Load Shifting Agents for Automated Demand Side Management in Micro Energy Grids

Abstract

This paper describes a novel approach for the automated management of micro energy grids. In particular a market based resource allocation mechanism is used to control energy generators and consumers within a micro energy grid. This approach requires energy consumers (producers) to buy (sell) their energy demands (supplies) through a specialized electronic auction platform. But as manually negotiating all energy demands and supplies on such a market is a tedious task, its automation is highly desirable and thus leads to the main contribution of this paper: The automation of the demand side bidding process through electronic bidding agents, which are equipped with an intelligent buying strategy that allows them to dynamically react to market changes and adapt their bidding behavior accordingly. More precisely, the agents are able to shift energy demand within certain boundaries from (expensive) peak hours to those times of the day where energy demand and thus energy prices are lower in order to minimize their cost. Moreover, as our results show, this behavior leads to a smoothed load curve for the whole system, i.e. demand peaks are reduced while base load increases.

Keywords: *Micro Energy Grids; Markets; Electronic Agents; Demand Side Management*

1 Introduction

Currently the electricity infrastructure in Europe is merely built on the back of a few centralized large-scale suppliers generating most of the electricity required, which is then distributed through a system of high-, medium-, and low-voltage transmission lines to the consumers. This approach was feasible throughout the last decades to reliably deliver power to customers, still it inherently bears several problems: (i) the most oftenly used steam-electric power plants usually achieve electric efficiency levels of only 33% - 48% relative to the heating value of the fuel consumed, (ii) another estimated 7% of the generated electricity is lost during transmission [21], and (iii) it becomes more and more difficult to control the system as a whole with rising numbers of distributed energy producers. The latter issue stems from the fact that decentralized energy generators (e.g. wind turbines) often have hard to predict production schedules, which become even more difficult to be forecasted with the continuously increasing amounts of distributed generator capacities installed in the field.

A promising approach to address these issues is to increasingly decentralize energy production using micro electricity grid concepts [1, 7, 15]. Our contribution is a market based control strategy for micro electricity grids which can be seamlessly extended to combined heat and power grids as well. The basic idea is to use double auctions as the core control mechanism. To allow different energy prices over time a regular day is divided into distinct time slots, as shown in Figure 1 with separate double auctions running for each time slot and each energy type. Participants of the microgrid can continuously trade energy in their preferred time slots and thus dynamically accommodate their (possibly changing) energy demands (supplies) by developing individual bidding strategies. Overall such a market mechanism assures an efficient matching of energy generators and consumers – *on average*.

But efficiency *on average* also means that there may occur specific situations in which buyers have to face the fact that they cannot acquire the amount of energy required while certain suppliers (e.g. an operator of a photovoltaic system) on the other side may not always be able to sell the energy they produce anyway. In other words, under certain circumstances, market based control may fail to guarantee a stable operation of the microgrid leaving the whole system exposed to the risk of brownouts or blackouts. This issue is addressed as follows: In our micro grid energy trading is allowed for future time slots only, i.e. buying and selling energy for a particular time slot is suspended as soon as it starts. This leaves participants with an even higher exposure risk as their real demand / supply in the present time slot might deviate from the previously predicted (and negotiated) amounts at short notice. These deviations are

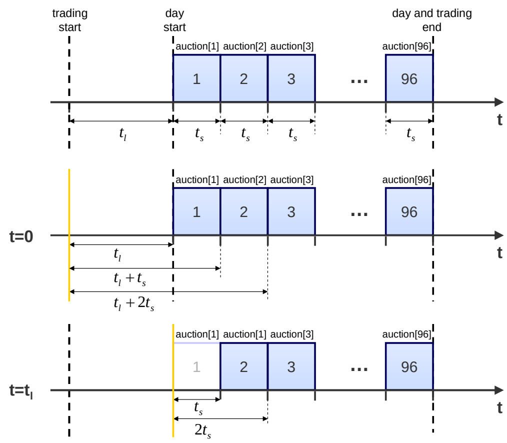

Figure 1. Simultaneous Future Markets

compensated by a technical balancing power provider.[1] The deviations between predicted (negotiated) energy amounts and the real consumption are metered on a per user basis so that afterwards the usage of balancing power can be charged on a per-individual basis. The price for the consumption of balancing power is determined ex-post to be at a certain percentage above the original market prices in order to maintain a strong incentive for all participants to negotiate their demands and supplies on the market. The market based coordination can be thus integrated with the technical stabilization of the microgrid in an incentive compatible manner.

In Block et al. [5] this market based coordination approach for combined heat and power microgrids is described in more detail. Therefore, in this paper we mainly focus on the automation of the consumer's bidding process which we try to automate through the utilization of electronic bidding agents. Automation is especially important as energy customers are likely to adopt a new energy system only if it is convenient to use, i.e. the necessary interaction with the system is reduced to a minimum.

The remainder of this paper is structured as follows. In section 2 we describe related work in this area of research before we introduce an agent based approach for the automation of the demand-side bidding process in section 3. Section 4 describes a prototypical implementation of our system which is subsequently evaluated by means of simulations in section 5. In section 6 we conclude the paper with a summary and an outlook on future research.

[1]For the provisioning of balancing power within a micro energy grid two different paradigms exist: The first one is to retrieve the required balancing power from the existing large scale power grid as it is done e.g. in Denmark today. The second one involves the installation of local balancing power providers like batteries, flywheels, condensators, compressed air energy storages and others. Bodach provides a detailed discussion on the feasibility of these technologies [6].

2 Related work

Related work on agent based energy trading and market based coordination of microgrids comes from different areas of research. Auction theory and mechanism design provide insights on how to set up market rules (mechanisms) in order to provide an incentive for individuals to maximize their own utility by trading certain goods in a way that simultaneously maximizes the overall welfare for the society [11, 16]. A lesson learned from previous research in this area is that mechanism design is a non-trivial task as even small adaptations of the rules can lead to significant changes in the outcomes achieved [14]. Still many different successful examples for the application of auction mechanisms to novel application areas can be found. In 2001 and 2002 for example, auctions were used to award spectrum licenses for the third generation of mobile networks to potential network operators [13], around the same time electronic auctions gained importance as an instrument for industrial sourcing [3], and since the deregulation of electricity markets auctions have become an important instrument for trading future contracts on energy generation and transmission capacities on a wholesale level [18].

Control theory as well Artificial Intelligence (AI) research are two more areas for related work in out context. A lot of work in these fields is devoted to electronic agents, which are usually described as hard or software systems that are able to operate *autonomously* (within certain boundaries), to *interact* with other agents, to *react* to events perceived from their environment, or even to actively take the initiative in order to achieve a certain goal [23]. Jennings et al. report on the successful application of an agent-based support system for electricity transport management at a Spanish utility company [12]. Here agents are used to support staff operating the energy grid but these agents do not act autonomously. Engler and Tsikalakis employ an agent based systems for the automated management of micro electricity grids [9, 20]. In this system each agent is able to start bilateral negotiations with other agents of the microgrid in order to buy or sell electricity on behalf of their owners. This work is merely focused on the technical stability of the grid especially as agents are allowed to dynamically join and leave the network. Akkermans developed a theory aimed at unifying control theory and microeconomic theory to provide an analytic framework for the assessment of agent based electronic markets [2]. One of the applications of this joint theory is the PowerMatcher system, which uses a cascade of markets in combination with electronic agents that trade on the different market levels to allocate energy resources in power grids [22, 15].

Last not least, research on energy and energy systems relates to our approach as well. In this area, literature is mostly focused on technical aspects of energy systems and energy system operation. Thus this part of literature provides the foundations for our work to build on. Bendel et al. for example develop a bidirectional energy management interface that is installed in private households [4]. It communicates directly with different energy consumers within a household and is able to actively control the operation of some of these (e.g. washing machines, heaters, etc.). On the one hand the interface is able to shift loads by influencing the household's energy consumption schedule. On the other hand the interface is able to communicate with a central grid-controller and to execute its commands in order to technically limit the energy flow from and to the household. The flexibility of such an intelligent demand side management system could be further improved with the installation of decentralized balancing power providers, which are able to stabilize the operation of a household (or a micro grid) even in islanding mode, i.e. the household being disconnected from the large scale grid. Bodach compares several different power storage technologies for low-voltage grids in order to identify suitable balancing power providers for micro energy grids [6]. Furthermore Rong et al. develop a technical control strategy for combined heat and power generators, which can be used by an energy interface like the one described above in order to technically determine the optimal operation schedule of its generators [17].

3 Agent-Based Demand Management

As described before, energy consumers within our micro grid (e.g. households) acquire energy for different times of a day (slots) through the participation in double auctions with separate auction instances running for each future timeslot. Consequently, households need to determine and / or plan their energy demands as precisely as possible prior to actually consuming it in order to avoid being charged higher prices for (non-market) balancing power consumption. Hence, a household needs to forecast its future demands for each future time slot of the day ahead. In order to successfully participate in the respective auctions and to acquire sufficient amounts of energy at competitive prices, a household also needs to predict the overall demand (or in other words the expected market prices for a future timeslot) as precisely as possible. As continuous trading is possible for all future timeslots, continuous readjustment of the forecasts is necessary too, especially as new information (e.g. generator outages) becomes available.

Before a household can place bids in certain timeslots, it has to determine the maximum willingness to pay (WTP) for that particular slot. This task is rather complex and challenging as currently consumers consider energy prices to be stable over a day and are probably unable to explicitly state how much energy they need in a certain time slot and at what maximum price. Eliciting these preferences is clearly fundamental for our approach but not within the scope of this paper. A combination of classical preference elicitation methods such as conjoint analysis and machine learning techniques for demand forecasting seem to be promising but need further investigation. Within this paper we assume reservation prices and load profiles to be given.

Once a household has determined its load profile and its reservation prices, it can start bidding in order to acquire energy for future time slots. Still the process remains complex as multiple parallel auctions (one for each time slot) have to be observed simultaneously and bidding strategy has to be adapted accordingly. In particular transaction prices, the share of energy acquired of a timeslot, the remaining quantities and also the success rate of the bids placed have to be monitored as they influence the household's bidding strategy over time.

Since energy supply is likely to change throughout the day due to exogenous factors (changing weather conditions, generator outages etc.) micro grid markets are subject to volatile energy demands and supplies.

In summary an energy consumer in our micro grid has to accomplish the following tasks in order to successfully participate in the energy auctions:

- **R1** Forecast future energy demands
- **R2** Determine reservation prices for each time slot
- **R3** Trade simultaneously on multiple markets
- **R4** React to changing environmental conditions
- **R5** Demand-side load management

In order to fulfill these requirements the household can (i) adjust its bid prices according to the observed market conditions, i.e. increasing limit prices in order to increase order execution probability and vice versa. Additionally a household can (ii) try to shift some of the forecasted loads from peak hours (where energy is most expensive) to time slots where energy supply is not scarce and thus cheaper. Manually managing these tasks is tedious and error prone and thus, in the next sections of this paper, we describe a trading strategy for electronic agents that is specifically tailored to meet the requirements R3 - R5 while – due to space limitations – requirements R1 and R2 are assumed to be given.

4 Agent Design and Implementation

In this section we present a demand agent design that aims at meeting the aforementioned requirements. In our paper, we focus (i) on the design of an appropriate bidding strategy and (ii) a means for load shifting. Both agent components are presented in the remainder of this section.

4.1 Bidding Strategy

After having determined the reservation prices and the amounts of electricity to be bought for different periods of time (load and price forecasting), a buyer agent has to decide on whether to submit bids or not. Furthermore a limit price (ask price or bid price) for a potential order needs to be calculated. Our novel fuzzy logic strategy (FL) that mimics human trader behavior and that reacts to external stimuli is presented in the following. The explanations below refer to a trader agent i that bids on the market for a certain time slot τ.

Basically, this strategy builds on three external factors to reflect the agent's current situation in a market: (i) the success rate S, (ii) the target profit margin μ and (iii) the level of desperation D. These factors are used to determine order prices and quantities. The success rate S describes the agent's share of successful bids in a market. It is weighted with a momentum to gradually reduce the influence of past transactions on the calculation of the current success rate. In other words, the more successful an agent recently acted on a particular market, the higher the success rate for it and vice versa. The target profit margin μ measures the minimum profitability for an order. In particular μ is calculated as the normalized difference between the actual bid price submitted to the market and the true private reservation value for it. If an agent submits a buy order to the market with a limit price of 20 cents per energy unit and its internal reservation price for that market is 18, μ is calculated as $\frac{(20-18)}{18} \approx 0.11$. The desperation D takes the remaining trade entitlement (the part of the originally required energy amount an agent still has to purchase) and the remaining time to bid into account. The less remaining time and the higher the remaining trade entitlement the higher the desperation. Overall, the agent strategy processes two steps after each trading cycle. First of all, it determines if the targeted profit margin $\mu(t)$ must be changed or not which depends on the current success rate in the market. To this end, a fuzzy system infers a value Δ for the profit margin alteration. This value is the amount the targeted profit margin is to be increased (or decreased) in the next round. After having determined Δ, the the new targeted profit margin μ_{new} for the next round is calculated as shown in equation 1. Subsequently the new bid price p_{new} for the next round is calculated according to equation 2.

$$\mu_{new} = \mu + \Delta \tag{1}$$

$$p_{new} = \begin{cases} (1-\mu_{new})\lambda & \text{agent is buyer, } \mu_{new} < 1 \\ (1+\mu_{new})\lambda & \text{agent is seller} \end{cases} \tag{2}$$

Here, λ is the reservation value (the maximum price a buyer is willing to buy energy at). In a second step, the strategy decides on the bid quantity for the next order. The quantity is a percentage q of the trade entitlement ϵ^t (amount of energy to be bought) and is derived by fuzzy inference as described later on. Based on the value of q, the bid quantity x is obtained as $x = \min\{q\epsilon^t, \epsilon^r\}$, which basically ensures that x is never greater than the remaining trade entitlement ϵ^r. If $x = 0$, no order is placed. With the new profit margin and the new bid quantity being calculated, the agent can now place a new bid on the market. The steps for determining the profit margin alteration Δ and the bid percentage q are presented in the following.

Determine Profit Margin Alteration Δ

First, the input values (i.e. success rate S and target profit margin μ) must be fuzzified as they serve as input for deciding on how μ needs to change for a potential order during the next round. To this end, three fuzzy sets are defined for each stimulus with the linguistic terms "low", "medium" and "high". A distinct membership function belongs to each fuzzy set. Figure 2 illustrates the membership functions for μ. The inference scheme subsequently processes the fuzzy rule base with the values derived from fuzzification. All rules are summarized in table 1. The rules mimic a market participant that is checking on how successful bids were and if profits were reasonable. As long as the success rate is low, the agent tries to place more successful orders by decreasing the targeted profit margin (decrease, decrmuch). This behavior results in higher bid prices (i.e. higher maximum willingness to pay) for bidders and lower ask prices for sellers. If the success rate is medium the agent waits and will not change the limit price for the moment (nochange). A high success rate on the other hand causes the agent to increase its targeted profit margin (increase, incrmuch). The defuzzification finally combines the inference results and converts them into a crisp (numerical) value for Δ using the "Center of Gravity" (COG) method.

		Success Rate S		
		low	medium	high
Profit Margin μ	low	decrease	nochange	incrmuch
	medium	decrease	nochange	increase
	high	decrmuch	nochange	increase

Table 1. Fuzzy Rules for Profit Margin Alteration

To illustrate the FL strategy, let there be an FL buyer agent with a reservation value of $\lambda = 18.00$ that receives the following, arbitrarily chosen market stimuli: $S = 0.8$, $\mu = 0.075$ and $D = 0.2$. The buyer's trade entitlement is $\epsilon^t = 200$ and since it has not purchased electricity yet, its remaining trade entitlement is $\epsilon^r = \epsilon^t = 200$.

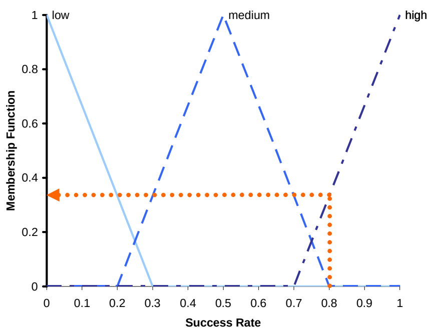

Figure 2. Fuzzy Sets for Agent Stimuli

Figure 2 visualizes the membership degrees for fuzzifying μ. The dotted lines represent the resulting fuzzy values. As far as the input μ is concerned, the membership degree for "medium" is 0.75 and for "low" it is 0.25. For μ let the membership degree for "high" be $0.\bar{3}$. Next, the rule base is applied. Rules for μ being "low" and "medium" and for S being "high" fire. The resulting membership degrees for the profit margin alteration Δ for "increasemuch" is 0.25 and for "increase" it is $0.\bar{3}$.

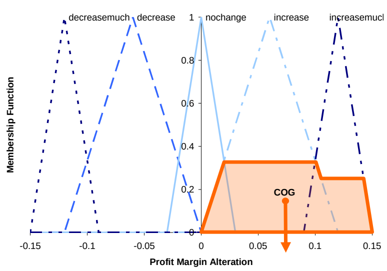

Figure 3. Defuzzification of Profit Margin Alteration

Figure 3 illustrates how the center of gravity is subsequently determined. The method calculates a crisp value for the profit margin alteration: $\Delta = 0.075$. Therefore equation 1 with $\beta = 0.1$ generates a new profit margin: $\mu_{new} = 0.075 + 0.075 = 0.150$ Hence, the new bid price is: $p_{new} = (1 - 0.15) \cdot 18.00 = 15.30$.

Determine Bid Percentage q

Once the bid price of a prospective bid is defined, the agent proceeds with determining the percentage of the remaining trade entitlement ϵ^r it wants to bid for. Also here a fuzzy inference system calculates this percentage q. To this end, the the desperation D is checked against the new profit margin μ_{new}. The two input values are fuzzified using the same linguistic terms as before. For the bid percentage q, the fuzzy sets with the following fuzzy terms are introduced: "verylow", "low", "medium", "high", "veryhigh". Similar to determining the profit margin alteration, a rule base with 9 rules is used for inferencing. There are two reasons for a trader to bid for many items at a time: (i) when the agent has little time to acquire much electricity (high desperation), or (ii) if the targeted profit margin is high. The lower the profit margin, the more reluctantly an agent trades and – provided that its desperation is low – places orders for fewer items. As before defuzzification and Center of Gravity method are used to determine the new value for the bid quantity q

4.2 Load Shifting

After a market clearing took place, i.e. after all matching bids and asks are executed through the market, a buyer agent that uses load shifting can adjust its demands (entitlements) according to changed market conditions potentially reducing demand for time slots with high prices and shifting these demands (within certain boundaries) to slots with lower prices. In this section, a new heuristic is introduced that allows electricity demands to be shifted between different time slots in order to enable agents to react to changing market conditions. There are two main reasons why a consumer might want to shift load: (i) to ensure that more demand can be satisfied even if supply is scarce and (ii) to save money.

Overall, the load shifting is based upon the idea of evaluating a "market utility" U_τ for each time slot τ. The market utility expresses the attractiveness of a market associated with slot τ by calculating the trader's potential utility from buying energy on that market. In order to accomplish this task the heuristic compares all market utilities and subsequently shifts loads from time slots with low "attractiveness" to time slots with higher ones (i.e. high market utilities). In the following each of these steps is described in more details.

1. Update the Market Utility Values

For updating the market utility U_τ of time slot τ in round t, an agent uses the following utility function:

$$U_\tau(t+1) = \beta u_\tau + (1-\beta)U_\tau(t) \qquad (3)$$

The factor β is introduced in order to smooth the changes in the market utility value, which helps to avoid strong fluctuations (i.e. high forth and back demand shifts between time slots) throughout the operation. u_τ is calculated as $u_\tau(t) = (1 + S_\tau(t))^{1.5}(1 - D_\tau(t))(1 + P_\tau(t))$ with successrate S_τ and desperation D_τ being derived as described before. The bargain factor P_τ compares the agent's order price $p_\tau(t)$ for time slot τ with the agent's order prices for all other time slots. For the time slot with the highest price the bargain factor is 0 and for the time slot with the lowest order price, this factor is 1. Basically, U_τ indicates how advantageous it is for a buyer to bid on a certain market. The more successfully an agent bids on the market associated with time slot τ, the higher the utility U_τ. Similarly, the utility decreases with increasing desperation. An agent considers bidding on a market as less advantageous if he still has to fulfill a large trade entitlement in a comparably short period of time. These two factors accommodate the need for demand satisfaction. Conversely, the bargain factor considers the agent's bid prices on all active markets. If the price on the market for slot τ is low compared to prices on other markets (time slots), the bargain factor will increase and so will the market utility. Therefore, this part of the equation accounts for the agent's aim to save money.

2. Compare The Market Utilities

In a second step, the heuristic determines the difference in the market utilities when load is shifted from one time slot τ to another slot $\bar{\tau}$. $\Delta^u_{\tau\bar{\tau}}$ is defined as:

$$\Delta^U_{\tau\bar{\tau}}(t) = U_{\bar{\tau}}(t) - U_\tau(t) \quad \text{with} \quad \tau \neq \bar{\tau} \tag{4}$$

$\Delta^U_{\tau\bar{\tau}}$ represents the change in utility for shifting one unit of energy demand from time slot τ to $\bar{\tau}$. Only future time slots are considered. The positive differences $\Delta^u_{\tau\bar{\tau}} \geq 0$ are collected in an ordered list that contains the vectors $\left(\Delta^U_{\tau\bar{\tau}}, \tau, \bar{\tau}\right)$. This list is ordered by decreasing values of $\Delta^U_{\tau\bar{\tau}}$. Beginning with the largest $\Delta^U_{\tau\bar{\tau}}$ in the list, the load shifting iterates steps 3 through 5 until the end of the list is reached. All values that are calculated in these steps refer to a single trading cycle t, thus t is omitted in the following.

3. Determine Maximum Shiftable Loads

In this step, the load shifting determines the maximum amount of load to be shifted from slot τ to $\bar{\tau}$ for the current vector $\left(\Delta^U_{\tau\bar{\tau}}, \tau, \bar{\tau}\right)$. To this end, restrictions on the maximum and minimum load per time slot have to be considered: the trade entitlement ϵ_τ can only be altered within a (given) range $\left[\epsilon^{min}_\tau, \epsilon^{max}_\tau\right]$ which can be set arbitrarily for each time slot. These restrictions represent technical constraints since we assume that only a certain percentage of the loads (that are produced by electrical appliances and devices) is shiftable. The maximum amount of load $\delta^{max}_{\tau\bar{\tau}}$ that can be shifted from τ to $\bar{\tau}$ is obtained from:

$$\delta^{max}_{\tau\bar{\tau}} = \min\left\{\epsilon_\tau - \epsilon^{min}_\tau, \epsilon^{max}_{\bar{\tau}} - \epsilon_{\bar{\tau}}\right\} \tag{5}$$

$\epsilon_\tau - \epsilon^{min}_\tau$ is the maximum amount that can be shifted from τ and $\epsilon^{max}_{\bar{\tau}} - \epsilon_{\bar{\tau}}$ is the maximum amount of load that can be moved to $\bar{\tau}$. Figure 4 illustrates the current trade entitlement ϵ with restrictions on the minimum and the maximum trade entitlements ϵ^{min} and ϵ^{max} for two time slots. As can be seen on the left diagram, the maximum shiftable amount is: $\delta^{max}_{\tau\bar{\tau}} = \epsilon^{max}_{\bar{\tau}} - \epsilon_{\bar{\tau}}$. If $\delta^{max}_{\tau\bar{\tau}}$ is shifted, no more load can be shifted to $\bar{\tau}$ and $\epsilon_{\bar{\tau}} = \epsilon^{max}_{\bar{\tau}}$ (right chart).

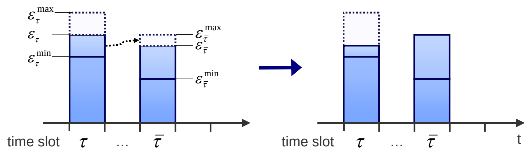

Figure 4. Maximum Load Shiftable from τ to $\bar{\tau}$

4. Determine Actual Load Shifting

$\Delta^U_{\tau\bar{\tau}}$ expresses a gain in utility. Hence, it is advantageous to actually shift much of the maximum shiftable amount $\delta^{max}_{\tau\bar{\tau}}$ for a high $\Delta^U_{\tau\bar{\tau}}$ whereas for small $\Delta^U_{\tau\bar{\tau}}$, only a small percentage should be shifted. The following expression is used to calculate the actual amount of load to be shifted:

$$\delta_{\tau\bar{\tau}} = \left\lfloor \delta^{max}_{\tau\bar{\tau}} \frac{\Delta^U_{\tau\bar{\tau}}}{\Delta^U_{max}} \right\rfloor \tag{6}$$

Δ^U_{max} is the maximum of all utility differences determined in the previous step. As only discrete integer values are allowed, a floor function is used.

5. Update Trade Entitlements

Finally, before processing the next item of the ordered list, the trade entitlements are updated if $\delta_{\tau\bar{\tau}} > 0$:

$$\epsilon^{new}_\tau = \epsilon_\tau - \delta_{\tau\bar{\tau}}, \epsilon^{new}_{\bar{\tau}} = \epsilon_{\bar{\tau}} + \delta_{\tau\bar{\tau}} \tag{7}$$

If the ordered list has a next element, the heuristic will start over and processes steps 3 through 5. Once the end of the list is reached, the load shifting is completed. For performance reasons, the market utilities u_τ are only calculated once at step 1 ignoring the fact that load shifting leads to slight changes of the desperation factors for the different time slots D_τ .

In the following example of an agent's load shifting behavior we assume market utility values, trade entitlements, and minimum / maximum trade entitlements as depicted in table 2 for an arbitrary trader agent that trades on four markets for time slots 1 to 4. After having determined the market utility values u_τ for all τ (c.f. Step 1), the load shifting logic computes the differences $\Delta^U_{\tau\bar{\tau}}$ as described in Step 2. Subsequently, the positive differences are sorted in descending order. Table 3 represents the ordered list with the results in form of vectors $\left(\Delta^U_{\tau\bar{\tau}}, \tau, \bar{\tau}\right)$. Here, the maximum increase in utility is $\Delta^U_{max} = 0.4$. Beginning with the first entry in

Timeslot (τ)	1	2	3	4
Market Utility (U_τ)	0.2	0.4	0.6	0.3
Original trade entitlement (ϵ_τ)	90	70	70	80
Min entitlement (ϵ_τ^{min})	60	50	40	70
Max entitlement (ϵ_τ^{max})	100	90	80	110

Table 2. Example values for Load Shifting

n	Source Slot (τ)	Target Slot ($\bar{\tau}$)	Utiltiy Increase ($\Delta^U_{\tau\bar{\tau}}$)
1	1	3	0.4
2	4	3	0.3
3	1	2	0.2
4	2	3	0.2
5	4	2	0.1
6	1	4	0.1

Table 3. List of Positive Utility Differences

the list, vector $(1; 3; 0.4)$, the heuristic determines the maximum amount that can be shifted from time slot 1 to time slot 3 by computing $\delta_{1,3}^{max} = \min\left\{\epsilon_1 - \epsilon_1^{min}, \epsilon_3^{max} - \epsilon_3\right\} = 10$. Hence, only 10 items of electricity can be shifted from slot 1 to slot 3. The actual amount $\delta_{1,3}$ to be shifted is: $\delta_{1,3} = 10$. Consequently, the maximum amount of units is shifted resulting in new trade entitlements for τ and $\bar{\tau}$: $\epsilon_1^{new} = \epsilon_1 - \delta_{1,3} = 80$ and $\epsilon_3^{new} = \epsilon_3 + \delta_{1,3} = 80$. Table 4 summarizes the 6 iterations of steps 3 through 5.

n	$\tau \rightarrow \bar{\tau}$	$\delta_{\tau\bar{\tau}}^{max}$	$\delta_{\tau\bar{\tau}}$	ϵ_1^{new}	ϵ_2^{new}	ϵ_3^{new}	ϵ_4^{new}
1	$1 \rightarrow 3$	10	10	80	70	80	80
2	$4 \rightarrow 3$	0	0	80	70	80	80
3	$1 \rightarrow 2$	20	10	70	80	80	80
4	$2 \rightarrow 3$	0	0	70	80	80	80
5	$4 \rightarrow 2$	10	2	70	82	80	78
6	$1 \rightarrow 4$	10	2	68	82	80	80

Table 4. Load Shifting Iterations

5 Evaluation

The following simulation experiments are used to evaluate the performance of our load shifting agents in market-controlled micro energy grids under realistic conditions. In particular the evaluation is twofold. In Setup 1 we access the system's capability of automatically recovering from exogenous shocks (e.g. generator outages) while in Setuo 2 the performance of the agent's load shifting behavior is assessed on a per-individual as well as on a society level.

Setup 1 – Automated recovery from exogenous shocks

The first experimental setup models a micro grid with 10 suppliers and 10 consumers. Agents of a homogeneous population can choose to arbitrarily bid on a market for one single time slot during 300 trading cycles. Interdependencies (such as intedependencies between adjacent timeslots and their respective markets) are not considered, instead trading is examined for one single time slot only. Consequently, load shifting is disabled in this setting.

As discussed in section 3, demand and supply in a micro grid is most likely to change over time (e.g. due to generator outages or changing weather conditions). This setup investigates how FL agents perform in such situations. In particular we investigate how fast the agents agents readjust themselves to a situation where (previously constant) energy supply is suddenly reduced e.g. due to a generator outage in trading rounds 30 and then increases again after the partly reconnection of that generator at trading round 50. The ZIP [8] and GD strategy [10] serve as benchmark strategies. To this end, simulations are conducted with homogeneous populations of i) ZIP agents, ii) GD agents, and iii) FL agents. In this simulation we model two events in a micro grid where supply and demand change during the simulation runtime. Table 5 summarizes the changes in the demand and supply during simulation runtime. The equilibrium price p_e and the equilibrium quantity q_e are determined by the intersection of the cumulated demand and supply curves and represent the optimal transaction price and the maximum quantity that can be traded.

Round	p_e	q_e
0	19	656
30	17	928
50	17.5	1063

Table 5. Changes in Demand and Supply

Table 6 summarizes the results of the three simulation runs. The total welfare and Smith's alpha are calculated in order to compare the agent strategies. Smith's Alpha measures the deviation of transaction prices from the equilibrium price and therefore indicates to what extent transaction prices converge to the theoretical equilibrium price. The last two factors – purchase ratio (percentage of satisfied demand) and average costs (for purchasing one unit of electricity) – concern demand agents only. With changing demand and supply, FL agents clearly outperform ZIP and GD agents. The total welfare indicating how much utility both supply and demand agents can gain from trading is higher for FL agents than for the other two strategies. Despite the fact that supply and demand is suddenly altered, FL agents can adapt quickly to a new equilibrium. Consequently, Smith's alpha is low compared to the value for

Strategy	Welfare	Smith's Alpha	Purchase Ratio	Avg. Costs
ZIP	3105	0.053	0.895	18.289
GD	2751	0.070	0.733	18.809
FL	3192	0.029	1	17.723

Table 6. Results of Setup 1

GD and ZIP agents. The benchmark strategies are not able to adjust to the market dynamics in an analogous manner. The deviations from the theoretical equilibrium price are 1.8 times higher for ZIP agents and 2.4 times higher for GD agents. Considering the demand side metrics, FL buyer agents yield the best results, too. These agents take advantage of a lower equilibrium price and a higher supply between round 30 and 50. As a result, they can satisfy 100% of their demands at lower average costs per unit. ZIP demand agents acquire 10.5% less than FL agents and the satisfied demand of GD buyers is even 26.7% lower. Hence, it is particularly advantageous for consumers to rely on FL agents in this scenario.

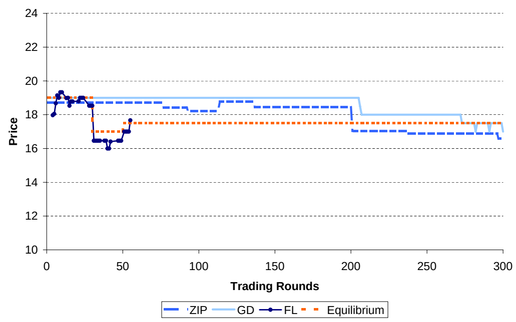

Figure 5. Automatic Readjustment to Exogenous Shocks in Rounds 30 and 50

Figure 5 visualizes the theoretical market equilibrium prices (dotted curve) as well as the observed prices from the simulation runs as produced by a ZIP agent population (dashed curve), a GD agent population (solid curve), and a FL agent population (solid curve with dots). The chart reveals that GD and ZIP agents can adapt their bidding behavior which results in transaction prices converging to the equilibrium. However, both strategies cannot react to the sudden changes in round 30 and 50. Only after a longer period of time (around 200 rounds for ZIP agents and more than 250 rounds for GD agents) the transaction prices for the ZIP and GD setups converge to the theoretical equilibrium price. FL agents on the contrary instantaneously react to a changing equilibrium which results in changed transaction prices on the market that quickly reflect the new situation.

To summarize, FL agents are shown to adjust well in situations where exogenous demand or supply shocks occur. The FL strategy described here takes prevailing market conditions and the agent's current state into account (successes, profits, desperation). Additionally, FL agents have comparably lower informational requirements as they does not require knowledge about bids placed by other market participants, while this information is necessary for ZIP and GD agents to run.

Setup 2 – Demand Peaks and Load Shifting

This setup consists of 15 FL agents that try to satisfy the energy demands of a whole day for their respective households. Therefore the day is divided into 96 time slots each of 15 minutes length. The consumers' demand profiles, i.e. the energy demand for each of these timeslots, are based on the VDEW-H0 load profile, which is a norm load profile that representats a German norm household [19]. The actual load profiles chosen for the agent bootstrapping were calculated for a norm workday during summertime for households of sizes between 1 and 2 MWh annual demand. In order to avoid overlay effects, the H0 profiles were salted with a slight random noise. In this setup the energy is produced at a constant level by 5 different suppliers that vary in their reservation prices only. In a real micro grid, such providers could e.g. be small hydropower generators or micro turbines. Lastly, supply and demand forecasts are not changing throughout the simulation runs.

Depending on the supplier, the costs (and thus the seller agent's reservation value) range between 0.15 EUR and 0.17 EUR per kWh. A supplier produces at the same costs for all time slots. The reservation values for demand agents are 0.20 EUR per kWh plus an increment that correlates with the amount of electricity to be acquired for a certain time slot. In this way, a buyer's reservation value is 0.25 EUR for the time slot with the highest and 0.20 EUR for the time slot with the lowest demand. This variation in reservation prices represents a consumer's knowledge about the micro grid's trading history: A buyer agent anticipates high prices in times of peak demands and therefore has a higher reservation value for the corresponding time slots.

Figure 6 shows the results of the simulations. One can see that without load shifting at least some of the consumer agents cannot satisfy their complete trade entitlement in this first scenario due to insufficient supply in peak times. This is the case in the periods between time slots 34 - 41, 46 - 56, and 74 - 91 where the aggregated initial demands of all consumers (dashed curve) exceed the aggregated supply of all producers (solid horizontal line). With load shifting however, demand agents are allowed to partly reallocate their energy consumption to other timeslots. In particular, the consumer agents are allowed to shift at most $\pm 30\%$ of their original energy demands to other timeslots. The light dashed curves in figure 6 illustrate this (aggregated) target corridor within which overall load shifting is permitted.

In order to evaluate the system and in particular the buyer agent's behavior, different measures are used. The total welfare generated by all traders for all slots is calculated and, for scenario a) with constant demand and supply curves, the average efficiency of all slots is determined. Moreover, the average Smith's alpha is calculated in order to measure deviations of transaction prices from the theoretical equilibrium prices. Concerning the demand side, additional measures are used. The purchase ratio indicates the percentage of the total demand satisfied (for all buyer agents and all slots) and the average costs indicate the average unit price (in EUR) a buyer had to pay for acquiring one kWh of electricity. Finally, the total amount of unsatisfied electricity demand (in kWh) is determined. Table 7 presents the results for the individual scenarios. During the first simulation run

Scenario	a)	b)
Total Welfare	21.676	21.878
Average Alpha	0.103	0.095
Purchase Ratio	0.954	0.984
Average Costs	0.192	0.189
Unsatisfied Demand	5.904	2.118

Table 7. Performance after Load-Shifting

no buyer agent is allowed to shift loads. As far as the demand side is concerned, buyer agents can satisfy 95.4% of their electricity demands. Due to demand peaks, 6% (5.904 kWh) cannot be bought.

After enabling the load shifting module and rerunning the simulation, the agents perform better than before. The agents were able to produce a slightly higher total welfare. Smith's alpha remains at a low level for FL agents, even decreases. Regarding the demand side, the buyer agents using load shifting were able to satisfy the complete total demand. The average costs for buying 1 kWh of energy are lower. Figure 6 illustrates the smoothed aggregated de-

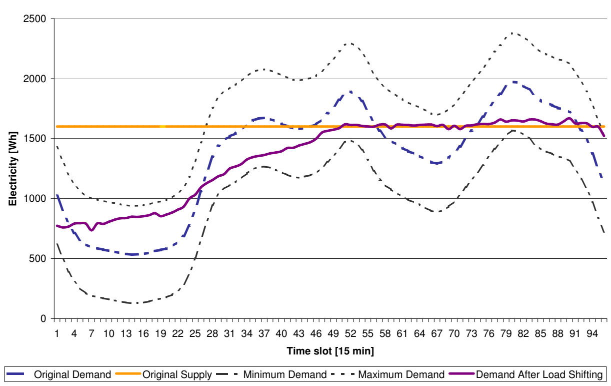

Figure 6. Cumulated Demand and Supply after Load Shifting

mand curve (solid curve) as a result of load shifting activities. The peak demands stemming from the original total demand (dashed curve) are noticeably reduced. In the real world, this means that expensive peak load generation capacities can be reduced. Despite the fact that demand agents have no information on the current availability of electricity for a time slot, they proved to correctly interpret the market signals: with the aid of load shifting, they could adjust their demand and satisfy virtually all demand with the existing supply (given that a reasonable minimum amount of energy supply is available). Overall, applying the FL strategy locally to decentral consumer agents also affects the society as a whole as the individual agent's load shifting behavior also leads to an overall better balanced energy grid through energy demands being more evenly distributed over time thanks to price signals (and thus consumer incentives) that reflect the true scarcity of the traded good.

6 Summary & Outlook

In this paper we presented a market-based approach for coordinating micro energy grids. In particular, our contribution is a fuzzy logic trading strategy (FL) that can be used by electronic agents to efficiently acquire energy on behalf of their owners, i.e. energy consumers such as households. In order to accomplish this task, our agents (i) automatically adjust their bidding behavior (reserve prices, demand quantities) to changing market conditions using a fuzzy logic approach and (ii) shift parts of their energy demands from expensive peak hours to cheaper times of the day where energy demands are lower.

Our evaluations show that FL agents readjust much quicker to sudden market changes (e.g. exogenous shocks such as generator outages) than classic ZIP or GD agents. Furthermore we can show that the myopic load shifting optimization performed by each individual agent is not only benefitial for the agent itself, but also leads to overall peak reduction on the society level. This effect helps saving energy and might also be an interesting possible solution approach for better integrating decentralized energy consumers and producers into our existing large scale energy grid infrastructure. Providing decentralized consumers and producers with the right (price) incentives gives them the possibility to adjust their consumption and production levels myopically and still leads to overall demand peak reductions.

In summary our work presented in this paper is very interesting as it opens up an ally for future research on various related topics. Further research needs to be conducted on the elicitation of consumer demand profiles. Currently they are assumed to be given exogenously but this clearly needs to change in future. Therefore a lot of additional data on requirements, habits and technical side constraints of energy consumers as well as energy producers have to be taken into account. Similarly the amount of energy that is shiftable between different time slots needs to be determined in more detail. Currently this amount is assumed to be a constant percentage of the whole energy demand for a certain time slot. In reality however the shiftable amount of energy is likely to vary over time and also heavily depends on the type of energy consuming devices that are running within a certain time slot.

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