_{WSM,t}\Delta t -$ (A.1)

ΔSC_{SYS}	$\sum_{t=1}^{8760} P_{RE,loc,t} MP_{glob} \Delta t - \sum_{t=1}^{8760} P_{RE,rem,t} \left(p_{WSM,t} + MP_{glob}\right) \Delta t$ $-\Delta E_{HP,tot} ECC_{HP,glob} + \Delta E_{HP,loc} c_{HGL} - \Delta \left(\sum_{t=1}^{8760} P_{HP,rem,t} p_{WSM,t} \Delta t\right) +$ $\Delta E_{RE,tot} MP_{glob} + \Delta \left(\sum_{t=1}^{8760} P_{RE,rem,t} p_{WSM,t} \Delta t\right)$	(A.2)
$\Delta SC_{SYS,REintegration}$	$\Delta E_{HP,loc} c_{HGL} + \Delta E_{RE,tot} MP_{glob} = \Delta E_{RE,tot} \left(c_{HGL} + MP_{glob}\right)$	(A.3)
$\Delta SC_{SYS,tech.eff.gains}$	$-\Delta E_{HP,tot} ECC_{HP,glob} - \Delta \left(\sum_{t=1}^{8760} P_{HP,rem,t} p_{WSM,t} \Delta t\right)$ $+\Delta \left(\sum_{t=1}^{8760} P_{RE,rem,t} p_{WSM,t} \Delta t\right)$	(A.4)
$SC_{DSO\|localpr.regime}$	$E_{HH,tot} \left(ECC_{HH,glob} - ECC_{HH,loc} - c_{LVG}\right) - E_{HH,loc} c_{HGL} +$ $E_{HP,tot} \left(ECC_{HP,glob} - ECC_{HP,loc} - c_{LVG}\right) - E_{HP,loc} c_{HGL} -$ $\sum_{t=1}^{8760} P_{RE,tot,t} \left(MP_{glob} - MP_{loc}\right) \Delta t - \sum_{t=1}^{8760} P_{RE,rem,t} \left(p_{WSM,t} - p_{loc,t}\right) \Delta t$	(A.5)
$SC_{DSO\|globalpr.regime}$	$-E_{HH,tot} \bar{c}_{LVG} - E_{HH,loc} c_{HGL} - E_{HP,tot} \bar{c}_{LVG} - E_{HP,loc} c_{HGL} +$ $\sum_{t=1}^{8760} \tilde{P}_{RE,t} p_{comp,t} \Delta t$	(A.6)
ΔSC_{DSO}	$-E_{HH,tot} \left(ECC_{HH,glob} - ECC_{HH,loc}\right) - E_{HP,tot} \left(ECC_{HP,glob} - ECC_{HP,loc}\right) -$ $\Delta E_{HP,loc} c_{HGL} + E_{RE,tot} \left(MP_{glob} - MP_{RE,loc}\right) + \sum_{t=1}^{8760} P_{RE,rem,t} \left(p_{WSM,t} -$ $p_{loc,t}\right) \Delta t + \sum_{t=1}^{8760} \tilde{P}_{RE,t\|no-flex} p_{comp,glob,t} \Delta t$	(A.7)

Here, E is the yearly amount of electricity consumed or generated, respectively. ΔSC_{SYS} stands for the difference in system cost savings achieved by the local pricing mechanism (i.e. system costs without DSM (and without local prices) compared to those using the local pricing mechanism). $\Delta SC_{SYS,REintegration}$ is the part of the system costs savings due to improved RE integration (in the given examples, amounting up to 343 €). The remainder is due to other effects such as the more efficient operation of the HPs, more cost-saving operation of HPs and its feedback effect on the market-based component of the RE revenues. Such remainder is called technical efficiency gains ($\Delta SC_{SYS,technicaleff.gains}$, in the examples being up to 280 €). In equations A.2 and A.7, it is assumed that the sum of all received grid charges for the LVG must remain unchanged (regardless of the implementation of a local pricing mechanism). For the grid charges for the HGL, this is not the case. In equation A.5, it should be noted that, for the presented case, the price divergence may only exist when $P_{RE,rem,t}$ is positive.

Appendix B - Summary of Test Case and Model Data

Table B.1: Summary of data used for the assessment

System	Data / Method	Source
System configuration		
Installed PV capacity	Scaling factor applied to existing PV capacity	Prognos AG, EWI, GWS (2014)
No. and location of households	Data of actual grid	Proprietary data of the DSO
Household loads	Data sets of actual grid	Proprietary data of the DSO
Number of households with HPs	Forecasted share of household applied to number of households	Biogasrat e.V. (2012)
PV data		
PV panel orientation and location	Data of actual grid	Proprietary data of the DSO
Maximum possible PV infeed	Calculation using PV panel orientation and location and irradiation data	Quaschning (1996)
Building configuration		
Building characteristics	Dimensions (floors, walls, windows), orientation, design heat load, design ambient temperature	DIN EN 12831 (2003), DIN EN ISO 13790 (2008)
Floor heating	Piping dimensions, floor thickness, circulation pump data	Schmidt et al. (2010), DIN EN 1264-2 (2013), Grundfos (2008)
Solar returns of the building	Calculation using window sizes, orientations and respective shading factors and irradiation data	Quaschning (1996), Schild and Willems (2011)
Internal returns of the building	Simplified load profile with habitable-surface-specific heat input for residential buildings	DIN V 4108-6 (2003), Michelsen and Madlener (2013)
Heating system		
HP layout	Thermal nominal capacity according to technical design criteria	Novelan (2013)
HP data	Manufacturers data (Panasonic WH-SDC09F3E8), approximation of performance map through linear	Panasonic Deutschland (2014a), Panasonic

	regression	Deutschland (2014c)
Thermal storage data	Manufacturers data (4 x PAW-TE50E3STD) supplemented by temperature limits	Panasonic Deutschland (2014a), E DIN EN 12897 (2014), Schmidt et al. (2010)
Environmental conditions		
Meteorological conditions	Hourly ambient temperature measurements, hourly irradiance observations at location closest to the considered grid	DWD (2015a), DWD (2015b)
Data for annuity calculation of additional flexibility measures of HP		
Investment cost	Prices of additional storage units (PAW-TE50E3STD) according to manufacturers price list, lump sum for additional accessories, smart grid investment cost estimated based on prices of similar modules	Panasonic Deutschland (2014a), Panasonic Deutschland (2014c), Panasonic Deutschland (2014b)
Operation and maintenance cost	Additional operation and maintenance cost (other than electricity cost) neglected	
Financial parameters	Payoff period of 20 years, interest rate according to the 2014-average yields for government bonds with 20-year maturity, nominal, all issuers whose rating is triple A in the Euro area (representing the lower bound to the effective interest rate relevant to investors).	European Central Bank (2016)
Electricity price level	Myopic expectations (savings dominated by regulatory price component)	
Market and regulatory conditions		
Wholesale market price	Hourly day-ahead electricity prices for the German-Austrian market zone	EPEX Spot SE (2014)
Regulatory conditions	End consumer charges, grid charges and renewables reimbursement based on German average data for 2014	BMWi (2015), BDEW (2014)

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6 CONCLUSION AND OUTLOOK

This thesis focuses on future electricity systems. Conditions, limitations and requirements for the participation of flexible grid users are analyzed and the impact of changing market rules is investigated.

6.1 RESULTS

Results regarding flexible grid users as well as suitable incentives within future electricity markets may be summarized as follows:

6.1.1 Flexibility of Consumers and Storage Operators

Specific types of grid users which may provide flexibility have been identified and analyzed: namely large-scale battery storage systems and heat pumps. As the flexibility of typical generators based on RES is restricted to a possible reduction of infeed, the focus is here on prosumers and consumers.
The economics taking into account the available flexibility are investigated for the systems 'battery storage system' and 'heat pump'. With an analysis of various operation modes, decision-making particularly under uncertainties is reflected. Estimations on relevant decision parameters such as prices are taken into account using heuristic operation modes as small-scale operators are not likely to have access to greater foresight and optimization tools.
Hereby battery storage systems have a large potential to adjust operation towards current supply and demand. In a market-oriented operation mode there are no external drivers for charging and discharging and the operation is oriented towards prices. Then the critical question is the predictability of price levels. Periods of high and low filling levels have to be chosen favorably. Decisions on these states of charge affect the profitability strongly. Moreover, profitability is affected significantly by the duration of service time. As this lifetime is depending on both the mode of operation and environmental conditions, estimating profitability is challenging. Finally, the profitability is not only a matter of suitably chosen operation modes and price prediction methods, but also of market characteristics and power capability. Namely, the Lithium-Ion battery is the most promising one, at least in a market with high price volatility. In fact, the occurence of high price spikes is a main driver for a profitable battery-storage-system operation. In this case generally the benefit of high power capability has to be emphasized, but also that the lack of predictability for prices implies high losses in comparison to theoretical profits under perfect information.
The large flexibility potential of heat pumps is due to the utilizable heat storage capacity. Yet, comfort conditions and system restrictions set clear limits to a flexible electricity consumption in reality. Thereby system dimensions have a strong impact: The heat-pump size, the building's heat capacity as well as existence and size of storage tanks are important. Additionally, weather conditions affect the heating performance twofold: Related heat losses of the building have to be covered and - in case of air-to-water heat pumps - the efficiency of

heat supply may be affected by the ambient temperature (being the source temperature). Concerning the desired flexibility in future electricity systems, one main conflict of heat pumps is relevant: Periods of high demand are a priori most promising, but in these periods a prompt supply of heat is required, as the system cools down rapidly. Additionally, uncertainties also limit flexibility in the case of heat pumps: With relatively long planning horizons, estimations on weather conditions may be incorrect and may induce an improper system behavior require instantaneous corrections in real-time in order to hold the system stable - which may be expensive for the operator. Short-term scheduling of operation decisions is of particular interest: Planning day-ahead for the following day may induce comfort losses for residential consumers, while hourly decisions with intraday procurement seem to be unproblematic in terms of comfort losses. With a high number of more or less flexible heat-pump operators, characterized each by different restrictions, flexibility in the overall consumption is substantial. But some restrictions are more or less common for all heat pumps: Heating periods do not differ significantly and extreme weather conditions are the same for neighbouring heating systems. The investigation of the implications of such general constraints are left to further analyses.

6.1.2 Market Instruments for Flexibility Coordination and their Consequences

From an economic point of view, a price is an efficient signal for the current market situation and may also be used to indicate scarcity situations to grid users. In order to incentivize a grid beneficial behavior, prices have to reflect the feed-in and load situation. Therefore a local pricing mechanism is required when congestion separates parts of the grid from the general market. Due to the fact that the participants' generation and consumption behavior on the one hand and the load situation on the other hand are interrelated, the local prices have to reflect the users' behavior promptly. Therefore an intensive exchange of information between the market participants and a market operator is needed. This thesis shows that instead of interchanging a large amount of detailed data, an iterative pricing mechanism can be applied. The algorithm implemented in this thesis determines suitable local price signals in real-time by using available automatic processes of electric devices and households. The introduced pricing algorithm allows the coordination of grid users, leading to a more efficient supply and consumption behavior. The algorithm considers the current load situation while requiring a minimum of data exchange. Yet, it has to be stated that the effectiveness of a local pricing system depends to a large extent on the available system flexibility. To be more precise, the higher the available system flexibility, the higher the potential welfare gains obtained by implementing a local pricing system using these flexibilities.
In view of a sufficient amount of flexibility for the overall system, it is of interest, which *types* of participants are available. A priori it is not obvious, what kind of flexibilities are needed or effective. But the advantages for the system, notably in terms of cost reduction for participants, tend to be low when there is little

flexibility available or it is not complementary to the system congestion situations. Therefore it is important to analyze in detail, which kinds of generators, prosumers and consumers do fit together. The investigations of this thesis show that heat pumps and PV systems are not that complementary. A grid system which faces frequent congestion due to PV-system infeed cannot be balanced by means of adjusting heat-pump operation solely. In low voltage grids, both types of systems are common, but a local market is likely to require more flexibility. Due to the heat pumps' individual restrictions and a low level of corresponding periods of operation (around midday, particularly in summer for PV systems vs. winter months for heat pumps), congestion cannot be handled adequately.
A critical point in an operational perspective is the time between detection of congestion situations, price determination and users' responses. Effective local prices improving the network utilization as well as small-scale consumers with specific restrictions require short term trading, preferably in real-time. This in turn implies a certain degree of technical equipment for both grid and consumption devices.
And even if an effective local market mechanisms is in place, distributional effects can be significant and have to be considered carefully. In order to avoid major disadvantages for some users in comparison to traditional market systems, the benefits have to be allocated to grid operators, generators and (flexible) consumers suitably. Depending on the achieved benefits, it may be difficult to implement distribution schemes attractive for all types of grid users. The assessment performed in this thesis shows that redistribution effects can significantly impact the benefits and costs of diverse market participants. E.g., the idea to remunerate not only provided flexibility but also to cover initially required investments in flexibility-enabling *devices*, would imply huge costs for other grid users. As a caveat, it should however to be stated that general rules can not be derived from single application cases.

6.2 IMPLICATIONS

Based on the results of this thesis it can be concluded that a reorganization of the electricity system with higher amounts of volatile infeed requires careful considerations in advance.
One important requirement for future electricity systems is undoubtly the provision of flexibility. Yet, this thesis shows that

(1) even with given appropriate technical equipment, certain types of flexibilities are limited by individual technical and utilization restrictions and that

(2) incentives for flexibility provision and coordination imply always significant costs, which have to be allocated among system participants. Notably, costs can be high in case the level of flexibility given in the system is inappropriate or too low.

Consequently, prior to a fundamental change of the electricity system, deeper understanding of the following aspects is needed:

- all types of flexible generation, storage and demand, including the specific limitations (e.g. E-Mobiles, typical household devices connected to smart devices,...)
- the effectiveness of different combinations of these flexible users, i.e. which combinations are beneficial or sufficient to balance supply and demand even in case of high shares of intermittent generation.

6.3 OUTLOOK

This thesis focuses on smart systems, a concept with a broad range of future applications. Thus, some of the issues raised in this thesis are of a more general nature. Besides the challenge to enable flexibility effectively and to find adequate combinations of different types of flexibility, data collection, data handling and data privacy become highly relevant. Connections of various (small-scale) grid users and automated devices as well as a novel quality of data exchange are a general issue in the on-going digital transformation. Related challenges regarding privacy, data security or consequences of technical outages are not yet fully known and therefore no full-fledged solution is readily available. Especially, converting a complex system like the European electricity system - consisting of a physical grid, several markets and multiple users - can only be a slow-moving process. Alone the required change in users' behaviors is a paradigm change. Consuming electricity not instantly on demand is novel and maybe as challenging as the provision of technical conditions of electrical devices and the transmission of suitable price signals.
However, the potential to provide adequate signals exists in electricity markets. Market liberalization and developments of various markets and new products have paved the way for an electricity consumption organized mainly in competitive markets. In particular, short term markets are developing in a beneficial way, e.g. the set of products is extended and market entry barriers are removed. This development has to be taken forward. Individually designed products, which are offered to certain flexible users, should be investigated and take into account specific restrictions of grid users. Further on, the aggregation of suitably chosen generators and consumers has a great potential. Concrete business models e.g. by municipal utilities will be helpful to pave the way further. Thereby the combination of different grid users, whose behavior depends on locally specific grid and environmental conditions, is a question worth investigating further. Specific complementarities and substitutes in the context of congestion situations may enable an improved functioning of electricity systems with high shares of renewable electricity generation.

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