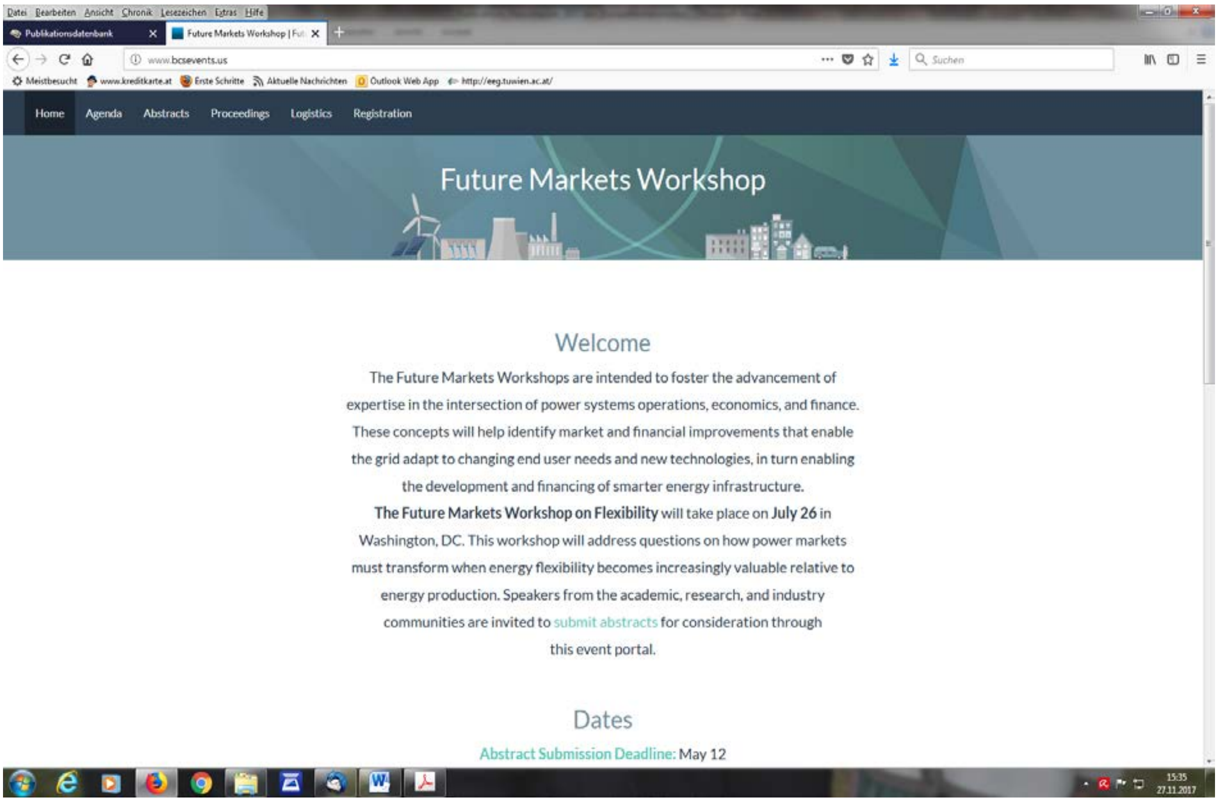

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Future Markets Workshop

Welcome

The Future Markets Workshops are intended to foster the advancement of expertise in the intersection of power systems operations, economics, and finance. These concepts will help identify market and financial improvements that enable the grid adapt to changing end user needs and new technologies, in turn enabling the development and financing of smarter energy infrastructure.

The Future Markets Workshop on Flexibility will take place on **July 26** in Washington, DC. This workshop will address questions on how power markets must transform when energy flexibility becomes increasingly valuable relative to energy production. Speakers from the academic, research, and industry communities are invited to submit abstracts for consideration through this event portal.

Dates

Abstract Submission Deadline: May 12

Sharing distributed energy resources in apartment buildings: the winner takes it all?

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1 Introduction

Solar generation is one of the key technologies in decarbonizing and decentralizing the energy system. While solar PV on single-family houses is a well-established and integrated solution, there have been relatively few such installations on multi-unit apartment buildings so far. Also, with the rapid urbanization, cities - mostly with a high share of apartment buildings - are becoming the largest energy consumers globally. Hence, to address the energy-climate challenge innovative solutions have to be developed to make better use of distributed energy resources (DERs) in urban locations.

By comparing apartment buildings with single-family houses, multiple differences can be identified: Firstly, a higher number of consumers (owners/tenants) are involved; secondly, consumers have to agree on an energy allocation method, because they share a common energy resource (e.g., solar PV, possibly combined with energy storage). Thirdly, individual consumer objectives have to be taken into account with the possibility of conflicting objectives between different parties. Finally, interactions with the surrounding system (local power grid, utility, electricity market) must be considered.

Publications in the literature address solar generation in multiple ways. Up to now, the studies focus on topics like grid parity[4], the power system's perspective[5] or grid integration concepts[6]. In the

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[3] Corresponding author: fleischhacker@eeg.tuwien.ac.at.
[4] G. Lettner and H. Auer, "PV PARITY, Report: Realistic roadmap to PV grid parity for all target countries" (2013), https://ec.europa.eu/energy/intelligent/projects/en/projects/pv-parity
[5] Michael Hartner et al., "East to west – The optimal tilt angle and orientation of photovoltaic panels from an electricity system perspective," *Applied Energy* 160 (2015), doi:10.1016/j.apenergy.2015.08.097
[6] Erin Baker et al., "The Economics of Solar Electricity," *Annual Review of Resource Economics* 5, no. 1 (2013), doi:10.1146/annurev-resource-091912-151843

recent years, advanced concepts and allocation schemes have been developed for microgrids[7][8][9], often times using game theoretical approaches[10][11][12].

Consequentially, we will further improve these applications and develop a framework for apartment houses. While many studies are dealing with multiple households and DERs, our study will focus on one solar generation plant in combination with a battery as a shared energy resource one apartment building. The novelty of this work is that we consider the consumers' preferences by allowing them to adjust the weights for multiple objectives in choosing between different energy resources. Additionally, we will develop a bi-level optimization model for clearing and pricing local generation and consumption. We will apply the model to a typical apartment building, under different technical and economic assumptions. The building has a shared solar PV plant, and we also consider battery as a shared energy storage resource. We define a set of individual consumer preferences and search for the optimal allocation of local and grid energy resources.

The paper is organized in following way. In Section 2, we will introduce a framework for sharing DERs in an apartment house. Section 3 includes the data assumptions for an illustrative example, while Section 4 shows the concurrent results. Section 5 discusses and concludes the paper.

2 Methodology

The proposed methodology addresses one single apartment house with $i \in \mathcal{N}$ consumers and $t \in \mathcal{T}$ periods[13]. Figure 1 shows the setup proposed in this paper. As we include two types of players, (i) the owner and (ii) the participating consumers, two individual objectives have to be considered. While consumers are characterized by demand $q_{t,i}^{L}$ (which has to be supplied by either local generation or the grid) and an individual utility function u_i^C. The PV plant and an additional battery are possessed by an owner who is interested in maximizing the operational revenues[14]. Any investment decisions are not within the scope of this paper and may be the object of future investigations.

In the following section, we will first describe the consumers' utility functions, secondly define the owner's revenue function and thirdly formulate a bi-level optimization model as shown in Figure 1.

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[7] Lu An et al., "Distributed Multi-Step Power Scheduling and Cost Allocation for Cooperative Microgrids," *CoRR* abs/1611.08770 (2016)

[8] Gabriele Comodi et al., "Multi-apartment residential microgrid with electrical and thermal storage devices: Experimental analysis and simulation of energy management strategies," *Applied Energy* 137 (2015), doi:10.1016/j.apenergy.2014.07.068, http://www.sciencedirect.com/science/article/pii/S030626191400751X

[9] Nian Liu et al., "Energy Sharing Management for Microgrids With PV Prosumers: A Stackelberg Game Approach," *IEEE Transactions on Industrial Informatics* 13, no. 3 (2017), doi:10.1109/TII.2017.2654302

[10] Yinliang Xu et al., "Cooperative Control of Distributed Energy Storage Systems in a Microgrid," *IEEE Transactions on Smart Grid* 6, no. 1 (2015), doi:10.1109/TSG.2014.2354033

[11] Tarek AlSkaif, "Energy Sharing in Smart Grids: A Game Theory Approach" (Dissertation, The Computer Architecture Department, Universitat Politècnica de Catalunya, 06.2016)

[12] Walid Saad et al., "Game-Theoretic Methods for the Smart Grid: An Overview of Microgrid Systems, Demand-Side Management, and Smart Grid Communications," *IEEE Signal Processing Magazine* 29, no. 5 (2012), doi:10.1109/MSP.2012.2186410

[13] In this paper the temporal resolution is at hour interval, while higher resolutions are conceivable for future investigations.

[14] Alternatively the PV plant could be owned by one or a group of consumers.

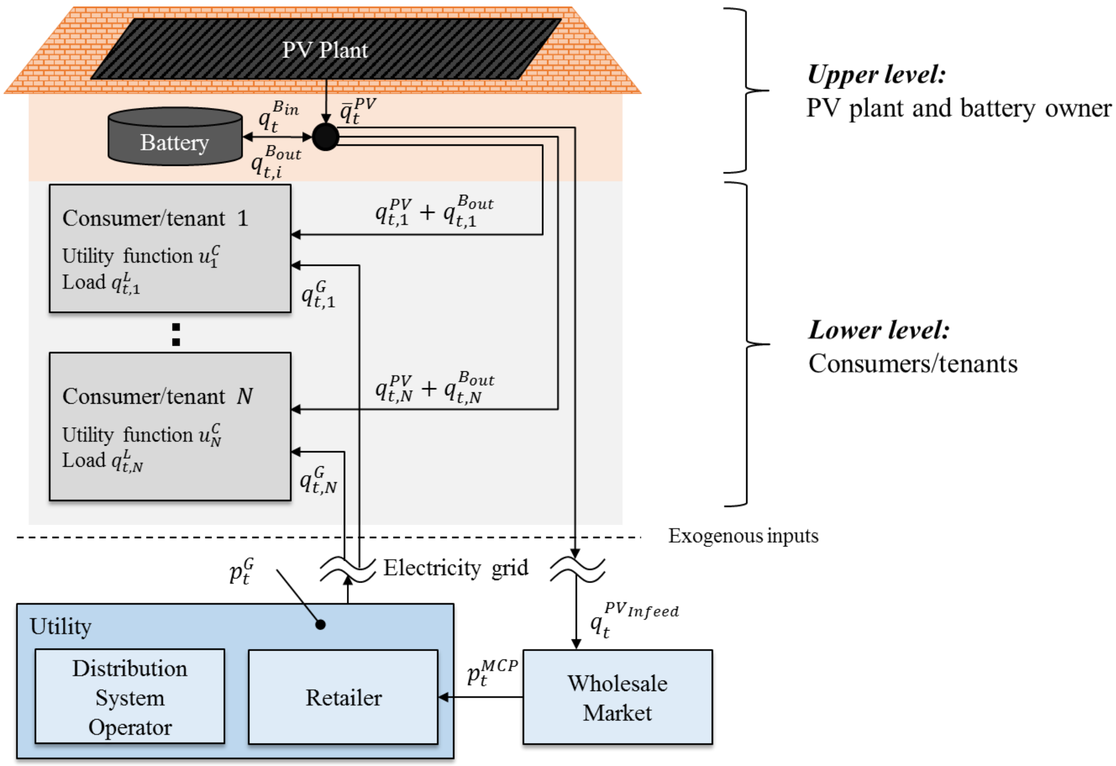

Figure 1: Graphical representation of the model's setup. While the owner is modeled as the upper level of the optimization model, consumers' are pictured by the lower level.

2.1 Consumer utility model

As stated in the literature[15], consumers are not only interested in minimizing the costs of electricity consumption, rather multiple objectives have to be considered. In the context of this paper, we model the consumer's utility as the sum of cost reduction[16], emission reduction[17] and degree of on-site-generation (OSG)[18]. Mathematically each consumer's utility could be expressed as

$$u_i^C = -costs_i^C - w_i^E emissions_i^C + w_i^{OSG} osg_i^C \tag{1}$$

whereas the signs of $costs_i^C$ and $w_i^E emissions_i^C$ are negative because the consumer is interested in minimizing/reducing this values. The value for $w_i^{OSG} osg_i^C$ is positive, as consumers do have interests in maximizing/increasing this value. We introduced the parameters w_i^E and w_i^{OSG} to express the consumers' preferences into monetary units, such as \$. Therefore, the corresponding units are $\left[w_i^E\right] = \$/\text{kg}_{\text{CO2}}$ and $\left[w_i^{OSG}\right] = \$/\text{kWh}_{\text{OSG}}$. These two parameters allow each consumer to express his preferences easily. E.g., the authors are thinking of the possibility of a Smartphone app

[15] Liu et al., "Energy Sharing Management for Microgrids With PV Prosumers: A Stackelberg Game Approach"
[16] The procurement of the commodity electricity is linked with costs, while consumers are interested in reducing them.
[17] Consumers are interested in reducing their carbon footprint and therefore value green electricity.
[18] As DER allows consumers to generate electricity locally, they may prefer local generation to grid consumption.

(see Figure 2) allowing the consumer to adjust his willingness to pay conveniently. By implementing this kind of data exchange, the preferences may be forwarded to the owner (or an entity managing local generation).

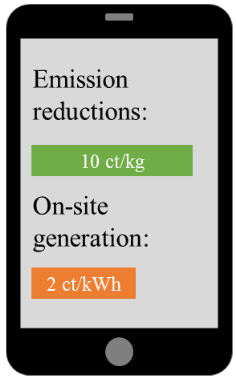

Figure 2: Simple representation of a Smartphone app allowing the consumer to express their preferences.

The values of the consumer's utility function are a result of the grid and local consumption as well as the corresponding prices. They are defined as

$$\begin{aligned} costs_i^C &= \sum_{t \in \mathcal{T}} p_{t,i}^O (q_{t,i}^{PV} + q_{t,i}^{B_{out}}) + \sum_{t \in \mathcal{T}} p_{t,i}^G q_{t,i}^G \\ emissions_i^C &= \sum_{t \in \mathcal{T}} e_t^G q_{t,i}^G \\ osg_i^C &= \sum_{t \in \mathcal{T}} q_{t,i}^{PV} + q_{t,i}^{B_{out}} \end{aligned} \tag{2}$$

while $p_{t,i}^G$ and $q_{t,i}^G$ are price and quantity of grid consumption, $q_{t,i}^{PV}$ and $q_{t,i}^{B_{out}}$ is the quantity of solar and battery consumption with a corresponding price level of $p_{t,i}^O$.

2.2 Owner revenues

For the sake of simplicity, local generation is operated by an owner, not a third party. The owner is interested in maximizing the revenues, defined as

$$rev^O = \sum_{i \in \mathcal{N}} \sum_{t \in \mathcal{T}} p_{t,i}^O (q_{t,i}^{PV} + q_{t,i}^{B_{out}}) + \sum_{t \in \mathcal{T}} p_t^{MCP} (q_t^{PV_{infeed}} + q_t^{B_{infeed}}). \tag{3}$$

We will investigate discriminatory auctions, resulting in individual consumer prices, only. Different auction schemes may be the object of future investigations. Additionally, electricity could be sold to the grid at a market price of p_t^{MCP}[19].

[19] Any subsidy mechanism, such as feed-in tariffs are neglected in this work. The market price in the later progress of this work is defined as the Spotmarket's Day-Ahead price

2.3 Bi-level optimization model

Subsequently, we developed an optimization model for local energy sharing. It is a bi-level optimization model (in the literature[20,21] also called Mathematical Program constrained by Equilibrium Problem (MPEC)). This type of model is understandable, as the model's lower level is a clearing process, including all consumers. The consumers are interested in satisfying their demand, in respect of maximizing their utility. As mentioned above, local generation is managed by an owner and pictured by the model's upper level. As he is in charge of operating the solar generation as well as the battery, a higher number or restrictions are necessary.

The MPEC is formulated as

$$
\begin{aligned}
\max_{\substack{\{p^O_{t,i}\}\\ \{q^G_{t,i}, q^{PV}_{t,i}, q^{B_{out}}_{t,i}\}}} \quad & rev^O = \sum_{t\in\mathcal{T}}\sum_{i\in\mathcal{N}} p^O_{t,i}(q^{PV}_{t,i} + q^{B_{out}}_{t,i}) + \sum_{t\in\mathcal{T}} p^{MCP}_t (q^{PV_{infeed}}_t + q^{B_{infeed}}_t) \\
\text{subject to} \quad & \sum_{t\in\mathcal{N}} q^{PV}_{t,i} + q^{PV_{infeed}}_t + q^{B_{in}}_t + q^{PV_{curtail}}_t = \bar{q}^{PV}_t \\
& SOC_t = SOC_{t-1} + q^{B_{in}}_t \eta^B - \sum_{i\in\mathcal{N}} q^{B_{out}}_{t,i}/\eta^B - q^{B_{infeed}}_t \quad \forall t \in \mathcal{T}\setminus\{0,T\} \\
& SOC_t = SOC^{init} \quad \forall t \in \{0,T\} \\
& 0 \le \sum_{i\in\mathcal{N}} q^{B_{out}}_{t,i} + q^{B_{infeed}}_t \le \bar{q}^B \\
& \sum_{i\in\mathcal{N}} q^{B_{out}}_{t,i} + q^{B_{infeed}}_t \le SOC_t \\
& 0 \le q^{B_{in}}_{t,i} \le \bar{q}^B \\
& \underline{SOC} \le SOC_t \le \bar{SOC} \\
& p^O_{t,i}, q^{B_{in}}_t, q^{B_{out}}_{t,i}, SOC_t \in \mathbb{R}^+ \\
& \max_{\{q^G_{t,i}, q^{PV}_{t,i}, q^{B_{out}}_{t,i}\}} \quad u^C_i = \\
& \qquad - \sum_{t\in\mathcal{T}} p^O_{t,i}(q^{PV}_{t,i} + q^{B_{out}}_{t,i}) + \sum_{t\in\mathcal{T}} p^G_{t,i} q^G_{t,i} \\
& \qquad - w^E_i \sum_{t\in\mathcal{T}} e^G_t q^G_{t,i} \\
& \qquad + w^{OSG}_i \sum_{t\in\mathcal{T}} q^{PV}_{t,i} + q^{B_{out}}_{t,i} \\
& \text{s. t.} \quad q^G_{t,i} + q^{PV}_{t,i} + q^{B_{out}}_{t,i} = q^L_{t,i} \quad (\lambda^L_{t,i}) \\
& \qquad\ \ q^G_{t,i}, q^{PV}_{t,i}, q^{B_{out}}_{t,i} \in \mathbb{R}^+ \quad (\mu^{G_{min}}_{t,i}, \mu^{PV_{min}}_{t,i}, \mu^{B_{min}}_{t,i})
\end{aligned}
\tag{4}
$$

[20] Steven A. Gabriel et al., *Complementarity modeling in energy markets* (New York, NY: Springer New York; Imprint: Springer, 2013)

[21] C. Ruiz and A. J. Conejo, "Pool Strategy of a Producer With Endogenous Formation of Locational Marginal Prices," *IEEE Transactions on Power Systems* 24, no. 4 (2009), doi:10.1109/TPWRS.2009.2030378

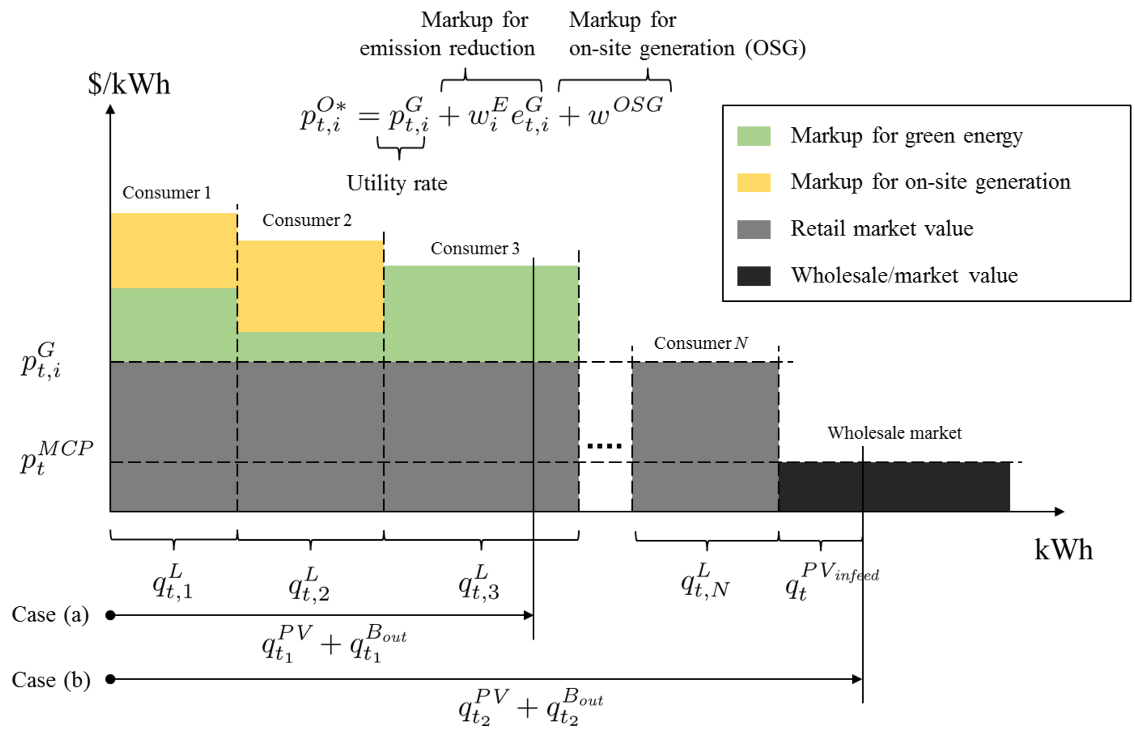

Figure 3: Local merit order, defined by the consumers' willingness to pay, while the wholesale market represents the backstop option in the case of a surplus generation. Two situations as shown: While case (a) with $\sum_i q_{t,i}^L > q_{t_1}^{PV} + q_{t_1}^{B_{out}}$ *shows case (b)* $\sum_i q_{t,i}^L < q_{t_2}^{PV} + q_{t_2}^{B_{out}}$.

A more detailed description of the model described in (4) can be found in Fleischhacker (2017)[22], and a comprehensive nomenclature in Appendix A. The model in this form is strongly nonlinear. Therefore, we use linearizing approaches for a successful implementation. Additional information regarding the linearization can also be found in Fleischhacker (2017).

The analytical solution of model (4), under the assumption of discriminatory auctions, indicates that the consumers are charged by their willingness to pay, defined as

$$p_{t,i}^{O*} = p_{t,i}^{G} + w_i^E e_t^G + w_i^{OSG} \tag{5}$$

Once the owner gets the consumers' preferences, he charges the consumer with their willingness to pay[23]. The equation (5) shows that the consumer preferences are added as markups to the utility rate $p_{t,i}^{G}$. Consequently, the preferences may be negative too[24], as $w_i^E, w_i^{OSG} \in \mathbb{R}$.

Figure 3 shows the merit order, which will be used by the owner for clearing purposes. Market price p_t^{MCP} defines the backstop price, whereas it is usually lower than the consumer's willingness

[22] A. Fleischhacker and A. Botterud, "Sharing solar PV and energy storage in apartment buildings: resource allocation and pricing," *Working paper*, 2017

[23] For a more detailed proof see Fleischhacker (2017).

[24] This is understandable as the consumer i is only willing to consumer local generation if it's price is lower than the utility rate. The owner would be willing to sell to this consumer, as long as $p_{t,i}^{O*} > p_t^{MCP}$.

to pay[25]. Emission reduction and on-site generation markups are added to the utility rate $p_{t,i}^{G}$ [26]. As the owner applies discriminatory prices, the consumers are ranked according to their willingness to pay $p_{t,i}^{O*}$. Furthermore, two cases are shown: (a) local generation is lower than consumption and (b) local generation is higher than consumption. In case (a) no feed-in is necessary as long as $p_{t,i}^{O*} > p_{t}^{MCP}$, while for case (b) feed-in, charging the battery or curtailment is necessary.

3 Illustrative example

For illustration, we will apply the framework to an exemplary day. As load data, we used six consumer load profiles from Massachusetts, measured by NREL[27]. As generation unit, we assume a single PV plant with a nominal power of 16.6 kWp. This plant size is equivalent to a roof area of 100 m^2[28]. Additionally, we consider a battery consisting of two Tesla Powerwalls[29]. For the utility rate, we assume two scenarios[30,31]:

- ***Flat tariff***: 0.12 $/kWh (energy component) plus 0.056 $/kWh as adjustments for transmission and distribution.
- ***Real-time pricing (RTP)***: Day-Ahead-Price with a markup of 0.013 $/kWh (energy component) plus 0.056 $/kWh as adjustments for transmission and distribution.

As wholesale prices affect the local dispatch, we used three representative days, in the following labeled as ***low***, ***base*** and ***high***[32]. Other essential inputs of the model are the emissions of grid procurement. We are using the marginal emissions rather than the system's average emissions. In that way, the value of additional consumption or generation is more accurate. As the ISOs or TSOs do not publish marginal emissions, we assume a merit-order based approach to calculate the marginal emissions. Therefore, we assumed following technologies: (i) RES and nuclear with 0 kg_{CO2}/MWh, Lignite with 1100 kg_{CO2}/MWh, Coal with 880 kg_{CO2}/MWh, Gas with 400 kg_{CO2}/MWh and Peak generation with 650 kg_{CO2}/MWh.

As shown in Figure 4, the relationship between Day-Ahead prices and emissions is used to calculate the marginal emissions as the emissions of the "price-setting" power plant of the three representative days. As the relationship between Day-Ahead prices and emissions is nonlinear, low prices do not automatically lead to low marginal emissions. Marginal emissions are highest at periods of Lignite generation.

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[25] Under the assumption of $p_{t,i}^{G} \geq p_{t}^{MCP}$ and $w_{i}^{E}, w_{i}^{OSG} \in \mathbb{R}^{+}$.

[26] For the sake of simplicity, utility rate of all consumers is equal, as $p_{t,i}^{G} = p_{t}^{G}$.

[27] N. Blair et al., "System Advisor Model, SAM 2014.1.14: General Description" (NREL/TP-6A20-61019, National Renewable Energy Laboratory, 2014), http://www.nrel.gov/docs/fy14osti/61019.pdf

[28] Andy Schroder, "Determination of annual optimal altitude and azimuth angles of fixed tilt solar collectors in the continental united states using the national solar radiation database," *Proceedings of the ASES National Solar Conference*, 2011, accessed 08.2017

[29] Tesla, "Powerwall," accessed 07.2017, https://www.tesla.com/powerwall

[30] City of Palto Alto, "RESIDENTIAL ELECTRIC SERVICE: UTILITY RATE SCHEDULE E-1," accessed 07.2017, http://www.cityofpaloalto.org/civicax/filebank/documents/8089

[31] Power Smart Pricing, "A smart electricity rate," accessed 08.2017, https://www.powersmartpricing.org

[32] Agora Energiewende, "Agorameter," accessed 07.2017, https://www.agora-energiewende.de/en/topics/-agothem-/Produkt/produkt/76/Agorameter/

In the previous section, we introduced the weights for emissions w_i^E and OSG w_i^{OSG}. Consequentially, we will assume following two scenarios for consumer preferences:

- ***Green consumers***: $w_i^E = [0.025, 0.05, 0.075, 0.1, 0.125, 0.15]$ \$/kg$_{CO2}$ and $w_i^{OSG} = 0, \forall i$.
- ***OSG consumers***: $w_i^{OSG} = [0.025, 0.05, 0.075, 0.1, 0.125, 0.15]$ \$/kWh and $w_i^E = 0, \forall i$.

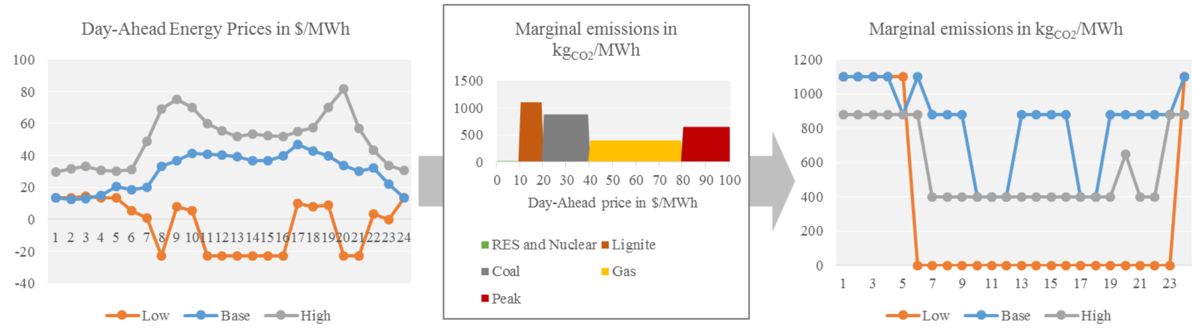

Figure 4: Marginal emissions of three representative days resulting from a static merit order.

The model was implemented in the Python framework Pyomo[33] and solved by Gurobi 7.0.2[34].

4 Results and discussion

In the following section, we apply the model, introduced in Section 2, on the data of Section 3. Firstly, we will show the resulting energy allocation of one day. Secondly, we analyze the effects of the consumers' utility and the owner's revenues. Additionally, thirdly, we will have a look at the corresponding prices. Fourthly, we will briefly investigate possible effects on the system.

As the input data does not originate from a single source only, consistency may not be fully given. Nevertheless, the objective of this paper is rather to give a first insight of the model's functionality and performance. Therefore, the results of this section shall mainly identify coherencies between model inputs, parameters, and outputs.

4.1 Energy allocation of one illustrative day

Figure 5 shows the results for one illustrative day, by investigating the green consumers' scenario. While consumer 6 values emission reduction most, weights for emission reduction are decreased up to consumer 1. Consequentially, energy is first delivered to consumer 6, followed by consumer 5 etc. The dispatch is based on the merit-order shown in Figure 3.

Whereas the allocation of solar generation is rather easy (e.g., by applying the idea of Figure 3), the inclusion of flexibility (e.g., by a battery) makes the analysis more difficult. As the battery is used as a flexible resource, the use of an optimization model (4) is necessary to calculate the optimum.

[33] William E. Hart et al., *Pyomo -- Optimization Modeling in Python*, 2nd ed. 2017, SpringerLink Bücher (Cham: Springer, 2017)
[34] Gurobi Optimization Inc., *Gurobi Optimizer Reference Manual* (2016), http://www.gurobi.com

Both values, of local generation and battery discharge are equal in a certain period.

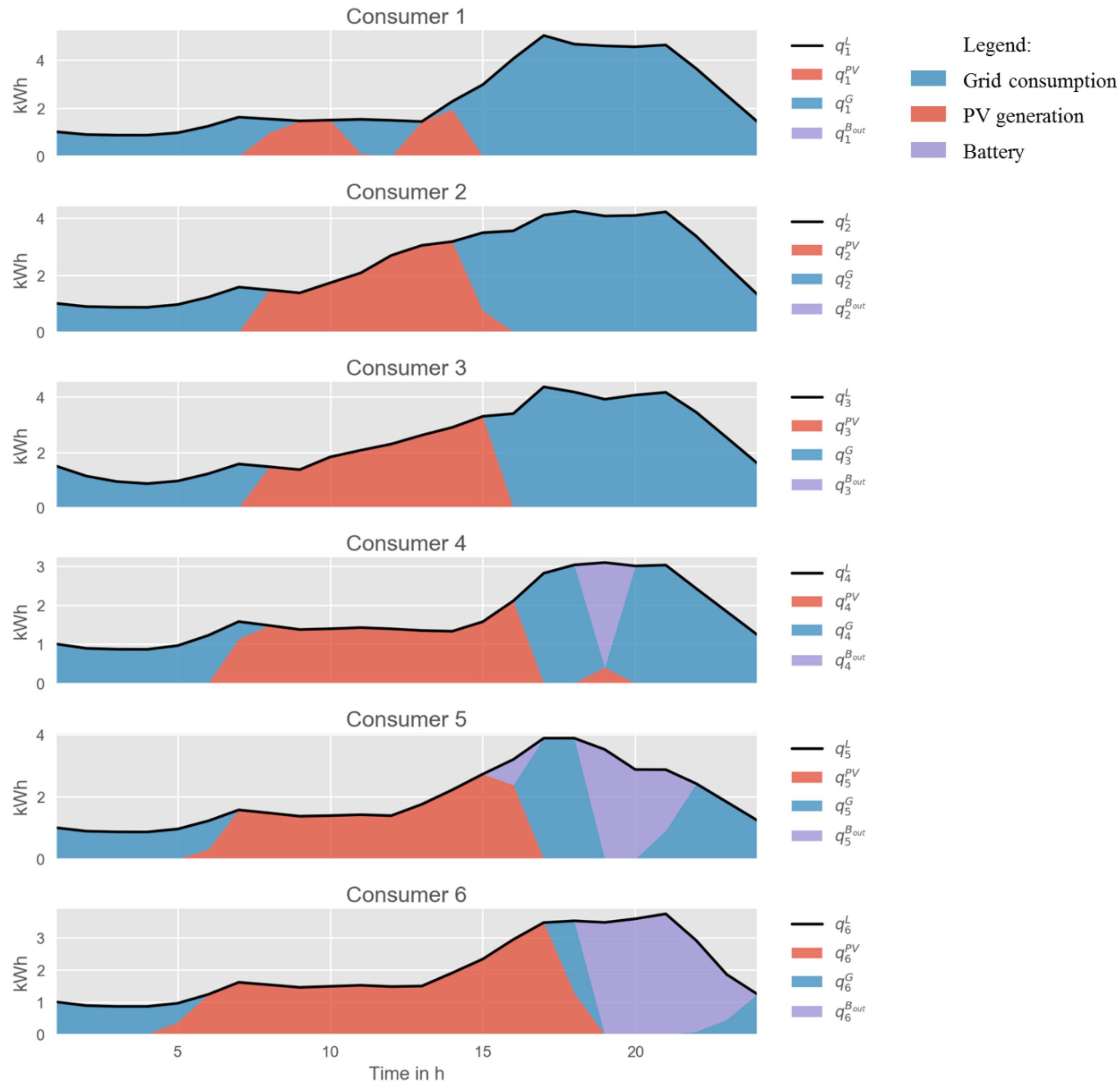

Figure 5: Energy allocation for green consumers. Scenario: high price and flat tariff.

4.2 Effect on the consumers' utility and the owner's revenues

In the presented framework the owner is able to identify the consumer's willingness to pay and consequentially add this value to the applied price. The effect of this allocation is shown in Figure 6.

As status quo (without shading) shows the results of the illustrative day without local generation, the owner does not have any revenues. On the other side, the consumers do have a negative utility, because energy consumption results in costs (which the consumer tries to minimize) and emissions (which the consumer tends to minimize too). As introduced in Section 3, consumer 1 values emission reduction lowest, whereas consumer 6 values emission reduction highest. Therefore, consumer 6 is affected from local emission mostly.

In the case of local generation (shaded plots in Figure 6), the consumers still have the same (negative) utility, but the weight changed. The owner set the prices for consumers by applying. On the one hand, local generation is reduced, but on the other hand, electricity procurement costs are increased. In total, the consumer utility with PV and battery is equal to status quo.

From the owner's perspective, revenues are maximized by applying the proposed framework (4). Figure 6 shows the revenues on the left-hand side.

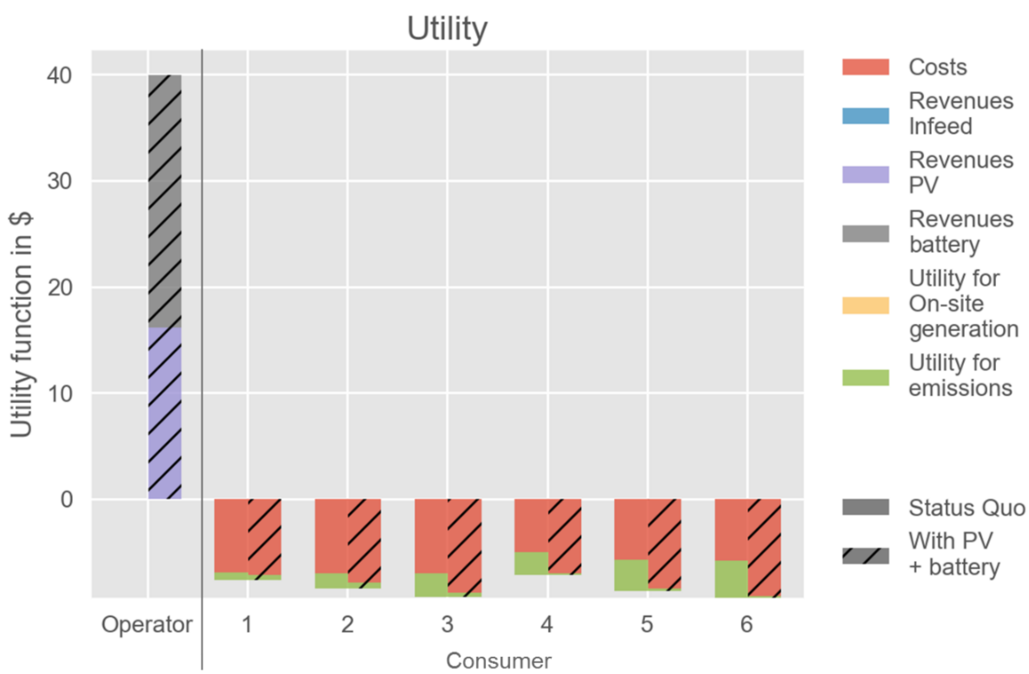

Figure 6: Owner revenues (left) and utility of consumer 1-6 (right). With and without DER (consisting of PV and battery). Scenario: green consumer, high price, flat tariff

4.3 Prices for locally generated electricity for discriminatory and uniform auctions

The following results address the questions about how the local discriminatory prices for the consumers look. The following Figure 7 and Figure 8 show the prices applied to the consumers. As indicated in Equation (5), markups for emission reduction is dependent on time as $e_t^G w_i^G$, while markups for OSG w_i^{OSG} are constant for all time periods. As there are periods without emissions (such as in the noon of the low scenarios), the equilibrium in these periods is not unique. On the other hand, any weights for OSG have a permanent effect.

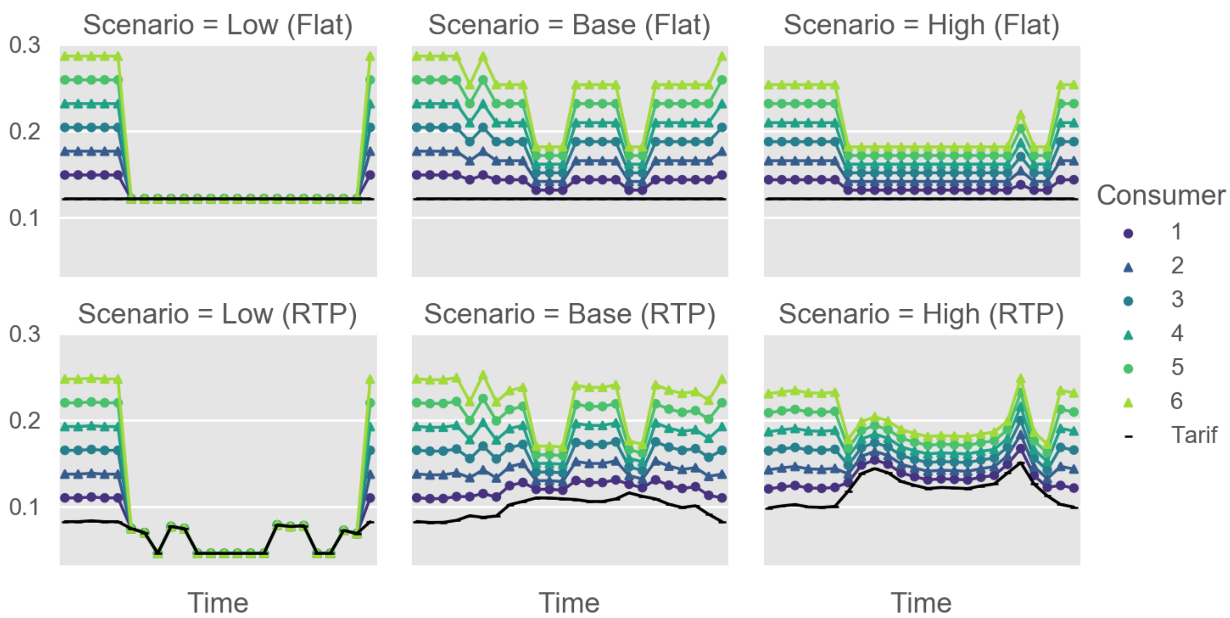

*Figure 7: Local prices $p_{t,i}^{O*}$ for **green consumers** and all scenarios.*

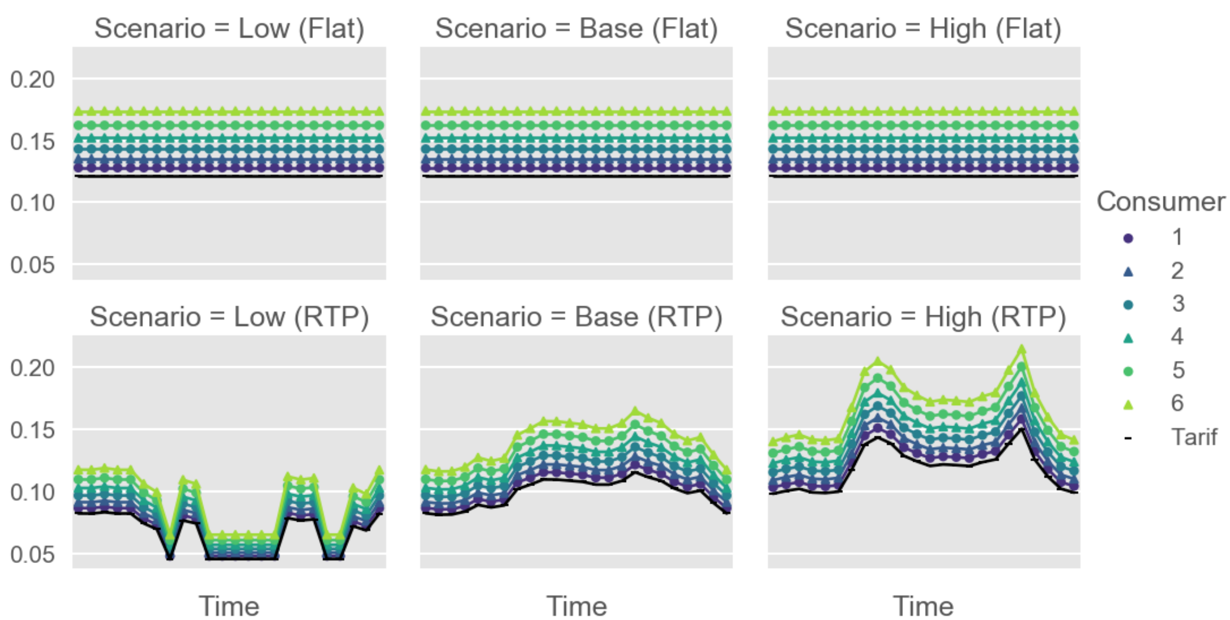

*Figure 8: Local prices $p_{t,i}^{O*}$ for **OSG consumers** and all scenarios.*

4.4 Effects on the system

Lastly, we will have a look at the effects of the system. Therefore, we introduce some key-performance indicators (KPI)

- ***Peak load***: the peak load of grid consumption, as $p^{G} = \max\left(\sum_i p_{t,i}^{G}\right)$.

- ***Peak-to-Average Ratio***: the ratio of peak load to average grid consumption $\overline{p}_t^G$ $\overline{p}_t^G = \sum_i \sum_t p_{t,i}^G / T$, defined as $PAR = p_i^G / \overline{p}_i^G$ with T as a number of time periods.
- ***Correlation coefficients*** [35] of grid consumption to PV generation $\rho^{G,PV}$ and grid consumption and wholesale market price $\rho^{G,MCP}$.
- ***Emissions*** caused by grid consumption.

As shown in the KPIs description, we do not investigate single consumer, rather the sum of all consumers is used for the calculation. Figure 9 shows the results. The peak load gets mainly reduced, except for low electricity prices and RTP. The reason is that the battery is charged via the grid during zero-emission periods[36], which can cause an increase even in peak load periods[37]. Consequentially, the PAR during this hours gets increased too. While the average consumption $\overline{p}_t^G$ gets reduced by local generation, PAR gets reduced, even if the peak load remains on the same level.

If the battery is not charged via the grid, neither the peak load nor PAR will be increased. As stated in the literature, ERCOT is a summer peaking system[38]. Therefore, solar generation contributes in reducing the system's peak, even though no flexibility is used.

For the correlation coefficients, we observe a substantial decrease (thereby anti-correlation), above 40 % for grid consumption and PV generation. Regarding the correlation coefficients of grid consumption and the wholesale market price, we see a reduction in the scenarios base and high and an increase for the scenario low. It is a result of reduced grid consumption during periods of high market prices. Obviously, the effect is more distinct at RTP than for flat pricing.

Emissions as shown in Figure 10, indicate that the emissions get reduced, whether the pricing is flat or RTP. As local renewable generation is a zero-emission technology[39], emissions are reduced. For the low scenario, no further emission reduction could be achieved, because the system's marginal emissions are zero during noon. Highest emissions reduction could be achieved for the base scenario, as coal-based generation could be substituted.

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[35] The correlation coefficients are defined as $\rho^{x,y} = E\left[\left(x-\overline{x}\right)\left(y-\overline{y}\right)\right] / \sigma_x \sigma_y$ with the mean value $\overline{x}$ and $\overline{y}$, the expected value $E[...]$ and the covariance σ^x and σ^y.

[36] The authors are aware that feasible battery charging schemes are manifold. As one of this paper's topics is to address emission reducing, we investigate emission reduction based battery charging algorithms.

[37] Hereby it also depends on the consumers' objective. If the consumer is willing to pay for emission reduction, the battery may be charged during periods with low grid emission too.

[38] Paul Denholm and Maureen Hand, "Grid flexibility and storage required to achieve very high penetration of variable renewable electricity," *Energy Policy* 39, no. 3 (2011), doi:10.1016/j.enpol.2011.01.019

[39] At least on an operational basis.

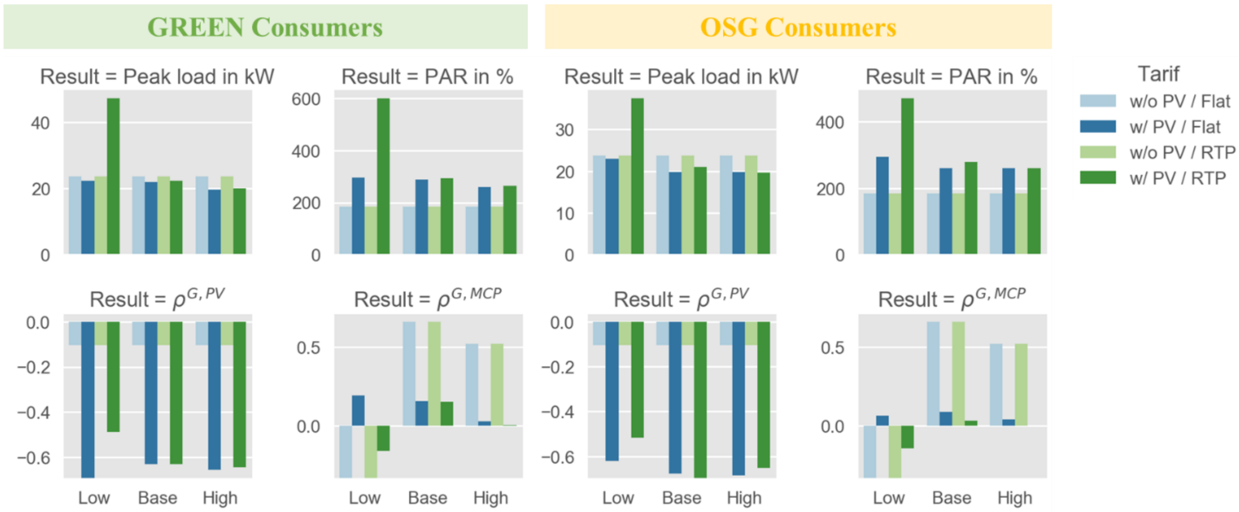

Figure 9: Effects on the system for green (left) and OSG consumers (right).

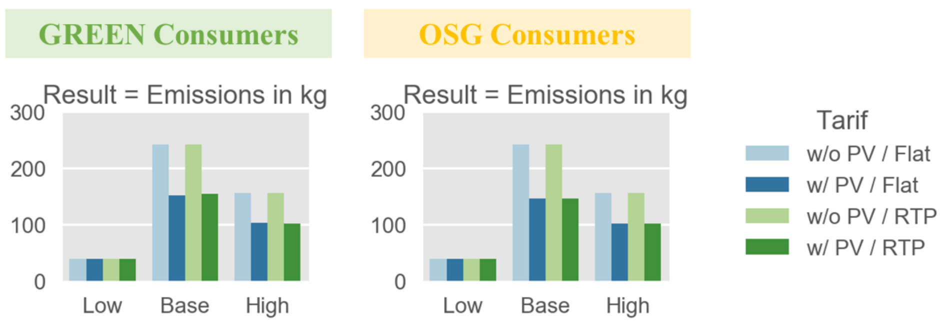

Figure 10: Emissions for green (left) and OSG consumers (right).

5 Conclusions

In this work, we have developed a mathematical framework for sharing distributed energy resources. We described each consumer's preferences by its values for emission reduction and on-site generation. The results show that an equilibrium based on the consumers' preferences could be calculated.

Consequentially, we applied the proposed model to an illustrative example. The results indicate that the framework is highly beneficial to the owner's revenues. Consumers' preferences for local generation and emissions reductions lead to local prices exceeding the utility rate. Hence, higher revenues can be achieved for the PV/battery owner. Increased revenues of DER may stimulate investments in PV solar generation and batteries, without the need for additional subsidy mechanisms.

From the consumers' perspective, our results show that a consumer's aggregate utility tends to stay constant by the application of the proposed energy allocation algorithm, whereas the composition of the utility function changes. By allowing the consumers to express their preferences for different criteria, an improved allocation of energy is achieved. In the case that consumers are not willing to pay more than the utility rate, the framework gives the same price to local and grid resources. This can be considered a lower benchmark, with no additional revenue for the solar PV and storage system. The proposed algorithm captures the local competition among the consumers for green and locally generated electricity. However, the question of potential strategic behavior (e.g., by hiding the true willingness-to-pay) is not considered in the current algorithm and is an interesting direction for future research.

As the effects on the system are also studied in this work, we conclude that total emissions are reduced (mostly because of solar generation). The building may become less predictable with the possibility of increases (or decreases) in peak load and Peak-to-Average ratio.

Finally, to address the question we pose in the title of this paper, the most as accurate answer would be “The highest-payer takes most of it!”.

Appendix: Nomenclature

Abbreviations

A Aggregator

B Battery

C Consumer

E Emissions

G Grid

L Load (energy demand)

MCP Market clearing price

OSG On-site generation

PV Photovolatic plant

Sets

$i \in \mathcal{I} = \{1, \ldots, N\}$ Consumer/tenants

$t \in \mathcal{T} = \{1, \ldots, T\}$ Time periods e.g. hours

Upper level decision variables

SOC_t Battery state of charge

$p_{t,i}^{B_{out}}$ Price for PV procurment applied to consumer i

$p_{t,i}^{PV}$ Price for PV procurment applied to consumer i

p_t^U Uniform price for PV and battery applied to all consumers

$q_{t,i}^{B_{in}}$ Power flow into the battery

$q_t^{PV_{curtail}}$ Power curtailment (of PV generation)

$q_t^{PV_{infeed}}$ Power feed (of PV generation) into the grid

Lower level decision variables

$costs_i$ Electricity costs of consumer i

$emissions_i$ Emissions caused by the electricity consumption of consumer i

osg_i Local generated electricity consumed by consumer i

$\lambda_{t,i}^L$ Dual variable of supply = demand constraint

$q_{t,i}^{B_{out}}$ Power flow from battery to consumer i

$q_{t,i}^G$ Power flow from grid to consumer i

$q_{t,i}^{PV}$ Power flow from PV plant to consumer i

u Utility of all consumers

u_i Utility of consumer i

Parameters

$q_{t,i}^L$ Load of consumer i

w_i^E Individual weight for emissions of consumer i in $\$/\mathrm{kg}_{CO_2}$

w_i^{OSG} Individual weight for on-site generation of consumer i in $\$/\%^{OSG}$

$\bar{q}^B$ Maximum charging and discharging battery power

$\bar{q}_t^{PV}$ Electricity generation of PV plant

η^B Efficiency factor of the battery

SOC^{init} Initial and end state of charge for period $\mathcal{T}$

$\overline{SOC}$ Maximum state of charge

$\underline{SOC}$ Minimum state of charge

p_t^{MCP} Wholesale market clearing price

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